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Article

Can Corporate Digital Transformation Reduce Stock Price Crash Risk? Evidence From China

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Abstract

Digital transformation has emerged as a key strategy for companies seeking competitive advantage, yet our understanding of how it affects capital market stability remains limited. Using data from China spanning 2007–2024, this paper shows that corporate digital transformation significantly reduces future crash risk. This conclusion remains robust after controlling for historical communication technology as an instrumental variable, accounting for exogenous shocks from digital economy policies, and addressing potential omitted variable bias. We provide evidence that corporate digital transformation reduces crash risk by lowering corporate opacity, improving the quality of internal controls, and strengthening operational resilience. Furthermore, we find that the effect is stronger among smaller firms, firms with lower institutional ownership, firms facing more intense market competition, and firms operating in regions with more developed digital infrastructure. This study demonstrates how digital transformation can act as a stabilizer of stock prices.

Keywords: corporate digital transformation; stock price crash risk; corporate opacity; internal control; operational resilience
JEL: G34, M21, M41

1. Introduction

At present, the digital technology revolution, represented by artificial intelligence, blockchain, cloud computing and big data, is profoundly reconstructing the global economic pattern. According to data from the China Academy of Information and Communication Research, the scale of the global digital economy will reach 50 trillion dollars in 2024, accounting for more than 40% of gross domestic product (GDP). Under this wave, digital transformation has jumped from a technological tool to a core strategic paradigm for the high-quality development of enterprises (He et al., 2024; Skare and Soriano, 2021). Specifically, enterprise digital transformation reshapes the enterprise value chain through the three dimensions of process intelligence (e.g., intelligent manufacturing systems can reduce production variance), decision-making data (e.g., customer behavior analysis optimizes resource allocation), and service ecology (e.g., industrial internet platform integrates the industrial chain) (Li et al., 2024; Verhoef et al., 2021; Wu et al., 2019). Notably, the Chinese government has positioned digital transformation as a national strategy, and the 14th Five-Year Plan for the Development of the Digital Economy explicitly proposes “promote the in-depth integration of the Industrial Internet and empower the innovation efficiency of the real economy”. At the micro level, leading companies such as Huawei and Haier have achieved operating profits through territory-wide digital transformation, confirming the foundational role of enterprise digital transformation in sustainable competitive advantage.

The literature has also extensively explored the economic consequences of corporate digital transformation. For instance, empirical evidence indicates that digital transformation can increase corporate investment rates by reducing transaction costs and empowering long-tail markets, thereby improving operational performance (Fang and Ju, 2024; Li et al., 2023; Mikalef et al., 2020). Simultaneously, digital transformation can foster technological innovation through knowledge spillovers and open innovation platforms (Li et al., 2024; Zhang et al., 2023). In recent years, given the growing prominence of financial security concerns, an increasing number of studies have examined how corporate digital transformation impacts capital market stability, particularly stock price crash risk. Such risks stem from the concentrated release of long-concealed negative corporate information (Chen et al., 2024; Hutton et al., 2009; Kim and Zhang, 2016), which has substantial negative effects on capital market stability. Wu et al. (2022) demonstrate that enhanced levels of corporate digital transformation help mitigate crash risk. Liang and Zhao (2024) further specify that the mechanism through which digital transformation reduces stock price crash risk lies in its ability to improve internal governance and increase analyst attention. Zhu et al. (2023) also report that firm ownership structure and industry characteristics significantly moderate this relationship. However, Ai et al. (2023) observe an inverted U-shaped relationship between digital transformation and stock price crash risk, attributing this to heightened information asymmetry during the initial stages of digital transformation, which subsequently diminishes as transformation deepens. These differences indicate that the relationship between the two warrants further exploration. Notably, existing studies predominantly utilize data from 2021 and earlier, failing to capture the full trajectory of corporate digitalization as it transitions from the technology investment phase to the business integration phase (Chen and Alexiou, 2025). A report by the international institution Gartner indicates that since 2021, beyond traditional digital economy sectors such as the internet, Chinese enterprises in finance, retail, and high-end manufacturing have achieved increasing maturity in digital transformation. A growing number of companies have advanced beyond automation upgrades, data-driven transformations, and management process reforms. Therefore, whether digital transformation can continue to serve as a "stock price stabilizer" remains to be tested. More importantly, the causal mechanisms linking corporate digital transformation to collapse risk remain unclear, and discussions on heterogeneity are notably scarce. For instance, the literature focuses primarily on the enhancement of information transparency and internal governance by digitalization and often overlooks its unique characteristics. These include its advantages in optimizing corporate governance and market oversight, improving risk prediction and response capabilities, and strengthening knowledge management and innovation capacity—thereby bolstering resilience against external shocks. Furthermore, heterogeneity analyses in prior research have largely been based on general corporate characteristics and have failed to highlight differences in digitalization contexts. Such variations also affect the effectiveness of digital transformation outcomes.

Given this, we collect data from Chinese listed firms from 2007 to 2024 to re-examine this issue. We believe that China's context is highly suitable for our research. First, China's digital economy policies have deepened in recent years, with enterprises exhibiting a transformation from technology investment toward deeper business integration. First, as of 2024, China's digital economy has grown to 7.9 trillion U.S. dollars, representing 42.8% of GDP—a figure that underscores its central role in the national economy. Additionally, the results of the fifth national economic census reveal that a significant proportion of enterprises have integrated digital and information technologies into all aspects of their production and operations, with corporate digital transformation steadily deepening and solidifying. Notably, development across China's regions remains uneven, with notable disparities in factor inputs and infrastructure. Therefore, investigating the consequences of corporate digital transformation within China's context holds strong practical significance. Second, stock price synchronization is high in the Chinese stock market, and tail risks occasionally occur (Ni and Jin, 2024). Notably, despite over three decades of development, China's capital market remains imperfect and is characterized by a high proportion of retail investors and widespread irrational investor behavior (Jones et al., 2025; Ju et al., 2024). These factors provide favorable conditions for exploring the differentiated consequences of digital transformation and clarifying the underlying determinants of crash risk. Using firm-level data, this paper reveals that corporate digital transformation helps reduce future crash risk through three channels: enhancing corporate transparency, improving the quality of internal controls, and reducing earnings volatility. A heterogeneity analysis indicates that digital transformation has a stronger effect when firms are smaller and have lower levels of institutional ownership. Moreover, the stabilizing effect of digital transformation on stock prices is particularly strong in highly competitive markets and regions with advanced digital infrastructure.

This study contributes to the literature by first examining the link between corporate digital transformation and stock price crash risk. Using a long sample spanning from 2007–2024, we find that as companies advance into the business integration phase of digitalization, they move beyond the stage dominated by initial agency costs. The main effect exhibits a stable linear negative correlation, which is in direct contrast with the findings of Ai et al. (2023) and aligns with the mainstream literature. More importantly, we deepen the understanding of the differentiated consequences of digital transformation for crash risk. Our findings reveal that the economic impact of digital transformation depends on firm-specific traits as well as market and regional conditions. These insights provide more actionable implications for regulators on how to better leverage the advantages of digital transformation. Second, while prior studies on crash risk determinants have focused primarily on traditional perspectives such as management characteristics, this research adopts a dynamic strategic transformation lens. Specifically, digital transformation addresses the lag in traditional governance's ex post oversight through real-time data processing, offering a novel analytical framework for dynamic risk management. For instance, beyond Chen and Alexiou's (2025) emphasis on market transparency, this study further reveals that digitalization can proactively curb negative information accumulation through real-time internal control optimization. This logic transcends the traditional single-framework approach that links information disclosure to risk mitigation. Additionally, we clarify that digital transformation reduces crash risk by lowering corporate earnings volatility—a mechanism not independently identified in existing research.

2. Hypothesis Development

Stock price crash risk refers to the likelihood of a sudden, severe decline in stock value. According to the information concealment hypothesis, managers may delay the release of negative news—such as poor earnings or volatility—to sustain short-term price stability. This causes negative information to accumulate and eventually be released all at once, triggering a crash (Hutton et al., 2009; Kim et al., 2011). Digital transformation refers to the adoption of digital technology by firms to improve business processes, business models, and customer experience for intelligent development, which empowers firms to collect and process information more efficiently. We believe that digital transformation, through technological empowerment, reshapes three key aspects of enterprises: information transmission, internal governance, and operational resilience. This approach curbs the accumulation of negative information and the outbreak of risks at their source.

First, corporate digital transformation can enhance information transparency and thus reduce management's bad news-hiding behavior. Digital technology systems can automate the capture and nontampering of operational data, significantly reducing the likelihood of human intervention in the generation of information. Such technological features force management to abandon selective disclosure strategies, thereby curbing the opportunity for financial whitewashing and information distortion at the source (Plekhanov et al., 2023). Furthermore, digitalization drives the standardization and structuring of information disclosure. Artificial intelligence (AI)-powered intelligent disclosure platforms can parse vast amounts of operational data to generate risk disclosure information in a unified format (such as digital transformation progress and risk explanations in annual reports), embedding it into mandatory disclosure documents and significantly reducing information decoding costs. This enables external investors and analysts to quickly and accurately grasp a firm's true operational status, reducing the opportunities for management to conceal negative information through textual complexity (Liang and Zhao, 2024).

Second, corporate digital transformation can reshape internal control paradigms and enhance risk prediction and response capabilities. Traditional internal controls rely on sampling audits and manual oversight and suffer from shortcomings such as incomplete coverage and delayed responses. Digital transformation, however, leverages technology to reconstruct internal control systems, shifting from passive error correction to proactive risk prevention. For instance, smart contract technology embeds governance rules directly into business processes. Enforcing procedural compliance, it ensures rigid rule execution, eliminating opportunities for management to abuse discretionary power. This reduces violations and negative disclosures stemming from internal control failures. Furthermore, digitalization enhances corporate risk forecasting capabilities. Big data analytics integrates internal and external data (e.g., industry cycles and market demand fluctuations) to precisely identify potential risk points, enabling enterprises to formulate proactive countermeasures (Li et al., 2023). Compared with traditional internal control post-event remediation models, digitalized controls reduce risk occurrence probabilities at the source, minimizing the generation and accumulation of negative information.

Third, digital transformation helps enterprises reduce profit volatility and enhance their operational resilience against external shocks. Profit fluctuations—such as underperforming results or declining earnings—are significant sources of negative information accumulation. Digital transformation strengthens knowledge management and innovation capabilities, thereby improving resilience to external shocks and stabilizing profit levels. First, enterprises accelerate technological iteration and product innovation through digital platforms that enable internal knowledge sharing and external knowledge spillover integration (Merín-Rodrigáñez et al., 2024). For instance, big data analytics precisely pinpoints customer needs and guides product development and market strategy adjustments to avoid profit fluctuations caused by misguided decisions. Second, amid heightened external uncertainties—such as post-pandemic market volatility and policy adjustments—digitally transformed enterprises can swiftly adapt through flexible organizational structures. When profitability remains consistently stable, management has no need to conceal negative information to mask declining performance. Investors develop more stable expectations, making it less likely that localized negative news triggers panic selling in the market and thereby mitigating the risk of stock price collapse.

Notably, regarding the debate over the inverted U-shaped relationship between digital transformation and stock price crash risk proposed by Ai et al. (2023), this study argues that this conclusion primarily applies to the early technology investment phase of digitalization, where organizational restructuring and increased agency costs may temporarily increase risk. However, extending the sample period to 2024 covers the business integration phase of Chinese enterprise digitalization. By this stage, companies have completed organizational adaptation and technology implementation, significantly alleviating initial agency cost issues. Consequently, the main effect of digital transformation on crash risk exhibits a stable linear negative correlation. Therefore, we propose the following:

H1: Corporate digital transformation can reduce stock price crash risk.

3. Research Design

3.1 Sample

We select a sample of listed companies in the China Stock Market and Accounting Research Database for the years 2007–2024. Specifically, the Stock Market Transactions subdatabase was used to calculate individual stock crash risk; the Financial Ratio Analysis subdatabase provided company financial data; and the Governance Structure subdatabase supplied corporate governance-related information. Additionally, textual data for digital transformation calculations originated from the Giant Tide Information Network. The internal control quality data were sourced from the China Listed Companies Internal Control Index published by Dibo. We subsequently conducted sample screening. First, we excluded financial firms from the sample, as their financial metrics exhibit significant logical differences from those of nonfinancial companies. Second, to ensure sample quality, following Xu et al. (2014), we removed samples with fewer than 30 trading weeks within the year. Samples with fewer than 30 trading weeks may fail to reflect the full volatility characteristics of the stock market, potentially leading to nonrepresentative results. Third, to ensure completeness, we excluded samples with missing values for key variables. Fourth, we removed samples of companies labeled as ST, *ST, or PT because of consecutive losses or delisting, as these data may exhibit anomalies and lack representativeness. We end up with 41,826 observations. We also winsorize the firm-level continuous variables at the 1% and 99% levels to overcome the effect of extreme values.

3.2 Variable Definitions

3.2.1 Stock Price Crash Risk

Following existing research (Kim et al., 2011; Kim and Zhang, 2014; Kim and Zhang, 2016; Xu et al., 2013; Xu et al., 2014), we use two measures of stock price crash risk, the negative stock return skewness coefficient (*NCSKEW*) and the "down-to-up" volatility ratio (*DUVOL*). First, we utilize the weekly return data of stock i to calculate the market-adjusted return of stock i according to Eqn. 1:

$$r_{i,t} = \alpha_i + \beta_1 r_{M,t-2} + \beta_2 r_{M,t-1} + \beta_3 r_{M,t} + \beta_4 r_{M,t+1} + \beta_5 r_{M,t+2} + \varepsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is the return of stock i in week t and $r_{m,t}$ is the average return of the A-share market in week t weighted by the outstanding market capitalization. Defining $W_{i,t}$ as the market-adjusted return of stock i in week t, we have the following:

$$W_{i,t} = ln\left(1 + \varepsilon_{i,t}\right) \tag{2}$$

where $\varepsilon_{i,t}$ are the residual terms from the results of Eqn. 2.

NCSKEW is calculated as shown in Eqn. 3, where n is the number of trading weeks for stock i in year t. If the yield distribution is negatively skewed, i.e., if the left tail is longer and thicker than the right, it means that there is a higher probability of extreme negative yields and a greater likelihood of a crash.

$$NCSKEW_{i,t} = -\left[n\left(n-1\right)^{3/2}\sum W_{i,t}^3\right] / \left[\left(n-1\right)\left(n-2\right)\left(\sum W_{i,t}^2\right)^{3/2}\right] \tag{3}$$

DUVOL is calculated as shown in Eqn. 4, with n_u denoting the number of weeks when stock i returns are above the average annual return and n_d denoting the number of weeks when stock i returns are below the average annual return. If a stock is significantly more volatile on the downside than on the upside, the market is reacting more strongly to negative information about the stock, and the crash risk is relatively high.

$$DUVOL_{i,t} = \log\left\{\left[\left(n_u - 1\right)\sum_{Down} W_{i,t}^2\right]\right\} / \left[\left(n_d - 1\right)\sum_{Up} W_{i,t}^2\right] \tag{4}$$

3.2.2 Digital Transformation

In general, companies' annual reports contain crucial information regarding development strategies such as digital transformation. Therefore, following Fang and Ju (2024) and Song et al. (2024), we measure digital transformation through the frequency of terms related to it in company annual reports. Combining the technical characteristics of digital transformation with text analysis standards, the variable construction process is as follows: First, we use Python (Version 3.12; Python Software Foundation, Wilmington, DE, USA) technology to crawl the annual reports of A-share listed companies from 2007 to 2024 from the China Securities Information Network and convert them into editable text.

We subsequently retained only three core sections from the annual reports: Management Discussion and Analysis, Review of Operating Conditions, and Future Development Plans, excluding non-core parts such as summaries, notes to financial statements, and legal statements. Additionally, we removed numbers, English letters, and other nonsubstantive words from the text. Second, we categorize digital transformation keywords into two tiers based on foundational technologies and application scenarios—the foundational technology layer (artificial intelligence, big data, cloud computing, and blockchain) and the practical application layer (smart manufacturing, digital marketing, industrial internet, etc.). This ensured comprehensive coverage of both the technological investment and business integration scenarios while also consolidating synonyms and similar expressions into unified categories. Third, we count the cumulative occurrences of digital keywords in the cleaned text. To mitigate the impact of outliers (high keyword repetition in some annual reports), we added 1 to the raw word frequency and took the natural logarithm, yielding the digital transformation index (*Digital*). We also randomly selected annual report samples for manual verification, confirming the high consistency between human and machine counts.

Notably, using annual report word frequency as a measure of digital transformation may reflect textual disclosure levels rather than actual transformation levels. Therefore, we also employed alternative indicators such as digital capital expenditures, digital-related research and development (R&D) expenses, digital-related patent counts, or the proportion of digital assets within the enterprise to conduct subsequent robustness tests.

3.2.3 Mechanism Variables

Our first mechanism variable is firm opacity (*AbsDA*). Following Wen et al. (2019), we measure opacity using the absolute value of manipulated accruals. The construction process is shown in Eqns. 5,6,7:

$$\frac{TA_{i,t}}{A_{i,t-1}} = \beta_0 \frac{1}{A_{i,t-1}} + \beta_1 \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}} + \beta_2 \left(\frac{PPE_{i,t}}{A_{i,t-1}} \right) + \varepsilon_{i,t} \tag{5}$$

$$NDA_{i,t} = \hat{\beta}_0 \frac{1}{A_{i,t-1}} + \hat{\beta}_1 \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}} + \hat{\beta}_2 \left(\frac{PPE_{i,t}}{A_{i,t-1}} \right) + \varepsilon_{i,t} \tag{6}$$

$$DA_{i,t} = \frac{TA_{i,t}}{A_{i,t-1}} - NDA_{i,t} \tag{7}$$

where *TA* denotes total accrued profit, measured as net profit minus operating cash flow; *A* represents total assets; $\triangle REV$ indicates the change in operating revenue; $\triangle REC$ signifies the change in accounts receivable; and *PPE* denotes net fixed assets. We perform industry-specific and year-specific regressions on Eqn. 5 and then substitute the obtained regression coefficients into Eqn. 6 to derive non-manipulated accruals (*NDA*). We subsequently substitute *NDA* into Eqn. 7 to obtain manipulable accruals (*DA*). A larger absolute value of *DA* indicates greater room for earnings management and reduced corporate transparency. We define the absolute value of the *DA* as *AbsDA*.

Our second mechanism variable is internal control quality (*IC*). Following Jin (2024), we use Dibo's internal control index to assess internal control quality. A higher value of this index indicates superior internal control quality. The index provides a comprehensive evaluation centered on the five elements of internal control, offering broad coverage and strong integration to effectively reflect the actual state of corporate internal controls.

Our third mechanism variable is operational resilience, measured by profit volatility (*Violat*). Following Deng et al. (2023), we use the rolling standard deviation of a firm's Earnings Before Interest, Taxes, Depreciation, and Amortization (*EBITDA)* margin over the past four years to represent profit volatility. The calculation is as follows:

$$Volat_{i,t} = \sqrt{\frac{1}{T-1} \sum_{t=1}^{T} \left(E_{i,t} - \frac{1}{T-1} \sum_{t=1}^{T} E_{i,t} \right)^2} \mid T = 4 \tag{8}$$

$$E_{i,t} = \frac{EBITDA_{i,t}}{A_{i,t-1}} \tag{9}$$

Eqn. 8 yields the profitability volatility measure *Volat*, where the input variable E is defined in Eqn. 9 as the firm's EBITDA margin. Substituting E from Eqn. 9 into Eqn. 8 completes the calculation, and a lower Volatility indicates greater corporate resilience.

3.2.4 Control Variables

Following Liu et al. (2024) and Ju et al. (2024), we also controlled for a series of factors influencing crash risk: *Sigma* denotes the standard deviation of weekly stock returns; *Ret* represents the mean stock return; *BM* indicates the book-to-market ratio, measured as book value divided by market capitalization; *Lev* signifies the debt ratio, calculated as total liabilities divided by total assets; *Roa* reflects the return on assets, measured as net profit divided by total assets; *Size* denotes firm size, measured by the natural logarithm of total assets; *Age* denotes firm age, measured by the natural logarithm of the difference between the observation year and the year of establishment; *Growth* denotes firm growth, measured by the revenue growth rate; and *Manage* denotes the proportion of shares held by management, measured by the number of shares held by directors, supervisors, and senior management divided by the total number of shares issued by the company.

3.3 Model

We develop Eqn. 10 to evaluate the proposed hypotheses:

$$Crash_{i,t+1} = \alpha_0 + \alpha_1 Digital_{i,t} + Controls_{i,t} + Year + Firm + \varepsilon_{i,t} \tag{10}$$

where *Crash* denotes two indicators of crash risk. *Digital* denotes a firm's digital transformation, and $Controls_{i,t}$ denotes the control variables. In addition, we control for year effects (*Year*) and firm effects (*Firm*). To mitigate the effects of heteroskedasticity and autocorrelation, we cluster standard errors at the company level.

4. Analysis of Empirical Results

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics for all the variables. The digital transformation (*Digital*) has a mean of 1.304 and a median of 1.099, indicating a right-skewed distribution. Both crash risk measures—*NCSKEW* (–0.289) and *DUVOL* (–0.180)—align with values reported in prior studies. All the other variables fall within the expected ranges.

Table 1. Descriptive statistics.

Variable	Obs.	Mean	Sd.Dev	Min	P50	Max
Digital	41,826	1.304	1.380	0	1.099	4.970
NCSKEW	41,826	–0.289	0.717	–2.449	–0.247	1.628
DUVOL	41,826	–0.180	0.474	–1.335	–0.181	1.032
Sigma	41,826	0.065	0.025	0.025	0.059	0.152
Ret	41,826	0.003	0.010	–0.018	0.002	0.037
Lev	41,826	0.433	0.204	0.057	0.428	0.899
BM	41,826	0.337	0.161	0.040	0.316	0.791
Roa	41,826	0.034	0.064	–0.260	0.036	0.195
Size	41,826	22.194	1.292	19.831	22.004	26.210
Age	41,826	2.924	0.344	1.946	2.944	3.611
Growth	41,826	0.351	0.989	–0.745	0.116	7.047
Manage	41,826	0.126	0.191	0	0.004	0.679

Notes: *Digital*, digital transformation; *NCSKEW*, negative stock return skewness coefficient; *DUVOL*, down-to-up volatility ratio; *Sigma*, the standard deviation of weekly stock returns; *Ret*, the mean stock return; *Lev*, the debt ratio, calculated as total liabilities divided by total assets; *BM*, book-to-market ratio; *Roa*, the return on assets, measured as net profit divided by total assets; *Size*, firm size, measured by the natural logarithm of total assets; *Age*, firm age, measured by the natural logarithm of the difference between the observation year and the year of establishment; *Growth*, firm growth, measured by the revenue growth rate; *Manage*, the proportion of shares held by management.

Table 2. Baseline regressions.

	(1)	(2)
	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
Digital	–0.011**	–0.006*
	(–1.996)	(–1.649)
Sigma	0.509**	0.763***
	(2.122)	(4.832)
Ret	6.960***	4.820***
	(11.399)	(11.984)
Lev	–0.416***	–0.247***
	(–8.836)	(–7.959)
BM	–0.476***	–0.280***
	(–10.501)	(–9.374)
Roa	–0.272***	–0.211***
	(–3.520)	(–4.140)
Size	0.037***	0.008
	(4.160)	(1.392)
Age	–0.250***	–0.223***
	(–4.067)	(–5.515)
Growth	0.003	–0.001
	(0.721)	(–0.164)
Manage	–0.233***	–0.150***
	(–4.768)	(–4.647)
_cons	–0.041	0.523***
	(–0.159)	(3.122)
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Obs.	41,826	41,826
Adj.R^2	0.074	0.082

Note: ***, ** and * represent t values significant at the 1%, 5% and 10% levels, respectively. The subsequent tables are consistent.

4.2 Baseline Regression Results

Table 2 presents the baseline regression results for the relationship between digital transformation and stock price crash risk. The coefficients for both crash risk measures (*NCSKEW* and *DUVOL*) are significantly negative, demonstrating that digital transformation decreases future crash risk. This coefficient also holds economic significance, as our results indicate that each additional standard deviation of Digital is associated with a 1.52% decrease in *NCSKEW* (0.011 × 1.380) and a 0.83% decrease in *DUVOL* (0.006 × 1.380). These findings confirm Hypothesis H1.

The signs and significance levels of the control variables generally align with expectations. We find that *Sigma*, *Ret*, and *Size* are positively correlated with crash risk. Moreover, *BM*, *Age*, and *Manage* are negatively correlated with crash risk. These results are consistent with those of previous research (Kim et al., 2011; Kim et al., 2014).

4.3 Robustness Tests

4.3.1 Instrument Variables Test

This conclusion may suffer from reverse causality concerns: firms with lower stock crash risk and more stable capital market performance may have both greater resources and stronger incentives to invest in digital transformation. Consequently, lower-risk firms attract more investor favor, leading to lower financing costs and easier access to transformation funds. Therefore, we employ an instrumental variables approach to mitigate this issue. Specifically, we utilize historical data at the city level related to information technology development as instrumental variables. On the one hand, a city's historical communication technology level can foster and influence the development of modern internet technology to some extent, thus satisfying the correlation requirements between historical communication levels and digital transformation. On the other hand, a city's historical information technology level has no direct relationship with corporate collapse risk, meeting the exogeneity requirement. In this regard, we use the number of post offices per 100 people (*Post*) and the number of telephones per 100 people (*Tel*) in each city in 1984 as instrumental variables for testing.

Table 3 presents the instrumental variable test results. Column (1) shows significantly positive coefficients for both *Pos* and *Tel*, suggesting that historical communication technology levels positively influence digital transformation. Columns (2) and (3) demonstrate that *Digital* continues to have a significantly negative coefficient, confirming that the conclusion is held after the instrumental variables test.

Table 3. Instrumental variables.

	(1)	(2)	(3)
	Digital	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
Digital		–0.115***	–0.119***
		(–4.130)	(–2.609)
Post	0.001*		
	(1.820)		
Tel	0.082***		
	(3.234)		
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Obs.	35,864	35,864	35,864
$Adj.R^2$	0.771	/	/

Notes: *** and * represent significance at the 1% and 10% statistical levels, respectively.

4.3.2 Considering Exogenous Shocks to Digital Economy Policies

To further address potential reverse causality issues, we employ the Broadband China pilot policy as an exogenous shock and implement a difference-in-differences framework for empirical testing. The rationale for selecting this policy lies in two key aspects: First, corporate digital transformation relies heavily on network infrastructure support, with its progress and outcomes directly constrained by external digital infrastructure levels. Second, the determination of pilot city lists possesses policy exogeneity, as corporate inclusion is not an autonomous decision—providing an ideal natural experimental setting for causal identification. On the basis of these considerations, we establish the following multiperiod difference-in-difference (DID) model in Eqn. 11:

$$Crash_{i,t+1} = \beta_0 + \beta_1 Broad_{i,t} + Controls_{i,t} + Year + Firm + \epsilon_{i,t} \tag{11}$$

where *Broad* represents the exogenous shock event of the Broadband China initiative. Firms located in cities designated as pilot zones receive a value of 1 starting from the policy's implementation year onward; all other firms are coded as 0. Following the model specification of Bai et al. (2018), we construct the interaction term *Broad*×*Digital* and incorporate it into Eqn. 12 to isolate the portion of information in corporate digital transformation attributable to the Broadband China pilot policy.

$$\begin{aligned} Crash_{i,t+1} = {} & \gamma_0 + \gamma_1 Broad_{i,t} + \gamma_2 Broad_{i,t} \\ & \times Digital_{i,t} + \gamma_3 Digital_{i,t} + Controls_{i,t} \\ & + Year + Firm + \varepsilon_{i,t} \end{aligned} \tag{12}$$

Columns (1) and (2) of Table 4 show that the coefficient of *Broad* is significantly negative, indicating that the Broadband China policy can mitigate the risk of collapse for enterprises in demonstration cities. According to Columns (3) and (4), the regression coefficients for *Broad*×*Digital* are –0.046 and –0.030, respectively, both of which are significant at the 1% level. This implies that under the exogenous shock of the Broadband China initiative, corporate digital transformation remains negatively correlated with crash risk, which is consistent with the baseline findings.

4.3.3 Omitted Variables Are Considered

Certain unobservable variables, such as management characteristics, the company's operational fundamentals, and external governance factors, may simultaneously influence both digital transformation decisions and crash risk. Failure to control for such variables could lead to erroneous estimates of benchmark regression coefficients. Therefore, our benchmark regression model incorporates macro- and microlevel control variables—including Managerial Risk Appetite (*Appet*), R&D Intensity (*Rd*), Media Attention (*Media*), and Regional Marketization Level (*Market*)—to minimize the impact of omitted variables. Managerial risk appetite is measured as the proportion of risk assets to total assets. Risk assets encompass trading financial assets, debt investments, other debt investments, other equity investment instruments, and investment property. R&D intensity is measured as the proportion of a firm's R&D expenditures relative to its operating revenue. Media attention is assessed using the natural logarithm of the combined frequency of online financial news and newspaper financial news coverage of listed companies from the Chinese Research Data Services Platform (CNRDS) database. The regional marketization level is measured using the marketization index proposed by Fang and Ju (2024).

In Table 5, we find that managerial risk preference is positively correlated with crash risk, media attention and marketization level are both negatively correlated with crash risk, and R&D intensity is not significantly related to crash risk. More importantly, we find that the negative correlation between digital transformation and crash risk persists.

4.3.4 Replacing the Key Variables

To eliminate interference from measurement errors, we further enhanced the robustness of our conclusions by swapping the key variables. First, for crash risk, we follow Cao et al. (2016) to calculate the probability of a crash risk (*Prob*). Specifically, we define crash risk as occurring when a firm's weekly return falls below 3.09 standard de-

Table 4. Considering digital economy policy.

	(1)	(2)	(3)	(4)
	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
Broad	–0.024**	–0.010*	–0.048**	–0.037***
	(–2.401)	(–1.901)	(–2.305)	(–2.666)
Broad×Digital			–0.046***	–0.030***
			(–5.900)	(–5.831)
Digital			–0.018**	–0.013***
			(–2.532)	(–2.666)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs.	37,795	37,795	37,795	37,795
Adj.R^2	0.073	0.081	0.074	0.082

Notes: ***, ** and * represent significance at the 1%, 5% and 10% statistical levels, respectively.

Table 5. Considering omitted variables.

	(1)	(2)
	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
Digital	–0.010*	–0.005**
	(–1.683)	(–2.124)
Appet	0.252***	0.163***
	(3.364)	(3.300)
RD	0.026	–0.033
	(0.186)	(–0.356)
Media	–0.013*	–0.008*
	(–1.731)	(–1.997)
Market	–0.019*	–0.007***
	(–1.732)	(–2.915)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Obs.	41,826	41,826
Adj.R^2	0.074	0.082

Notes: ***, ** and * represent significance at the 1%, 5% and 10% statistical levels, respectively.

viations below the mean for that year, corresponding to a *probability* value of 1. As shown in Column (1) of Table 6, the coefficient for *Digital* is still significantly negative, indicating that the conclusions remain unchanged.

For corporate digital transformation, we have replaced its proxy variable. Previously, we quantified digital transformation by analyzing the frequency of digital-related terminology in corporate annual reports. However, the mere occurrence of these terms does not necessarily indicate that a company has undergone transformation. To address this, we collected data on corporate digital investment (*Digi_Invest*) and the number of digital invention patents (*Digi_Patent*) from the CSMAR database and used these as new proxy variables to measure digital transformation. Digital investment is calculated as the proportion of digital investment relative to operating revenue. Digital invention patents are calculated by taking the natural logarithm of the number of digital invention patents plus one. On the basis of Columns (2) to (5), we find that the coefficients for both *Digi_Invest* and *Digi_Patent* are significantly negative, indicating that our baseline regression conclusions are robust.

4.3.5 Changing Sample Interval

International financial crises and major public health crises have significantly affected China's stock market and corporate investment decisions. Ignoring such factors may introduce bias into the conclusions of this study. To address this, we replaced the original sample with data spanning five years—covering the global financial crisis (2008, 2009) and the COVID-19 period (2020, 2021, 2022)—and reexamined our findings.

Table 7 presents descriptive statistics for digital transformation and crash risk during noncrisis periods. We find that the distribution of core variables differs little from that of the full sample, indicating that the noncrisis period sample remains representative.

Second, Table 8 reports the relationships during both noncrisis and crisis periods. We find that digital transformation continues to mitigate collapse risk regardless of crisis status, which is consistent with the baseline findings. Notably, the results also indicate that during international crises, the risk-reducing impact of digital transformation is further amplified. These findings are equally plausible, as uncertain investor sentiment during crises necessitates enhanced information transparency through digital transformation to bolster investor confidence. Furthermore, the unstable business environment during crises heightens the need for operational resilience gains delivered by digital transformation.

4.4 Influence Mechanism

This section examines the possible mechanisms through which digital transformation affects stock price crashes. In the theoretical derivation section, we argue that

Table 6. Replace the key variables.

	(1)	(2)	(3)	(4)	(5)
	$Prob_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
Digital	-0.002^{***}				
	(−2.785)				
Digi_Invest		-0.134^{**}	-0.031^{**}		
		(−2.428)	(−2.506)		
Digi_Patent				-0.011^{*}	-0.005^{**}
				(−1.915)	(−2.258)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Obs.	41,826	41,826	41,826	41,826	41,826
Adj.R^2	0.028	0.074	0.082	0.074	0.082

Notes: ***, ** and * represent significance at the 1%, 5% and 10% statistical levels, respectively.

Table 7. Descriptive statistics (excluding macroeconomic crises).

Variable	Obs.	Mean	Sd. Dev	Min	P50	Max
Digital	28,415	1.212	1.357	0	0.693	4.970
NCSKEW	28,415	−0.287	0.723	−2.449	−0.243	1.628
DUVOL	28,415	−0.179	0.482	−1.335	−0.181	1.032

Table 8. Results in noncrisis periods versus crisis periods.

	(1)	(2)	(3)	(4)
	Non crisis		Crisis	
	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
Digital	-0.011^{*}	-0.003^{*}	-0.019^{*}	-0.017^{**}
	(−1.680)	(−1.790)	(−1.685)	(−2.342)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs.	27,700	27,700	13,071	13,071
Adj.R^2	0.092	0.095	0.057	0.074

Notes: ** and * represent significance at the 5% and 10% statistical levels, respectively.

digital transformation has three effects: First, digital transformation significantly enhances information transparency, reduces information asymmetry and consequently diminishes management's incentive to conceal negative news. Second, digital transformation can have a governance effect that reduces crash risk by strengthening the quality of internal controls. Third, digital transformation can help businesses reduce profit volatility and enhance operational resilience in the face of external shocks.

4.4.1 Corporate Opacity

We first measure information opacity (*Opacity*) using the absolute value of manipulable accrued profits. Specifically, we use the residuals of the modified Jones model to calculate manipulability accruals (Chen et al., 2024), whose absolute value (*AbsDA*) reflects the extent to which management purposefully controls external financial reporting for private gain. The calculation method for *AbsDA* is described in Section 3.2.

In Column (1) of Table 9, we find that digital transformation does indeed reduce corporate opacity. We subsequently simultaneously incorporate digital transformation and corporate opacity into the baseline model. The results indicate that corporate opacity serves as a mechanism through which digital transformation affects crash risk. Columns (2) and (3) show significantly positive coefficients for *AbsDa*, indicating that corporate opacity functions as a transmission channel through which digital transformation influences crash risk.

Table 9. Influence mechanisms (opacity).

	(1)	(2)	(3)
	AbsDa	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
Digital	-0.001^{***}	-0.011^{**}	-0.005^{**}
	(−2.594)	(−1.961)	(−2.516)
AbsDA		0.228^{***}	0.131^{***}
		(3.565)	(3.104)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Obs.	40,751	40,751	40,751
Adj.R^2	0.167	0.074	0.082

Notes: *** and ** represent significance at the 1% and 5% statistical levels, respectively.

Table 10. Influence mechanisms (internal control).

	(1)	(2)	(3)	(4)	(5)	(6)
	IC	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	*Defect*	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
Digital	0.054***	–0.010*	–0.005**	–0.001**	–0.012**	–0.005**
	(2.689)	(–1.770)	(–2.264)	(–2.441)	(–2.057)	(–3.456)
IC		–0.019***	–0.015***			
		(–4.471)	(–5.248)			
Defect					0.049***	0.035***
					(3.908)	(4.204)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	38,517	38,517	38,517	37,531	37,531	37,531
$Adj.R^2$	0.148	0.076	0.085	0.555	0.073	0.081

Notes: ***, ** and * represent significance at the 1%, 5% and 10% statistical levels, respectively. IC, internal control.

4.4.2 Corporate Internal Control Quality

Second, we assess internal control quality (*IC*) using Dibo's published internal control index for the sample firms. A higher value indicates superior internal control quality. In Column (1) of Table 10, the coefficient of *Digital* is significantly positive, indicating that digital transformation indeed enhances internal control levels. Furthermore, Columns (2) and (3) demonstrate that internal control mitigates the risk of collapse, confirming that it is an influential mechanism.

Furthermore, we assigned values on the basis of whether internal control deficiencies exist within the company and used this as a proxy variable. A value of 1 indicates the presence of internal control deficiencies, whereas 0 indicates their absence. Data on internal control deficiencies were sourced from the CSMAR database. We found that the conclusions remain unchanged.

4.4.3 Corporate Operational Resilience

Finally, we argue that corporate digital transformation enhances resilience to external shocks by strengthening knowledge management and innovation capabilities, thereby stabilizing profitability and ultimately curbing the accumulation of bad news. We measure profit volatility (*Volat*) using the rolling standard deviation of a firm's EBITDA margin to capture the resilience effect of digital transformation. In Table 11, Column (1) reveals a significantly negative coefficient for *Digital*, demonstrating that digital transformation reduces corporate profit volatility. Columns (2) and (3) further confirm that profit volatility serves as an intermediary mechanism through which digital transformation influences crash risk.

Table 11. Influence mechanisms (operational resilience).

	(1)	(2)	(3)
	Volat	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
Digital	–0.003***	–0.009**	–0.007*
	(–2.762)	(–2.427)	(–1.754)
Volat		0.050**	0.030**
		(2.456)	(2.347)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Obs.	32,672	32,672	32,672
$Adj.R^2$	0.276	0.079	0.089

Notes: ***, ** and * represent significance at the 1%, 5% and 10% statistical levels, respectively.

5. Further Discussion

This section further examines the heterogeneous impact of digital transformation on crash risk to provide additional evidence on the underlying mechanisms of digitalization. Specifically, we consider two firm-level characteristics—firm size and institutional ownership—alongside two external environmental characteristics: market competition and regional digital infrastructure development levels.

5.1 Considering Firm Size

We believe that the inherent shortcomings of small enterprises can amplify the marginal effects of digital transformation. This is because, compared with large enterprises, small businesses generally suffer from low information transparency and weak internal control systems (Hao and Xiong, 2021). Digital transformation can directly address these shortcomings through technological empowerment. For instance, small enterprises can rapidly enhance information transparency by standardizing operational data disclosure via digital tools, significantly reducing management's ability to conceal negative information. Conversely, large enterprises already possess robust information environments and internal control mechanisms, leaving limited room for improvement through digital transformation. Furthermore, the empowerment premium of digital transformation is more pronounced for small enterprises. Small enterprises face competitive disadvantages in the marketplace (Boulland et al., 2025), making enhanced profit stability from digital transformation critical to their survival and growth. When digital transformation reduces profit volatility in small firms, their stock prices become significantly less sensitive to negative information. Consequently, compared with that of large firms, the risk-mitigating effect of digital transformation on small enterprise collapse is more pronounced.

We split the sample at the median firm size, assigning a value of 1 to firms above the median (larger firms) and 0 to those below. We then constructed the interaction term *Size×Digital* between firm size and digital transformation and included it in the regression. In Column (1) of Table 12, the coefficient of *Size×Digital* is significantly positive, indicating that smaller firms benefit more from digital transformation; thus, this conjecture is confirmed.

Table 12. Considering firm size.

	(1)	(2)
	NCSKEW	*DUVOL*
Digital	–0.009**	–0.002**
	(–2.024)	(–2.142)
Digital×Size	0.002***	0.006***
	(–3.305)	(–3.357)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Obs.	41,826	41,826
Adj.R^2	0.074	0.082

Notes: *** and ** represent significance at the 1% and 5% statistical levels, respectively.

5.2 Consider Institutional Ownership

According to agency theory and external governance theory, institutional investors can alter the intensity of external oversight, thereby influencing the governance effects of digital transformation. As professional external governance entities, institutional investors can constrain management behavior through mechanisms such as voting power intervention, exit threats, and analyst tracking linkage (Rong et al., 2017). Companies with high institutional ownership exhibit robust external oversight, significantly curbing management's motivation and ability to conceal negative information, thereby weakening the supplementary role of digital transformation in internal controls. Conversely, firms with low institutional ownership typically face insufficient external oversight and severe agency conflicts, making management more prone to manipulating information and withholding negative news to harm shareholder interests (He et al., 2019). Digital transformation effectively bridges external oversight gaps by restructuring internal governance through technological means, yielding a more pronounced mitigating effect on stock price crash risk than in firms with high institutional ownership.

Accordingly, we divided the sample into two groups on the basis of the median institutional ownership ratio, assigning a value of 1 to samples above the median to indicate higher ownership. We subsequently constructed the interaction term *Insiti×Digital* between the institutional ownership ratio and digital transformation and incorporated it into the regression. As shown in Columns (1) and (2) of Table 13, the coefficient for *Insiti×Digital* is significantly positive, indicating that the governance effect of digital transformation is stronger when external oversight is weaker.

Table 13. Considering institutional ownership.

	(1)	(2)
	NCSKEW	*DUVOL*
Digital	–0.017***	–0.009**
	(–2.707)	(–2.138)
Digital×Insiti	0.015**	0.007*
	(2.040)	(1.799)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Obs.	41,826	41,826
Adj.R^2	0.075	0.083

Notes: ***, ** and * represent significance at the 1%, 5% and 10% statistical levels, respectively.

5.3 Considering Market Competition

We also examined the impact of market competition, positing that competitive intensity moderates the effects of digital transformation by influencing firms' operational pressure and disclosure incentives. Firms operating in highly competitive industries confront intensified profitability challenges and heightened survival pressures. To maintain stable stock prices, management tends to conceal negative information such as operational losses and regulatory violations (Chen et al., 2021). In such contexts, digital transformation can fundamentally curb the accumulation of negative information by enhancing transparency and profit stability, thereby significantly mitigating crash risk. Conversely, firms in low-competition industries enjoy stable profits and secure market positions, reducing management's incentive to conceal negative information. For these companies, the marginal improvement in stock price collapse risk from enhanced transparency and profit stability brought by digital transformation is limited. Therefore, we conclude that digital transformation has a greater effect on firms operating in more intensely competitive environments.

We measure market competition using the Herfindahl-Hirschman Index, which is calculated by summing the squared market shares (based on main business revenue) of all the firms within each industry. A higher Herfindahl-Hirschman Index indicates less market competition. For interpretive purposes, we define samples below the median Herfindahl-Hirschman Index (HHI) as 1 (*Compet* = 1), signifying more intense market competition. By constructing interaction terms, we subsequently find that the coefficient for *Digital*×*Compet* is significantly negative, as shown in Table 14. This implies that the more intense the market competition, the more pronounced the effect of digital transformation in mitigating crash risk.

Table 14. Considering market competition.

	(1)	(2)
	NCSKEW	*DUVOL*
Digital	–0.002**	–0.001**
	(–2.355)	(–2.020)
Digital×*Compet*	–0.016**	–0.010**
	(–2.215)	(–2.241)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Obs.	41,826	41,826
Adj.R^2	0.074	0.083

Notes: ** represents significance at the 5% statistical level.

5.4 Considering the Construction of Digital Infrastructure

The connection between corporate digital transformation and crash risk is further influenced by regional digital infrastructure development levels. In areas with robust digital infrastructure—such as 5G base stations, data centers, and cloud computing resources—companies experience lower technical access costs and achieve deeper implementation of digital transformation. For instance, enterprises can readily utilize industrial internet platforms to optimize supply chains and leverage big data analytics for precise market risk forecasting. The three core mechanisms of digital transformation can function effectively, significantly mitigating crash risk. Conversely, regions with weak infrastructure face constraints in terms of transformation. Enterprises encounter difficulties in terms of technology access, low data processing efficiency, and insufficient policy support. Digital transformation often remains superficial, failing to genuinely improve information environments and internal control quality, thereby significantly weakening its mitigating effect on stock price crash risk.

To measure regional digital infrastructure development levels, we begin by analyzing annual government work reports from prefecture-level cities to identify terminology related to digital infrastructure. We subsequently counted the total number of words in each report and the number of digital infrastructure-related terms and calculated the proportion of new digital infrastructure terminology to derive the digital infrastructure level (*Infra*). Similar to the previous methodology, we divided the sample into two groups on the basis of the median Infra value and constructed an interaction term between digital transformation and digital infrastructure development: *Digital*×*Infra*. As shown in Table 15, *Digital*×*Infra* is significantly negative, indicating that regional digital infrastructure development strengthens the mitigating effect of digital transformation on crash risk.

Table 15. Considering the construction of digital infrastructure.

	(1)	(2)
	NCSKEW	*DUVOL*
Digital	–0.001*	–0.002**
	(–1.994)	(–2.191)
Digital×*Infra*	–0.014**	–0.009**
	(–2.027)	(–2.054)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Obs.	41,826	41,826
Adj.R^2	0.074	0.082

Notes: ** and * represent significance at the 5% and 10% statistical levels, respectively.

6. Conclusions

On the basis of data from China, this study demonstrates that corporate digital transformation significantly reduces stock price crash risk. These results remain robust across multiple sensitivity checks. Moreover, the mechanism through which digital transformation reduces crash risk lies in its ability to decrease corporate opacity, enhance the quality of internal controls, and mitigate earnings volatility. Further evidence indicates that digital transformation has a greater effect when companies are smaller in scale, have lower institutional ownership, face more intense market competition, and operate in regions with higher levels of digital infrastructure development. This study provides new evidence on how digital transformation influences corporate stock market performance.

These findings offer practical guidance for policymakers, regulators, and publicly traded companies. First, at the governmental level, efforts should focus on resource allocation and foundational support to address uneven transformation. A differentiated digital subsidy and technical support system should be established. For instance, creating dedicated digital transformation subsidies and building shared digital platforms for small and medium-sized enterprises (SMEs) can lower barriers to accessing technologies such as AI and big data, thereby compensating for resource constraints among smaller enterprises. Additionally, governments must promote balanced regional development of digital infrastructure. The deployment of 5G base stations, data centers, and cloud computing nodes should be increased in regions with weak digital infrastructure to narrow regional gaps in transformation implementation. For regulators, strengthening oversight coordination and disclosure standards is essential for enhancing transformation quality. For instance, institutional investors should be guided to participate in transformation oversight. Guidelines should be issued to encourage institutional investors to conduct specialized digital transformation research on companies with low institutional ownership, incorporating transformation outcomes into investment evaluation systems. Mandatory disclosure standards for digital governance must be established. Companies should be required to disclose digital transformation information categorically on the basis of foundational technology investment, application scenario implementation, and risk control measures, preventing superficial transformations that prioritize disclosure over execution. Finally, listed companies must precisely align their transformation strategies with their unique characteristics to maximize their impact. For instance, small-scale enterprises and those in regions with weak digital infrastructure should prioritize low-cost, quick-win transformation directions. They can leverage shared government platforms to reduce technological investment, rapidly address information transparency and internal control deficiencies through digitalization, and then gradually advance business integration—rather than blindly pursuing end-to-end digitalization. Enterprises in highly competitive industries must deeply integrate digitalization with core operations to enhance profitability stability, thereby offsetting competitive pressure and strengthening transformational support for stock price stability.

This study has certain limitations that warrant refinement in future research. First, although it primarily measures transformation depth using the natural logarithm of digital keyword frequency in annual reports—supplemented by robustness tests with alternative variables such as digital investment and digital patents—these metrics may still deviate from actual transformation depth. Future research could integrate internal digital process data, management interviews, or machine learning methods to construct more comprehensive transformation indices that accurately capture transformation quality. Second, regarding endogeneity, this study mitigates issues through instrumental variables (historical communication levels), difference-in-differences (the Broadband China policy), and controlling for omitted variables (management risk appetite, media attention). However, unobserved confounding variables—such as management digital literacy and corporate digital culture—may still exist, potentially influencing both transformation decisions and stock crash risk. Future research could incorporate variables such as management's digital background and organizational digital atmosphere or employ more precise quasinatural experiments to further isolate causal relationships. Third, while this study's sample covers Chinese A-share listed companies from 2007 to 2024 across multiple sectors, including manufacturing, services, and retail, potential industry imbalances may limit the generalizability of the findings to certain sectors. Future research could expand to single-industry or multinational samples or compare transformation effects across different industries and institutional environments.

Availability of Data and Materials

All data reported in this paper will be shared by the corresponding author upon reasonable request.

Author Contributions

JW: Conceptualization, Data curation, Funding acquisition. XF: Investigation, Methodology, Writing - original draft, Writing - review & editing. HZ: Supervision, Validation, Writing - review & editing, Data curation. All authors contributed to editorial changes in the manuscript. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

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Conflicts of Interest

The authors declare no conflicts of interest.

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