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ORIGINAL RESEARCH

Digital Transformation as a Catalyst for Resilience in Stock Price Crisis: Evidence from A 'New Quality Productivity' Perspective

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Abstract

This study explores the impact of digital transformation on stock price crash risk using Chinese A-share listed enterprises from 2011 to 2022. Leveraging the TF-IDF algorithm and deep learning models, it contextualizes digital transformation within China's "new quality productivity" framework, which prioritizes technological innovation over traditional productivity drivers. The findings reveal that digital transformation significantly reduces stock price crash risk, particularly in labor and capital-intensive sectors, by enhancing market transparency and decreasing information asymmetry. Furthermore, the integration of digital transformation with the "new quality productivity" framework amplifies this protective effect, with pronounced benefits for large firms and those covered by analysts or research reports. Conversely, smaller firms or those without such coverage experience a smaller impact. By demonstrating how advanced digital technologies bolster operational agility and investor confidence, this study highlights the critical role of digital transformation in fostering resilience and stabilizing stock prices during crises.

Keywords Digital transformation · Stock price crashes · New quality productivity · China

JEL Classification O33 · O38 · L25

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1 Introduction

The digital transformation of Chinese firms is reshaping the global digital economy, highlighting China's emerging prominence alongside high-income economies. Significant investments in infrastructure, such as 5G networks and AI advancements, and the increasing adoption of digital platforms underpin this transformation. Although many Chinese firms are still in the early stages of digitalization, progress is evident, particularly in the IT services industry. This sector has emerged as a source of higher pay and social mobility compared to traditional high-paying fields like finance since 2020 (World Bank, 2023).

The concept of "Total Enterprise Reinvention" signals a new era of transformation, with 2% of Chinese firms already engaged and 53% planning to increase digitalization efforts in 2023 (Accenture, 2023). Additionally, the "New Quality Productivity" initiative, launched in 2023, emphasizes innovation-driven productivity as a cornerstone of China's modernization strategy (Song et al., 2024). Together, these trends illustrate the critical role of digital transformation in enhancing China's global competitiveness and building a more inclusive digital economy.

Digital transformation, while central to economic modernization, poses challenges, particularly concerning stock market dynamics. Whilst current research suggests that the impact of digital transformation on firms performance is rather nuanced (Chen et al., 2024a, 2024b), there are studies indicating that in the initial stages of digital transformation, firms face heightened risks of stock price collapse due to factors like agency costs, managerial overconfidence, and increased information asymmetry (2023b; Ai et al., 2023a; Zhao et al., 2023). Zhu et al. (2023) also highlight that digitalization can exacerbate market instability due to uneven access to information and suboptimal firm performance. Structural barriers, including disparities in digital infrastructure, outdated science and technology policies, and insufficient digital talent pipelines, further hinder the ability of firms to mitigate these risks (Song et al., 2024). These systemic challenges limit the effectiveness of digital transformation in reducing stock price risks and restrict firms' capacity to fully leverage the benefits of innovation-led growth.

Understanding and addressing the risks associated with digital transformation is critical for China's financial stability and broader economic modernization. Failure to manage these risks could lead to increased market volatility, reduced investor confidence, and hindered growth potential. Furthermore, effectively integrating "New Quality Productivity" principles with digital transformation is vital to fostering equitable and sustainable growth while positioning China as a leader in the global digital economy.

To address the existing challenges in the literature, this study employs a robust quantitative methodology as this reflected by Term Frequency-Inverse Document Frequency (TF-IDF) model to analyze the annual reports of A-share listed companies over the period 2011 to 2022. By quantifying the degree of digital transformation at the firm level, this piece of research investigates its impact on stock price crash risks whilst by leveraging the "New Quality Productivity" framework

we explore how digital transformation reduces market volatility by addressing information asymmetry. Through innovative methods, the research introduces a novel indicator to measure information disparity between informed and uninformed traders, offering novel insights into how digitalization fosters transparency. Additionally, the study examines the heterogeneity of digital transformation's impact across sectors and firm sizes, identifying key attributes that shape its influence on market stability.

As such, this piece of research explores how digital transformation impacts stock price crash risks among Chinese firms, examining its effects across different industries and firms. It further investigates the role of "New Quality Productivity" in mitigating these risks, by highlighting its potential to align innovation-driven productivity with market stability. Also, central to this inquiry are the mechanisms through which digital transformation enhances market transparency and reduces information asymmetry, offering insights into how digitalization fosters a more stable financial environment. Additionally, the study delves into how firm-specific attributes, such as size and sector, shape the variability in the effects of digital transformation on stock price stability. Finally, it assesses whether the integration of "New Quality Productivity" amplifies the positive impact of digital transformation which further reduces stock price crash risks whilst at the same time supporting resilient market dynamics.

The significance of this study is of paramount importance, as it sheds light on the strategic role of digital transformation in stabilizing financial markets by mitigating risks such as information asymmetry. By addressing these issues, the research provides actionable insights for policymakers and businesses aiming to enhance market resilience, align with "New Quality Productivity" goals, and support China's modernization and global economic leadership.

The rest of this paper is organized as follows: Sect. 2 expounds on the pertinent literature and hypothesis development by delving into the interplay between firms' digital transformation and stock crash risk, and the concept of new quality productivity. Section 3 touches on the empirical strategy whilst Sect. 4 presents the results. Section 5 discusses the findings and finally, Sect. 6 provides some concluding remarks.

2 Pertinent Literature and Hypotheses Development

2.1 Firms' Digital Transformation and Stock Crash Risk

In today's dynamic financial landscape, firms' digital transformation has emerged as a critical factor influencing their performance, resilience, and valuation in capital markets. The adoption of advanced digital technologies reshapes business models, enhances operational efficiency, and improves decision-making. However, this transition is not without risks. As firms integrate these technologies, they may face heightened exposure to cyber threats, execution challenges, and market uncertainties, which can exacerbate stock crash risks. This interplay between digital transformation and stock volatility warrants deeper exploration to understand how strategic

tech adoption can mitigate or amplify financial vulnerabilities in an increasingly digital economy.

In the context of the Chinese economy, various factors affecting stock price crash risk include *inter alia* fund style drift, which amplifies crash risk through its mediating effect on financial risk, especially in non-state enterprises compared to state-owned ones (Sun et al., 2023), and management's geographical proximity, which intensifies crash risk in regions with weaker legal environments and stronger Confucian culture, with significant ties to firm characteristics such as information transparency, over-investment, and tax aggressiveness (Jin et al., 2022).

On the empirical front however, recent research has increasingly focused on the interplay between digital transformation and the risk of stock price crashes, revealing a nuanced relationship that underscores the protective role of technological advancements in financial markets. Studies such as Ma's (2024) investigation into corporate shared prosperity highlight that lower levels of digital transformation correlate with increased risk of stock price crashes, suggesting digital advancements as a key factor in enhancing financial stability. Liu et al. (2024) extend this insight by demonstrating that digital transformation not only stabilizes stock prices but also improves stock market health through enhanced liquidity. Additionally, Tandon et al. (2024) analysis on the disparity between declared digital efforts and actual implementation cautions against the superficial adoption of digital transformation, emphasizing the need for genuine and comprehensive digital strategies to effectively shield against market downturns.

There is no doubt that by leveraging advanced technologies such as data analytics, automation, and artificial intelligence, firms can improve operational efficiency, strengthen risk management, and respond proactively to market disruptions. Moreover, enhanced transparency and data-driven insights foster investor confidence, reducing the likelihood of panic-driven sell-offs that often precipitate stock price crises. However, while the potential stabilizing effects of digital transformation are promising, the relationship remains complex and multifaceted, necessitating further research to evaluate how effectively these innovations shield firms from extreme market fluctuations. As such, this paper proposes the following hypothesis:

H1 Firms' digital transformation can inhibit the risk of stock price crisis.

2.2 New Quality Productivity

The concept of New Quality Productivity gains renewed significance in the context of digital transformation, where advanced technologies reshape how organizations enhance quality and productivity. The fusion of digital transformation and new quality productivity not only drives efficiency but also positions organizations to thrive in a competitive, tech-driven landscape.

The literature on new quality productivity, framed along these lines, examines how firms' digital transformation can serve as a stabilizing force against stock price crashes. Song et al. (2024) found that ESG development enhances new quality productivity, suggesting improved stakeholder relations and lower costs as stabilizing

factors for stock prices whilst Chen et al. (2024a, 2024b) advocate for a strategic approach to digital governance and technological development to bolster this productivity. Di and Pan (2024) offer a theoretical framework linking technological and social structures to the evolution of new quality productivity under digital transformation, while Li and Zhao (2023) underscore the role of digital economy integration in driving industrial advancement. In view of the above, it is thought that digital transformation, embedded within the concept of new quality productivity, could mitigate stock market volatility through systemic improvements in corporate governance, stakeholder engagement, and technological innovation. As new quality productivity amplifies the benefits of digital transformation, such as more reliable processes and data-driven decision-making, it strengthens investor confidence and reduces the likelihood of market shocks. Research into this relationship can illuminate how new quality productivity acts as a multiplier, enhancing the protective effects of digital transformation against stock price volatility. Based on this rationale this paper proposes the second hypothesis to be tested:

H2 The effect of firms' digital transformation in reducing stock price crash risk increases with the increase of new quality productivity.

2.3 Digitalization and Information Asymmetry

Corporate digital transformation plays a pivotal role in reducing information asymmetry, thereby decreasing the risk of stock price crises. By embracing digital technologies, companies enhance transparency and improve communication with investors. Digital transformation, by enhancing information transformation mechanisms, effectively reduces credit spreads through the mitigation of information asymmetry between firms and investors, while simultaneously lowering corporate default risk by bolstering operational efficiency (Jiang et al., 2024), thereby fostering a more stable financial environment. Real-time data sharing and the use of digital platforms for investor relations allow for more accurate and timely information dissemination. This transparency helps mitigate misunderstandings and panic selling, stabilizing stock prices. Furthermore, digital transformation strengthens data analysis capabilities, enabling companies to better predict business trends and adjust strategies proactively. The reduction in information asymmetry through digital means not only fosters a more informed and efficient market but also significantly lowers the likelihood of stock price volatility caused by sudden negative information or strategic missteps.

The relationship between digitalization and information asymmetry is intricately linked to how organizations manage and process information in the digital age. Extant studies such as those by Aben et al. (2021) and Li et al. (2023) highlight the transformative power of digital technologies in reducing information asymmetry and enhancing governance mechanisms. Aben et al. (2021) emphasize the necessity of identifying information requirements and diminishing uncertainty as foundational to leveraging digital transformation for clearer information sharing and interpretation. Li et al.'s (2023) research further supports this, demonstrating how digital

transformation can lead to reduced agency costs and a decrease in the extent of supply chain relational transactions, thereby alleviating information asymmetry.

Conversely, Risin et al. (2020), Lauer and Wieland (2021) provide insights into the ongoing challenges and the nuanced impact of digitalization on information asymmetry. Risin et al. (2020) assess the asymmetry within the Russian banking sector, pointing out the influential role of digitalization in banking activities and its effect on interbank competition, yet noting that a complete digital overhaul remains to be achieved. Lauer and Wieland (2021) investigate the human-AI interaction in industrial settings, finding that different interaction models can significantly affect the forecasting accuracy and decision-making processes, suggesting that information asymmetry can still pose limitations even as digitalization progresses. These studies illustrate the dual nature of digitalization as both a facilitator for reducing information asymmetry and a domain where asymmetry can be redefined or persist due to new challenges in human-AI collaboration and the pace of digital integration. Based on the above, this paper envisages a third hypothesis which is couched in follows:

H3 A Company's digital transformation decreases the risk of stock price crashes through the mediating effect of reduced information asymmetry.

3 Empirical Investigation

3.1 Methodology

A crucial use of artificial intelligence and natural language processing (NLP) lies in the automated categorization of documents to efficiently, transparently, and reliably handle the vast volumes of documents produced annually in both business and governmental sectors. The foundational studies by Jagdale et al. (2016) along with Ahnve et al. (2020) underscore the successful merger of machine learning, natural language processing, and financial theory in predicting stock market movements. These research initiatives leverage text-based data through methodologies like TF-IDF and implement sophisticated models such as Hidden Markov Models and Logistic Regression. Not only do these techniques enhance prediction accuracy, but they also demonstrate how these models can be seamlessly incorporated into algorithmic trading strategies.

In the realm of information retrieval and data mining, particularly concerning the analysis of corporate disclosures from public companies, there exists a discernible research void with regard to the deployment of TF-IDF (Term Frequency-Inverse Document Frequency) techniques. The data processing phase often includes a step called stemming, which involves replacing words with their root forms, as identified in Mittermayer's work (2004). The TF-IDF method, which draws from Fuhr's principles established in Fuhr (1992), prioritizes terms based on their contribution to the document's overall significance. This is computed through the product of Term Frequency (TF) and Inverse Document Frequency (IDF), as delineated in the Eqs. (1) and (2):

$$\mathrm{IDF}\,(\mathrm{term}) = \ln\left(\frac{N_{\mathrm{Documents}}}{N_{\mathrm{Documents\ containing\ term}}}\right) \tag{1}$$

$$\mathrm{TF} - \mathrm{IDF} = \mathrm{TF} \times \mathrm{IDF}(\mathrm{term}) \tag{2}$$

3.2 The Variables

3.2.1 Dependent Variable: Stock Price Crash Risk

In our context, risk of a stock price crash is captured by the negative coefficient of return skewness (SKEW) and the ratio of the company's fluctuations of stock return (FLUC). These measures are described as follows:

Equation (3) describes the relationship between c ($R_{i,t}$), and the market return ($R_{m,t}$). Where ($R_{i,t}$) represents the rate of return on the asset or portfolio at point in time (t), and ($R_{m,t}$), ($R_{m,t-1}$), ($R_{m,t-2}$), ($R_{m,t+1}$), and ($R_{m,t+2}$) represent the market rate of return at points in time (t), ($t-1$), ($t-2$), ($t+1$), and ($t+2$), respectively.

$$R_{i,t} = \alpha_i + \beta_1 R_{m,t-2} + \beta_2 R_{m,t-1} + \beta_3 R_{m,t} + \beta_4 R_{m,t+1} + \beta_5 R_{m,t+2} + \varepsilon_{i,t} \tag{3}$$

$\left(\alpha_i\right)$ is a constant term that represents the expected return on an asset or portfolio when the market rate of return is zero. $\left(\beta_1\right)$, $(\beta 2)$, $(\beta 3)$, $(\beta 4) and (\beta 5)$ are regression coefficients indicating the strength of the effect of the market rate of return on the return of an asset at different points in time. $\left(\varepsilon_{i,t}\right)$ is the error term representing the effect of all unobserved factors other than market returns on asset returns.

This equation is commonly used in the context of Capital Asset Pricing Models (CAPMs) and multi-factor models, to analyse and predict how market movements at different points in time will affect the returns of a particular asset or portfolio. By analysing the significance and magnitude of these coefficients, investors and analysts can better understand the impact of market dynamics on asset performance.

In Eq. (3), $R_{i,t}$ refers to the return of stock i in week t considering the reinvestment of cash dividends, and $R_{m,t}$ refers to the average return of all A-share stocks in week t weighted by the outstanding market capitalization. In this paper, we add lagged and ahead terms of market returns to Eq. (3) to adjust for the effect of asynchronous stock trading (Dimson, 1979), and $\varepsilon_{i,t}$ are the regression residuals in the model.

Next, we can derive the market-adjusted return $W_{i,t}$ (weekly idiosyncratic return) for week t of stock i as Eq. (4):

$$W_{i,t} = \ln\left(1 + \varepsilon_{i,t}\right) \tag{4}$$

Furthermore, in line with Liu and Liu (2022) as well as Callen and Fang (2015), we select the negative coefficient of return skewness (*SKEW*), the ratio of upward and downward fluctuations in company stock returns (*FLUC*) that is commonly used in the academic world.

Two measures of stock price crash risk are constructed based on the firm's weekly idiosyncratic returns. One is to use the negative coefficient of skewness (*SKEW*) to measure stock price crash risk. The specific Eq. (5) is:

$$SKEW_{i,t} = -\frac{n(n-1)^{3/2}\sum W_{i,t}^3}{(n-1)(n-2)(\sum W_{i,t}^2)^{3/2}} \tag{5}$$

where n is the number of trading weeks in a given year for stock i. So, larger values of *SKEW* imply larger negative return skewness coefficients and a higher risk of stock price collapse.

The second assessment employs the down-to-up volatility (*FLUC*) ratio of returns to assess the danger of a decline in stock prices. Each company and year are analysed to identify the weeks in which the idiosyncratic return is below the average, which are labelled as down weeks. In contrast, the weeks in which the idiosyncratic return is above the average are labelled as up weeks. The subsequent procedure involves calculating the standard deviation of the idiosyncratic returns for weeks with negative returns and weeks with positive returns individually, with the goal to determine the down volatility and up volatility, respectively. To calculate the *FLUC* metric for every business in a yearlong sample, divide the down volatility by the up volatility and then take the natural logarithm. The method of calculation for Eq. (6) is as follows:

$$FLUC_{i,t} = log\frac{(n_u-1)\sum_{down} W_{i,t}^2}{(n_d-1)\sum_{up} W_{i,t}^2} \tag{6}$$

where n_u and n_d represent the number of weeks in which the week-specific return on the stock price of firm t, $W_{i,t}$, is greater and less than its average annual return, respectively. Larger values of *FLUC* represent a more left-skewed distribution of returns and a greater risk of stock price collapse.

SKEW and *FLUC* are expected to be positively related to stock price crash risk; that is, firms with higher *SKEW* and *FLUC* values have higher stock price crash risk.

3.2.2 Independent Variable: Digital

While traditional research might use indicators like intangible or software asset values to gauge a company's digital integration, such methods often fall short in reflecting true digital adoption levels. To more precisely quantify a company's digital capabilities within a specific year, we utilize the statistical approach of Term Frequency-Inverse Document Frequency (TF-IDF). This technique assesses a term's significance within a corpus of documents, enabling us to pinpoint the keywords in annual reports that are essential to discerning a company's digital advancement (Bao et al., 2023). We use a more precise indicator of the degree of digital technology adoption in the enterprise (digital) which is constructed as the Eq. (7):

$$\text{digital}_{i,t} = \sum_{d\in D} TF_{dit} \times IDF_{dt} \tag{7}$$

The lexicon set D for calculating digital empowerment indicators has been determined based on the research needs of this paper and the work of Chen and Srinivasan

(2023). D represents the set of digital empowerment indicators and includes the following keywords: AI technology, artificial intelligence, technological advances in computers, technological intelligence, automation, neural network, virtual reality, data science, data mining, digitization, informatization strategy, informatization, biometrics, recognition of facial features, deep learning, machines learning, natural language processing, image recognition, speech recognition, cloud computing, cloud platform, cloud security, Internet of Things, and big data. The digital empowerment index (digital) developed in this study measures the capacity of publicly traded firms to effectively leverage business resources and information, as well as enhance supplier connections using digital technologies such as big data, cloud computing, and artificial intelligence.

3.2.3 Mediating Variable: New Quality Productivity Index

In September 2023, Chinese President Xi Jinping visited Northeast China, a region once central to China's heavy industry but now lagging behind in development. During this visit, he introduced the concept of "new quality productive forces," highlighting the need to upgrade traditional manufacturing industries to promote regional growth (People's Daily, 2024). This concept was further emphasized by Premier Li Qiang during the 'Two Sessions' in March 2024, where he announced that accelerating the development of new quality productive forces would be the government's top economic priority for the year (People's Daily, 2024). The term refers to productivity driven by technological innovation, characterized by high-tech, high efficiency, and high quality, marking a shift from traditional growth models (National Development and Reform Commission, 2024).

New quality productivity plays a critical role in China's economic modernization, with digital transformation as a key enabler. As these technologies improve transparency, reduce information asymmetry, and strengthen market responsiveness, they help stabilize market conditions, making new quality productivity a vital element in addressing financial vulnerabilities. By incorporating advanced digital technologies, Chinese firms can enhance efficiency and mitigate risks, including stock price crises, ensuring more resilient market practices. "New Quality Productivity" measures productivity, which evaluates productivity through two main components: labor and production tools (see Song et al., 2024). Labor is subdivided into active labor and objectified labor, while production tools are split into hard and soft technology. For active labor, indicators include R&D personnel wages, their proportion in the workforce, and the ratio of highly educated staff. Objectified labor is gauged by the share of fixed assets, emphasizing the role of advanced machinery in high-tech manufacturing sectors, where a higher share of manufacturing costs is noted due to machinery replacing human labor. Hard technology factors are measured by the share of direct R&D investments, depreciation and amortization, and leasing costs, along with the proportion of intangible assets to consider the impact of non-physical resources. Soft technology factors include total asset turnover and the equity multiplier, where the latter is used inversely to indicate financial risk, with a higher reciprocal implying lower risk and indicating better productivity. For specific

firm-specific new quality productivity indicator components, (see Table 10 in the "Appendix").

The New Quality Productivity Index is chosen as a mediating variable due to its direct relevance to the study's theoretical framework, capturing the interplay between digital transformation and financial stability. This index reflects innovation-driven efficiency through labor and technology components, aligning with digital transformation's goals of enhancing transparency, responsiveness, and operational efficiency. Its focus on R&D intensity, technology adoption, and productivity measures makes it a robust proxy for firm-level transformations. Using this variable in the model allows for the analysis of both direct and indirect effects of digital transformation on stock price crash risks, ensuring robust findings by addressing omitted variable biases. Additionally, its alignment with the policy discourse on "New Quality Productivity" ensures the model's practical relevance and generalizability across industries, providing insights for corporate strategies and national economic priorities.

3.2.4 Control Variables

As per previous studies (Chang et al., 2017; Chauhan et al., 2017; Chen et al., 2001; Kim et al., 2011), the current study investigates the impact of digital transformation of firms on the likelihood of stock market collapses. In this study, careful selection of control variables has been made to guarantee the fact that the analysis considers many elements that could potentially contribute to a company's susceptibility to drops in stock prices. One of the factors that is utilized is the logarithm of the firm's age (lnage), which signifies the degree of market maturity. The variable "firm size" is quantified by taking the logarithm of the sum of all assets, and it is employed to assess the financial structure and debt levels of a corporation. The return on assets (ROA) can be used as a metric to evaluate profitability. The model is enhanced by consist of supplementary variables such as average annual weekly stock returns (Ret), the standard deviation of annual weekly firm returns (Sigma), the natural logarithm of board scale (lnBoard), cash flow ratio (Cashflow), or the year and industry fixed effects. Integrating a diverse set of control variables is essential for separating the influence of digital transformation on reducing the frequency of stock price collapses. This ensures that the study is conducted with rigidity and considers many factors that could impact the outcomes (Refer to Table 11 in the "Appendix" for the definition of variables).

3.3 Data

The annual reports for publicly traded companies are obtained from the official websites of the Shanghai and Shenzhen Stock Exchanges. The CSMAR and Wind databases provide information on certain corporate characteristics (see "Appendix" for a detailed account of the data sources). It should be stressed that from the dataset we

have excluded organizations in the banking[1] and real estate industries due to the substantial differences in their debt structure compared to other industries. Additionally, companies that bear the *ST[2] or ST[3] labels are not included. In order to enhance the dependability of the indicators used to predict the likelihood of a stock price crash, the research excludes yearly data from companies that have less than 30 weekly return observations every year. In addition, the study excludes companies who fail to disclose information about their intangible assets. The investigation period spans from 2011 to 2022, coinciding with improvements in the information disclosure procedures of Chinese companies listed on the public market. For the purpose to mitigate the impact of outliers, all continuous control and dependent variables are subjected to winsorization at the 1% level. The definition of variables and the sources together with the descriptive statistics of the variables employed in the analysis are presented in Table 2A and 3A whilst the cross-sectional correlations are shown in Fig. 1 in the "Appendix".

3.4 Model Specification

We use panel data and a two-way fixed-effects regression approach, that accounts for variations across individual entities and time periods, hence, addressing consistency challenges. To evaluate Hypothesis 1, the following models are established:

$$SKEW_{t+1} = \beta_0 + \beta_1 Digital_{i,t} + \beta Control_{i,t} + \sum Ind + \sum Year + \epsilon_{i,t+1} \tag{8}$$

$$FLUC = \beta_0 + \beta_1 Digital_{i,t} + \beta Control_{i,t} + \sum Ind + \sum Year + \epsilon_{i,t+1} \tag{9}$$

Both Eqs. (8 and 9) integrate the metrics of stock price volatility with digital factors, denoted as ($Digital_{i,t}$) and a set of control variables ($\beta Control_{i,t}$). Industry-specific and year-specific effects are accounted for with dummy variables to control for fixed effects, while the error term captures the influence of unobserved variables.

To examine Hypothesis 2, the following model is constructed:

$$SKEW_{t+1} = \beta_0 + \beta_1 Digital_{i,t} + \beta_2 Digital_{i,t} \cdot Npro_{i,t} + \beta Control_{i,t} + \sum Ind + \sum Year + \epsilon_{i,t+1} \tag{10}$$

$$FLUC_{t+1} = \beta_0 + \beta_1 Digital_{i,t} + \beta_2 Digital_{i,t} \cdot Npro_{i,t} + \beta Control_{i,t} + \sum Ind + \sum Year + \epsilon_{i,t+1} \tag{11}$$

[1] Additional justification as to why we decided to exclude the banking sector from the study can be summarized as follows: (a) Regulatory and structural differences as banks operate under strict regulatory frameworks that influence their digital transformation processes and resilience strategies in ways that are fundamentally different from other sectors; (b) Distinct risk profiles as the stock price dynamics of banking institutions are often tied to macroeconomic factors, which may overshadow the impact of digital transformation on resilience and (c) by excluding the banking sector we can ensure that findings are more generalizable across industries where digital transformation plays a more typical and directly comparable role in operational resilience and stock performance.

[2] This type of stock has the risk of delisting.

[3] ST stock (Special Treatment) refers to the Shanghai and Shenzhen stock exchanges for special treatment of stock trading of listed companies with abnormal financial or other conditions.

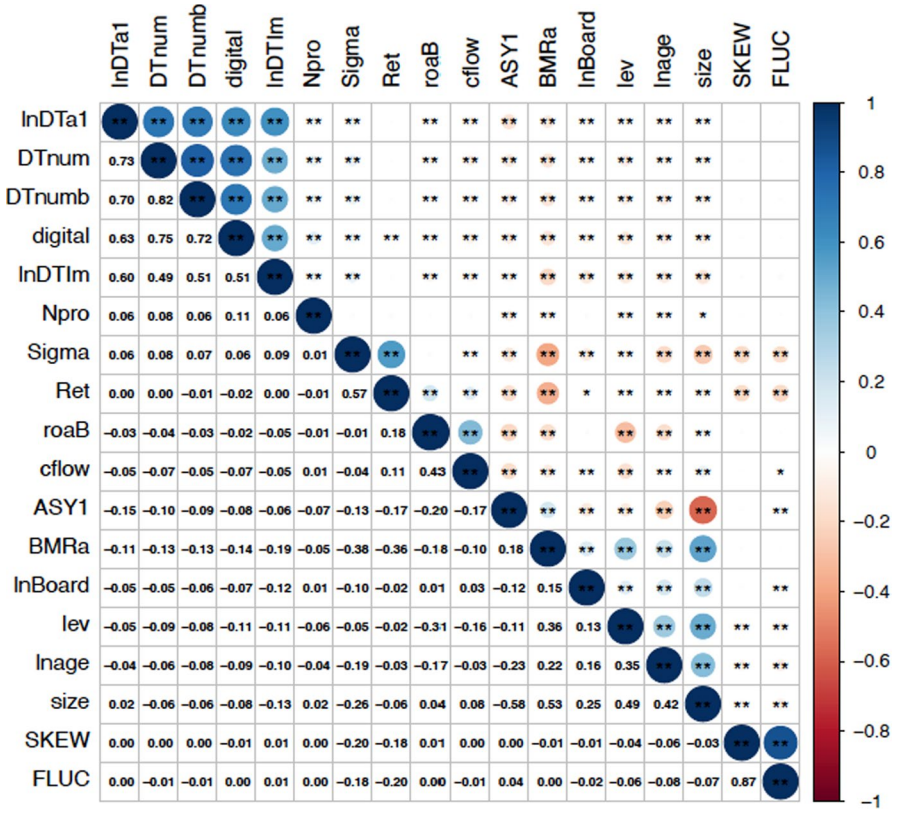

Fig. 1 Pearson correlation coefficients

Equations (10) and (11) are different from the preceding models in that they interact digital factors with new quality productive ($Npro_{i,t}$), in order to gauge the combined effect on the financial metrics. Control variables ($Control_{i,t}$) are included with their own coefficient to account for other firm-specific effects. Both models incorporate industry ($\sum Ind$) and year ($\sum Year$) fixed effects to adjust for broader sectoral and temporal trends, respectively. The error term ($\epsilon_{i,t+1}$) captures the unobserved factors affecting the next period's conditional skewness ($SKEW_{t+1}$) and downside/upside volume ($FLUC_{t+1}$) for firm i. These models collectively demonstrate how digital attributes and strategies, when controlled for firm, industry, and temporal characteristics, may predict financial outcomes.

For the analysis of Hypothesis 3, the following distinct model are presented:

$$ASY_{t+1} = \beta_0 + \beta_1 Digital_{i,t} + \beta Control_{i,t} + \sum Ind + \sum Year + \epsilon_{i,t+1} \quad (12)$$

$$SKEW_{t+1} = \beta_0 + \beta_1 Digital_{i,t} + \beta_2 ASY_{t+1} + \beta Control_{i,t} + \sum Ind + \sum Year + \epsilon_{i,t+1} \quad (13)$$

$$FLUC_{t+1} = \beta_0 + \beta_1 Digital_{i,t} + \beta_2 ASY_{t+1} + \beta Control_{i,t} + \sum Ind + \sum Year + \epsilon_{i,t+1} \tag{14}$$

Equation (12) captures the impact of digitalization on future information asymmetry while controlling for other known influences. The first equation predicts ASY_{t+1}, which could be a financial return of information asymmetry at a future time $t + 1$, using a digital factor ($Digital_{i,t}$) that measures the degree of digitalization at the firm level, along with control variables ($Control_{i,t}$) to adjust for other firm-specific influences. Industry ($\sum Ind$) and year ($\sum Year$) fixed effects are included to control for unobserved heterogeneity across industries and over time, respectively. The error term ($\epsilon_{i,t+1}$) captures all other unmodeled influences on ASY_{t+1}.

Equations (13) and (14) used similar structures to model $SKEW_{t+1}$ and $FLUC_{t+1}$, respectively, which may represent measures of skewness and volume or volatility in financial returns. These models of mediating effects explore the impact of digitalization though information asymmetry (ASY_{t+1}), while controlling for the same set of variables and fixed effects.

4 Results

4.1 Baseline Results

We employ an instrumental variable methodology that addresses endogeneity in regression models while efficiently absorbing high-dimensional fixed effects, allowing for robust and computationally efficient estimation in the presence of large datasets and complex error structures. It performs a 2SLS by first predicting the endogenous variables using the instruments and then regressing the dependent variable on the predicted values. In this context, the first instrument is, lnDTIm the natural logarithm of the median digital transformation within an industry and the second one is the DTnumb which quantifies the proportion of digital transformation, (Zhao et al., 2021), which is scaled by a factor of 1000. These two instrumental variables are appropriate as lnDTIm captures industry-level digital transformation trends, which are correlated with firm-level digital transformation but not directly with the firm's stock price crash risk whilst DTnumb, on the other hand, reflects the proportion of digital transformation within a firm, directly related to the firm's digital efforts but not immediately affected by stock price fluctuations. Both instruments address endogeneity by being correlated with the endogenous variable (digital transformation) while remaining exogenous to the dependent variable (stock price crash risk).

The coefficients for 'digital' in Table 1 are consistently negative and statistically significant in all models. This suggests that digital transformation is linked to a reduction in the probability of a stock price crash risk. These coefficients are typically significant at the 1% level, indicating a high level of confidence in the results. Furthermore, the variable 'DTnum' is also noteworthy as it exhibits a negative sign, suggesting a comparable correlation with decreased crash risk.

In Table 2, the coefficient for lnDTIm is statistically significant at the 1% level when predicting 'digital', albeit the effect size is relatively small (0.000131). This

Table 1 Baseline regression

	(1) F.SKEW	(2) F.SKEW	(3) F.FLUC	(4) F.FLUC
Digital	− 33.9475***		− 25.4591***	
	(− 4.8400)		(− 5.5001)	
DTnum		− 0.1740***		− 0.1072***
		(− 4.5302)		(− 4.2356)
Ret	8.0031***	8.0555***	5.4702***	5.6068***
	(8.7421)	(9.1429)	(9.0542)	(9.6634)
Sigma	− 1.0409***	− 1.0914***	− 1.1572***	− 1.2429***
	(− 2.9162)	(− 3.1595)	(− 4.9128)	(− 5.4638)
Size	0.1273***	0.1316***	0.0635***	0.0652***
	(7.8835)	(8.6888)	(5.9561)	(6.5389)
cflow	− 0.0222	− 0.0063	− 0.0414	− 0.0295
	(− 0.2348)	(− 0.0717)	(− 0.6625)	(− 0.5120)
lnBoard	− 0.0802	− 0.0521	− 0.0346	− 0.0298
	(− 1.5238)	(− 1.0352)	(− 0.9960)	(− 0.8983)
lev	− 0.2833***	− 0.2712***	− 0.1782***	− 0.1637***
	(− 4.5277)	(− 4.5752)	(− 4.3163)	(− 4.1940)
BMRa	− 0.4880***	− 0.4949***	− 0.3138***	− 0.3189***
	(− 10.2155)	(− 10.8203)	(− 9.9546)	(− 10.5861)
roaB	− 0.1036	− 0.1391	− 0.0984	− 0.1145*
	(− 0.9824)	(− 1.3704)	(− 1.4143)	(− 1.7127)
lnage	− 0.1841***	− 0.1968***	− 0.1528***	− 0.1591***
	(− 7.3740)	(− 8.2963)	(− 9.2699)	(− 10.1825)
_cons	− 1.9906***	− 1.9076***	− 0.7777**	− 0.7002**
	(− 3.7300)	(− 3.8053)	(− 2.2082)	(− 2.1211)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	19,877	21,399	19,877	21,399
R^2	0.060	0.058	0.063	0.061

t statistics in parentheses

*$p<0.1$, **$p<0.05$, ***$p<0.01$

indicates that higher median industry digital transformation, when log-transformed, slightly increases the firm's digital score. However, lnDTIm is significant in F.FLUC but insignificant in F.SKEW, suggesting that the median industry digital transformation has a limited impact on the stock crash risk when it's log-transformed.

DTnumb presents with a highly significant coefficient (0.00199) at the 1% level in the digital model. For F.SKEW and F.FLUC, the coefficients are negative and significant, indicating that a higher proportion of digital transformation correlates with a lower likelihood of stock price crashes.

Table 2 Instrument variable regression

	(1) Digital	(2) F.SKEW	(3) F.FLUC	(4) digital	(5) F.SKEW	(6) F.FLUC
lnDTIm	0.000131***					
	(7.56)					
DTnumb				0.00199***		
				(106.05)		
Digital		− 101.1	− 133.8*		− 50.13***	− 32.56***
		(− 0.90)	(− 1.79)		(− 4.56)	(− 4.50)
Ret	− 0.00218*	7.364***	5.046***	− 0.00123	7.714***	5.315***
	(− 1.73)	(6.67)	(6.88)	(− 1.57)	(8.44)	(8.82)
Sigma	− 0.000170	− 0.902**	− 1.100***	− 0.000325	− 1.111***	− 1.187***
	(− 0.35)	(− 2.19)	(− 4.02)	(− 1.06)	(− 3.12)	(− 5.06)
Size	0.000233***	0.196***	0.117***	0.0000522***	0.141***	0.0710***
	(9.79)	(5.83)	(5.22)	(3.89)	(8.95)	(6.84)
cflow	0.0000377	− 0.117	− 0.0958	− 0.0000286	− 0.0157	− 0.0403
	(0.28)	(− 1.04)	(− 1.28)	(− 0.35)	(− 0.17)	(− 0.65)
lnBoard	0.000222***	− 0.0211	− 0.0125	0.0000249	− 0.0825	− 0.0396
	(2.90)	(− 0.30)	(− 0.27)	(0.55)	(− 1.57)	(− 1.14)
lev	− 0.0000535	− 0.390***	− 0.253***	0.000143***	− 0.304***	− 0.188***
	(− 0.57)	(− 4.87)	(− 4.76)	(2.70)	(− 4.90)	(− 4.59)
BMRa	− 0.0000842	− 0.562***	− 0.372***	− 0.00000952	− 0.515***	− 0.329***
	(− 1.23)	(− 9.45)	(− 9.40)	(− 0.23)	(− 10.88)	(− 10.53)
roaB	− 0.0000993	− 0.249**	− 0.219***	− 0.0000363	− 0.119	− 0.112
	(− 0.72)	(− 2.11)	(− 2.78)	(− 0.40)	(− 1.13)	(− 1.61)
lnage	0.000203***	− 0.160***	− 0.119***	0.0000645***	− 0.189***	− 0.155***
	(5.25)	(− 4.00)	(− 4.46)	(3.04)	(− 7.63)	(− 9.52)
N	15,000	15,000	15,000	19,610	19,610	19,610
R^2		0.016	0.017		0.024	0.024
Wald F		57.19	57.19		11,247.7	11,247.7
LM stat		68.64***	68.64***		7812.2***	7812.2***
F	57.19	28.93	27.00	11,247.7	41.32	40.38

t statistics in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

The diagnostics from the instrumental variable regression models show that the instruments used to examine the relationship between firm digital transformation and stock crash risk are robust and valid. The Kleibergen-Paap rk LM Statistic, Cragg-Donald Wald F Statistic, and Kleibergen-Paap Wald rk F Statistic are all significant at the 1% level across the models, indicating that the instruments are strongly correlated with the endogenous explanatory variable, 'digital', and are not weak instruments. The high values of the Wald F and Kleibergen-Paap Wald rk F statistics, which are well above the commonly used threshold, further confirm the

strength and relevance of the instruments in predicting the digital transformation of firms. This robustness check lends credibility to the IV regression results, suggesting that the positive association found between firm digital transformation and a reduction in stock crash risk is reliable hence supporting H1.

To further ensure the robustness of our results we also used an alternative construction method of digital transformation, referred to as lnDTa1 which represents the natural logarithm of the total of 1 plus the word frequencies, mathematically expressed as ln (DTa + 1). While TF-IDF accounts for term uniqueness and document-specific relevance, ln (DTa + 1) emphasizes the aggregate presence of digital transformation-related terms, reflecting their overall usage without the contextual weighting inherent in TF-IDF.

According to Table 3, the lagged variable of lnDTa1 (L.lnDTa1) shows a statistically significant negative relationship with both F.SKEW and F.FLUC in columns (1) and (2), at the 5% level. This means that higher past values of digital transformation discourse are linked with lower subsequent values of financial skewness and volatility, which could imply that companies with more utility on digital transformation might experience less financial variability and less extreme financial outcomes.

4.2 Mechanism Analysis

4.2.1 Moderating Effect: New Quality Productivity (Npro)

As we discussed previously new quality productivity is driven by technological innovation, fuelled by the forces of innovation, liberation, and development. Through the moderating process, we explore how new quality productivity influences the interplay between digital transformation and stock price crashes. It offers new insights into how digitization affects corporate risk and identifies critical financial metrics that should be taken into account when evaluating the risks associated with stock investments.

In models (1) and (2) of Table 4, the variable digital shows a significant negative relationship with SKEWt1, suggesting that digital transformation may be associated with a lower likelihood or magnitude of negative stock price shocks. Model (2) reveals that 'Npro' also has a negative and significant impact on SKEWt1, albeit with a smaller coefficient. This suggests that new quality productivity, on its own, might also contribute to reducing such risks. However, when considering the interaction term in model (3), 'interNpro' the negative coefficient is more pronounced, which indicates a moderating effect where the combination of digital transformation and new quality productivity leads to further reduction in the skewness of stock price distributions. For FLUCt1, the digital variable shows a positive and significant impact in models (4) and (5), implying that digital transformation correlates with an increase in asymmetric stock volatility, which may indicate heightened stock price crisis sensitivity. However, the interaction term 'interNpro' in model (6) is again negative and significant, suggesting that the interplay between digital transformation and new quality productivity can mitigate this increased volatility.

Table 3 Other robustness tests: lnDTa1

	(1) F.SKEW	(2) F.FLUC
L.lnDTa1	− 0.0153**	− 0.0093**
	(− 1.7991)	(− 1.6663)
Ret	8.8137***	5.9434***
	(8.8190)	(9.0339)
Sigma	0.1344	− 0.5564**
	(0.3392)	(− 2.1340)
Size	0.1325***	0.0660***
	(7.3932)	(5.5925)
cflow	− 0.0531	− 0.0783
	(− 0.5373)	(− 1.2037)
lnBoard	− 0.0594	− 0.0411
	(− 1.0471)	(− 1.1004)
lev	− 0.2898***	− 0.1674***
	(− 4.2308)	(− 3.7121)
BMRa	− 0.4239***	− 0.2915***
	(− 8.1776)	(− 8.5442)
roaB	− 0.1677	− 0.1245*
	(− 1.4992)	(− 1.6905)
lnage	− 0.3490***	− 0.2679***
	(− 9.8051)	(− 11.4334)
_cons	− 2.2332***	− 0.8212*
	(− 3.1761)	(− 1.7742)
Year FE	Yes	Yes
Industry FE	Yes	Yes
N	18,057	18,057
R^2	0.063	0.066

t statistics in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

The evidence suggests that digital transformation exhibits a complex relationship with stock price crisis indicators—reducing the likelihood of negative price shocks but possibly increasing volatility. Importantly, the interaction of digital transformation with new quality productivity (interNpro) consistently shows a significant negative association with both measures of stock price crisis. This indicates that the combination of digital advancements and productivity improvements has a stabilizing effect on stock prices. It implies that companies engaging in digital transformation could potentially buffer and reduce the impact of stock price crises if such transformation is accompanied by substantive improvements in new quality productivity. Given the existing evidence of market irregularities and irrational investor behavior as factors that might trigger stock market variability (Rehan et al., 2021) the findings of this study are of great importance for investors and company strategists alike

Table 4 New quality productivity: Npro

	(1) SKEWt1	(2) SKEWt1	(3) SKEWt1	(4) FLUCt1	(5) FLUCt1	(6) FLUCt1
digital	− 33.9879***	− 31.0565***	− 2.8219	− 25.4841***	− 23.1075***	− 6.5820
	(− 4.8457)	(− 4.3193)	(− 0.2210)	(− 5.5055)	(− 4.8711)	(− 0.7813)
Npro		− 0.0091**	− 0.0031		− 0.0082***	− 0.0047
		(− 2.0163)	(− 0.6169)		(− 2.7447)	(− 1.4037)
interNpro			− 3.6019***			− 2.1082**
			(− 2.6757)			(− 2.3736)
Ret	7.9868***	8.9641***	8.9172***	5.4599***	6.0683***	6.0408***
	(8.7248)	(9.4814)	(9.4319)	(9.0378)	(9.7286)	(9.6842)
Sigma	− 1.0369***	− 0.6787*	− 0.6764*	− 1.1550***	− 0.9921***	− 0.9907***
	(− 2.9051)	(− 1.8270)	(− 1.8209)	(− 4.9034)	(− 4.0476)	(− 4.0425)
Size	0.1279***	0.1256***	0.1271***	0.0637***	0.0627***	0.0636***
	(7.9223)	(7.7053)	(7.7912)	(5.9808)	(5.8329)	(5.9091)
cflow	− 0.0225	− 0.0583	− 0.0619	− 0.0417	− 0.0684	− 0.0705
	(− 0.2371)	(− 0.6045)	(− 0.6421)	(− 0.6663)	(− 1.0755)	(− 1.1089)
lnBoard	− 0.0821	− 0.0877*	− 0.0898*	− 0.0354	− 0.0416	− 0.0428
	(− 1.5603)	(− 1.6466)	(− 1.6863)	(− 1.0188)	(− 1.1830)	(− 1.2181)
lev	− 0.2846***	− 0.2792***	− 0.2799***	− 0.1787***	− 0.1706***	− 0.1710***
	(− 4.5491)	(− 4.4041)	(− 4.4156)	(− 4.3283)	(− 4.0787)	(− 4.0887)
BMRa	− 0.4880***	− 0.4563***	− 0.4588***	− 0.3139***	− 0.2971***	− 0.2985***
	(− 10.2154)	(− 9.3771)	(− 9.4272)	(− 9.9576)	(− 9.2538)	(− 9.2979)
roaB	− 0.1038	− 0.1121	− 0.1158	− 0.0985	− 0.1022	− 0.1043
	(− 0.9847)	(− 1.0517)	(− 1.0863)	(− 1.4159)	(− 1.4533)	(− 1.4840)
lnage	− 0.1841***	− 0.2297***	− 0.2316***	− 0.1527***	− 0.1775***	− 0.1786***
	(− 7.3725)	(− 8.5065)	(− 8.5760)	(− 9.2680)	(− 9.9668)	(− 10.0276)
_cons	− 2.0004***	− 1.8661***	− 1.9213***	− 0.7818**	− 0.6874*	− 0.7197**
	(− 3.7486)	(− 3.4800)	(− 3.5810)	(− 2.2198)	(− 1.9430)	(− 2.0331)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	19,877	19,482	19,482	19,877	19,482	19,482
R^2	0.060	0.063	0.064	0.063	0.066	0.067

t statistics in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

when evaluating the risk profile of companies, especially in the context of technological and productivity enhancements.

4.3 Mediating Effect: Information Asymmetry (ASY1)

This study utilizes individual company stocks to innovatively construct three liquidity indicators: the liquidity ratio, the illiquidity ratio, and the return reversal

indicator. These indicators aim to capture the degree of information asymmetry between informed and uninformed traders regarding the value of firms in the securities market. Through principal component analysis, a comprehensive indicator of information asymmetry was further developed. This indicator not only reveals the level of information asymmetry between capital providers and companies but also reflects the differences in the extent of information disclosure by listed companies. The development and application of this indicator are significant for delving deeper into the formation mechanism of information asymmetry in the securities market. In analyzing the relationship between corporate digitalization and stock price crashes, this comprehensive information asymmetry indicator serves as a key variable. It helps researchers understand how information asymmetry during the digital transformation process influences the stability of stock prices and predicts the risks that companies may face. This enriches the theoretical research on securities markets and provides valuable data support for empirical analysis, offering significant reference value to researchers in the field of economics.

In this direction, following the methodologies of Song et al. (2021) and Yu et al. (2012), we use Liquidity Ratio (LR), the Illiquidity Ratio (ILL), and the Return Reversal Indicator (GAM) (Amihud, 2002; Amihud, & Mendelson, 1986; Amihud et al., 1997; Pástor & Stambaugh, 2003). The premise is that the lower the liquidity of a stock, the higher the level of information asymmetry. Using principal component analysis we produce a composite Information Asymmetry (ASY) index as follows:

$$LR_{it} = -\frac{1}{D_{it}}\sum_{k=1}^{D_{it}}\sqrt{\frac{V_{it}(k)}{|r_{it}(k)|}} \tag{16}$$

$$ILL_{it} = \frac{1}{D_{it}}\sum_{k=1}^{D_{it}}\left|\frac{r_{it}(k)}{\sqrt{V_{it}(k)}}\right| \tag{17}$$

$$GAM_{ii} = |\gamma_{it}| \tag{18}$$

Liquidity Ratio (LR_{it}) measures the liquidity of stock i over a certain period t. It is calculated as the negative average of the ratio of trading volume $V_{it}(k)$ to the square root of the absolute value of the price change $|r_{it}(k)|$ over days D_{it} within time t. However, the illiquidity ratio (ILL_{it}) is the opposite of the Liquidity Ratio. Return reversal indicator (GAM_{ii}) captures the absolute value of the change in returns for stock i at time t indicating the magnitude of price volatility. In essence, a higher degree of information asymmetry correlates with lower stock liquidity, resulting in larger values for the LR, ILL, and GAM indicators. A larger ASY value indicates a higher degree of information asymmetry.

Table 5 suggests that the variable "digital," representing corporate digitalization, shows a consistently negative association with both SKEWt1 and FLUCt1, which are proxies for stock price crash risk. The coefficients range from − 10.0123 to − 10.3868 for SKEWt1 and from − 6.5301 to − 6.8243 for FLUCt1, all statistically significant at the 1% level. Similarly, "digital" is negatively correlated with ASY1,

Table 5 Information asymmetry: ASY1

	(1) SKEWt1	(2) ASY1	(3) SKEWt1	(4) FLUCt1	(5) FLUCt1
digital	− 10.0123***	− 5.7367***	− 10.3868***	− 6.5301***	− 6.8243***
	(− 2.8090)	(− 5.0710)	(− 2.9122)	(− 2.7846)	(− 2.9083)
ASY1			− 0.0619***		− 0.0506***
			(− 2.9767)		(− 3.7006)
Ret	9.5350***	8.9023***	10.0891***	6.4225***	6.8859***
	(11.2315)	(33.2891)	(11.5869)	(11.4983)	(12.0202)
Sigma	− 2.2811***	− 4.4685***	− 2.5441***	− 1.8305***	− 2.0491***
	(− 7.2073)	(− 45.0434)	(− 7.7272)	(− 8.7907)	(− 9.4599)
Size	0.0237***	− 0.3391***	0.0027	− 0.0040	− 0.0214***
	(3.9916)	(− 1.8e + 02)	(0.2868)	(− 1.0332)	(− 3.5135)
cflow	− 0.0237	− 0.0323	− 0.0233	− 0.0348	− 0.0356
	(− 0.2958)	(− 1.3075)	(− 0.2907)	(− 0.6602)	(− 0.6753)
lnBoard	− 0.0424	0.0046	− 0.0413	− 0.0268	− 0.0259
	(− 1.5751)	(0.5423)	(− 1.5313)	(− 1.5110)	(− 1.4590)
lev	− 0.0647*	0.3005***	− 0.0459	− 0.0407*	− 0.0259
	(− 1.8959)	(27.9888)	(− 1.3219)	(− 1.8130)	(− 1.1343)
BMRa	− 0.2655***	0.9986***	− 0.2020***	− 0.1190***	− 0.0665***
	(− 8.7678)	(107.1163)	(− 5.4553)	(− 5.9737)	(− 2.7281)
roaB	0.0550	− 0.3419***	0.0353	0.0196	0.0030
	(0.6297)	(− 13.1385)	(0.4029)	(0.3414)	(0.0521)
lnage	− 0.0697***	− 0.0300***	− 0.0707***	− 0.0498***	− 0.0507***
	(− 9.3930)	(− 12.7563)	(− 9.5163)	(− 10.1969)	(− 10.3704)
_cons	− 0.2930**	6.8946***	1.8553**	0.2431***	1.7988***
	(− 2.3184)	(173.7422)	(2.5704)	(2.9238)	(3.7880)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	19,876	23,346	19,864	19,876	19,864
R^2	0.058	0.735	0.058	0.062	0.063
Sobel_Z			2.57***		2.567***

t statistics in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

the measure of information asymmetry, with a coefficient of − 5.7367, again significant at the 1% level. The mediator variable ASY1 itself also shows significant negative effects on SKEWt1 and FLUCt1, with coefficients of − 0.0619 and − 0.0506 in the column (3) and column (5) respectively. The implication of this evidence is of great significance indicating that as companies become more digitally integrated, they may enjoy more transparent and symmetric information distribution, which in turn appears to stabilize stock prices and mitigate the risk of drastic price drops.

This points to digitalization not just as a business efficiency enhancer but also as a potential factor in fostering more resilient financial markets.

4.4 Heterogeneity Analysis

4.4.1 Industry Heterogeneity Analysis: Labor-Intensive, Capital-Intensive and Technology-Intensive Industry

To investigate the effect of industry heterogeneity on the relationship between digital transformation and stock price crash risk among Chinese listed companies, we categorize industries into three types according to China's industry standards: labor-intensive, capital-intensive and technology-intensive. This classification aims to explore how different industry characteristics influence the impact of digital transformation on stock price crash risk. We hypothesize that the nature of the industry -whether it is labor, capital, or technology-intensive—moderates the effects of digital transformation, potentially leading to varying outcomes in stock price crash risk across different sectors.

The regression analysis in Table 6 reveals that digital transformation consistently reduces stock price crash risk across labor-intensive, capital-intensive, and technology-intensive industries in China, with significant negative coefficients found in measures of both overall crash risk (SKEWt1) and down-up volatility (FLUCt1). However, the effect is most pronounced in labor and capital-intensive industries compared to technology-intensive ones, indicating that while digitalization contributes to stock stability across the board, industries with pre-existing digital integration show smaller changes. This implies that digital transformation acts as a stabilizing factor for stock prices, potentially due to improved operational efficiencies and enhanced information transparency. Additionally, regional disparities and policy influences play a critical role, as green credit policies have been found to negatively impact digital innovation, particularly in state-owned enterprises, firms lacking financially experienced executives, and in China's eastern regions (Lu et al., 2023).

4.4.2 Industry Heterogeneity Analysis: High-Tech Industries and Non-high-tech Industries

We explore further the impact of digital transformation and its impact on the risk of stock price crashes categorizing the industries into high-tech industries and non-high-tech industries.

The results in reported Table 7, suggest that for high-tech industries, the coefficients for digital transformation on SKEWt1 and FLUCt1 are insignificant whist for non-high-tech industries, digital transformation shows a highly significant negative relationship with both SKEWt1 (-51.2221) and FLUCt1 (-35.5824). These findings suggest non-high-tech industries vis-à-vis high-tech industries appear to benefit significantly more from digital transformation,

Table 6 Labor-intensive, Capital-intensive and Technology-intensive

	(1)	(2)	(3)	(4)	(5)	(6)
	Labor-intensive industries		Capital-intensive industries		Technology-intensive industries	
	SKEWt1	FLUCt1	SKEWt1	FLUCt1	SKEWt1	FLUCt1
digital	− 84.8893***	− 55.1894***	− 80.2108**	− 62.9425***	− 23.1696***	− 17.3212***
	(− 2.6028)	(− 2.6123)	(− 2.3382)	(− 2.7767)	(− 3.0601)	(− 3.4360)
Ret	14.0222***	9.5855***	6.9180***	4.6928***	6.6450***	4.4424***
	(6.7846)	(7.1598)	(3.8102)	(3.9114)	(5.2254)	(5.2469)
Sigma	− 2.0703***	− 2.1587***	− 0.4882	− 0.5594	− 0.6516	− 0.9178***
	(− 2.6635)	(− 4.2875)	(− 0.7037)	(− 1.2202)	(− 1.2975)	(− 2.7449)
Size	0.0858**	0.0530**	0.1540***	0.0897***	0.1600***	0.0755***
	(2.2697)	(2.1624)	(4.5851)	(4.0450)	(6.8558)	(4.8593)
cflow	− 0.2544	− 0.1438	0.0597	0.0043	0.1680	0.0570
	(− 1.3598)	(− 1.1867)	(0.3359)	(0.0368)	(1.1463)	(0.5844)
lnBoard	− 0.0457	− 0.0246	− 0.0420	− 0.0034	− 0.0898	− 0.0303
	(− 0.4237)	(− 0.3522)	(− 0.3901)	(− 0.0484)	(− 1.1830)	(− 0.6005)
lev	− 0.2268	− 0.1774*	− 0.3686***	− 0.2251***	− 0.2292**	− 0.1262**
	(− 1.6011)	(− 1.9335)	(− 2.8138)	(− 2.6000)	(− 2.5468)	(− 2.1059)
BMRa	− 0.3917***	− 0.2874***	− 0.4793***	− 0.3101***	− 0.6127***	− 0.3956***
	(− 3.8949)	(− 4.4125)	(− 4.8951)	(− 4.7936)	(− 8.9694)	(− 8.6999)
roaB	0.1269	− 0.1274	− 0.4739**	− 0.3171**	− 0.0707	− 0.0524
	(0.4510)	(− 0.6992)	(− 2.1760)	(− 2.2037)	(− 0.5090)	(− 0.5669)
lnage	− 0.1614***	− 0.1352***	− 0.1523***	− 0.1511***	− 0.1814***	− 0.1539***
	(− 2.9085)	(− 3.7623)	(− 2.9043)	(− 4.3581)	(− 5.2162)	(− 6.6450)
_cons	− 0.7905	− 0.3598	− 3.4383***	− 2.0506***	− 2.5186***	− 0.7183
	(− 0.6891)	(− 0.4841)	(− 2.9631)	(− 2.6744)	(− 2.6175)	(− 1.1212)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4730	4730	5108	5108	10,040	10,040
R^2	0.076	0.078	0.059	0.067	0.066	0.071

t statistics in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

indicating a substantial decrease in stock price crash risk, which could reflect a larger scope for improvement in digital practices within these sectors.

4.4.3 Firm Heterogeneity Analysis: Large Size and SMEs

The diversity presents among various types of businesses, particularly in terms of how digital transformation influences the risk of significant drops in stock prices, plays a crucial role. To explore this, companies have been divided into two categories based on their size: large enterprises and Small and Medium-sized Enterprises (SMEs). This categorization serves to examine how the specific attributes of Chinese listed companies, in terms of their size, affect the relationship between digital transformation and the potential for stock price collapses.

Table 7 High-tech industries and Non-high-tech industries

	(1)	(2)	(3)	(4)
	HighTech		Non-HighTech	
	SKEWt1	FLUCt1	SKEWt1	FLUCt1
digital	− 15.9430	− 15.2384*	− 51.2221***	− 35.5824***
	(− 1.4749)	(− 2.1152)	(− 5.2347)	(− 5.5835)
Ret	7.3877***	4.6150***	9.2993***	6.8785***
	(6.0343)	(5.6560)	(6.6188)	(7.5172)
Sigma	− 0.6647	− 0.7779**	− 1.3897**	− 1.5697***
	(− 1.3954)	(− 2.4502)	(− 2.5351)	(− 4.3966)
Size	0.1652***	0.0830***	0.0908***	0.0440***
	(7.5031)	(5.6563)	(3.5080)	(2.6108)
cflow	0.0190	− 0.0866	− 0.0167	0.0210
	(0.1390)	(− 0.9515)	(− 0.1241)	(0.2389)
lnBoard	− 0.1219*	− 0.0555	0.0073	0.0179
	(− 1.7180)	(− 1.1738)	(0.0894)	(0.3373)
lev	− 0.2840***	− 0.1647***	− 0.2837***	− 0.1742***
	(− 3.2935)	(− 2.8658)	(− 2.8818)	(− 2.7174)
BMRa	− 0.5577***	− 0.3585***	− 0.4357***	− 0.2949***
	(− 8.5388)	(− 8.2344)	(− 5.9936)	(− 6.2293)
roaB	− 0.1820	− 0.0992	− 0.0427	− 0.1007
	(− 1.3010)	(− 1.0642)	(− 0.2539)	(− 0.9196)
lnage	− 0.1666***	− 0.1413***	− 0.1778***	− 0.1574***
	(− 4.9560)	(− 6.3048)	(− 4.5205)	(− 6.1452)
_cons	− 3.2646***	− 1.6153**	− 1.5746**	− 0.5695
	(− 3.0500)	(− 2.2643)	(− 2.1333)	(− 1.1847)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	11,071	11,071	8808	8808
R^2	0.067	0.070	0.057	0.064

t statistics in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table 8 reveals a stark contrast in the effect of digitalization on stock price crash risk between large firms and small and medium-sized enterprises (SMEs). For large firms (size > 20.0301), digitalization is associated with a significant decrease in crash risk, as evidenced by the negative coefficients for both SKEWt1 (-33.8788) and FLUCt1 (-25.7185), both statistically significant at the 1% level. Conversely, for SMEs (size ≤ 20.0301), the relationship between digitalization and stock price crash risk is insignificant.

Table 8 Large size and SMEs

	(1) Large size	(2)	(3) SMEs	(4)
	SKEWt1	FLUCt1	SKEWt1	FLUCt1
digital	− 33.8788***	− 25.7185***	189.9569	196.2015
	(− 4.7878)	(− 5.5091)	(1.0112)	(1.5089)
Ret	7.9642***	5.4285***	8.9750	13.4633
	(8.6287)	(8.9147)	(0.7331)	(1.5887)
Sigma	− 0.9608***	− 1.1086***	− 13.2126***	− 12.8474***
	(− 2.6715)	(− 4.6722)	(− 2.9815)	(− 4.1881)
Size	0.1268***	0.0646***	0.1817	− 0.0073
	(7.6085)	(5.8793)	(0.2960)	(− 0.0172)
cflow	− 0.0403	− 0.0604	2.3263***	1.2267**
	(− 0.4189)	(− 0.9506)	(3.3037)	(2.5169)
lnBoard	− 0.0777	− 0.0346	1.2246	0.5738
	(− 1.4656)	(− 0.9884)	(1.4056)	(0.9515)
lev	− 0.2861***	− 0.1751***	0.7025	0.5983
	(− 4.4872)	(− 4.1631)	(0.4964)	(0.6108)
BMRa	− 0.4906***	− 0.3165***	− 1.9037**	− 1.1679**
	(− 10.1989)	(− 9.9725)	(− 2.2709)	(− 2.0126)
roaB	− 0.1230	− 0.1106	− 0.5414	− 0.8613
	(− 1.1499)	(− 1.5675)	(− 0.4589)	(− 1.0546)
lnage	− 0.1790***	− 0.1498***	− 0.8488**	− 0.7613***
	(− 7.0957)	(− 9.0035)	(− 2.1752)	(− 2.8182)
_cons	− 1.9993***	− 0.8146**	− 3.9280	0.7595
	(− 3.6928)	(− 2.2807)	(− 0.3143)	(0.0878)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	19,695	19,695	184	184
R^2	0.060	0.063	0.364	0.386

t statistics in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

4.4.4 Firm Heterogeneity Analysis: Attention by Analysts and Research Reports

There exists a variance among different kinds of companies, especially in terms of how digital transformation affects the risk of severe declines in stock prices. To understand this better, companies have been categorized by the degree of attention they receive from analysts. This classification aims to explore how the specific attributes of companies listed in China can impact the relationship between digital transformation and the risk of stock price plunges.

For firms under the scrutiny of analysts, digital transformation is linked to a marked reduction in stock price crash risk in Table 9, with the results indicating a

Table 9 Attention by analysts and research reports

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Attention by analysts ≠ 0		Attention by analysts = 0		Attention by research reports ≠ 0		Attention by research reports = 0	
	SKEWt1	FLUCt1	SKEWt1	FLUCt1	SKEWt1	FLUCt1	SKEWt1	FLUCt1
digital	− 37.5898***	− 27.6277***	− 9.7238	− 8.6433	− 38.3387***	− 28.4832***	− 6.0354	− 5.7336
	(− 4.8931)	(− 5.3025)	(− 0.3852)	(− 0.5552)	(− 5.0254)	(− 5.5076)	(− 0.2344)	(− 0.3612)
Ret	7.6469***	5.4051***	8.2677***	4.1447**	7.5887***	5.3910***	8.3071***	4.2054**
	(7.5765)	(7.8959)	(3.0380)	(2.4691)	(7.5222)	(7.8829)	(3.0344)	(2.4920)
Sigma	− 1.1610***	− 1.2179***	1.5687*	0.4889	− 1.1913***	− 1.2324***	1.6349*	0.4951
	(− 2.7256)	(− 4.2155)	(1.8613)	(0.9404)	(− 2.7970)	(− 4.2686)	(1.9284)	(0.9474)
Size	0.0968***	0.0532***	0.2707***	0.1453***	0.0962***	0.0534***	0.2666***	0.1406***
	(4.7922)	(3.8813)	(5.2095)	(4.5313)	(4.7840)	(3.9180)	(5.1013)	(4.3647)
cflow	0.0288	− 0.0655	− 0.0599	− 0.0196	0.0232	− 0.0692	− 0.0312	− 0.0031
	(0.2513)	(− 0.8433)	(− 0.2924)	(− 0.1549)	(0.2028)	(− 0.8926)	(− 0.1514)	(− 0.0246)
lnBoard	− 0.0910	− 0.0256	− 0.1119	− 0.0661	− 0.0826	− 0.0217	− 0.1168	− 0.0620
	(− 1.4787)	(− 0.6130)	(− 0.8309)	(− 0.7951)	(− 1.3435)	(− 0.5209)	(− 0.8632)	(− 0.7429)
lev	− 0.2395***	− 0.1508***	− 0.5521***	− 0.3191***	− 0.2289***	− 0.1492***	− 0.5690***	− 0.3213***
	(− 3.1465)	(− 2.9221)	(− 3.4185)	(− 3.2032)	(− 3.0150)	(− 2.8990)	(− 3.4861)	(− 3.1941)
BMRa	− 0.5396***	− 0.3822***	− 0.4911***	− 0.2739***	− 0.5456***	− 0.3842***	− 0.4809***	− 0.2722***
	(− 9.7947)	(− 10.2296)	(− 3.2952)	(− 2.9791)	(− 9.9201)	(− 10.3046)	(− 3.2097)	(− 2.9476)
roaB	− 0.1811	− 0.1565*	− 0.3628*	− 0.1617	− 0.1665	− 0.1541	− 0.3632*	− 0.1648
	(− 1.3065)	(− 1.6639)	(− 1.6847)	(− 1.2175)	(− 1.2020)	(− 1.6408)	(− 1.6811)	(− 1.2371)
lnage	− 0.1558***	− 0.1473***	− 0.3348***	− 0.2724***	− 0.1601***	− 0.1493***	− 0.3227***	− 0.2705***
	(− 5.4484)	(− 7.5944)	(− 3.9962)	(− 5.2720)	(− 5.6091)	(− 7.7150)	(− 3.7824)	(− 5.1437)
_cons	− 1.2012*	− 0.2069	− 4.2406***	− 2.1148**	− 1.1976*	− 0.2136	− 4.1624***	− 2.0297**
	(− 1.7029)	(− 0.4324)	(− 3.1383)	(− 2.5374)	(− 1.6995)	(− 0.4471)	(− 3.0674)	(− 2.4266)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Attention by analysts ≠ 0		Attention by analysts = 0		Attention by research reports ≠ 0		Attention by research reports = 0	
	SKEWt1	FLUCt1	SKEWt1	FLUCt1	SKEWt1	FLUCt1	SKEWt1	FLUCt1
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14,830	14,830	5049	5049	14,861	14,861	5018	5018
R^2	0.068	0.072	0.068	0.077	0.068	0.072	0.067	0.076

t statistics in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

strong and negative coefficient for both SKEWt1 and FLUCt1. This indicates that when attention of analysts is considered a company's digital initiatives are likely to be associated with a lower probability of stock price crashes. On the other hand, for firms that do not attract analyst attention, the coefficients for SKEWt1 and FLUCt1are insignificant. This implies that digital transformation may not have the same protective influence on stock price crash risk in firms outside the analysts' radar.

The diversity inherent in various types of businesses, especially regarding how digital transformation influences the risk of sharp declines in stock prices, is noteworthy. Enterprises have been divided into categories based on the level of attention they receive in research reports. This categorization is intended to explore how the attributes of enterprises, specifically those listed in China, affect the relationship between digital transformation and the potential for stock price collapses. In Table 9, companies that are covered in research reports (where the attention from reports is not equal to zero), there is a statistically significant negative correlation between digital transformation and stock price crash risk. The coefficients are -38.3387 for SKEWt1 and -28.4832 for FLUCt1, both of which are significant, implying a strong effect of digital initiatives in reducing crash risk where there is analyst scrutiny. In the case of companies not covered by research reports (where the attention from reports is equal to zero), the coefficients for digital transformation's impact on stock price crash risk are not significant.

5 Discussion of Results

This paper explores the relationship between digital transformation within firms and the risk of stock price crashes by utilizing for the first time in this context a Term Frequency-Inverse Document Frequency (TF-IDF) algorithm (Ni et al., 2021; Zhuohao et al., 2021), calculating features of keywords related to digital transformation to quantitatively measure the extent of digital transformation among Chinese publicly listed companies.

This study delves into the intricate relationship between digital transformation and the risk of stock price crashes, unveiling nuanced insights across various dimensions of corporate and industry characteristics. At its core, the analysis establishes a foundational negative correlation between digital transformation efforts and the propensity for stock price downturns, which is consistent with the result of Jiang et al. (2022). This relationship suggests that as companies further their digitalization agendas, they inherently reduce the likelihood of experiencing severe stock price declines. This baseline understanding is fortified through robustness tests, which underscore the resilience of this negative correlation amidst different analytical conditions, thereby reinforcing the protective effect of digital transformation against stock price volatility.

The research further explores the mechanism analysis of digital transformation's effects on stock markets and shows that it not only directly reduces the likelihood of negative stock price shocks but also enhances stability when combined with new quality productivity. Moreover, the transformation acts as a mediator by reducing

information asymmetry, leading to more transparent and stable markets, echoes the findings of Zhu et al. (2023). Furthermore, the heterogeneity analysis indicates that digital transformation notably diminishes the risk of stock price crashes in Chinese listed companies, with the most pronounced effects seen in labor and capital-intensive industries as opposed to those that are technology-intensive. For large firms, digitalization significantly lowers the risk of stock price crashes, whereas it seems to have no noticeable impact on small and medium-sized enterprises, which parallels the research outcomes of Ai et al. (2023a, 2023b). The granularity of the analysis extends to the examination of digital transformation's effects on various types of firms within China. But standing in contrast to the findings of Jiang et al. (2022), we found that companies with analyst or research report coverage are found to benefit more from digital transformation in mitigating stock price crash risk, indicating the value of digital initiatives in contexts where external scrutiny and information dissemination play crucial roles. However, the study also points out the limitations of digital transformation's protective effects, such as its negligible impact in small and medium-sized enterprises suggesting areas where digital transformation alone may not suffice to shield against stock price volatility.

Through meticulous analysis, this study highlights the multifaceted role of digital transformation in safeguarding against stock price crashes. It underscores the importance of digitalization in enhancing transparency, improving internal governance, and adapting to industry-specific dynamics, thereby offering a roadmap for companies aiming to leverage digital transformation as a strategic tool for financial stability.

6 Conclusions

This paper has effectively demonstrated that digital transformation plays an instrumental role in mitigating the risk of stock price crashes in Chinese listed companies. Employing advanced analytical techniques such as the Term Frequency-Inverse Document Frequency (TF-IDF) algorithm, this research has highlighted the profound impact of digitalization across the background of implement the new quality productivity in China.

Further, the research employed panel data analyses and robustness tests which consistently confirmed a negative correlation between digital transformation and stock price crash risk. These findings suggest that as firms advance their digital transformation efforts, the likelihood of their stock prices experiencing significant declines diminishes. Digital transformation is linked to a lower chance of negative stock price shocks, but when combined with new quality productivity, it significantly reduces risks associated with stock price crises. Additionally, the mediating effect of reduced information asymmetry indicates that digital transformation contributes to more transparent markets, potentially leading to more stable stock prices.

From an impact perspective, this research underscores the importance of digital transformation as a strategic imperative for firms aiming to enhance market stability and reduce vulnerability to stock price shocks. Notably, the largest benefits were observed in labor and capital-intensive industries, as well as in large firms, whereas

small and medium-sized enterprises did not experience significant effects. This disparity highlights the need for targeted policies to support digital transformation in smaller firms, such as subsidies for technology adoption and training initiatives to build digital capabilities. Policymakers should also advocate for stronger corporate governance practices in digitally transforming firms, leveraging digitalization to improve transparency and accountability, which in turn can stabilize financial markets. Companies, particularly those in labor and capital-intensive sectors or those monitored by analysts, should prioritize investments in digital technologies to align with the "New Quality Productivity" framework and bolster financial resilience.

The Chinese government has long emphasized the role of industrial policies in shaping the nation's economic trajectory, particularly through initiatives like Made in China 2025, which aims to transform China into a global manufacturing powerhouse by 2025. As this policy nears its endpoint, the introduction of the concept of new quality productive forces signals the next phase in China's industrial strategy. This concept aligns with the government's policy cycle and provides a framework for the development of future industrial and innovation policies, especially as the country faces economic challenges.

The new quality productive forces framework is expected to play a central role in guiding the design and implementation of national strategies that promote digital transformation in key industries. By fostering technology-driven productivity and innovation, the government aims to reduce economic vulnerabilities, including those related to stock price crises. As digital transformation improves transparency, reduces information asymmetry, and strengthens market responsiveness, it helps stabilize financial markets. Therefore, integrating digital technologies into the policy framework is crucial for mitigating risks associated with stock price crashes. Looking ahead, the implementation of these policies will be essential for ensuring that the benefits of digital transformation are widely realized across sectors. As the Chinese government prepares for the release of its next Five-Year Plan in 2026, it is anticipated that a series of new industrial strategies will focus on advancing technology, innovation, and digitalization. These policies will be critical not only for bolstering productivity but also for addressing financial vulnerabilities in the increasingly digitized economy.

Looking ahead, future research could explore the differential effects of digital transformation across various industry sectors and firm sizes in more detail. Further studies could also examine the long-term effects of digital transformation on stock price stability, including during periods of market volatility. Additionally, exploring the role of government policies and sector-specific strategies in supporting digital transformation efforts could provide valuable insights for policymakers and business leaders aiming to harness the benefits of digitalization in the corporate sector.

Appendix

See Tables 10, 11, 12 and Fig. 1.

Table 10 New quality productivity

Factors	Subfactor	Indicator	Indicator value description	Weights
Labor force	Workforce	R&D personnel salary ratio	R&D expenses-salaries/operating income	28
		Proportion of R&D personnel	Number of R&D personnel/number of employees	4
		Proportion of highly educated personnel	Number of people with bachelor's degree or above/number of employees	3
	Materialized labor (labor object)	Proportion of fixed assets	Fixed assets/total assets	2
		Manufacturing overhead ratio	(Subtotal of cash outflow from operating activities + depreciation of fixed assets + amortization of intangible assets + provision for impairment—cash paid for goods purchased and services received—wages paid to and for employees) / (Subtotal of cash outflow from operating activities + fixed assets Depreciation + amortization of intangible assets + impairment provision)	1
Production tool	Hard technology	R&D depreciation and amortization ratio	R&D expenses-depreciation and amortization/operating income	27
		R&D rental fee ratio	R&D expenses-lease fees/operating income	2
		Proportion of direct investment in R&D	R&D expenses-direct investment/operating income	28
		Proportion of intangible assets	Intangible assets/total assets	3
	Soft Technology	total asset turnover ratio	Operating income/average total assets	1
		Reciprocal Equity Multiplier	Owner's Equity/Total Assets	1
New quality productivity				100

Table 11 Definition of variables

	Variable name	Variable notation	Variable definition	Sources
Independent variable	Firms' digital transformation	digital	Digital empowerment index; TF-IDF	Wu et al. (2021) and Annual reports (http://www.cninfo.com.cn/new/index)
		DTnum	Percentage of digital transformation; (degree of digital transformation A/total length of text in English and Chinese in the model A) × 1000; (Wu et al., 2021)	
		lnDTa1	Natural logarithmic total of 1 plus word frequencies; ln (DTa + 1)	
Dependent variable	Stock crash	SKEW	The negative coefficient of skewness (SKEW)	CSMAR (https://data.csmar.com) and Wind databases (https://www.wind.com.cn)
		FLUC	The down-to-up volatility (FLUC) ratio of returns	
Control variable		Ret	Average annual weekly stock returns	Wind databases (https://www.wind.com.cn)
		Sigma	standard deviation of annual weekly firm returns	
		size	Company scale = ln(total asset)	
		cflow	Free cash flow per share of the business; The ratio of the number of Outside Shares in circulation to the firm's free cash flow	
		lnBoard	The natural logarithm of board scale	
		lev	Total liabilities/total assets	
		BMRa	Book-to-market ratio = book value/ market value	
		roaB	ROA, total asset net profit margin	
		lnage	ln (Year-Listed); reduced the year to go public in 2022	

Table 11 (continued)

	Variable name	Variable notation	Variable definition	Sources
Instrument variable		lnDTIm	The natural logarithm of the industry median of digital transformation	Annual Reports Sourced from Shanghai (http://www.sse.com.cn/) and Shenzhen Stock Exchanges (http://www.szse.cn/market/index.html)
		DTnumb	Percentage of digital transformation; (degree of digital transformation B/total length of text in English and Chinese in the model B)×1000	
Mediator index	Information Asymmetry	ASY1	The information asymmetry (ASY) composite indicator is obtained by principal component analysis of LR, ILL, GAM) (Amihud, 2002; Amihud et al., 1997; Pástor & Stambaugh, 2003)	Original Data from Stock Market and WIND Database; Indicator Derived through Calculation
	New quality productivity	Npro	New quality productivity is calculated by taking into account the factors detailed in Table 10 in line with Song et al. (2014)	Derived from Calculations on Corporate Financial Statements

Table 12 Descriptive statistics

Variables	Obs	Mean	Std. dev	Min	Max	p1	p99	Skew	Kurt
digital	23,385	0.001	0.002	0	0.024	0	0.01	4.418	29.167
lnDTa1	23,385	1.543	1.446	0	6.38	0	5.231	0.668	2.569
DTnum	23,385	0.115	0.27	0	5.169	0	1.343	5.473	48.255
SKEW	23,385	− 0.317	0.717	− 2.692	2.223	− 2.368	1.499	− 0.299	3.996
FLUC	23,385	− 0.205	0.474	− 1.604	1.288	− 1.328	0.945	0.027	3.027
Ret	23,385	0.003	0.01	− 0.021	0.068	− 0.015	0.033	1.221	6.553
Sigma	23,385	0.064	0.026	0.019	0.232	0.027	0.149	1.604	7.069
size	23,385	22.378	1.361	15.577	28.636	19.992	26.449	0.843	4.168
cflow	23,385	0.048	0.075	− 1.938	0.876	− 0.151	0.249	− 0.855	29.567
lnBoard	23,385	2.121	0.197	1.099	2.89	1.609	2.639	− 0.301	4.056
lev	23,385	0.429	0.203	0.032	0.927	0.061	0.881	0.166	2.237
BMRa	23,385	0.63	0.251	0.004	1.601	0.119	1.187	0.068	2.451
roaB	23,385	0.042	0.076	− 1.324	1.285	− 0.224	0.229	− 1.266	27.73
lnage	23,385	2.148	0.839	0	3.497	0	3.367	− 0.607	2.565
DTnumb	23,385	0.35	0.527	0	7.297	0	2.655	3.883	25.058
ASY1	23,385	− 0.271	0.463	− 2.072	0.651	− 2.072	0.466	− 1.364	5.587
Npro	23,385	5.152	5.779	0.04	804.493	0.699	14.747	107.842	14,888.931

Data Availability Data is available upon request from the authors.

Declarations

Conflict of interest There is no conflict of interest.

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