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Can ESG Buffer the Pains of Digital Transformation? Evidence from Chinese Listed Companies

Yanfei Wu

Corporate Finance Center, School of Finance, National Research University Higher School of Economics,
Moscow, Russia,
yavu@hse.ru, [ORCID](#)

Abstract

Despite the strategic imperative of digitalization, its impact on firm performance remains debated, often showing initial negative effects. Using a panel of 1,543 Shanghai Stock Exchange (SSE) listed firms (2013-2023), we investigate the dynamic relationship between digital transformation (DT) and financial performance. Employing two-way fixed-effects models and path analysis, we uncover dynamic effect: DT negatively impacts financial performance contemporaneously, mediated by increased financing constraints, but yields positive returns in the long run. Crucially, we find that strong Environmental, Social, and Governance (ESG) performance mitigates the negative short-term effects of DT. Robustness checks, including replacement variables, PSM-DID and addressing endogeneity, confirm our findings. This study contributes by reconciling mixed evidence on DT's value, identifying financing constraints as a key mechanism, and demonstrating strong ESG enhances early-stage financial resilience.

Keywords: digital transformation, digitalization paradox, financial performance, ESG, financing constraints, moderating effects, China

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Introduction

In the digital era, traditional industrial enterprises are implementing digital transformation strategies to respond to rapid market changes and competitive pressures. The 2022 Global Digital Economy Competitiveness Development Annual Report ranks China second in digital economy competitiveness, just behind the United States [1].

Previous research has shown the economic role of digital technologies in optimizing supply chains, enhancing operational efficiency [2] and improving firms' ability to cope with complex environments [3]. However, a 2021 survey by the Tencent Research Institute revealed a set of obstacles, including a "lack of funds", a "lack of leadership support", and, more critically, difficulties in internal organizational coordination [4] and challenges related to complex digital tools and solutions [5; 6]. Scholars indicate that as many as 70% of digital transformation have led to economic losses for enterprises [7], with actual returns frequently falling short of expectations [8]. A key contributing factor is management's lack of expertise and leadership in navigating digital transformation, which exacerbates challenges associated with the digital divide [9]. Additionally, digital disruption can destabilize industries, and only a minority of organizations are adequately prepared to address such disruptions [10]. A variety of factors leads to the "digitalization paradox" where expected financial gains do not proportionally reflect the scale of digital investments [8]. Despite the growing body of research on the effects of digital transformation, a critical gap remains in understanding the underlying mechanisms by which digital transformation can negatively impact the financial performance of large-scale corporations in the short term. In addition, there is a shortage of evidence on whether ESG at the corporate level can mitigate this adverse effect of digital transformation. What expectations should the management and board of directors of large companies have when engaging in such a twin transformation?

We focus on China for several reasons. Under pressure from global competition, Chinese companies need to strategize between transformation and rising costs. Especially as China's demographic dividend gradually fades, with increasing technology and labour costs, it remains an open question whether the investment in transformation by Chinese enterprises can proportionally match the benefits brought by the latter in the short term [11]. Second, to compete in global markets, Chinese companies have to align with new sustainable development objectives, making ESG corporate innovation more urgent. For this reason, our study focuses on companies listed on the main board of the Shanghai Stock Exchange (SSE), exploring their performance and challenges during twin innovations. These companies are typically large and have a long operating history, mature business models, and stable performance, representing high-quality enterprises with significant industry and public effects. However, they have bigger systems and infrastructure and stronger organizational inertia, creating substantial difficulties in structural transformation [12] and making the challenges more com-

plex. When involved in the digital transformation process, companies that emphasize the principles of sustainability in their strategies are more likely to gain loyalty and recognition from shareholders and other stakeholders [13]. Nevertheless, studies exploring the synergistic effects of ESG and digital transformation are still scarce. We conceptualize ESG as a managerial innovation that encompasses both internal governance and external evaluation dimensions and explore its moderating influence on the link between digital transformation and corporate performance, particularly through the lens of financing constraints.

This study offers two key contributions to the literature. First, it elucidates the specific mechanisms underpinning the dynamic effect of digital transformation (DT) on financial performance – initial decline followed by long-term gains. Focusing on mature Chinese firms, we pinpoint financing constraints as a critical, yet underexplored, channel driving the short-term dip. We argue that the substantial investments, high failure rates, slow returns, and disruptive uncertainty associated with DT heighten information asymmetries and perceived risks, thereby restricting firms' financing capabilities in the initial phase. This finding extends the concept of the 'digitalization paradox' [8] by providing a concrete explanatory mechanism. Second, this research demonstrates the synergistic interplay between ESG performance and DT. We reveal that strong ESG credentials act as a significant moderator, effectively buffering the negative short-term financial consequences of digital initiatives. This suggests a practical solution to the digitalization paradox: integrating robust sustainability practices can mitigate the initial downsides of DT. Our findings highlight the necessity of examining these corporate strategies jointly and underscore the strategic value of embedding sustainability within digital transformation efforts to maximize benefits and minimize risks.

Literature review

Impact of digital transformation on financial performance

Simply introducing and applying technologies does not equate to digital transformation: true digital transformation occurs when technologies are used to fundamentally alter how a company generates profit. At the same time, the impact of digital transformation on financial performance is a subject of considerable debate in the research community.

Existing studies suggest that investments in digital transformation have a positive impact on financial performance by reducing information asymmetry levels [14], lowering costs [14; 15], obtaining additional cash flow [16], improving inventory turnover and total asset turnover [17], enhancing capital utilization efficiency [18], and increasing economies of scale by leveraging the resources and experience of partners [19]. However, some research suggests that the correlation between the two depends on the stage of digital transformation, the speed of transformation, the level of investment in transformation, the financial condi-

tion, and the strategic orientation of the firm. According to Fabian et al. [20], although the implementation of lower levels of digital transformation can enhance efficiency, such endeavours often encounter diminishing returns, limiting profits. In contrast, Yonghong et al. [17] state that although corporate profitability decreases in the initial stages of digital transformation, the firm's net profit margin gradually increases as the digital process deepens. Meanwhile, Sun et al. [21] explore the impact of the speed of digital transformation on corporate financial distress, finding a U-shaped relationship between the two, with the CEO's IT background modifying this relationship into an inverted U-shape. Research by Vu et al. [22] using the fixed effects quantile method shows that only high-performance companies benefit from digital transformation, while other companies do not. Guo's [23] study reveals that digital transformation has a U-shaped relation with profit-oriented financial performance and is positively correlated with process-oriented operational performance. Fabian [24] indicates that firms inclined towards radical changes and those with more rigid organizations obtain lower returns from digital transformation.

Some scholars view the relationship negatively [25]. Among them, Solow [26] proposes the "productivity paradox", arguing that information technology investment does not affect or even negatively impacts corporate financial performance. Matt et al. [27] corroborate this view, demonstrating that over half of the businesses using digital transformation strategies have seen a decline in performance compared to their pre-transformation levels, with some even running the risk of bankruptcy. Xie et al. [28] argue that corporate digital transformation needs to go through two periods – "overcoming organizational inertia" and "forming new management routines" – during which learning costs inevitably rise, limiting the positive impact on financial performance. Hanelt et al. [29] further highlight that digital transformation does not inherently guarantee profitability, as it often brings additional operational and integration costs that can erode financial returns. In this perspective, Jardak and Ben Hamad [30] note that the benefits of IT investments and digital marketing may take years to materialize, with the high value of IT assets not being immediately amortized, which can negatively impact return on assets (ROA) in the short term. Other scholars study individual industries. For example, Forcadell [13] indicates that for banks, the challenges brought by digital transformation may hinder potential gains and threaten their survival, whereas the reputation established by corporate sustainability compensates for these weaknesses in digital capabilities. Isma Coryanata et al. [31] examine banking firms listed on the Indonesia Stock Exchange and show that the implementation of digital transformation by banks leads to a decrease in their return on investment.

This paper aims to reconcile conflicting perspectives on the impact of digital transformation on financial performance by examining the complex interplay of mediators and moderators.

Impact of ESG on firm performance

Existing research on ESG mostly analyses its influence on corporate financial performance and risk management capabilities. Most studies indicate that excellent ESG performance can enhance financial performance [32], an effect that is more pronounced for larger companies [33]. However, this impact is not always linear and depends on different factors, including the market in which the company is operating and its size. Research by Garcia et al. [34] illustrates the market heterogeneity characteristic of ESG's financial impact, demonstrating a significant positive relationship between the two in companies from developed countries yet a negative correlation in companies from emerging markets. Bruna [35], using data from 350 European listed companies, finds that the marginal impact of ESG performance on financial performance is nonlinear and varies with the level of ESG performance scores and company size. Conversely, some studies make the opposite conclusion. For instance, research by Landi et al. [36] on Italian listed companies suggests that investors do not seem to value corporate social responsibility (CSR). Saygili et al.'s [37] study on companies listed on the Istanbul Stock Exchange indicates that environmental disclosure significantly harms corporate financial performance.

Moreover, research suggests that CSR serves as a risk management instrument with the capacity to mitigate risks during crises and safeguard firms against negative effects on their cash flow [38; 39]. Benlemlih et al. [40] indicate that companies that engage in extensive and objective environmental and social disclosure build good reputation and trust among stakeholders, thereby helping to mitigate their idiosyncratic and operational risks. Sassen et al. [41], using a sample of European panel data from 2002 to 2014, demonstrate that corporate social performance significantly reduces idiosyncratic, total, and systematic risks. Albuquerque et al. [42] study how CSR investments can improve product differentiation, thereby reducing exposure to systemic risk. Hoepner et al. [43] also find that engagement in ESG transformation can reduce downside risk. However, Korinth et al. [44] provide evidence from the German stock market showing that ESG investments initially reduce systemic risk, yet excessive investment ultimately increases systemic risk, leading to a U-shaped dependence.

Recent academic research has done a lot to examine the direct impact of ESG practices on corporate financial performance and risk management. However, studies on the synergistic effects of ESG and digital transformation are still sparse. The few available ones indicate that a firm's sustainability reputation affects the relationship between digital disclosure and stock market valuation [45], while the breadth and concentration of sustainability play a moderating role between digital reputation and financial performance [46]. Forcadell's [13] study of the banking industry suggests that the challenges posed by digital transformation may hinder potential gains and harm resilience, while the reputation generated by corporate sustainability could mitigate these digital transformation shortcomings.

Therefore, examining how ESG functions as a moderating variable in the relationship between digital transformation and financial performance will address existing research gaps, extend sustainability research to ESG indicators, and reveal how ESG practices can optimize financial performance during digital transformation.

Hypotheses

Impact of digital transformation on financial performance

From the perspective of resource-based theory, digital transformation leverages data as an independent production factor to create value by improving efficiency [47; 48], increasing revenue [49], saving costs [50], and controlling risks [51], thereby indirectly enhancing the productivity and financial performance of enterprises. However, few studies mention the resource consumption issues within digital transformation. As a form of innovation, digital transformation is a resource-consuming activity that initially necessitates significant ongoing investment: the fixed investment in high-cost digital infrastructure and the subsequent maintenance and upgrade costs [49; 52], the expenses for recruiting digital technology professionals and daily digital training for employees [53], and the coordination costs associated with integrating digital technologies with existing resources and abilities [54].

Over half of Chinese enterprises are still at the initial stages of digital technology application (National Information Center, 2020), making funding a significant challenge for digital transformation [55]. Furthermore, in the early phase, the complete benefits of digital transformation have yet to manifest, while the expenses associated with integration may offset the promotion of digital transformation for business growth [23], resulting in a disproportionate increase in operational costs relative to revenue. This may lead to an initial decline in return on assets. This process is particularly evident in large enterprises with more extensive systems and infrastructure, organizational inertia, and long-existing mindsets and processes [56], leading to higher communication, coordination, and integration costs. Excessively rapid digital transformation can easily create an insurmountable gap between the company's existing resources and capabilities, directly impacting internal management decisions and resource allocation efficiency. Consequently, the organization may lack the capacity to continue supporting the deep implementation of digital transformation and fail to adjust internal activities and structures dynamically to adapt to external environmental changes [57], potentially impacting its financial performance.

Although studies show that digital transformation can help mitigate principal-agent conflicts and strengthen internal corporate governance structures [58], it can also create greater uncertainty and operational risk, exacerbate external and internal information asymmetry, and increase financing constraints, which can negatively affect financial performance. Previous research has mostly assumed the

success of digital transformation, almost unequivocally affirming the positive signals it sends. The effectiveness of digital transformation heavily relies on how prepared an organization is to embrace and implement digital innovation. The high probability of digital failure and slow return on investment exacerbate operational uncertainty for enterprises [8]. In addition, digital transformation redefines markets, disrupts traditional business models and industry divisions, and shatters competitive landscapes [59]. It poses an existential threat to mature, large-cap companies that thrived during the pre-digital era [60]. The boundaries between product categories and industries are becoming indistinct, while competitiveness increasingly depends on multisided platforms [61]. In the face of greater uncertainty risks, information on firms' investments becomes more complex and variable, increasing specific risks and information asymmetries [62] and directly impacting the expenses associated with corporate debt and equity financing [63].

Moreover, cross-industry operations that follow digital transformation require significant investments unrelated to the core business. To maintain digital agility, companies must continually modify and reallocate current digital assets [64]. However, this "reallocation of resources" can have competitive effects and negatively impact core business performance [27; 59]. Based on signalling theory, external investors may adopt a cautious attitude towards the enterprise's future profitability and operational stability due to concerns over the potential negative impact on the core business or the failure of digital investments, leading to financing constraints and adversely affecting subsequent financial performance.

H1: Digital transformation can negatively impact the financial performance of mature, large-cap corporations in the short term.

H2: Digital transformation increases financing constraints, thereby negatively affecting the financial performance of mature, large-cap corporations in the short term.

Moderating role of ESG innovative practices

Enhanced ESG performance signifies a firm's strong sustainability and promotes reputation and stakeholder trust [65]. Stakeholder trust can not only offset the potential downsides of digital transformation [66] and enhance its market expectations [67], but it can also bring competitive advantages and brand premiums [68], thereby increasing stakeholder tolerance for temporary declines in operational and financial performance during digital transformation.

Firms with good ESG innovative practices enhance the quality of their human capital, facilitating integration of digital technologies with existing resources and organizational structures. The digital transformation process encounters risks like the shortage of skilled labour and the loss of experienced managers [69]. However, companies with strong ESG performance attract high-quality talent by adopting green human resource management strategies

[70], which enhance employees' sense of belonging and self-respect and their work motivation [71] and ultimately promote improvements in financial performance.

Good ESG practices lead to superior risk management capabilities [72], transparency, and compliance, while reducing risks associated with information asymmetry, including firm-specific and operational risks [40]. Digital transformation in mature, large-cap enterprises entails significant operational risks and uncertainties. However, firms with strong ESG innovative practices and results are more adept at handling technology compliance, market resistance, and regulatory shifts, which helps them to safeguard internal stability and protect core operations and financial performance.

H3: ESG innovative practices can mitigate the adverse effect of digital transformation on the financial performance of mature, large-cap corporations.

Moderating role of ESG innovative practices in the mediating mechanism of financing constraints

According to signalling theory, strong ESG performance serves as a positive signal that companies send in situations of information asymmetry within capital markets [73]. This signal indicates that the company is not merely pursuing short-term profits but incorporating sustainable development strategies as part of its long-term plan for digital transformation. It demonstrates a comprehensive and long-term commitment to the goals of digital transformation, thereby mitigating the impact of negative signals such as potential failure and slow return on investment during the digital transformation process. This releases positive signals about the company's internal risk resilience and legitimacy, increases the support of different stakeholders such as investors, consumers, and government departments, and secures more stable long-term capital to alleviate potential financing constraints during digital transformation.

Good ESG innovative practices and performance enhance the firm's overall market image [74] and shows investors that it possesses strong operational signals and risk resilience, thereby boosting external investor confidence [75]. Such practices can increase stakeholders' tolerance for temporary operational or financial performance declines during digital transformation, thereby reducing external financial constraints and debt costs [76]. Additionally, good ESG practices lower regulatory risks and operational uncertainties by ensuring compliance and mitigating risks related to products and technologies [77]. This can increase information transparency, which enables the company to establish a broad network and broaden financing access [78]. For instance, good ESG practices encourage companies to issue green bonds [79] and funds in equity crowdfunding [80], thus easing the capital constraints faced during digital transformation.

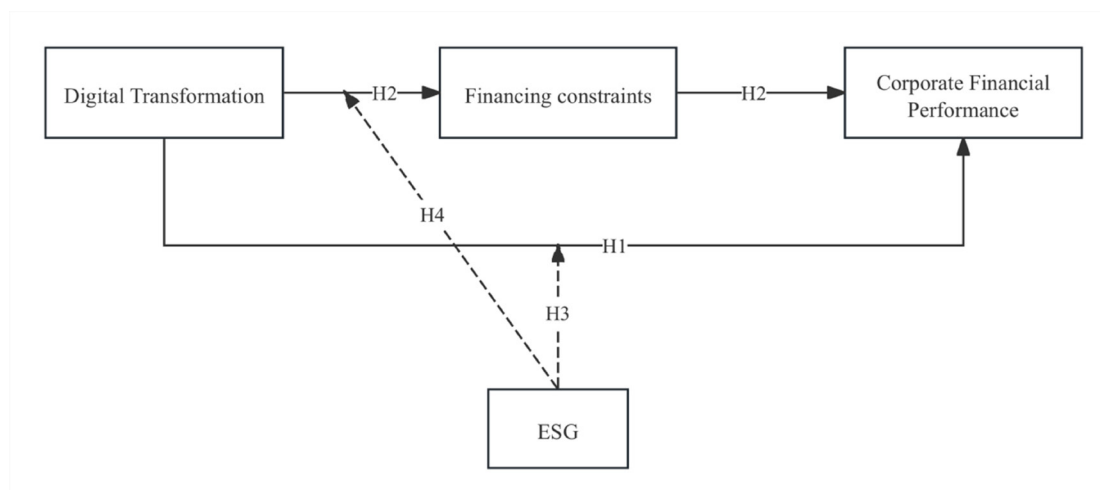
Strong ESG performance presents a responsible and trustworthy image to stakeholders. This can help to establish long-term stable supply chain partnerships, strengthening the company's cohesion with its suppliers and customers [81], and reduce the incidence of commercial fraud [82], which in turn facilitates greater access to commercial credit financing [83] and supports long-term sustainable development strategic goals.

Furthermore, good ESG is often related to high levels of environmental awareness and commitment, signalling organizational legitimacy that helps to attract long-term investors, secure stable long-term funds that can be used for digital transformation, and gain the support of government regulatory bodies. This enhances access to financing privileges and government resources, such as fiscal subsidies [84; 85].

H4: ESG innovative practices alleviate the financing constraints caused by digital transformation, thereby promoting corporate financial performance.

Figure 1 provides a visual representation of the research model for this study.

Figure 1. Research model



Research design

Data sources

This study uses a sample of companies listed on the main board of the Shanghai Stock Exchange (SSE) from 2013 to 2023. The choice of observation period is explained by several factors. In 2013, the Chinese government introduced a policy initiative to promote information consumption and expand domestic demand, launching the national informationization strategy and providing support for digital transformation. Additionally, 2013 marked the beginning of construction work on China's 4G network, rapidly advancing mobile internet technology and supporting digital transformation [86]. Our data on digital transformation was manually collected, as well as being sourced from the Wind Financial Terminal and CSMAR databases. The sample selection was based on the following principles: 1) excluding samples with insufficient data; 2) omitting financial and insurance companies due to their particularities [87]; and 3) excluding ST, PT, and *ST companies [88]. The final dataset consists of 1,543 sample companies and 12,833 sample observations. We used Stata 17.0 software for empirical analysis.

Description of variables

Dependent variable: corporate financial performance (CFP). This paper measures CFP using return on assets. To confirm the robustness of the model, our research also uses return on equity (ROE) in place of ROA for regression.

Independent variable: digital transformation (DT). Most of the current literature employs textual analysis to represent DT using keyword word frequencies associated with DT in companies' annual reports [86; 89]. While word frequency reflects executives' awareness of DT, awareness does not necessarily translate into action [90]. Digital intangibles make more economic sense than word-frequency analysis, because they measure a company's investment in DT. Thus, this study aligns with previous research [90; 91] to measure DT as the proportion of intangible assets associated with digital transformation keywords like *software*, *artificial intelligence*, and *big data* disclosed in annual financial statements. This proportion of relevant intangible assets to total assets at year-end serves as a proxy for DT.

Mediating variable: financing constraints (FC). Scholars have proposed various metrics to measure financing constraints, including single factors such as asset size and dividend payout ratio and composite indices like the SA index [92], KZ index [93], and WW index [94]. Among these, the KZ index indicates the extent to which a firm's investment depends on internal cash flow, thereby reflecting the size of financing constraints [95]. The KZ index integrates multiple dimensions of a company's financial position and market conditions, providing a comprehensive understanding of how financing constraints influence financial decisions, capital structure and, ultimately, financial performance. Therefore, aligning with previous studies [96–98], we adopt the KZ index, as originally proposed by Kaplan and Zingales [93]. The KZ index is constructed as follows:

$$KZ = \sum_{j=1}^5 KZ_j \quad (1)$$

In Equation (1), the value of KZ_1 is 1 if the ratio of operating cash flow to total assets for the prior period ($CF_{i,t}/Asset_{i,t-1}$) is below the median, and 0 otherwise. The value of KZ_2 is 1 if the ratio of cash dividends to total assets for the prior period ($DIV_{i,t}/Asset_{i,t-1}$) is below the median, and 0 otherwise. The value of KZ_3 is 1 if the ratio of cash holdings to total assets for the prior period ($C_{i,t}/Asset_{i,t-1}$) is below the median, and 0 otherwise. The value of KZ_4 is 1 if the debt-to-asset ratio is above the median, and 0 otherwise. The value of KZ_5 is 1 if Tobin's Q is above the median, and 0 otherwise. We sum these indicators using Equation (1) to calculate the KZ index. Then, the regression coefficients are estimated using *ordered logistic regression*, utilizing the KZ index as the dependent variable. A higher KZ index suggests that firms are experiencing more severe financing constraints.

Moderator variable. The Huazheng ESG rating is taken as the moderator variable due to its comprehensive coverage, frequent updates, and advanced calculation techniques [99]. Widely recognized and employed in various studies to evaluate ESG [67; 100], this index offers an extensive evaluation with over 300 indicators spanning environmental, social, and governance dimensions. Its quarterly updates provide more timely data compared to other indices that are updated only semi-annually or annually. Furthermore, the integration of semantic analysis and natural language processing algorithms enhances the index's precision and reliability. The Huazheng ESG rating index also includes detailed scores for the three individual dimensions, allowing for a more in-depth analysis. These strengths make it an excellent tool for measuring ESG performance.

Control variables. Based on prior research [23; 101], we chose the following control variables for the model: firm size (Size), age (Age), revenue growth rate (Growthrate), debt-to-asset ratio (Lev), firm research and development expenditures (R&D), fixed asset ratio (FA), Tobin's Q (TobinQ), property rights contexts (SOE), board of directors' independence (Ind), and shareholding concentration (Top1). Finally, we incorporate the COVID-19 pandemic as a dummy variable to capture the influence of this significant global health event on CFP, ensuring that our analysis accurately reflects the effects of DT and other factors, independent of the disruptions caused by the pandemic. These variables collectively provide a comprehensive framework for analysing the factors affecting CFP.

Table 1. Description of variables

Variable type	Variable name	Symbols	Variable description
Dependent variable	Corporate Financial Performance	CFP	Return on assets
		ROE	Return on equity
Explanatory variable	Digital Transformation	DT	Proportion of intangible assets related to digital transformation keywords to total assets at year-end
Mediator variable	Finance constraints	FC	KZ index
Moderator variable	Corporate ESG	ESG	Huazheng ESG Rating
	Enterprise size	Size	Logarithm of total assets
	Enterprise age	Age	Logarithm of (years of observation minus years of establishment)
	Growth rate of revenue	Growthrate	(Current operating income minus prior operating income) divided by prior operating income
	Gearing	Lev	Total liabilities divided by total assets
	R&D expenditure	R&D	Logarithm of total firm R&D expenditures
	Fixed Asset Ratio	FA	Fixed assets at the end of the period as a percentage of total assets
	Property rights contexts	SOE	1 for state-owned enterprises, and 0 otherwise
	Board independence	Indep	Ratio of independent directors to the total number of directors
	Shareholding concentration	Top1	Proportion of shares owned by the largest shareholder of the enterprise
	Future growth opportunities	TobinQ	Market value of the company / replacement cost of assets
	Dummy variables	COVID-19	0 if the year precedes the outbreak of COVID-19 and 1 if it follows the outbreak
Control variable			

Note: The table comprehensively explains and quantifies all variables.

Model design

A firm's financial performance is greatly affected by specific and unobservable firm individual characteristics [102], such as corporate culture [103; 104] and management style [105; 106]. This model can effectively mitigate the influence of unobservable variables related to year and firm decrease estimation biases, and improve the statistical reliability of the results [107]. However, it necessitates the utilization of panel data and substantial sample observations [108]. This paper employs panel data for regression analysis on 12,833 observations, qualifying for the use of this model.

To test the correlation of DT and CFP, the following regression model is constructed:

$$CFP_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \alpha_2 Controls_{i,t} + \sum Year + \sum Firm + v_{i,t}, \quad (1)$$

where i indicates the company, t represents time, $CFP_{i,t}$ indicates the corporate financial performance of company i in year t , $DT_{i,t}$ represents the level of digital transformation of company i in year t , $Controls_{i,t}$ indicate all control variables, $\sum Year$ and $\sum Firm$ represent the time and firm fixed effects, and $v_{i,t}$ is the exogenous disturbance term, which has a normal distribution with mean 0 and variance σ^2 .

To examine the mediating effect of financing constraints, this study employs the causal steps approach to mediation [109; 110]. Expanding on regression Model (1), we construct Models (2) and (3):

$$FC_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \beta_2 Controls_{i,t} + \sum Year + \sum Firm + v_{i,t}, \quad (2)$$

$$CFP_{i,t} = \gamma_0 + \gamma_1 DT_{i,t} + \gamma_2 FC_{i,t} + \gamma_3 Controls_{i,t} + \sum Year + \sum Firm + v_{i,t}, \quad (3)$$

where $FC_{i,t}$ represents the corporate financing constraints, while the other variables are the same as in the above model. If β_1 and γ_2 are significant at the same time, there is a mediating effect of financing constraints between the two. According to the previous theoretical analysis, this paper predicts β_1 to be significantly positive and γ_2 to be significantly negative.

To verify the moderating effect of ESG, we build Model (4), drawing on the moderating effect model [109]:

$$CFP_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \alpha_2 ESG_{i,t} + \alpha_3 ESG_{i,t} \times DT_{i,t} + \alpha_4 Controls_{i,t} + \sum Year + \sum Firm + v_{i,t}, \quad (4)$$

where $ESG_{i,t} \times DT_{i,t}$ is the interaction term. According to the theoretical analysis in Section 2, α_3 is expected to be significantly positive.

Based on the interpretation of Edwards and Lambert [109] of the moderated mediation effect model, Models (5) and (6) are constructed for confirming the moderating effect of ESG on the first half of the mediation effect path, while Model (7) is built for confirming the direct moderating effect of ESG on the mediation effect path:

$$FC_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \beta_2 ESG_{i,t} + \beta_3 Controls_{i,t} + \sum Year + \sum Firm + v_{i,t}, \quad (5)$$

$$FC_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \beta_2 ESG_{i,t} + \beta_3 ESG_{i,t} \times DT_{i,t} + \beta_4 Controls_{i,t} + \sum Year + \sum Firm + v_{i,t}, \quad (6)$$

$$CFP_{i,t} = \gamma_0 + \gamma_1 DT_{i,t} + \gamma_2 ESG_{i,t} + \gamma_3 FC_{i,t} + \gamma_4 ESG_{i,t} \times DT_{i,t} + \gamma_5 Controls_{i,t} + \sum Year + \sum Firm + v_{i,t}. \quad (7)$$

If β_3 of $ESG_{i,t} \times DT_{i,t}$ is significant, then ESG moderates financing constraints caused by digital transformation. If γ_4 is significant, then the moderating effect of ESG does not work entirely through the mediating variable $FC_{i,t}$. According to the theoretical analysis, the predictive coefficient β_3 is significantly negative and γ_4 is significantly positive.

Results and discussion

Main effect regression analysis

Table 2 shows the relationship between DT and CFP. Column 1 shows the results without control variables and without firm and time fixed effects. Column 2 presents the results of the two-way fixed effects model without control variables. Column 3 shows the findings after including all control variables and accounting for year, industry, and city effects. Column 4 presents the findings of regressions that incorporate control variables and utilize a two-way fixed effects model (Model (1)). The results consistently demonstrate that DT has a negative impact on CFP at the 1% significance level. This finding supports the previous theory and confirms Hypothesis 1.

Table 2. Benchmark regression results

	Model (1)			
	CFP	CFP	CFP	CFP
DT	-0.0316*** (-10.39)	-0.0135*** (-2.78)	-0.0123*** (-4.21)	-0.0175*** (-4.17)
Size			0.0106*** (21.92)	0.0071*** (5.72)
Age			-0.0011*** (-14.18)	-0.0037** (-2.09)
Growthrate			0.0383*** (27.65)	0.0356*** (27.65)
Lev			-0.1022*** (-59.81)	-0.0953*** (-51.92)
R&D			0.0001 (0.59)	0.0003** (2.51)
FA			-0.0569*** (-13.72)	-0.0845*** (-12.59)

	Model (1)			
	CFP	CFP	CFP	CFP
SOE			-0.0054***	-0.0040
			(-3.84)	(-1.29)
Indep			-0.0004	-0.0003
			(-0.39)	(-0.19)
Top1			0.0003***	0.0003***
			(8.87)	(3.23)
TobinQ			0.0045***	0.0022***
			(16.61)	(6.61)
COVID-19			-0.0150***	0.0060
			(-4.81)	(0.36)
Constant	0.0443***	0.0513***	-0.1800***	-0.0300
	(67.54)	(25.31)	(-8.63)	(-1.00)
Year FE	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No
City FE	No	No	Yes	No
Firm FE	No	Yes	No	Yes
Observations	12,833	12,833	12,833	12,833
R-squared	0.008	0.018	0.402	0.273

Note: The T statistic is in parentheses; *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

Mediating effect analysis

The regression results for the mediating effect are shown in Table 3. In Model (2), the estimated coefficient of DT on FC is significantly positive at the 5% level (0.3405). It means that as DT increases, the FC faced by firms also rises. In column 3, the coefficient of FC is significantly negative at the 1% level (0.0103). These findings suggest that DT, by increasing the FC of firms, leads to a decrease in CFP. This finding further supports Hypothesis 3.

Moreover, Model (3) demonstrates that the estimated coefficient of DT on CFP is significantly negative at the 1% level (0.014), while the absolute value of this coefficient is lower than the absolute value of the coefficient in Model (1), implying that FC partially mediates this relationship. Specifically, DT influences CFP partly through the mediating role of FC and partly through *direct effects*.

Table 3. Mediating effect

	Model (1) CFP	Model (2) FC	Model (3) CFP
DT	-0.0175***	0.3405***	-0.0140***
	(-4.17)	(2.99)	(-3.47)
FC			-0.0103***
			(-30.89)
Size	0.0071***	0.1536***	0.0087***
	(5.72)	(4.57)	(7.28)
Age	-0.0037**	0.3207***	-0.0004
	(-2.09)	(6.73)	(-0.22)

	Model (1) CFP	Model (2) FC	Model (3) CFP
Growthrate	0.0356*** (27.65)	-0.7747*** (-22.19)	0.0276*** (21.87)
Lev	-0.0953*** (-51.92)	0.3952*** (7.93)	-0.0912*** (-51.62)
R&D	0.0003** (2.51)	0.0073** (2.13)	0.0004*** (3.23)
FA	-0.0845*** (-12.59)	2.4960*** (13.70)	-0.0588*** (-9.05)
SOE	-0.0040 (-1.29)	0.1339 (1.60)	-0.0026 (-0.87)
Indep	-0.0003 (-0.19)	-0.0344 (-0.88)	-0.0006 (-0.45)
Top1	0.0003*** (3.23)	-0.0130*** (-5.83)	0.0001* (1.67)
TobinQ	0.0022*** (6.61)	0.1483*** (16.63)	0.0037*** (11.58)
COVID-19	0.0060 (0.36)	-3.4629*** (-7.58)	-0.0297* (-1.83)
Constant	-0.0300 (-1.00)	-4.8431*** (-5.96)	-0.0799*** (-2.78)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	12,833	12,833	12,833
R-squared	0.273	0.127	0.329

Note: The T statistic is in parentheses; *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

Moderating effect and moderated mediation effects analysis

Model (4) in Table 4 shows the *total moderating effect* of ESG. The coefficient of the interaction term DT×ESG is significantly positive at the 1% level (0.0028). This means that good ESG performance can significantly alleviate the negative impact of DT on CFP. Consequently, in firms with superior ESG performance, the detrimental effects of DT on CFP are less severe.

Figure 2 and Table 5 depict the two-way interactions. They demonstrate that when ESG performance is poor, the linear slope is negative (-0.123). Conversely, when ESG performance is high, the slope becomes positive (0.035), indicating that in the case of higher ESG scores, the negative impact of DT turns into a positive effect.

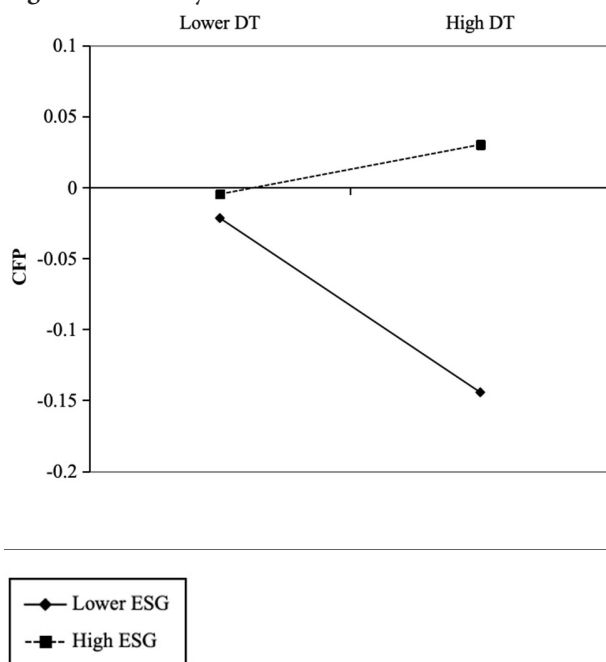
In Model (6) of Table 4, the interaction term DT×ESG has an estimated coefficient that is significantly negative at the 5% level (-0.0376), indicating that ESG significantly moderates the relationship between DT and FC. In brief, as ESG performance improves, the positive impact of DT on FC weakens, thus verifying Hypothesis 4.

The results of Model (7) in Table 4 show that the estimated coefficient of DT×ESG is significantly positive at the 1% level (0.0024), suggesting that the moderating effect of ESG is not entirely mediated by FC. Moreover, the coefficient of DT×ESG in the *direct effect* is smaller than that in the *total effect* of ESG (0.0024 in Model (7) compared to 0.0028 in Model (4)), suggesting that the moderation effect of ESG is *partially* mediated by FC. This further confirms that good ESG performance can both directly mitigate the negative impact of DT on CFP and enhance CFP by reducing the increase in FC caused by DT.

Table 4. Moderating effects and moderated mediation effects

	Model (4) CFP	Model (5) FC	Model (6) FC	Model (7) CFP
DT	-0.2253*** (-5.84)	0.3504*** (3.08)	3.1138*** (2.97)	-0.1935*** (-5.22)
ESG	0.0003** (2.19)	-0.0103*** (-3.16)	-0.0069** (-1.96)	0.0002* (1.71)
DT×ESG	0.0028*** (5.40)		-0.0376*** (-2.65)	0.0024*** (4.86)
FC				-0.0102*** (-30.69)
Size	0.0065*** (5.21)	0.1634*** (4.84)	0.1649*** (4.89)	0.0081*** (6.83)
Age	-0.0042** (-2.38)	0.3311*** (6.93)	0.3305*** (6.92)	-0.0008 (-0.47)
Growthrate	0.0359*** (27.96)	-0.7783*** (-22.29)	-0.7804*** (-22.35)	0.0279*** (22.15)
Lev	-0.0950*** (-51.79)	0.3857*** (7.73)	0.3893*** (7.80)	-0.0911*** (-51.51)
R&D	0.0003*** (2.60)	0.0074** (2.16)	0.0072** (2.09)	0.0004*** (3.31)
FA	-0.0842*** (-12.55)	2.4681*** (13.54)	2.4835*** (13.62)	-0.0588*** (-9.06)
SOE	-0.0038 (-1.24)	0.1328 (1.59)	0.1316 (1.57)	-0.0025 (-0.84)
Indep	-0.0005 (-0.37)	-0.0300 (-0.76)	-0.0297 (-0.76)	-0.0008 (-0.60)
Top1	0.0003*** (3.12)	-0.0128*** (-5.76)	-0.0128*** (-5.75)	0.0001 (1.58)
TobinQ	0.0022*** (6.68)	0.1483*** (16.64)	0.1481*** (16.61)	0.0037*** (11.61)
COVID-19	-0.0326 (-1.07)	-4.3839*** (-5.32)	-4.6700*** (-5.62)	-0.0803*** (-2.73)
Constant	-0.0895*** (-2.84)	-3.3463*** (-4.02)	-3.5837*** (-4.27)	-0.1316*** (-4.39)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	12,833	12,833	12,833	12,833
R-squared	0.276	0.128	0.129	0.332

Note: The T statistic is in parentheses; *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

Figure 2. Two-way linear interactions**Table 5.** Simple slope tests

	Lower ESG	High ESG
Gradient of slope	-0.123	0.035
t-value of slope	-6.484	3.295
p-value of slope	0.000	0.001

Robustness tests

Alternative variables

In alignment with previous studies [15; 30], this paper substitutes ROE for CFP to verify the findings' robustness. Column 1 of Table 6 displays that the effect of DT on ROE is significantly negative at the 5% level (0.0849). This corroborates the reliability of our findings. To address concerns regarding the external validity of the KZ index, particularly its sensitivity to the sample and specific time period used for its construction, we employ the WW index [111] as an alternative measure. A robustness check using the WW index confirms the consistency of our results.

PSM-DID

To effectively mitigate the policy shocks associated with the "Action Plan for Industrial Internet Development" policy introduced by the Chinese government and to prevent systematic differences in the financial performance of firms in pilot and non-pilot cities, we employ propensity score matching-difference-in-differences (PSM-DID) analysis to incorporate the policy shocks into the regression model. This method allows us to redefine the control group sample to ensure a direct comparison and analysis between the control and treatment groups [112]. Initially, we categorize

the overall sample based on the digitization pilot city documents issued by China, distinguishing between the experimental group (enterprises located in the digitization pilot cities) and the control group (enterprises located outside the digitization pilot cities). Then, the Logit model is used to compute the propensity scores for DT. Third, matching is performed using the 1:1 nearest neighbour matching method. We chose all control variables for logistic regression and propensity matching scores. The outcomes of the balance hypothesis test are presented in Figure 3. There is a significant common support region for the propensity scores of the experimental and control groups, and most of the samples' propensity scores fall within this region, indicating that the propensity score distributions of the two groups are generally balanced. Figure 4 illustrates a notable decrease in the standard deviation of most variables, indicating that the PSM method employed in this research effectively mitigates the sample selection bias. Figure 5 shows that the propensity score density curves differ significantly between the two groups before matching but become similar after matching, indicating that PSM effectively reduces selection bias.

In the PSM-matched sample, test for consistent trends in the CFP between the treatment and control groups before the policy was implemented. Figure 6 provides strong evidence supporting the *parallel trend assumption*. The coefficients for the pre-treatment period (time -4 to 0) are close to zero, with their confidence intervals including zero, suggesting no systematic differences in the outcome variable trends between the treatment and control groups prior to the policy implementation. This indicates that, in the absence of treatment, the trajectories of the outcome variable for the two groups would have evolved similarly over time.

The model after considering policy shocks is specified as follows:

$$CFP_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \alpha_1 DID + \alpha_2 Controls_{i,t} + \sum Year + \sum Firm + v_{i,t}, \quad (8)$$

Here, DID represents the policy shocks, other variables are the same as the above model.

Column 4 of Table 6 shows that in the matched sample, after accounting for policy shocks, the effect of DT on CFP remains consistent with the results of previous studies, showing a negative effect at the 1% level (-0.0156).. This provides additional evidence of the reliability of the research findings.

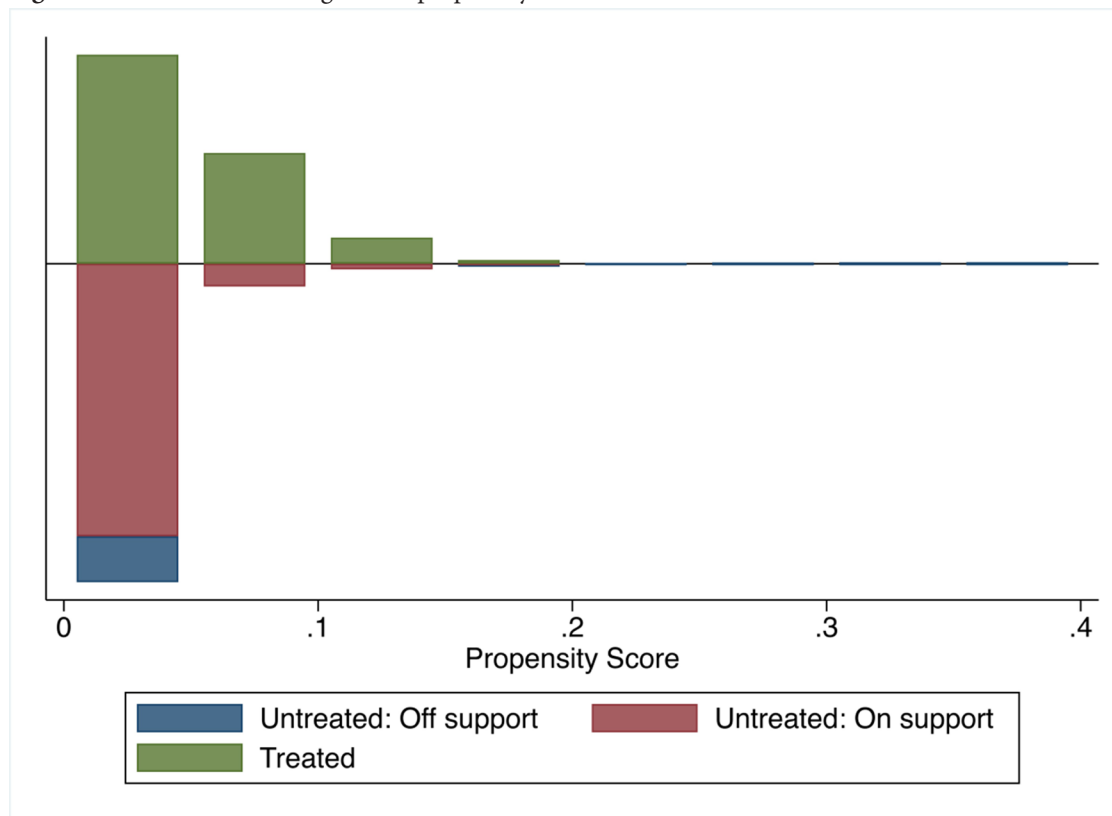
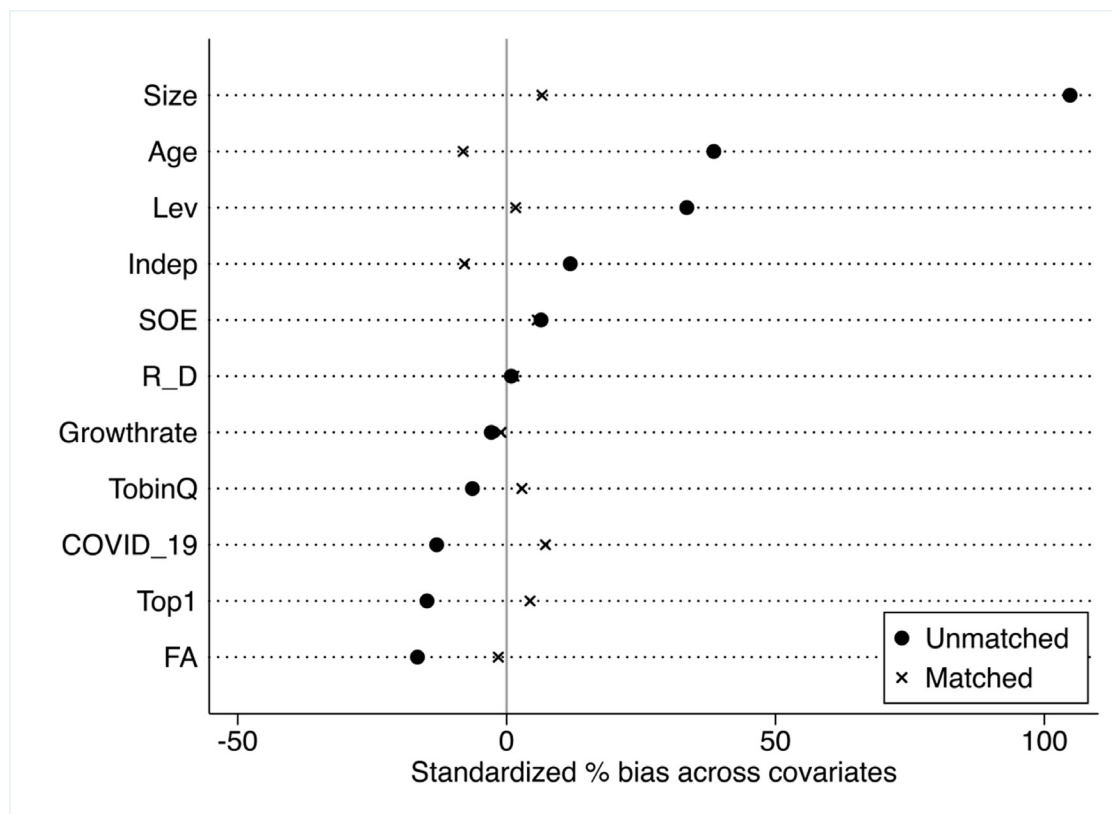
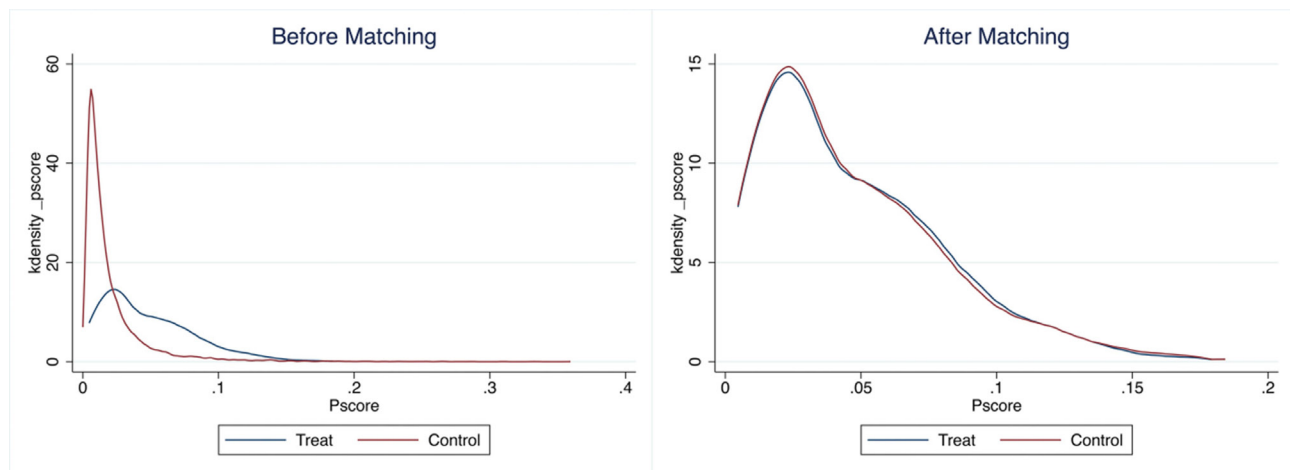
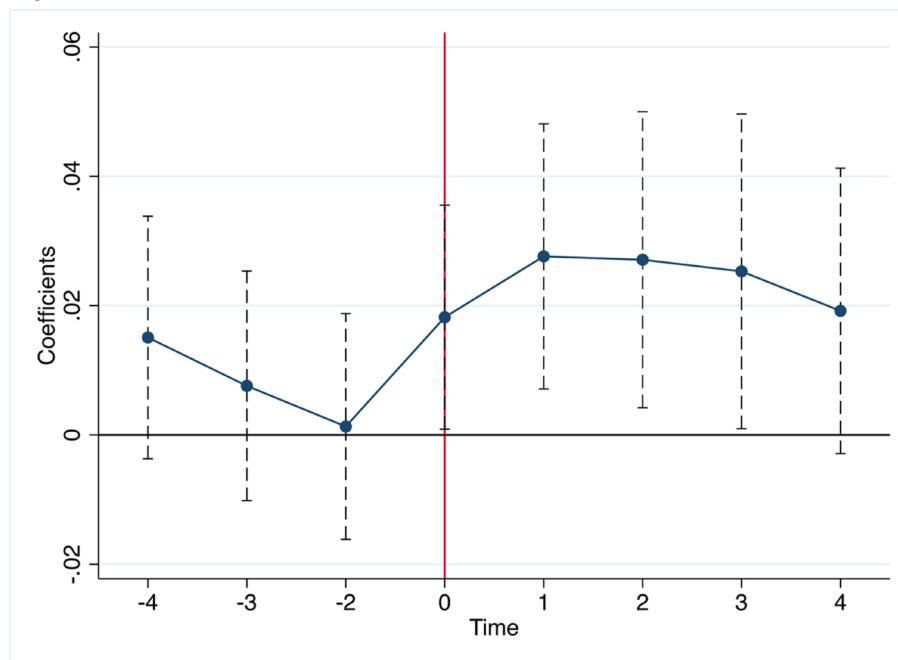
Figure 3. Common value range of the propensity score**Figure 4.** Standardized bias for each variable

Figure 5. Kernel density before and after PSM**Figure 6.** Parallel-trend test

Endogeneity test

Although individual and time effects were incorporated into the baseline regressions to manage heterogeneity in firms' financial performance, endogeneity problems may still persist due to reverse causality. High ROA not only reflects strong profitability but also a higher competitiveness and risk tolerance, making companies more willing to invest in DT even if the latter causes short-term financial pressure. To address this issue, we selected the lagged one-period year-end ratio of mobile phone subscribers in the city where the company operates ($MphoneUsers_{t-1}$) [113] and the lagged one-period degree of Digital Economy Index (DEI_{t-1}) of cities as instrumental variables (IV).

The digital transformation of a firm is closely linked to the external digital environment of its region. The mobile phone penetration rate in the city where the firm's headquarters is located serves as an indicator of the local digital infrastructure. This infrastructure influences the parent company's digital adoption and its efforts to implement

digital technologies in subsidiaries across various cities. Due to the differences in urban development across China, firms based in cities with higher mobile phone penetration are generally more advanced in digital transformation [114], thereby satisfying the relevance condition for this instrument. Additionally, the exogeneity condition is met, as the local mobile penetration rate is unlikely to have a direct impact on the company's financial performance. Similarly, following Tao et al. [115], a city-level DEI index was constructed using data from the *China Urban Statistical Yearbook* and *Local Statistical Yearbook*, applying the entropy weight method. The DEI_{t-1} reflects the overall digital infrastructure and digital economy level in a city, but it does not directly influence a company's financial performance.

The first stage in Table 6 reveals that the coefficients for $MphoneUsers_{t-1}$ and DEI_{t-1} are significantly positive, indicating that the IV and endogenous explanatory variables are highly correlated. In Column (5), the p-value of the Klei-

bergen-Paap rk LM statistic is below 0.01, signifying that the null hypothesis of “under-identification of IV” is rejected at the 1% level of significance. The Cragg-Donald Wald F statistic and the Kleibergen-Paap Wald rk F statistic both surpass the 10% critical threshold (19.93), rejecting the null hypothesis of “weak IV”. P-value for the Hansen J-test test is higher than 0.1, suggesting the absence of an over-iden-

tification problem. The results of the second stage indicate that the impact of DT on CFP is significantly negative at the 1% level (-0.0799). Moreover, the absolute value of the coefficients of DT increase compared to the two-fixed effects regression (-0.0175). Thus, the estimated impact of DT on CFP is greater after accounting for endogeneity, indicating that the findings derived in this paper are robust.

Table 6. Robustness test and endogeneity test results

	Alternative variable			PSM-DID	TSLS-First stage		TSLS-Second stage
	ROE	WW	CFP	CFP	DT	DT	CFP
DT	-0.0849** (-2.27)	0.0947*** (4.09)	-0.0170*** (-4.06)	-0.0156*** (-3.85)			-0.0799*** (-3.48)
WW			-0.0049*** (-2.89)				
DID				0.0110** (2.02)			
Mphone Users _{<i>t-1</i>}					0.1637*** (4.07)		
DEI _{<i>t-1</i>}						0.0965*** (4.21)	
Size	0.0376*** (3.42)	-0.1295*** (-18.95)	0.0065*** (5.13)	0.0122*** (9.20)	-0.0063** (-2.27)	-0.0186*** (-6.92)	0.0140*** (13.44)
Age	-0.0055 (-0.35)	-0.0052 (-0.53)	-0.0037** (-2.11)	-0.0034** (-2.07)	0.0023 (0.58)	0.0035 (0.91)	-0.0009*** (-6.72)
Growthrate	0.0911*** (7.96)	-0.0716*** (-10.09)	0.0352*** (27.26)	0.0330*** (27.01)	-0.0006*** (-2.94)	-0.0005*** (-3.09)	0.0003 (1.16)
Lev	-0.0979*** (-6.00)	-0.0550*** (-5.43)	-0.0955*** (-52.02)	-0.1665*** (-33.94)	0.0001 (0.02)	0.0436*** (4.44)	-0.1356*** (-19.28)
R&D	-0.0004 (-0.40)	-0.0011 (-1.52)	0.0003** (2.47)	0.0000 (0.04)	-0.0015*** (-5.46)	-0.0007*** (-2.95)	-0.0001 (-0.25)
FA	-0.1909*** (-3.20)	-0.1646*** (-4.45)	-0.0853*** (-12.71)	-0.0489*** (-7.04)	-0.1048*** (-6.98)	-0.0674*** (-5.04)	-0.0381*** (-4.92)
SOE	-0.0286 (-1.04)	-0.0228 (-1.34)	-0.0041 (-1.32)	0.0006 (0.21)	0.0194*** (2.80)	0.0044 (0.74)	-0.0082*** (-3.42)

	Alternative variable			PSM-DID	TSLS-First stage		TSLS-Second stage
	ROE	WW	CFP	CFP	DT	DT	CFP
Indep	-0.0077 (-0.60)	-0.0000 (-0.01)	-0.0003 (-0.19)	-0.0001 (-0.05)	0.0001 (0.02)	-0.0020 (-0.71)	-0.0006 (-0.35)
Top1	0.0006 (0.80)	0.0003 (0.67)	0.0003*** (3.25)	0.0003*** (4.16)	0.0005*** (2.76)	0.0003* (1.69)	0.0003*** (4.04)
TobinQ	0.0092*** (3.16)	-0.0003 (-0.18)	0.0022*** (6.60)	0.0029*** (7.69)	-0.0015** (-2.10)	-0.0008 (-1.26)	0.0048*** (3.24)
COVID-19	0.0054 (0.04)	0.1213 (1.31)	0.0066 (0.39)	0.0021 (0.13)	0.0421 (1.12)	0.0212 (0.66)	-0.0041* (-2.00)
Constant	-0.6354** (-2.39)	2.0176*** (12.22)	-0.0201 (-0.67)	-0.1250*** (-3.91)	0.2574*** (2.81)	0.2139*** (3.24)	-0.2022*** (-9.17)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12.833	12.833	12.833	9.898	10.439	10.439	10.439
R-squared	0.013	0.196	0.273	0.215	0.027	0.054	0.2305
Kleibergen-Paap rk LM statistic							105.696 [0.0000]
Kleibergen-Paap rk Wald F statistic							68.994
Cragg-Donald Wald F statistic							408.492
Hansen J test							0.049 [0.8254]

Note: The T statistic is in parentheses; *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively; the P value is in brackets.

Dynamic Analysis

Building upon our baseline findings which consistently indicated a negative contemporaneous association between digital transformation and firm performance, we further investigate the temporal dynamics of this relationship. Recognizing that the impacts of strategic investments like DT often unfold over time and may involve initial costs followed by eventual benefits, we employ a distributed lag model (DLM). This allows us to disentangle the immediate versus lagged effects of DT on ROA, while controlling for performance persistence (ROA_{t-1}). The model takes the form:

$$CFP_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \alpha_2 DT_{i,t-1} + \alpha_3 ROA_{i,t-1} + \alpha_4 Controls_{i,t} + \sum Year + \sum Firm + v_{i,t}, \quad (9)$$

In Table 7, the DLM estimation yields nuanced insights that refine our initial baseline interpretation. First, the coefficient on lagged ROA is significantly positive at the 1% level, confirming the expected performance persistence. Second, consistent with our baseline static models, the coefficient on contemporaneous DT remains significantly negative. This reinforces the finding that, in the short term, engaging in DT is associated with lower ROA, likely reflecting the significant upfront investments, implemen-

tation challenges, and potential operational disruptions inherent in these initiatives. Crucially, however, the dynamic analysis reveals a contrasting picture over a slightly longer horizon. The coefficient on the first lag of DT is significantly positive. This suggests that the performance benefits derived from digital transformation—such as enhanced efficiency, improved innovation, or better market positioning—begin to materialize and outweigh the initial costs in the period following the primary investment and implementation phase.

Taken together, the DLM results reconcile the negative finding from the static baseline model with the strategic imperative often ascribed to digitalization. The negative contemporaneous effect primarily captures the initial investment phase and adjustment costs, while the positive lagged effect signals the eventual realization of benefits. This pattern strongly suggests a J-curve dynamic, where performance initially dips due to DT implementation before subsequently improving as the transformation matures and yields returns.

Table 7. Dynamic Analysis

	Model (9)			
	CFP	CFP	CFP	CFP
DT	-0.0288*** (-4.93)	-0.0179*** (-2.91)	-0.0188*** (-3.38)	-0.0128** (-2.22)
ROA _{t-1}	0.5505*** (73.39)	0.1967*** (20.78)	0.3638*** (43.10)	0.0968*** (10.34)
DT _{t-1}	0.0123** (2.10)	0.0166*** (2.72)	0.0143** (2.57)	0.0142** (2.47)
Size			0.0094*** (19.30)	0.0206*** (14.42)
Age			-0.0005*** (-6.17)	-0.0037** (-2.24)
Growthrate			0.0011*** (6.58)	0.0010*** (6.58)
Lev			-0.0931*** (-29.19)	-0.1756*** (-32.86)
R&D			-0.0000 (-0.15)	0.0002 (1.56)
FA			-0.0285*** (-7.15)	-0.0598*** (-8.45)
SOE			-0.0023* (-1.77)	-0.0015 (-0.47)
Indep			0.0002 (0.20)	-0.0009 (-0.60)
Top1			0.0002*** (5.56)	0.0004*** (4.26)
TobinQ			0.0026*** (9.90)	0.0025*** (7.64)

Model (9)				
	CFP	CFP	CFP	CFP
COVID-19			-0.0067**	0.0025
			(-2.37)	(0.18)
Constant	0.0168***	0.0307***	-0.1696***	-0.3089***
	(26.83)	(17.07)	(-8.65)	(-9.26)
Year FE	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No
City FE	No	No	Yes	No
Firm FE	No	Yes	No	Yes
Observations	11,131	11,131	11,131	11,131
R-squared	0.332	0.058	0.436	0.171

Note: The T statistic is in parentheses; *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

Heterogeneity analysis

Heterogeneity in shareholdings

According to the resource-based view (RBV), state-owned enterprises (SOEs) benefit from unique resource endowments that enable them to secure government funding and policy advantages [117; 118]. This support allows SOEs to more effectively manage the high costs and inherent risks of digital transformation. These enterprises can not only leverage government-provided resources and policies to alleviate financial pressures during the initial stages of digital transformation but also fulfil public policy objectives [119] and social responsibilities, thereby enhancing the drive for long-term sustainable development through digital transformation [120]. This approach strengthens relationships with stakeholders, allowing SOEs to gain more social capital and market trust and mitigating the short-term negative impacts of transformation on financial performance. In contrast, private enterprises often face greater challenges in the process of digital transformation, especially in the context of “ownership discrimination” in China, where they struggle to obtain credit support comparable to that of SOEs [113]. Financing constraints impose greater financial pressure on private enterprises, making it difficult for them to advance digital agendas smoothly, which may lead to a deterioration in financial performance. We conduct heterogeneity analysis to verify the differences between firms with different equity natures. We set SOE = 1 if the enterprise is an SOE, and SOE=0 otherwise. The results in Table 8 show that the effect of digital transformation on financial performance

is significantly negative (-0.0317) at the 1% level in private enterprises and that the effect is not significant in SOEs. This confirms our view above.

Heterogeneity of the competitive market environment

The intensity of market competition may directly influence firms’ resource allocation and strategic choices regarding digital transformation, leading to potential variations in the latter’s impact on financial performance across different competitive environments. In this study, the Herfindahl-Hirschman Index (HHI) is used as a proxy variable for the degree of market competition, and heterogeneity is analysed based on the median split of HHI. HHI = 0 if HHI is greater than the median, and HHI = 1 otherwise. Typically, industries with lower HHI values experience more intense competition. The results in Table 8 indicate that in highly competitive environments (HHI = 1), the coefficient for digital transformation is negative at the 1% significance level (-0.0293), whereas in less competitive environments (HHI = 0), the relationship is not statistically significant.

Overall, intense market competition challenges firms’ profitability [121]. It also necessitates substantial resource allocation across multiple domains, including product development, marketing, and digital infrastructure. On account of limited resources, firms may struggle to balance these investments, constraining the depth and efficiency of their transformation efforts [122]. This directly impacts internal management decisions and resource allocation efficiency, hindering the ability to rapidly achieve

profitability through digital transformation and negatively affecting financial performance. Conversely, in less competitive markets, firms face reduced external pressures and are less disrupted by competitors with regard to resources and financing channels [123]. This allows for more deliberate planning and implementation of digital transformation. Such firms have sufficient time and resources to integrate digital technologies with existing business models, enhancing operational efficiency without significantly increasing costs. Therefore, in less competitive markets, digital transformation is unlikely to negatively impact financial performance and may even contribute to long-term financial gain, though this result is not statistically significant.

Heterogeneity of firm age

We further categorized enterprises by the number of years since IPO, using the sample median. Enterprises with an IPO age greater than 13 years were assigned Age = 1, while those with an IPO age of 13 years or less were assigned Age = 0. The results in Table 8 indicate that digital transformation has a significantly negative impact on financial performance for long-listed enterprises, while the impact is not significant for younger enterprises.

Long-listed enterprises typically possess substantial industry experience and resource accumulation, but they also face significant challenges related to organizational inertia and structural change [12]. During the digital transformation process, these well-established firms often need to invest heavily in system upgrades and process reengineering, which not only incurs financial costs but may also disrupt existing business models and competitive advantages [59]. According to the resource-based view (RBV), this process of reconfiguring resource allocation can lead to a short-term decline in financial performance, posing a threat to the survival of large, well-established firms that were successful during the pre-digital economy era [60], especially if they fail to effectively manage organizational changes during the transformation. In contrast, younger enterprises are typically more flexible and adaptable, allowing them to swiftly adjust their business models and integrate new technologies with existing resources during digital transformation. Although younger firms also face the challenge of resource consumption during the transformation, their lower organizational inertia and higher innovation capacity result in a smaller negative impact on financial performance, and they may even benefit from the transformation. The results of this heterogeneity test further validate the findings in our benchmark regression.

Table 8. Heterogeneity test of shareholdings, competitive market environment, and firm age

	SOE = 0	SOE = 1	HHI = 0	HHI = 1	Age = 0	Age = 1
	CFP	CFP	CFP	CFP	CFP	CFP
DT	-0.0317*** (-4.70)	-0.0044 (-0.85)	0.0026 (0.40)	-0.0293*** (-4.88)	0.0096 (1.39)	-0.0258*** (-4.31)
Size	0.0060*** (2.90)	0.0157*** (9.46)	0.0059*** (3.03)	0.0104*** (5.22)	0.0247*** (9.95)	0.0096*** (5.32)
Age	-0.0050* (-1.94)	-0.0024 (-1.02)	-0.0010 (-0.38)	-0.0057** (-2.33)	-0.0064*** (-3.10)	-0.0031 (-1.10)
Growthrate	0.0477*** (23.33)	0.0245*** (15.50)	0.0389*** (21.20)	0.0348*** (18.17)	0.0482*** (24.32)	0.0287*** (15.92)
Lev	-0.0916*** (-42.05)	-0.1784*** (-27.85)	-0.0911*** (-43.04)	-0.1550*** (-20.46)	-0.1812*** (-23.08)	-0.0893*** (-39.77)
R&D	0.0003 (1.44)	0.0005*** (3.29)	0.0003 (1.37)	0.0003* (1.83)	0.0002 (0.71)	0.0003* (1.69)
FA	-0.1080*** (-9.54)	-0.0509*** (-6.21)	-0.0654*** (-7.09)	-0.0892*** (-8.47)	-0.0990*** (-9.76)	-0.0777*** (-7.65)
SOE			0.0026 (0.53)	-0.0058 (-1.34)	-0.0003 (-0.06)	-0.0004 (-0.09)
Indep	0.0039 (1.34)	-0.0024 (-1.50)	-0.0020 (-1.02)	0.0014 (0.61)	-0.0011 (-0.47)	0.0003 (0.12)

	SOE = 0	SOE = 1	HHI = 0	HHI = 1	Age = 0	Age = 1
	CFP	CFP	CFP	CFP	CFP	CFP
Top1	0.0000 (0.30)	0.0003*** (3.26)	0.0005*** (3.89)	-0.0000 (-0.08)	0.0001 (1.09)	0.0003* (1.94)
TobinQ	0.0026*** (5.87)	0.0006 (1.22)	0.0025*** (5.85)	-0.0011** (-1.98)	0.0030*** (5.57)	0.0014*** (2.73)
COVID-19	0.0046 (0.19)	-0.0085 (-0.37)	-0.0144 (-0.59)	0.0182 (0.78)	0.0087 (0.43)	0.0015 (0.06)
Constant	-0.0050 (-0.11)	-0.1955*** (-4.40)	-0.0423 (-0.90)	-0.0397 (-0.86)	-0.3997*** (-7.24)	-0.0766 (-1.32)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,247	6,586	6,500	6,333	5,757	6,383
R-squared	0.367	0.172	0.345	0.163	0.282	0.307

Note: The T statistic is in parentheses; *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

Heterogeneity in environmental, social, and governance performance

Given the distinct characteristics of the three ESG dimensions, this study groups firms by their average environmental, social, and governance scores to investigate the effect of these differences on the relationship between digital transformation and financial performance. The findings in Table 9 show that variations in environmental performance have little effect on this relationship: digital transformation negatively impacts financial performance regardless of environmental performance. However, differences in social responsibility and governance performance significantly influence this relationship. When social responsibility and governance are weak, digital transformation notably harms financial performance, but when they are strong, this negative impact becomes insignificant.

Further analysis reveals that strong social responsibility and governance performance send positive signals to the market, boosting investor confidence and support [65], attracting government policy support and financial subsidies [84], and increasing opportunities for credit financing within the supply chain [83]. These factors alleviate the financial pressures associated with the significant investments required for digital transformation [78], thereby improving financial performance. Additionally, high levels of social responsibility and internal governance can attract top-tier human resources [70], providing sustained momentum for digital transformation, increasing its efficiency, and mitigating the negative impacts of initial cost increases and profitability declines. This helps buffer the risk of deteriorating financial performance. These findings offer a deeper analysis of the moderating role of ESG performance and further clarify how each dimension individually influences this relationship.

Table 9. Heterogeneity test of environmental, social, and governance performance

	E_high	E_low	S_high	S_low	G_high	G_low
	CFP	CFP	CFP	CFP	CFP	CFP
DT	-0.0226*** (-3.28)	-0.0157*** (-2.59)	0.0014 (0.26)	-0.0332*** (-4.53)	-0.0057 (-1.16)	-0.0221*** (-2.91)
Size	0.0144*** (7.08)	0.0088*** (4.63)	0.0209*** (11.45)	0.0027 (1.27)	0.0106*** (6.60)	0.0051** (2.17)
Age	-0.0043** (-2.08)	-0.0030 (-1.02)	-0.0041** (-2.16)	-0.0029 (-0.79)	-0.0046** (-2.47)	-0.0033 (-0.98)
Growthrate	0.0399*** (21.30)	0.0325*** (17.45)	0.0357*** (20.75)	0.0352*** (17.04)	0.0388*** (25.34)	0.0315*** (13.82)
Lev	-0.1987*** (-26.55)	-0.0861*** (-40.92)	-0.1881*** (-26.50)	-0.0841*** (-37.95)	-0.1493*** (-25.07)	-0.0874*** (-34.20)

	E_high	E_low	S_high	S_low	G_high	G_low
	CFP	CFP	CFP	CFP	CFP	CFP
R&D	-0.0001 (-0.54)	0.0004* (1.91)	-0.0000 (-0.17)	0.0007*** (2.93)	-0.0000 (-0.25)	0.0008*** (3.07)
FA	-0.0851*** (-8.68)	-0.0710*** (-6.76)	-0.0728*** (-7.07)	-0.0789*** (-7.61)	-0.0697*** (-9.53)	-0.0925*** (-6.92)
SOE	-0.0043 (-0.95)	-0.0075 (-1.59)	-0.0004 (-0.10)	-0.0066 (-1.26)	-0.0037 (-1.01)	-0.0064 (-1.16)
Indep	0.0002 (0.10)	-0.0016 (-0.70)	-0.0005 (-0.28)	-0.0014 (-0.52)	0.0002 (0.11)	-0.0021 (-0.65)
Top1	0.0003** (2.52)	0.0003** (2.41)	0.0004*** (3.29)	0.0003** (2.01)	0.0004*** (4.59)	0.0002 (1.42)
TobinQ	0.0046*** (6.10)	0.0009** (2.22)	0.0069*** (11.17)	-0.0001 (-0.17)	0.0050*** (10.96)	0.0006 (1.12)
COVID-19	0.0142 (0.70)	-0.0079 (-0.28)	0.0045 (0.25)	-0.0031 (-0.09)	0.0195 (1.10)	-0.0012 (-0.04)
Constant	-0.1467*** (-3.10)	-0.0703 (-1.53)	-0.3099*** (-7.52)	0.0660 (1.17)	-0.0963*** (-2.64)	0.0190 (0.33)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,059	6,774	7,014	5,819	7,602	5,231
R-squared	0.234	0.322	0.212	0.340	0.224	0.317

Note: The T statistic is in parentheses; *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

Conclusion and discussion

Our results show that digital transformation as a means of innovation policy has a complex dynamic effect on the financial performance of mature, large-cap Chinese firms. Specifically, we observe an initial detrimental impact, contrasting with some prior studies [2; 47; 48]. This research focuses on Chinese enterprises characterized by organizational inertia, extensive infrastructure, and heavy reliance on traditional business models. Moreover, unlike previous scholars who measure digital transformation using words frequency [86] or a dummy variable [48], we adopt digital assets as an indicator of the digital transformation level. Digital assets serve as a better explanatory variable for studying the effect of digital transformation on return on assets, providing a more accurate reflection of a firm's involvement in digital innovation. Our findings offer a new perspective by highlighting that, for mature enterprises, digital transformation is still largely at the digital equipment and technology application stage, which requires substantial initial investments. This upfront investment explains the initial negative impact on ROA. However, consistent with a J-curve dynamic often seen in large-scale investments, the benefits of digital transformation are not immediate but manifest later, leading to disproportionate increases in operational costs relative to revenue and, consequently, a short-term decline in return on assets. Additionally, this study examines the considerable failure rate

of digital transformation and the resulting operational uncertainties, particularly with regard to traditional business model changes and the impact on the core business. These circumstances support the digitalization paradox theory [8], which links digital investments to challenges in revenue growth. Our study goes further by providing a more comprehensive analysis of how these digital investments lead to imbalanced costs and returns over time, negatively impacting overall financial performance initially, and identifying the mediating role of financing constraints in this process.

In light of these findings highlighting the dynamic, J-curve-like nature of returns, it is essential for firms to recognize the potential for temporary financial setbacks during the initial phases of digital technology adoption. These challenges largely stem from increased capital expenditures, heightened operational costs, and the complexities of integrating digital technologies into existing business processes before the longer-term benefits materialize. To mitigate these risks, companies must adopt a strategic approach that carefully aligns digital transformation initiatives with their core business objectives. A targeted, phased implementation strategy, where key business functions are prioritized for digital integration, can help minimize operational disruptions and optimize resource allocation. Furthermore, firms must enhance their risk assessment and management frameworks to better navigate the uncertainties inherent in digital transformation. By refining their digital strategies

and improving risk management practices, firms can better balance the initial costs inherent in this dynamic effect with the long-term benefits of digital transformation.

Furthermore, this research highlights the crucial synergy between digital innovation and ESG management innovation in improving the financial performance of large, mature firms from a sustainable development perspective. It underscores the importance for companies to integrate sustainability principles into their digital transformation initiatives. The findings show that ESG effectively alleviates the adverse effects of digital transformation (particularly the initial downturn) by reducing financing constraints. Strong ESG performance enhances stakeholder tolerance for financial performance declines during digital transformation and raises expectations for its eventual success. Strong ESG practices also help to address challenges in human capital, facilitate the smoother integration of digital technologies, improve risk management, and reduce uncertainties associated with the transformation's dynamic payoff structure. From a signalling theory perspective, ESG sends positive signals to capital markets about a firm's long-term sustainable development goals, countering potential negative signals of digital transformation failures and slow returns and easing financing constraints. Moreover, ESG strengthens trust with suppliers, customers, and regulators, expanding financing channels. It further supports Yin's [124] argument that integrating digital technologies with green activities is a crucial factor in boosting digital competitiveness.

Our research findings provide new strategic ideas for firms on advancing digital transformation agendas and offsetting the dynamic short-term financial pressures brought by digital transformation through an improvement of ESG performance, ultimately promoting long-term sustainable development. At the same time, enhanced ESG performance is a focus for companies aiming to bolster their market reputation and financing capacity.

References

1. Xiao Q., Gao M., Chen L., et al. Dynamic multi-attribute evaluation of digital economy development in China: a perspective from interaction effect. *Technological and Economic Development of Economy*. 2023;29(6):1728–1752. <https://doi.org/10.3846/tede.2023.20258>
2. Tian M., Chen Y., Tian G., et al. The role of digital transformation practices in the operations improvement in manufacturing firms: A practice-based view. *International Journal of Production Economics*. 2023;262:108929. <https://doi.org/10.1016/j.ijpe.2023.108929>
3. Wamba SF, Gunasekaran A, Akter S, et al. Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*. 2017;70:356–365. <https://doi.org/10.1016/j.jbusres.2016.08.009>
4. Liu S., Yan J., Zhang S., et al. Can corporate digital transformation promote input-output efficiency. *Journal of Management World*. 2021;37(5):170–190. (In Chinese) <https://doi.org/10.19744/j.cnki.11-1235/f.2021.0072>
5. Lim J.-H., Stratopoulos T.C., Wirjanto T.S. Role of IT executives in the firm's ability to achieve competitive advantage through IT capability. *International Journal of Accounting Information Systems*. 2012;13(1):21–40. <https://doi.org/10.1016/j.accinf.2011.07.001>
6. Liu H., Ke W., Wei K.K., et al. The impact of IT capabilities on firm performance: The mediating roles of absorptive capacity and supply chain agility. *Decision Support Systems*. 2013;54(3):1452–1462. <https://doi.org/10.1016/j.dss.2012.12.016>
7. Tabrizi B., Lam E., Girard K., et al. Digital transformation is not about technology. *Harvard Business Review*. 2019;13:1–6. URL: <https://hbr.org/2019/03/digital-transformation-is-not-about-technology> Accessed on 01.12.2024
8. Gebauer H., Fleisch E., Lamprecht C., et al. Growth paths for overcoming the digitalization paradox. *Business Horizons*. 2020;63(3):313–323. URL: <https://doi.org/10.1016/j.bushor.2020.01.005> Accessed on 01.12.2024
9. Shakina E., Parshakov P., Alsufiev A. Rethinking the corporate digital divide: The complementarity of technologies and the demand for digital skills. *Technological Forecasting and Social Change*. 2021;162:120405. <https://doi.org/10.1016/j.techfore.2020.120405>
10. Appio F.P., Frattini F., Petruzzelli A.M., et al. Digital transformation and innovation management: A synthesis of existing research and an agenda for future studies. *Journal of Product Innovation Management*. 2021;38(1):4–20. <https://doi.org/10.1111/jpim.12562>
11. Delin Z., Jiawei C., Taohua O. A Research on Digital Transformation: Integration Framework and Prospects. *Foreign Economics & Management*. 2021;43(5):63–76. <https://doi.org/10.16538/j.cnki.fem.20210406.101>
12. Rolland K.-H., Hanseth O. Managing path dependency in digital transformation processes: A longitudinal case study of an enterprise document management platform. *Procedia Computer Science*. 2021;181:765–774. <https://doi.org/10.1016/j.procs.2021.01.229>
13. Forcadell F.J., Aracil E., Ubeda F. Using reputation for corporate sustainability to tackle banks digitalization challenges. *Business Strategy and the Environment*. 2020;29(6):2181–2193. <https://doi.org/10.1002/bse.2494>
14. Liu J., Zhou K., Zhang Y., et al. The effect of financial digital transformation on financial performance:

- the intermediary effect of information symmetry and operating costs. *Sustainability*. 2023;15(6):5059. <https://doi.org/10.3390/su15065059>
15. Zhai H., Yang M., Chan K.C. Does digital transformation enhance a firm's performance? Evidence from China. *Technology in Society*. 2022;68:101841. <https://doi.org/10.1016/j.techsoc.2021.101841>
 16. Vial G. Understanding digital transformation: A review and a research agenda. *Managing digital transformation*. 2021:13-66. <https://doi.org/10.4324/9781003008637-4>
 17. Yonghong L., Jie S., Ge Z., et al. The impact of enterprise digital transformation on financial performance—Evidence from Mainland China manufacturing firms. *Managerial and Decision Economics*. 2023;44(4):2110-2124. <https://doi.org/10.1002/mde.3805>
 18. Scafarto V., Dalwai T., Ricci F., et al. Digitalization and firm financial performance in healthcare: the mediating role of intellectual capital efficiency. *Sustainability*. 2023;15(5):4031. <https://doi.org/10.3390/su15054031>
 19. Eisenmann T., Parker G., Van Alstyne M.W. Strategies for two-sided markets. *Harvard Business Review*. 2006;84(10):92. URL: <https://ssrn.com/abstract=2409276> Accessed on 01.12.2024
 20. Fabian NE, Broekhuizen T, Nguyen DK. Digital transformation and financial performance. *Managing Digital Transformation: Understanding the Strategic Process*. 2021. <https://doi.org/10.4324/9781003008637-25>
 21. Sun B., Zhang Y., Zhu K., et al. Is faster really better? The impact of digital transformation speed on firm financial distress: Based on the cost-benefit perspective. *Journal of Business Research*. 2024;179:114703. <https://doi.org/10.1016/j.jbusres.2024.114703>
 22. Vu D.A., Van Nguyen T., Nhu Q.M., et al. Does increased digital transformation promote a firm's financial performance? New insights from the quantile approach. *Finance Research Letters*. 2024;64:105430. <https://doi.org/10.1016/j.frl.2024.105430>
 23. Guo L., Xu L. The effects of digital transformation on firm performance: Evidence from China's manufacturing sector. *Sustainability*. 2021;13(22):12844. <https://doi.org/10.3390/su132212844>
 24. Etienne Fabian N., Dong J.Q., Broekhuizen T., et al. Business value of SME digitalisation: when does it pay off more? *European Journal of Information Systems*. 2023;33(3):383-402. <https://doi.org/10.1080/0960085X.2023.2167671>
 25. Hajli M., Sims J.M., Ibragimov V. Information technology [IT] productivity paradox in the 21st century. *International Journal of Productivity and Performance Management*. 2015;64(4):457-478. <https://doi.org/10.1108/IJPPM-12-2012-0129>
 26. Solow R. We'd better watch out. *New York Times Book Review*. 1987. URL: <http://digamo.free.fr/solow87.pdf> Accessed on 01.12.2024
 27. Matt C., Hess T., Benlian A. Digital transformation strategies. *Business & information systems engineering*. 2015;57:339-343. <https://doi.org/10.1007/s12599-015-0401-5>
 28. Xie K., Wu Y., Xiao J., et al. Strategic risk control in organizational change: a multi-case study of organizational transformation towards Internet. *Management World*. 2016;(2):133-148. (in Chinese) <https://d.wanfangdata.com.cn/periodical/glsj201602013>
 29. Hanelt A., Bohnsack R., Marz D., et al. A systematic review of the literature on digital transformation: Insights and implications for strategy and organizational change. *Journal of management studies*. 2021;58(5):1159-1197. <https://doi.org/10.1111/joms.12639>
 30. Jardak M.K., Ben Hamad S. The effect of digital transformation on firm performance: evidence from Swedish listed companies. *The Journal of Risk Finance*. 2022;23(4):329-348. <https://doi.org/10.1108/JRF-12-2021-0199>
 31. Coryanata I., Ramli E.H., Puspita L.M.N., et al. Digitalization of Banking and Financial Performance of Banking Companies. *International Journal of Social Service and Research*. 2023;3(2):366-371. <https://doi.org/10.46799/ijssr.v3i2.254>
 32. Chen, Simin, Yu Song, and Peng Gao. Environmental, social, and governance (ESG) performance and financial outcomes: Analyzing the impact of ESG on financial performance. *Journal of environmental management* 345 (2023): 118829. <https://doi.org/10.1016/j.jenvman.2023.118829>
 33. Kim S., Li Z. Understanding the impact of ESG practices in corporate finance. *Sustainability*. 2021;13(7):3746. <https://doi.org/10.3390/su13073746>
 34. Garcia A.S., Mendes-Da-Silva W., Orsato R.J. Sensitive industries produce better ESG performance: Evidence from emerging markets. *Journal of Cleaner Production*. 2017;150:135-147. <https://doi.org/10.1016/j.jclepro.2017.02.180>
 35. Bruna M.G., Loprevite S., Raucci D., et al. Investigating the marginal impact of ESG results on corporate financial performance. *Finance Research Letters*. 2022;47(A):102828. <https://doi.org/10.1016/j.frl.2022.102828>

36. Landi G, Sciarelli M. Towards a more ethical market: the impact of ESG rating on corporate financial performance. *Social Responsibility Journal*. 2019;15(1):11-27. <https://doi.org/10.1108/SRJ-11-2017-0254>
37. Saygili E., Arslan S., Birkan A.O. ESG practices and corporate financial performance: Evidence from Borsa Istanbul. *Borsa Istanbul Review*. 2022;22(3):525-533. <https://doi.org/10.1016/j.bir.2021.07.001>
38. Sharfman M.P., Fernando C.S. Environmental risk management and the cost of capital. *Strategic management journal*. 2008;29(6):569-592. <https://doi.org/10.1002/smj.678>
39. Broadstock D.C., Chan K., Cheng L.T., et al. The role of ESG performance during times of financial crisis: Evidence from COVID-19 in China. *Finance Research Letters*. 2021;38:101716. <https://doi.org/10.1016/j.frl.2020.101716>
40. Benlemlih M., Shaukat A., Qiu Y., et al. Environmental and social disclosures and firm risk. *Journal of Business Ethics*. 2018;152:613-626. <https://doi.org/10.1007/s10551-016-3285-5>
41. Sassen R., Hinze A.-K., Hardeck I. Impact of ESG factors on firm risk in Europe. *Journal of business economics*. 2016;86:867-904. <https://doi.org/10.1007/s11573-016-0819-3>
42. Albuquerque R.A., Koskinen Y., Yang S., et al. Love in the time of COVID-19: The resiliency of environmental and social stocks. *Review of Corporate Finance Studies*. 2020. <https://doi.org/10.2139/ssrn.3583611>
43. Hoepner A.G., Oikonomou I., Sautner Z., et al. ESG shareholder engagement and downside risk. *Review of Finance*. 2024;28(2):483-510. <https://doi.org/10.1093/rof/rfad034>
44. Korinth F., Lueg R. Corporate sustainability and risk management—The u-shaped relationships of disaggregated esg rating scores and risk in the German capital market. *Sustainability*. 2022;14(9):5735. <https://doi.org/10.3390/su14095735>
45. Ricci F., Scafarto V., Ferri S., et al. Value relevance of digitalization: The moderating role of corporate sustainability. An empirical study of Italian listed companies. *Journal of Cleaner Production*. 2020;276:123282. <https://doi.org/10.1016/j.jclepro.2020.123282>
46. Rosamartina S., Giustina S., Domenico D.F., et al. Digital reputation and firm performance: The moderating role of firm orientation towards sustainable development goals [SDGs]. *Journal of Business Research*. 2022;152:315-325. <https://doi.org/10.1016/j.jbusres.2022.07.025>
47. Zhang T, Shi Z-Z, Shi Y-R, Chen N-J. Enterprise digital transformation and production efficiency: Mechanism analysis and empirical research. *Economic Research-Ekonomska istraživanja*. 2022;35(1):2781-2792. URL: <https://hrcak.srce.hr/302483> Accessed on 01.12.2024
48. Peng Y., Tao C. Can digital transformation promote enterprise performance?—From the perspective of public policy and innovation. *Journal of Innovation & Knowledge*. 2022;7(3):100198. <https://doi.org/10.1016/j.jik.2022.100198>
49. Alrawadieh Z., Alrawadieh Z., Cetin G. Digital transformation and revenue management: Evidence from the hotel industry. *Tourism Economics*. 2021;27(2):328-345. <https://doi.org/10.1177/1354816620901928>
50. Schwertner K. Digital transformation of business. *Trakia Journal of Sciences*. 2017;15(1):388-393. <https://doi.org/10.15547/tjs.2017.s.01.065>
51. Tian G., Li B., Cheng Y. Does digital transformation matter for corporate risk-taking? *Finance Research Letters*. 2022;49:103107. <https://doi.org/10.1016/j.frl.2022.103107>
52. Varian H.R. *Artificial intelligence, economics, and industrial organization*. USA: National Bureau of Economic Research Cambridge; 2018. <https://doi.org/10.3386/w24839>
53. Lokuge S., Sedera D., Grover V., et al. Organizational readiness for digital innovation: Development and empirical calibration of a construct. *Information & management*. 2019;56(3):445-461. <https://doi.org/10.1016/j.im.2018.09.001>
54. Liu D.Y., Chen S.W., Chou T.C. Resource fit in digital transformation: Lessons learned from the CBC Bank global e-banking project. *Management Decision*. 2011;49(10):1728-1742. <https://doi.org/10.1108/00251741111183852>
55. Yaya S., Deming Y. Business model innovation and earnings management in the era of digital economy. *Science Research Management*. 2021;42(4):170-179. URL: <https://www.kygl.net.cn/EN/Y2021/V42/I4/170> Accessed on 01.12.2024
56. Parviainen P., Tihinen M., Kääriäinen J., et al. Tackling the digitalization challenge: how to benefit from digitalization in practice. *International journal of information systems and project management*. 2017;5(1):63-77. <https://doi.org/10.12821/ijispm050104>
57. Hess T., Matt C., Benlian A., et al. Options for formulating a digital transformation strategy. *MIS Quarterly Executive*. 2016;15(2):123-139. URL: <https://aisel.aisnet.org/misqe/vol15/iss2/6> Accessed on 01.12.2024

58. Ivaninskiy I., Ivashkovskaya I., McCahery J.A. Does digitalization mitigate or intensify the principal-agent conflict in a firm? *Journal of Management and Governance*. 2023;27(3):695-725. <https://doi.org/10.1007/s10997-021-09584-8>
59. Carcary M., Doherty E., Conway G. A dynamic capability approach to Digital transformation: A focus on key foundational themes. In: *Proceedings of the European Conference on IS Management and Evaluation, ECIME*. 2016:20-28.
60. Sebastian I.M., Ross J.W., Beath C., et al. How big old companies navigate digital transformation. In: *Strategic information management*. Routledge; 2020. <https://doi.org/10.4324/9780429286797-6>
61. Cozzolino A., Verona G., Rothaermel F.T. Unpacking the disruption process: New technology, business models, and incumbent adaptation. *Journal of Management Studies*. 2018;55(7):1166-1202. <https://doi.org/10.1111/joms.12352>
62. Li K., Xia B., Chen Y., et al. Environmental uncertainty, financing constraints and corporate investment: Evidence from China. *Pacific-Basin Finance Journal*. 2021;70:101665. <https://doi.org/10.1016/j.pacfin.2021.101665>
63. Bradley D., Pantzalis C., Yuan X. Policy risk, corporate political strategies, and the cost of debt. *Journal of Corporate Finance*. 2016;40:254-275. <https://doi.org/10.1016/j.jcorpfin.2016.08.001>
64. Eggers J., Park K.F. Incumbent adaptation to technological change: The past, present, and future of research on heterogeneous incumbent response. *Academy of Management Annals*. 2018;12(1):357-389. <https://doi.org/10.5465/annals.2016.0051>
65. Wang K., Li T., San Z., et al. How does corporate ESG performance affect stock liquidity? Evidence from China. *Pacific-Basin Finance Journal*. 2023;80:102087. <https://doi.org/10.1016/j.pacfin.2023.102087>
66. da Cunha Bezerra MC, Gohr CF, Morioka SN. Organizational capabilities towards corporate sustainability benefits: A systematic literature review and an integrative framework proposal. *Journal of Cleaner Production*. 2020;247:119114. <https://doi.org/10.1016/j.jclepro.2019.119114>
67. Chang K., Cheng X., Wang Y., et al. The impacts of ESG performance and digital finance on corporate financing efficiency in China. *Applied Economics Letters*. 2023;30(4):516-523. <https://doi.org/10.1080/13504851.2021.1996527>
68. Kramer M.R., Porter M.E. Strategy and society: The link between competitive advantage and corporate social responsibility. *Harvard Business Review*. 2006;84(12):78-92. URL: <https://hbr.org/2006/12/strategy-and-society-the-link-between-competitive-advantage-and-corporate-social-responsibility> Accessed on 01.12.2024
69. Skare M., de Obesso M.M., Ribeiro-Navarrete S. Digital transformation and European small and medium enterprises [SMEs]: A comparative study using digital economy and society index data. *International Journal of Information Management*. 2023;68:102594. <https://doi.org/10.1016/j.ijinfomgt.2022.102594>
70. Liu L., Nemoto N. Environmental, social and governance [ESG] evaluation and organizational attractiveness to prospective employees: Evidence from Japan. *Journal of Accounting and Finance*. 2021;21(4). <https://doi.org/10.33423/jaf.v21i4.4522>
71. Lee CC, Park S. Impact of ESG on employees' intrinsic motivation across generations. *Korea Review of International Studies*. 2023;16(50):97-119.
72. Gomez-Valencia M., Gonzalez-Perez M.A., Gomez-Trujillo A.M. The "Six Ws" of sustainable development risks. *Business Strategy and the Environment*. 2021;30(7):3131-3144. <https://doi.org/10.1002/bse.2794>
73. Bai X., Han J., Ma Y., et al. ESG performance, institutional investors' preference and financing constraints: Empirical evidence from China. *Borsa Istanbul Review*. 2022;22(S2):S157-S68. <https://doi.org/10.1016/j.bir.2022.11.013>
74. Xie H., Lyu X. Responsible multinational investment: ESG and Chinese OFDI. *Econ Res J*. 2022;57(03):83-99. (in Chinese)
75. <http://e-learning.uibe.edu.cn/meol/analytics/resPdfShow.do;jsessionid=EF392FE110464016F4D32FA0041B68BC?resId=39308&lid=15505>
76. Azmi W., Hassan M.K., Houston R., et al. ESG activities and banking performance: International evidence from emerging economies. *Journal of International Financial Markets, Institutions and Money*. 2021;70:101277. <https://doi.org/10.1016/j.intfin.2020.101277>
77. Raimo N, Caragnano A, Zito M, Vitolla F, Mariani M. Extending the benefits of ESG disclosure: The effect on the cost of debt financing. *Corporate Social Responsibility and Environmental Management*. 2021;28(4):1412-1421. <https://doi.org/10.1002/csr.2134>
78. Folqué M., Escrig-Olmedo E., Corzo Santamaría T. Sustainable development and financial system: Integrating ESG risks through sustainable investment strategies in a climate change context. *Sustainable Development*. 2021;29(5):876-890. <https://doi.org/10.1002/sd.2181>
79. Hu A., Yuan X., Fan S., et al. The impact and mechanism of corporate ESG construction on the efficiency of regional green economy: an empirical

- analysis based on signal transmission theory and stakeholder theory. *Sustainability*. 2023;15(17):13236. <https://doi.org/10.3390/su151713236>
80. Wang S., Wang D. Exploring the relationship between ESG performance and green bond issuance. *Frontiers In Public Health*. 2022;10:897577. <https://doi.org/10.3389/fpubh.2022.897577>
 81. Vismara S. Sustainability in equity crowdfunding. *Technological Forecasting and Social Change*. 2019;141:98-106. <https://doi.org/10.1016/j.techfore.2018.07.014>
 82. Li Y., Han Y., Fok R.C. Do cross-border mergers and acquisitions affect acquirers' trade credit? Evidence from an emerging market. *International Review of Economics & Finance*. 2020;70:423-439. <https://doi.org/10.1016/j.iref.2020.06.041>
 83. Yan Y., Cheng Q., Huang M., et al. Government environmental regulation and corporate ESG performance: evidence from natural resource accountability audits in China. *International Journal of Environmental Research and Public Health*. 2022;20(1):447. <https://doi.org/10.3390/ijerph20010447>
 84. Huang Y., Bai F., Shang M., et al. On the fast track: the benefits of ESG performance on the commercial credit financing. *Environmental Science and Pollution Research*. 2023;30(35):83961-83974. <https://doi.org/10.1007/s11356-023-28172-x>
 85. Zhang X., Zhang J., Feng Y. Can companies get more government subsidies through improving their ESG performance? Empirical evidence from China. *Plos one*. 2023;18(10):e0292355. <https://doi.org/10.1371/journal.pone.0292355>
 86. Yang C., Zhu C., Albitar K. ESG ratings and green innovation: A U-shaped journey towards sustainable development. *Business Strategy and the Environment*. 2024;33(5):4108-4129. <https://doi.org/10.1002/bse.3692>
 87. Liu M., Li C., Wang S., et al. Digital transformation, risk-taking, and innovation: Evidence from data on listed enterprises in China. *Journal of Innovation & Knowledge*. 2023;8(1):100332. <https://doi.org/10.1016/j.jik.2023.100332>
 88. Wang J., Liu Y., Wang W., et al. How does digital transformation drive green total factor productivity? Evidence from Chinese listed enterprises. *Journal of Cleaner Production*. 2023;406:136954. <https://doi.org/10.1016/j.jclepro.2023.136954>
 89. Tang M., Liu Y., Hu F., et al. Effect of digital transformation on enterprises' green innovation: empirical evidence from listed companies in China. *Energy Economics*. 2023;128:107135. <https://doi.org/10.1016/j.eneco.2023.107135>
 90. Wu K., Fu Y., Kong D. Does the digital transformation of enterprises affect stock price crash risk? *Finance Research Letters*. 2022;48:102888. <https://doi.org/10.1016/j.frl.2022.102888>
 91. Jiang K., Du X., Chen Z. Firms' digitalization and stock price crash risk. *International review of financial analysis*. 2022;82:102196. <https://doi.org/10.1016/j.irfa.2022.102196>
 92. Chen N., Sun D., Chen J. Digital transformation, labour share, and industrial heterogeneity. *Journal of Innovation & Knowledge*. 2022;7(2):100173. <https://doi.org/10.1016/j.jik.2022.100173>
 93. Hadlock C.J., Pierce J.R. New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies*. 2010;23(5):1909-1940. <https://doi.org/10.1093/rfs/hhq009>
 94. Kaplan S.N., Zingales L. Do investment-cash flow sensitivities provide useful measures of financing constraints? *The Quarterly Journal of Economics*. 1997;112(1):169-215. <https://doi.org/10.1162/003355397555163>
 95. Whited T.M., Wu G. Financial constraints risk. *The Review of Financial Studies*. 2006;19(2):531-559. <https://doi.org/10.1093/rfs/hhj012>
 96. Zhu W. Can the digital transformation of finance companies within business groups alleviate the financing constraints of enterprises within the same group? *Applied Economics*. 2024;1-18. <https://doi.org/10.1080/00036846.2024.2386848>
 97. Hu Y., Che D., Wu F., et al. Corporate maturity mismatch and enterprise digital transformation: Evidence from China. *Finance Research Letters*. 2023;53:103677. <https://doi.org/10.1016/j.frl.2023.103677>
 98. He L.-Y., Chen K.-X. Digital transformation and carbon performance: Evidence from firm-level data. *Environment, Development and Sustainability*. 2023;1-26. <https://doi.org/10.1007/s10668-023-03143-x>
 99. Chan C.-Y., Chou D.-W., Lo H.-C. Do financial constraints matter when firms engage in CSR? *The North American Journal of Economics and Finance*. 2017;39:241-259. <https://doi.org/10.1016/j.najef.2016.10.009>
 100. Zhang J., Li Y., Xu H., et al. Can ESG ratings mitigate managerial myopia? Evidence from Chinese listed companies. *International Review of Financial Analysis*. 2023;90:102878. <https://doi.org/10.1016/j.irfa.2023.102878>
 101. Deng X., Li W., Ren X. More sustainable, more productive: Evidence from ESG ratings and total factor productivity among listed Chinese firms. *Finance Research Letters*. 2023;51:103439. <https://doi.org/10.1016/j.frl.2022.103439>

102. Xu N., Lv W., Wang J. The impact of digital transformation on firm performance: a perspective from enterprise risk management. *Eurasian Business Review*. 2024;1-32. <https://doi.org/10.1007/s40821-024-00264-9>
103. Hendricks K.B., Singhal V.R. Firm characteristics, total quality management, and financial performance. *Journal of Operations Management*. 2001;19(3):269-285. [https://doi.org/10.1016/S0272-6963\(00\)00049-8](https://doi.org/10.1016/S0272-6963(00)00049-8)
104. Zhao H., Teng H., Wu Q. The effect of corporate culture on firm performance: Evidence from China. *China Journal of Accounting Research*. 2018;11(1):1-19. <https://doi.org/10.1016/j.cjar.2018.01.003>
105. Han H. The relationship among corporate culture, strategic orientation, and financial performance. *Cornell Hospitality Quarterly*. 2012;53(3):207-219. <https://doi.org/10.1177/1938965512443505>
106. <https://doi.org/10.1177/1938965512443505>
107. Miloloža I. Impact of leadership style to financial performance of enterprises. *Business Systems Research Journal*. 2018;9(1):93-106. <https://doi.org/10.2478/bsrj-2018-0008>
108. Chiou J.-S., Chang T.-Z. The effect of management leadership style on marketing orientation, service quality, and financial results: A cross-cultural study. *Journal of Global Marketing*. 2009;22(2):95-107. <https://doi.org/10.1080/08911760902767961>
109. Adamopoulos T., Brandt L., Leight J., et al. Misallocation, selection, and productivity: A quantitative analysis with panel data from China. *Econometrica*. 2022;90(3):1261-1282. <https://doi.org/10.3982/ECTA16598>
110. Cheng H., Li Y., Pang Y., et al. Can digital transformation change a firm's green innovation strategy? Evidence from China's heavily polluting industries. *Heliyon*. 2024;10(3): e24676. <https://doi.org/10.1016/j.heliyon.2024.e24676>
111. Edwards J.R., Lambert L.S. Methods for integrating moderation and mediation: a general analytical framework using moderated path analysis. *Psychological Methods*. 2007;12(1):1-22. <https://doi.org/10.1037/1082-989X.12.1.1>
112. Baron R.M., Kenny D.A. The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*. 1986;51(6):1173-1182. <https://doi.org/10.1037/0022-3514.51.6.1173>
113. Whited TM, Wu G. Financial constraints risk. *The review of financial studies*. 2006;19(2):531-59. <https://doi.org/10.1093/rfs/hhj012>
114. Zhang B., Dong W., Yao J. How does digital transformation of city governance affect environmental pollution: a natural experiment from the pilot policy of "National Information City for Public Service" in China. *Sustainability*. 2022;14(21):14158. <https://doi.org/10.3390/su142114158>
115. Chen X., Yan Y., Qiu J. Can enterprise digital transformation reduce the reliance on bank credit? Evidence from China. *Economic Modelling*. 2024;132:106632. <https://doi.org/10.1016/j.econmod.2023.106632>
116. Zhang W., Zhou H., Chen J., et al. An empirical analysis of the impact of digital economy on manufacturing green and low-carbon transformation under the dual-carbon background in China. *International Journal of Environmental Research and Public Health*. 2022;19(20):13192. <https://doi.org/10.3390/ijerph192013192>
117. Wu LX, Ning L, Yunfei X. Digital Economy, Manufacturing Agglomeration and Carbon Productivity. *Journal of Zhongnan University of Economics and Law*. 2022(6):131-45. (in Chinese) https://xuebao.zuel.edu.cn/_upload/article/files/fc/7f/a003daec42b28630c5e84b048ef1/7c4cf495-78e6-4e3b-ab8c-3b828e9910c9.pdf
118. Jiang W., Wang A.X., Zhou K.Z., et al. Stakeholder relationship capability and firm innovation: A contingent analysis. *Journal of Business Ethics*. 2020;167:111-125. <https://doi.org/10.1007/s10551-019-04161-4>
119. Cheng W., Li C., Zhao T. The stages of enterprise digital transformation and its impact on internal control: Evidence from China. *International Review of Financial Analysis*. 2024;92:103079. <https://doi.org/10.1016/j.irfa.2024.103079>
120. Gao D., Yan Z., Zhou X., et al. Smarter and prosperous: digital transformation and enterprise performance. *Systems*. 2023;11(7):329. <https://doi.org/10.3390/systems11070329>
121. Cunningham P.H. State-owned enterprises: Pursuing responsibility in corporate social responsibility. *Management Communication Quarterly*. 2011;25(4):718-724. <https://doi.org/10.1177/0893318911419935>
122. Yan L., Ling X., Wang Z., et al. Can mixed-ownership reform boost the digital transformation of state-owned enterprises? *Economic Analysis and Policy*. 2023;79:647-663. <https://doi.org/10.1016/j.eap.2023.05.012>
123. Wang F., Jia Y., Li G., et al. An Empirical Study of the Relationship Between Digital Transformation, Corporate Social Responsibility and Financial

Performance. *Business Ethics and Leadership*. 2024;8(1):57-73. [https://doi.org/10.61093/bel.8\(1\).57-73.2024](https://doi.org/10.61093/bel.8(1).57-73.2024)

124. Zhao X., Chen Q.-A., Zhang H., et al. A study on the influencing factors of corporate digital transformation: empirical evidence from Chinese listed companies. *Scientific Reports*. 2024;14(1):6243. <https://doi.org/10.1038/s41598-024-56729-4>
125. Yin S., Yu Y. An adoption-implementation framework of digital green knowledge to improve the performance of digital green innovation practices for industry 5.0. *Journal of Cleaner Production*. 2022;363:132608. <https://doi.org/10.1016/j.jclepro.2022.132608>