Synergistic Effects of Digital Transformation and ESG Practices on New Quality Productivity in Chinese Enterprises

Yanfei Wu and Irina Ivashkovskaya

Corporate Finance Center, Higher School of Economics, Russia

Abstract

This research analyzes a dataset of 4,376 Chinese listed companies (2013-2022) to investigate how digital transformation and Environmental, Social, and Governance (ESG) performance influence new quality productivity. The findings indicate that digital transformation, ESG performance, and their synergy significantly enhance new quality productivity. Our findings hold after robustness checks and addressing endogeneity. This effect varies by ownership structure and public attention, and the synergies are significant only among non-state-owned enterprises (non-SOEs) and companies with high public attention. As one of the first empirical investigations into new quality productivity, this research offers valuable support for fostering high-quality enterprise development.

Keywords: Digital transformation; ESG performance; New quality productivity; Synergistic effects; China

JEL code: M14; O33; D24

1. Introduction

New quality productivity is currently a highly discussed topic in China, introduced by President Xi Jinping in September 2023. Unlike traditional productivity, which depends predominantly on capital and labor, this new approach emphasizes innovation-driven and green development (Xi, 2023). Characterized by high technology, efficiency, and quality, it seeks to transcend traditional growth paths and become a new source of economic momentum (Xi, 2024).

China's 14th Five-Year Plan explicitly delineates the "Digital China" strategy, which promotes the in-depth integration of digital technologies with physical economies. Existing research indicates that digital transformation optimizes production processes, enhances operational efficiency (Demartini et al., 2019; Khin & Ho, 2019), improves R&D productivity (Zhuo & Chen, 2023), and optimizes labor structures (Ulas, 2019), thus increasing total factor productivity (Jianlong Wang et al., 2023). These digital technologies drive industries towards greater intelligence, presenting new opportunities to enhance new quality productivity. Nonetheless, systematic empirical analyses exploring the effects of digital transformation on new quality productivity remain limited.

In addition to digital technologies, low-carbon technologies present a new and more pragmatic development trajectory (Song et al., 2024). President Xi has emphasized that "new quality productivity is inherently green productivity" (Xi, 2024). Within this framework, prioritizing ESG practices effectively reduces pollution and waste, enhances compliance and transparency, leading to the sustainable advancement of new quality productivity. While substantial studies have explored the connections between ESG and various dimensions like financing costs (Eliwa et al., 2021; Raimo et al., 2021), financial performance (Bruna et al., 2022; Friede et al., 2015), firm value (Brooks & Oikonomou, 2018), risk management (Landi et al., 2022), and total factor productivity (Deng et al., 2023), a huge gap remains regarding the effect of ESG on new quality productivity.

However, both digital and ESG transitions also encounter multiple challenges that may hinder their effectiveness and diminish their contributions to enhancing new quality productivity. *The 14th Five-Year Plan* emphasizes the importance of "advancing the integration of digitalization and green growth". This integration emphasizes that digital transformation and ESG initiatives might mitigate the challenges faced by each other and amplify each other's impact on new quality productivity. Embedding ESG factors in digital transformation in firms promotes sustainability and accountability in the process, ensuring compliance and quality. In turn, digital technologies can increase the intrinsic motivation to implement ESG practices and improve the efficiency and execution of ESG initiatives (Fang et al., 2023; Wang & Esperança, 2023). Based on this reciprocal relationship, we investigate the synergies of digital transformation and ESG practices in enhancing new quality productivity, addressing critical gaps in the current literature.

The innovations of this study are as follows: (1) This research provides one of the first quantitative analyses of new quality productivity, employing empirical methods to explore how digital transformation and ESG practices drive this concept in Chinese enterprises, addressing a critical research gap. (2) Innovatively integrates these two elements into a coherent theoretical framework, revealing their synergistic economic effects, which enhance each other's quality and efficiency while mitigating implementation challenges. This synergy emphasizes the necessity of combining sustainable practices with technological advancement to foster new quality productivity. (3) Using different methods for measuring digital transformation, our study reveals that digital transformation and its synergies with ESG lead to a more powerful improvement in new quality productivity by translating digital awareness and strategy into actual investment. (4) This research conducts an analysis across various ownership structures and levels of public attention, providing evidence for the evolution of high quality among diverse kinds of companies.

2. Hypothesis

2.1. Digital transformation and new quality productivity

As a novel factor of production, digitalization plays a critical function in resource creation and distribution within enterprises (Jiang & Li, 2024). By leveraging digitization, companies can extract real-time insights into resource conditions, production status, and market trends, improving the efficiency of data processing and forecast accuracy. Externally, this enhances flexibility in responding to market changes (Warner & Wäger, 2019), captures timely and accurate external market information, increases operating income, and promotes asset turnover. Internally, it can optimize internal workflows (Demartini et al., 2019; Khin & Ho, 2019), facilitate refined quality management and organizational flattening (Mirković et al., 2019), reduce barriers to information dissemination and decision-making resistance, and accelerate resource exchange and integration, leading to reduced operational costs and expenses, increased productivity, and management efficiency.

Within enterprises, digital technologies also facilitate intelligent upgrades by breaking the boundaries of digital application scenarios through digitalized R&D and automated production lines, shortening the R&D cycle, optimizing the allocation of established innovation resources, and enhancing independent innovation capabilities (Liu et al., 2021; Zhuo & Chen, 2023). While at the supply chain level, by sharing production and supply chain data with suppliers, partners, and customers, firms can collaboratively explore technological pathways and solutions, facilitating collaborative innovation (Zhuo & Chen, 2023).

Moreover, digital transformation optimizes the human capital structure by elevating the demand for highly qualified professionals (Li et al., 2024) and enhancing the digital competencies of existing employees, thereby fostering new labor paradigms. This shift reduces production costs for enterprises and increases labor productivity and the efficiency of specialization (Acemoglu & Restrepo, 2020; Song et al., 2022), thereby advancing new quality productivity.

In summary, we propose the following hypothesis:

Hypothesis 1: Digital transformation contributes to the improvement of new quality productivity.

2.2. ESG and new quality productivity

ESG practices reflect a corporation's commitment to green transformation and sustainability. Integrating ESG principles into process design and manufacturing improvements in production activities facilitates the creation of environmentally friendly, high-quality products and services. It implies lower operational legal and compliance risks (Pollman, 2019), mitigates information asymmetry (Kim & Park, 2023), thereby enhancing stakeholder trust (Chernev & Blair, 2015; Ramesh et al., 2019). This trust enhances competitive advantage and profitability (Aydoğmuş et al., 2022) and provides essential soft technology support for productivity enhancement. It also attracts institutional investors, alleviates financial constraints, and optimizes the financing structure (Bai et al., 2022). This initiates a virtuous cycle that drives the evolution of new quality productivity (Tan & Zhu, 2022).

In addition, ESG practices encourage firms to consider external stakeholders more comprehensively and promote good relations among them, facilitating access to diverse external knowledge and insights, thus supporting innovation activities (Choi & Wang, 2009). ESG also improves managers' environmental awareness, promotes green innovation (Tan & Zhu, 2022; Juxian Wang et al., 2023), and increases new quality productivity.

Companies with outstanding ESG performance can attract high-quality talent by implementing green human resource management strategies (Liu & Nemoto, 2021), especially high-quality R&D talents (Ge et al., 2022). ESG initiatives also improve employees' belonging and honor, improving motivation and injecting a high-quality workforce into the new quality productivity exploitation.

In summary, we propose the following hypothesis:

Hypothesis 2: ESG contributes to the enhancement of new quality productivity.

2.3. Synergistic effects of digital transformation and ESG practices

The application of digital technology also introduces uncertainty, as increased efficiency does not always mean increased effectiveness (Heiko et al., 2024). High initial investment and costs of digital transformation exert pressure on resources and core business (Matt et al., 2015), while the complexity of digital applications raises “black box” issues such as privacy, security, social equity, and ethical concerns (Charlwood & Guenole, 2022; Rodgers et al., 2023). Such uncertainties can exacerbate information asymmetries and limit new quality productivity gains. Additionally, a focus on short-term shareholder value may cause managers to prioritize efficiency over the quality, compliance, and sustainability of technological implementation. However, new quality productivity emphasizes both efficiency and quality. ESG practices address obstacles to digital transformation by mitigating uncertainties and fostering transformation compliance to reduce risk (Qi et al., 2024). According to signaling theory, by incorporating ESG practices into digital transformation norms, it implies that firms are not only committed to immediate profitability but also to sustainability goals. This increases stakeholder trust and secures long-term funding to support digital transformation, improving the quality of productivity.

While ESG initiatives advance corporate sustainability objectives, their associated high costs and lack of immediate financial returns may diminish companies' intrinsic motivation for ESG transformation. Conversely, digital technologies can support ESG development (Fang et al., 2023; Lu et al., 2024), improve corporate environmental compliance (Chen & Hao, 2022), social responsibility (Roša & Lobanova, 2022; Zheng & Zhang, 2023) and governance (Tokmakov, 2021). Through digital transformation, companies can use big data analytics to obtain high-quality external market information (Pergelova et al., 2019), track and manage internal data more effectively (Zhao & Cai, 2023), and accelerate internal and external knowledge integration (Yin & Yu, 2022). This, in turn, reduces the costs and increases intrinsic motivation associated with ESG practices. In addition, digital technologies increase the transparency of ESG-related information, making ESG disclosures accurate and timely (Fang et al., 2023), strengthening ESG capabilities and stakeholder trust, thereby attracting resources for sustainable growth.

In conclusion, we propose the following hypothesis:

Hypothesis 3: The synergistic effects between digital transformation and ESG practices promote the new quality productivity.

3. Research design

3.1. Data sources

We utilize data from A-share listed Chinese firms between 2013 and 2022, and the original data are obtained from the Wind Financial Terminal and the CSMAR database, with digital transformation data manually compiled. Data processing involved the exclusion of samples missing relevant variables, omitting financial and insurance companies due to their particularity, and removing ST, PT, and *ST companies. To mitigate the impact of outliers, continuous variables are winorized at the 1% and 99% levels. The final dataset consists of 4,376 sample companies and 29,271 sample observations, with empirical analyses performed using Stata 17.0 software.

3.2. Description of variables

3.2.1. New Quality Productivity (Npro)

According to Song et al. (2024), *Npro* is measured using the entropy method, grounded in the two-factor productivity theory using labor and production tools as key indicators.

First, industries closely associated with new quality productivity, specifically strategic emerging and future industries, are selected as the sample, given their relevance to new quality productivity measures. Next, this research creates a comprehensive indicator system for new quality productivity based on financial statement metrics according to the two-factor productivity theory (Song et al., 2024). Finally, a weight is assigned to each indicator using the entropy method: dimensions are initially standardized, followed by the calculation of each indicator's proportion and information entropy redundancy. Indicator weights are then calculated, and a final composite score is determined by weighting. Details of indicator values and their respective weights are provided in **Table 1**.

Table 1 New quality productivity indicators of companies.

Factor	Sub-Factor	Indicator	Description of Indicator Value	Feature	Weight
Labor	Active Labor	R&D Personnel Salary Expense Ratio	R&D Expenses-Employee Salary/Operating Revenue	+	26
		R&D Personnel Ratio	Number of R&D Personnel/Number of Employees	+	2
		Proportion of Highly Educated Personnel	Number of Personnel with Bachelor's Degree or Above/Number of Employees	+	3
	Materialized Labor (Object of Labor)	Proportion of fixed assets	Fixed Assets/Total Assets	+	1
		Proportion of Manufacturing Costs	(Operating Activities Cash Outflows Subtotal + Depreciation of Fixed Assets + Amortization of Intangible Assets + Provision for Impairment - Cash Paid for Goods and Services - Cash Paid to and for Employees)/(Subtotal Cash Outflow from Operating Activities + Depreciation of Fixed Assets + Amortization of Intangible Assets + Provision for Impairment)	+	1
Means of	Hard	Proportion of R&D	R&D Expenses-Depreciation and	+	24

Production	Technology	Depreciation and Amortization	Amortization/Operating Revenue		
		Proportion of R&D Lease Expense	R&D Expenses-Rental Costs/Operating Revenue	+	13
		Proportion of R&D Direct Input	R&D Expenses-Direct Input/Operating Revenue	+	27
		Proportion of Intangible Assets	Intangible Assets/Total Assets	+	1
	Soft Technology	Total Asset Turnover Rate	Operating Revenue/Average Total Assets	+	1
		Inverse of Equity Multiplier	Owner's Equity/Total Assets	+	1
	New Quality Productivity				100

"+" signifies a positive association between the variable and the outcome.

3.2.2. Corporate Digital Transformation (DT)

Following the methods of previous studies (Chen et al., 2022; Jiang et al., 2022), *DT* is measured as the proportion of intangible assets linked to digital transformation (identified by digital relevant keywords) disclosed in annual financial report notes against the total intangible assets reported at year-end. Digital intangible assets are selected as they capture a firm's long-term investment in digital technology and innovation, aligning with the goals of new quality productivity driven by technology. Furthermore, data on digital intangible assets is more consistent and accessible, thus enhancing model stability and reliability.

To further validate model robustness, this study utilizes word frequency statistics analysis (Wu et al., 2021; Wu et al., 2022), calculating the proportion of digital transformation-related keywords in the annual report, adding one, and then taking the natural logarithm as a supplementary metric (DT_2), enhancing the reliability of digital transformation measurement.

3.2.3. ESG performance (ESG)

This paper adopts the Huazheng ESG Rating, noted for its wide coverage, frequent updates, and sophisticated methodology, and widely applied in prior research (Shen et al., 2023). The Huazheng system classifies a firm's ESG performance into nine grades, from C to AAA. We assign values from 1 to 9 to these levels, averaging quarterly scores to obtain an annual ESG performance score. For robustness testing, we employ the Wind ESG indicator as a proxy variable. Given that the Wind ESG ratings commenced in 2018, the sample spans from 2018 to 2022.

3.2.4. Control variables

Indicators potentially affecting new quality productivity were selected for inclusion as control variables in this study, according to prior studies (Jianlong Wang et al., 2023; Yang et al., 2024) and data availability. **Table 2** details and quantifies all variables, while **Table 3** reports the descriptive statistics. *Npro* has a range between 0.046 and 173.3, and the standard deviation is 2.814, which suggests that new quality productivity development varies considerably across firms.

Table 2 Description of variables.

Variable type	Variable name	Symbols	Variable description
Dependent variable	New quality productivity	Npro	Composite index calculated on the basis of the two-factor theory of productivity
Explanatory variable	Digital Transformation	DT	Proportion of intangible assets related to digital transformation keywords to total intangible assets as of year-end
		DT_2	The proportion of occurrences of keywords related to digital transformation in the current year to the total length of the annual report is 1, then the natural logarithm is taken
	ESG	ESG	Huazheng ESG Rating
		ESG_{wind}	Wind ESG Rating
Control variable	Return on total assets	ROA	Net profit divided by total assets
	Gearing ratio	Lev	Total liabilities divided by total assets
	Growth rate of revenue	Growth	(Current operating income minus prior operating income) divided by prior operating income
	Board of directors	Boards	The total count of board members
	Board independence	Ind	Proportion of independent directors on the Board
	Future growth opportunities	TobinQ	Market value of the firm divided by replacement cost of assets
	Enterprise size	Size	Ln (total assets)
	Enterprise age	Age	Years of observation minus years of establishment and taking natural logarithms
	Property rights contexts	SOE	A value of "1" is assigned for state-owned enterprises, and "0" for others
	Audit quality indicator	Big4	This dummy variable is "1" if a "Big Four" accounting firm conducts the annual audit; otherwise, it is coded as "0"
	Shareholding concentration	Top1	The shareholding percentage held by the largest shareholder

Table 3 Descriptive statistics of the variables.

Variables	**N**	**Mean**	**SD**	**Min**	**Max**
Npro	29,271	5.269	2.814	0.046	173.300
DT	29,271	0.005	0.014	0.000	0.604
DT_2	24,877	1.597	1.427	0.000	6.306
ESG	29,271	4.120	0.965	1.000	7.750
ESG_{wind}	17,635	6.110	0.744	0.000	9.330
ROA	29,271	0.039	0.110	-9.117	7.109
Lev	29,271	0.431	1.078	-0.195	178.300
Growth	29,271	0.328	7.240	-1.309	944.100
Boards	29,271	6.392	3.899	0.000	18.000

Ind	29,271	3.140	0.554	0.000	8.000
TobinQ	29,271	2.131	2.616	0.000	192.700
Size	29,271	22.280	1.332	16.160	28.640
Age	29,271	11.210	7.820	0.682	32.080
SOE	29,271	0.351	0.477	0.000	1.000
Big4	29,271	0.060	0.238	0.000	1.000
Top1	29,271	33.670	14.890	0.286	89.990

3.3. Model design

To mitigate biases from unobservable year and individual-related variables and to improve the statistical reliability of the findings (Adamopoulos et al., 2022), this paper employs two-way fixed effects models for Models (1)-(4) to test the validity of hypotheses 1-3:

$$Npro_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \alpha_2 Controls_{i,t} + \sum Year + \sum Ind + \varepsilon_{i,t} \quad (1)$$

$$Npro_{i,t} = \beta_0 + \beta_1 ESG_{i,t} + \beta_2 Controls_{i,t} + \sum Year + \sum Ind + \varepsilon_{i,t} \quad (2)$$

$$Npro_{i,t} = \gamma_0 + \gamma_1 DT_{i,t} + \gamma_2 ESG_{i,t} + \gamma_3 Controls_{i,t} + \sum Year + \sum Ind + \varepsilon_{i,t} \quad (3)$$

$$Npro_{i,t} = \delta_0 + \delta_1 DT_{i,t} + \delta_2 ESG_{i,t} + \delta_3 DT_{i,t} \times ESG_{i,t} + \delta_4 Controls_{i,t} + \sum Year + \sum Ind + \varepsilon_{i,t} \quad (4)$$

Here, i indicates the company, t represents time, and $Npro_{i,t}$, $DT_{i,t}$ and $ESG_{i,t}$ indicate the new quality productivity, the level of digital transformation, and the level of ESG performance of company i in year t, respectively. $Controls_{i,t}$ encompasses all control variables, and $\Sigma Year$ and ΣInd represent the time and individual fixed effects. Model (3) incorporates both digital transformation and ESG to investigate their respective impacts on new quality productivity. In Model (4), $DT_{i,t} \times ESG_{i,t}$ is included to examine the synergistic effects between *DT* and *ESG*.

4. Results and discussion

4.1. Main effect regression analysis

Table 4 presents the regression results for Models (1)-(4). In Column 1, for each 1% increase in *DT* investment, *Npro* increases significantly by 15.971% at the 1% significance level. Similarly, Column 2 indicates that with a 1% growth in *ESG* score, *Npro* grows by 0.032% at the 1% significance level, thus supporting **Hypothesis 1** and **Hypothesis 2**. Column 3 displays that both *DT* and *ESG* retain significant positive effects on *Npro* when controlled together in the model. Column 4 investigates the synergistic effects between *DT* and *ESG* by introducing an interaction term. The coefficient of *DT×ESG* is significantly positive at the 1% level, indicating that *DT* and *ESG* enhance each other's impact on *Npro*, i.e., there is a synergistic effect between the two to promote the improvement of *Npro*. **Hypothesis 3** is verified.

Table 4 Benchmark regression results.

	Model (1)	Model (2)	Model (3)	Model (4)
	Npro	**Npro**	**Npro**	**Npro**
DT	15.971***		15.952***	5.287
	(15.66)		(15.64)	(1.61)
ESG		0.032***	0.030***	0.019
		(2.80)	(2.70)	(1.58)
DT×ESG				2.610***
				(3.41)
ROA	-1.185***	-1.280***	-1.191***	-1.178***
	(-12.83)	(-13.81)	(-12.89)	(-12.74)
Lev	-0.108***	-0.060***	-0.108***	-0.081***
	(-11.09)	(-6.46)	(-11.10)	(-6.35)
Growth	0.004***	0.004***	0.004***	0.004***
	(3.35)	(3.41)	(3.41)	(3.41)
Boards	-0.007	-0.007	-0.006	-0.006
	(-0.58)	(-0.58)	(-0.49)	(-0.53)
Ind	-0.056*	-0.055*	-0.058**	-0.056*
	(-1.88)	(-1.86)	(-1.96)	(-1.90)
TobinQ	0.013***	0.014***	0.013***	0.013***
	(3.37)	(3.69)	(3.41)	(3.38)
Size	0.118***	0.095***	0.112***	0.109***
	(6.04)	(4.82)	(5.72)	(5.57)
Age	0.132***	0.142***	0.133***	0.133***
	(30.20)	(32.33)	(30.32)	(30.31)
SOE	0.064	0.086*	0.065	0.063
	(1.25)	(1.68)	(1.28)	(1.24)
Big4	-0.012	0.009	-0.015	-0.016
	(-0.16)	(0.12)	(-0.21)	(-0.21)
Top1	-0.000	-0.002	-0.001	-0.001
	(-0.31)	(-1.15)	(-0.39)	(-0.41)
Constant	1.118***	1.480***	1.109***	1.209***
	(2.68)	(3.54)	(2.66)	(2.89)
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	29,271	29,271	29,271	29,271
R-squared	0.152	0.143	0.152	0.152

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

4.2. Robustness tests

4.2.1. Exclusion of specific subsamples

To check the robustness of the models, we exclude the possible impact of the *COVID-19* epidemic, which significantly affected firm productivity. Consequently, our study excludes samples from 2020 and subsequent years, retaining only sample data from the period of 2013-2019. The test results presented in **Table 5** align with the conclusions derived from the preceding analysis.

4.2.2. Alternative variables

This study utilizes Wind ESG ratings to substitute for the core dependent variable ESG and substitutes the baseline *DT* measure with DT_2. The findings in **Table 5** align with the previous conclusions, further validating the study's robustness. However, the effect of DT_2 on *Npro* is significantly weaker than that based on *DT*. This discrepancy likely arises because word frequency reflects executives' awareness and strategies of digital transformation, yet awareness does not necessarily translate into action (Jiang et al., 2022). In contrast, digital intangibles represent actual investment in transformation, yielding a more substantial impact on *Npro*.

Both Wind and Huazheng ESG ratings have consistent coefficients (0.032) on *Npro*, reinforcing our findings. Additionally, the synergy between DT_2 and ESG_{wind} is considerably smaller than that in the benchmark regression, suggesting that digital transformation only generates substantial synergies with ESG performance when firms translate digital awareness and strategy into actual investments.

Table 5 Robustness test.

	Exclusion of specific subsamples				Alternative variables			
	Npro	Npro	Npro	Npro	Npro	Npro	Npro	Npro
DT	20.317***		20.359***	8.051*				
	(12.44)		(12.46)	(1.66)				
ESG		0.042***	0.043***	0.031*				
		(2.63)	(2.77)	(1.91)				
DT×ESG				2.975***				
				(2.70)				
DT_2					0.057***		0.050***	-0.091
					(4.75)		(3.60)	(-1.35)
ESG_{wind}						0.032**	0.055***	0.012
						(2.04)	(3.26)	(0.48)
DT_2×ESG_{wind}								0.023**
								(2.14)
ROA	-0.995***	-1.084***	-1.002***	-1.000***	-1.287***	-0.651***	-0.615***	-0.617***
	(-8.54)	(-9.27)	(-8.59)	(-8.58)	(-13.06)	(-7.17)	(-6.72)	(-6.74)
Lev	0.126***	0.155***	0.129***	0.141***	0.057	-0.052***	0.059*	0.059*
	(3.21)	(3.91)	(3.28)	(3.56)	(1.59)	(-5.89)	(1.93)	(1.92)
Growth	0.012***	0.012***	0.012***	0.012***	0.005*	0.003*	0.007***	0.007***
	(5.44)	(5.48)	(5.55)	(5.55)	(1.95)	(1.75)	(3.45)	(3.42)
Boards	-0.026*	-0.024	-0.025	-0.025	-0.018	0.001	-0.004	-0.004
	(-1.65)	(-1.49)	(-1.56)	(-1.59)	(-1.43)	(0.07)	(-0.28)	(-0.26)
Ind	-0.011	-0.011	-0.014	-0.012	-0.012	-0.007	0.016	0.017
	(-0.27)	(-0.26)	(-0.33)	(-0.30)	(-0.39)	(-0.20)	(0.45)	(0.46)
TobinQ	0.009**	0.011**	0.009**	0.009**	0.016***	0.024***	0.020**	0.020**
	(2.02)	(2.42)	(2.05)	(2.07)	(3.72)	(2.90)	(2.24)	(2.27)
Size	0.143***	0.138***	0.135***	0.136***	0.074***	-0.206***	-0.260***	-0.261***

	(5.18)	(4.94)	(4.87)	(4.89)	(3.38)	(-7.08)	(-8.65)	(-8.67)
Age	0.184***	0.193***	0.186***	0.186***	0.143***	0.071***	0.074***	0.074***
	(26.82)	(27.98)	(26.97)	(26.97)	(29.51)	(11.80)	(11.81)	(11.81)
SOE	0.099	0.095	0.097	0.090	0.071	-0.064	-0.082	-0.080
	(1.18)	(1.13)	(1.16)	(1.08)	(1.36)	(-1.15)	(-1.48)	(-1.44)
Big4	0.077	0.106	0.075	0.075	0.131*	0.129	0.167*	0.165*
	(0.72)	(1.00)	(0.71)	(0.70)	(1.65)	(1.47)	(1.82)	(1.81)
Top1	0.001	0.000	0.001	0.001	0.000	0.001	0.002	0.002
	(0.44)	(0.13)	(0.36)	(0.34)	(0.32)	(0.27)	(1.09)	(1.08)
Constant	-0.332	-0.410	-0.354	-0.316	1.957***	9.162***	10.022***	10.284***
	(-0.57)	(-0.70)	(-0.61)	(-0.54)	(4.20)	(14.58)	(15.46)	(15.59)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,756	17,756	17,756	17,756	24,877	17,635	15,243	15,243
R-squared	0.189	0.181	0.190	0.190	0.163	0.019	0.027	0.027

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

4.3. Endogeneity test

Despite incorporating individual and time effects in the benchmark regressions to account for firm-level heterogeneity in *Npro*, endogeneity concerns may still arise due to potential reverse causality. High levels of *Npro* reflect a firm's advanced technological capabilities, green production mindset, and operational efficiency, potentially boosting its performance and risk tolerance, which may increase its willingness to invest in *DT* and *ESG* initiatives. To tackle this issue, our study employs the first lag of digital transformation (DT_{t-1}) and the digital economy index (*DEI*) of the firm's city as instrumental variables (*IVs*) for *DT*, and the first lag of ESG performance (ESG_{t-1}) as an *IV* for *ESG*.

Column (1) in **Table 6** shows significant positive coefficients for *DEI* and DT_{t-1}, while Column (3) indicates a significant positive coefficient for ESG_{t-1}, indicating a high correlation of the chosen *IVs* with endogenous explanatory variables. The p-value of the Kleibergen-Paap rk LM test are all below 0.01, rejecting the null hypothesis of "underidentification" at the 1% level. Both the Cragg-Donald Wald F and the Kleibergen-Paap Wald rk F statistic exceed the 10% critical values for weak *IVs* (19.93 for *DT* and 16.38 for *ESG*), indicating no weak *IVs* issues. The Sargan test p-value is above 0.1, suggesting no overidentification issues for the IVs associated with DT. The second-stage regression shows significant positive impacts of *DT* and *ESG* on *Npro,* with coefficients of 8.025 and 0.100, both at the 1% significance level. This verifies the findings remain valid after addressing endogeneity.

Table 6 Endogeneity test results.

	TSLS First stage	**TSLS Second stage**	**TSLS First stage**	**TSLS Second stage**
	DT	**Npro**	**ESG**	**Npro**
DEI	0.002***			
	(3.20)			
DT_{t-1}	0.649***			
	(109.99)			
DT		8.025***		
		(4.65)		

ESG_{t-1}			0.473***	
			(75.23)	
ESG				0.100***
				(4.00)
ROA	-0.005***	-1.215***	0.296***	-1.288***
	(-9.07)	(-11.89)	(5.44)	(-12.62)
Lev	0.003***	-0.085***	0.009*	-0.061***
	(58.21)	(-7.88)	(1.72)	(-6.44)
Growth	0.000	0.010***	-0.003***	0.010***
	(0.21)	(4.82)	(-2.90)	(5.09)
Boards	0.000	-0.003	-0.029***	-0.000
	(0.22)	(-0.24)	(-4.39)	(-0.04)
Ind	0.000	-0.049	0.065***	-0.056*
	(0.23)	(-1.58)	(3.86)	(-1.78)
TobinQ	0.000**	0.008*	-0.001	0.008*
	(2.09)	(1.77)	(-0.49)	(1.76)
Size	-0.001***	0.057***	0.087***	0.027
	(-4.87)	(2.65)	(7.48)	(1.21)
Age	0.000***	0.155***	-0.006**	0.165***
	(17.34)	(32.35)	(-2.57)	(35.29)
SOE	0.001***	0.017	0.012	0.035
	(3.00)	(0.33)	(0.44)	(0.68)
Big4	0.001	0.110	0.112***	0.111
	(1.64)	(1.42)	(2.71)	(1.43)
Top1	-0.000***	0.002	-0.000	0.001
	(-3.00)	(1.25)	(-0.26)	(0.75)
Constant	0.006***	1.920***	0.269	2.126***
	(2.66)	(4.18)	(1.10)	(4.63)
Number of code	3,856	3,856	3,856	3,856
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	24,701	24,701	24,701	24,701
R-squared	0.522	0.117	0.231	0.110
Kleibergen-Paap rk LM statistic		115.666[0.000]		2311.855[0.000]
Kleibergen-Paap rk Wald F statistic		64.108		4054.095
Cragg-Donald Wald F statistic		6056.595		5659.724
Sargan test		0.005[0.9426]		-

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

5. Heterogeneity analysis

5.1. Nature of shareholding

Firms with varying equity structures possess distinct resource endowments. In comparison with non-SOEs, SOEs (state-owned enterprises) often have easier availability of government funding, subsidies, land, and other scarce resources (Zhou et al., 2017). Consequently, SOEs are less reliant on social capital and external resources for development (Jiang et al., 2020). To examine these differences, we conducted a heterogeneity analysis.

Table 7 indicates that *DT* and *ESG* have a stronger direct impact on *Npro* in SOEs than in non-SOEs. However, the synergies of *DT* and *ESG* on *Npro* are significant only in non-SOEs. This disparity may stem from SOEs' access to more resources for *DT* and *ESG*, which enhances their direct contributions to *Npro*. Nonetheless, bureaucratic inefficiencies in resource allocation and decision-making processes may hinder the effective integration of *DT* and *ESG* strategies in SOEs. Conversely, non-SOEs, despite facing resource constraints, benefit from greater flexibility and an innovation-driven culture, allowing for more effective integration of *DT* and *ESG*, ultimately enhancing their *Npro* amid intense market competition. Additionally, non-SOEs typically encounter more intense market competition, which compels them to maximize the effectiveness of their *DT* and *ESG* investments to achieve a higher competitive advantage under limited resources.

Table 7 Heterogeneity analysis: nature of shareholding.

	SOEs				Non-SOEs			
	Npro	**Npro**	**Npro**	**Npro**	**Npro**	**Npro**	**Npro**	**Npro**
DT	27.019***		26.969***	26.015***	13.826***		13.800***	1.252
	(10.03)		(10.01)	(3.32)	(12.34)		(12.32)	(0.34)
ESG		0.068***	0.067***	0.066***		0.024*	0.021	0.006
		(3.31)	(3.27)	(3.11)		(1.74)	(1.56)	(0.39)
DT×ESG				0.237				3.045***
				(0.13)				(3.61)
ROA	-0.763***	-0.789***	-0.743***	-0.742***	-1.314***	-1.405***	-1.317***	-1.306***
	(-3.00)	(-3.09)	(-2.92)	(-2.92)	(-13.30)	(-14.18)	(-13.33)	(-13.21)
Lev	-0.697***	-0.608***	-0.661***	-0.661***	-0.110***	-0.069***	-0.110***	-0.078***
	(-4.86)	(-4.21)	(-4.60)	(-4.60)	(-11.15)	(-7.41)	(-11.15)	(-5.78)
Growth	0.011***	0.011***	0.011***	0.011***	0.002	0.002	0.002	0.002
	(4.02)	(4.14)	(4.14)	(4.14)	(1.58)	(1.61)	(1.61)	(1.60)
Boards	0.023	0.028	0.025	0.025	-0.044***	-0.049***	-0.044***	-0.045***
	(1.21)	(1.50)	(1.35)	(1.35)	(-2.84)	(-3.12)	(-2.79)	(-2.86)
Ind	-0.071*	-0.078*	-0.077*	-0.077*	-0.015	-0.004	-0.016	-0.012
	(-1.65)	(-1.81)	(-1.80)	(-1.79)	(-0.36)	(-0.08)	(-0.38)	(-0.29)
TobinQ	-0.007	-0.006	-0.007	-0.006	0.016***	0.017***	0.016***	0.016***
	(-0.69)	(-0.62)	(-0.64)	(-0.64)	(3.82)	(4.15)	(3.84)	(3.78)
Size	0.286***	0.250***	0.272***	0.272***	0.029	0.007	0.024	0.021
	(7.57)	(6.54)	(7.14)	(7.13)	(1.19)	(0.27)	(0.99)	(0.87)
Age	0.099***	0.113***	0.100***	0.100***	0.158***	0.167***	0.159***	0.158***
	(13.70)	(15.77)	(13.92)	(13.92)	(27.30)	(28.67)	(27.30)	(27.24)
Big4	-0.320***	-0.289***	-0.319***	-0.319***	0.327***	0.348***	0.323***	0.323***
	(-2.91)	(-2.61)	(-2.91)	(-2.91)	(3.16)	(3.35)	(3.12)	(3.12)
Top1	0.003	0.004*	0.003	0.003	-0.001	-0.003	-0.001	-0.002
	(1.34)	(1.66)	(1.37)	(1.37)	(-0.76)	(-1.57)	(-0.82)	(-0.88)
Constant	-2.534***	-2.187***	-2.529***	-2.523***	3.225***	3.640***	3.235***	3.347***
	(-3.21)	(-2.76)	(-3.21)	(-3.19)	(6.29)	(7.07)	(6.31)	(6.51)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,279	10,279	10,279	10,279	18,992	18,992	18,992	18,992
R-squared	0.119	0.110	0.120	0.120	0.189	0.181	0.189	0.190

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

5.2. Corporate public attention

Public attention, functioning as an informal oversight mechanism (Li et al., 2022), can exert compliance pressure on publicly listed companies, thereby safeguarding stakeholder interests (Xie & Cao, 2023; Zhang & Zhang, 2024). Companies with high public attention tend to demonstrate stronger ESG performance (Zhang & Zhang, 2024), potentially contributing more substantially to the improvement of *Npro,* but this oversight can also restrict the efficiency of digital transformation by enforcing strict compliance.

To further examine this, we segmented the dataset into two clusters based on each company's average search volume on the *Baidu Index* (https://index.baidu.com). *Baidu Index* records internet search behavior from users across all cities in China (Cheng & Liu, 2018) and is widely regarded as a direct and objective measure of public attention (Subramaniam & Chakraborty, 2020).

Results in **Table 8** reveal that firms with lower public attention primarily promote *Npro* through the direct impact of *DT,* while this impact declines significantly in firms that attract higher levels of public attention. It indicates that *DT* more efficiently boosts productivity with less external supervision, while higher public attention imposes strict standards for quality and sustainability, slightly diminishing *DT's* direct impact on *Npro*. However, under heightened public attention, *ESG* and its synergies with *DT* significantly contribute to improvements in *Npro*, promote sustainable practices, and reinforce sustainable momentum in *Npro.*

Table 8 Heterogeneity analysis: corporate public attention.

	Low public attention				**High public attention**			
	Npro	**Npro**	**Npro**	**Npro**	**Npro**	**Npro**	**Npro**	**Npro**
DT	20.304***		20.319***	12.602*	14.288***		14.269***	5.795
	(8.71)		(8.72)	(1.87)	(12.47)		(12.45)	(1.51)
ESG		-0.004	-0.008	-0.016		0.034**	0.033**	0.023
		(-0.22)	(-0.37)	(-0.75)		(2.48)	(2.40)	(1.62)
DT×ESG				1.998				2.049**
				(1.22)				(2.32)
ROA	-0.743***	-0.851***	-0.743***	-0.734***	-1.349***	-1.469***	-1.349***	-1.343***
	(-5.07)	(-5.79)	(-5.07)	(-5.00)	(-9.44)	(-10.25)	(-9.43)	(-9.39)
Lev	-0.169***	-0.101***	-0.169***	-0.147***	-0.118	-0.084	-0.103	-0.097
	(-11.22)	(-7.81)	(-11.23)	(-6.27)	(-1.46)	(-1.03)	(-1.27)	(-1.20)
Growth	0.001	0.001	0.001	0.001	0.006***	0.006***	0.006***	0.006***
	(0.79)	(0.76)	(0.79)	(0.78)	(2.71)	(2.86)	(2.80)	(2.81)
Boards	0.006	-0.002	0.006	0.006	-0.016	-0.015	-0.015	-0.015
	(0.27)	(-0.07)	(0.27)	(0.25)	(-1.16)	(-1.06)	(-1.06)	(-1.09)
Ind	-0.119*	-0.095	-0.118*	-0.117*	-0.033	-0.036	-0.036	-0.035
	(-1.79)	(-1.41)	(-1.77)	(-1.76)	(-0.99)	(-1.06)	(-1.06)	(-1.03)
TobinQ	0.054***	0.057***	0.053***	0.054***	0.001	0.000	0.001	0.001
	(5.54)	(5.83)	(5.53)	(5.54)	(0.23)	(0.09)	(0.20)	(0.20)

Size	0.068*	0.051	0.068*	0.065*	0.134***	0.108***	0.125***	0.124***
	(1.76)	(1.33)	(1.78)	(1.69)	(5.42)	(4.31)	(5.03)	(4.97)
Age	0.139***	0.150***	0.138***	0.138***	0.127***	0.136***	0.128***	0.128***
	(13.98)	(15.04)	(13.86)	(13.85)	(24.39)	(26.08)	(24.51)	(24.49)
SOE	0.047	0.043	0.047	0.046	0.092	0.124*	0.092	0.092
	(0.51)	(0.47)	(0.51)	(0.50)	(1.44)	(1.95)	(1.45)	(1.45)
Big4	0.298*	0.327*	0.297*	0.305*	-0.056	-0.035	-0.060	-0.061
	(1.71)	(1.87)	(1.71)	(1.75)	(-0.66)	(-0.41)	(-0.71)	(-0.72)
Top1	0.002	0.001	0.002	0.002	0.000	-0.001	0.000	0.000
	(0.90)	(0.46)	(0.92)	(0.95)	(0.19)	(-0.45)	(0.15)	(0.13)
Constant	2.822***	3.176***	2.834***	2.924***	0.498	0.916*	0.528	0.600
	(3.51)	(3.93)	(3.52)	(3.62)	(0.95)	(1.74)	(1.01)	(1.14)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,233	9,233	9,233	9,233	20,038	20,038	20,038	20,038
R-squared	0.100	0.090	0.100	0.101	0.168	0.161	0.169	0.169

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

6. Conclusion and implications

This research demonstrates that digital transformation, ESG performance, and the synergistic effects between the two can significantly enhance new quality productivity among Chinese listed companies. Moreover, digital transformation and its synergies with ESG performance have a greater impact on new quality productivity if companies translate their digital awareness and strategy into real investments. Furthermore, this synergy is significant only in non-SOEs and firms with high public attention. Findings underscore the critical need to integrate ESG objectives into digital transformation strategies as an important way to achieve sustainable and high-quality productivity growth. Leveraging digital technologies to strengthen ESG practices can accelerate the shift towards green productivity, fostering a balance between technological investments and sustainability.

In light of these insights, policymakers and business executives are advised to prioritize the integration of digital transition with ESG initiatives. Such an integrated approach promotes synergies between efficiency and responsible management, which would not only be in line with sustainable growth objectives but also enhance long-term competitiveness and ultimately drive a new quality of productivity.

Data availability

Data will be made available on request.

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