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Impact of Digital Transformation and Green Innovation Investments on Corporate Labour Productivity in China: A Regional Heterogeneity Analysis¹

Abstract. In the context of a labour shortage, increasing labour productivity becomes the main way to address the challenges facing companies. This article assesses the impact of digital transformation on labour productivity using the example of Chinese enterprises, with a focus on investments in green innovation and regional heterogeneity. Using a panel dataset of A-share listed firms from 2007 to 2023, we construct a firm-level Digital Transformation Index (DTI) based on textual analysis of annual reports, measuring the frequency of keywords related to digital technologies. Labour productivity is proxied by the natural logarithm of operating revenue per employee. Employing two-way fixed effects regressions with lagged explanatory variables to address endogeneity, we find that digital transformation enhances labour productivity. Mechanism tests reveal that green innovation investment, measured by the log-transformed number of granted green patents, partially mediates this relationship, consistent with the weak form of the Porter Hypothesis. Digital technologies facilitate cleaner production, improve resource efficiency, and enhance operational performance, thereby increasing output per employee. Heterogeneity analyses further indicate that these effects are stronger in non-high-tech industries, likely due to greater catch-up potential and larger marginal gains from digital adoption, as well as in eastern China, where superior digital infrastructure, deeper talent pools, and higher levels of marketization may facilitate the realization of digital benefits. By contrast, the effects are insignificant in high-tech sectors, potentially reflecting technological saturation and higher adjustment costs, and in central and western regions, where persistent digital divides may constrain the productivity-enhancing effects of digital technologies. These findings highlight the productivity-enhancing potential of digital transformation, particularly when integrated with green innovation, and underscore the importance of complementary regional conditions in their realizing and confirm such investments effectiveness in countries with developing economies.

Keywords: China's macro-regions, company' labour productivity, business digitalization, green innovation, mediation effect, Chinese listed companies, Porter hypothesis

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Региональная неоднородность влияния цифровой трансформации и инвестиций в зеленые инновации на производительность труда компаний в Китае

Аннотация. В условиях дефицита рабочей силы повышение производительности труда становится ключевым способом решения проблем, с которыми сталкиваются компании. На примере китайских предприятий в статье оценивается влияние цифровой трансформации на производительность труда, при этом делается акцент на инвестиции в зелёные инновации и региональные различия. На основе панельных данных компаний, торгующихся на рынке А-акций, за 2007–2023 гг. был построен индекс цифровой трансформации фирмы (Digital Transformation Index, DTI). Он основан на текстовом анализе годовых отчётов и отражает частоту упоминания ключевых слов, связанных с цифровыми технологиями. Производительность труда оценивается через натуральный логарифм операционной выручки в расчёте на одного сотрудника. С помощью регрессий с двусторонними фиксированными эффектами и лагированными объясняющими переменными, позволяющими учесть проблему эндогенности, показано, что цифровая трансформация повышает производительность труда. Анализ механизмов позволяет сделать вывод, что инвестиции в зелёные инновации, измеряемые логарифмом числа выданных зелёных патентов, частично опосредуют эту связь, что согласуется со слабой формой гипотезы Портера. Цифровые технологии способствуют более чистому производству, повышают эффективность использования ресурсов и улучшают операционные показатели, тем самым увеличивая выпуск в расчёте на одного сотрудника. Анализ неоднородности показывает, что эти эффекты сильнее выражены в нетехнологичных отраслях, вероятно, благодаря более высокому потенциалу «догоняющего» развития и более значительным предельным выгодам от внедрения цифровых технологий. Эффекты также сильнее выражены в Восточном Китае, где развитая цифровая инфраструктура, значительный кадровый потенциал и развитая рыночная среда способствуют реализации выгод от цифровизации. Напротив, в высокотехнологичных секторах эффекты статистически незначимы, что может объясняться технологическим насыщением и более высокими издержками адаптации. Незначимы они и в центральных и западных регионах, где сохраняющийся цифровой разрыв ограничивает влияние цифровых технологий на производительность. Полученные результаты подчёркивают потенциал цифровой трансформации для роста производительности, особенно в сочетании с зелёными инновациями, указывают на важность взаимодополняющих региональных условий для его реализации и подтверждают эффективность подобных инвестиций в странах с развивающейся экономикой.

Ключевые слова: макрорегионы Китая, производительность труда в организации, цифровизация бизнеса, эффект медиации, китайские компании, котирующиеся на бирже, гипотеза Портера

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Introduction

Digital transformation has become an important component of firm-level modernization and industrial upgrading. Digital technologies such as big data analytics, cloud computing, artificial intelligence, industrial internet platforms, and blockchain can reduce information frictions, improve production coordination, and support data-based decision-making. However, the productivity effects of digital transformation are not automatic. The literature on general-purpose technologies emphasizes that productivity gains usually depend on complementary investments in organizational capital, skills, management practices, and process redesign (Bresnahan et al., 2002; Bloom et al., 2012; Brynjolfsson et al., 2000).

For Chinese firms, this issue is especially relevant because enterprises operate under rising labour costs,

demographic transition, environmental constraints, and substantial regional disparities. Labour productivity is a central indicator of firm efficiency because it reflects the amount of operating output generated per employee. At the same time, the uneven distribution of digital infrastructure, skilled labour, innovation services, and market institutions across Chinese regions may cause the same level of digital transformation to generate different productivity outcomes.

Existing studies have examined the relationship between digital transformation and firm performance, total factor productivity, innovation, and green transformation (Autor et al., 2003; Zhao et al., 2021; Hu et al., 2022; Wang et al., 2023; Lv et al., 2024). Text-based measures of digital transformation have become common in empirical research because annual reports provide compara-

ble firm-level information about digital strategy and technology adoption (Loughran & McDonald, 2016; Xiao et al., 2022; Yuan et al., 2021; Sun & Guo, 2022; Su et al., 2023). Nevertheless, two gaps remain. First, the mechanism through which digital transformation is linked to labour productivity requires further clarification, especially when green innovation is considered as an intermediate channel. Second, regional heterogeneity has not been sufficiently integrated into the theoretical explanation of digital productivity effects.

The purpose of this study is to examine whether and under what conditions digital transformation is associated with corporate labour productivity in Chinese listed companies. Unlike studies that treat digitalization as a universally productivity-enhancing factor, this paper emphasizes the conditional and regionally heterogeneous nature of digital productivity effects.

To achieve this purpose, the study addresses four research tasks. First, it evaluates the baseline association between firm-level digital transformation and labour productivity. Second, it examines whether green innovation acts as a mediating mechanism linking digital transformation to labour productivity. Third, it tests whether this relationship differs between high-tech and non-high-tech industries. Fourth, it investigates regional heterogeneity across eastern, central, and western China.

Based on the theoretical framework, four hypotheses are formulated.

H1: Digital transformation is positively associated with corporate labour productivity, but the magnitude of this relationship may be economically moderate.

H2: Green innovation partially mediates the relationship between digital transformation and corporate labour productivity.

H3: The association between digital transformation and labour productivity differs between high-tech and non-high-tech industries.

H4: The association between digital transformation and labour productivity varies across Chinese regions, being stronger in regions with more developed digital infrastructure and complementary resources.

The contribution of this paper is threefold. First, it provides firm-level evidence on the relationship between digital transformation and labour productivity in China. Second, it connects digital transformation with green innovation and the weak Porter Hypothesis. Third, it explains regional heterogeneity through the lens of location theory, complementary assets, and regional development conditions.

Theoretical Foundations and Analytical Framework

Digital transformation is not merely the adoption of isolated digital tools; it is a process through which

firms reorganize production, management, information flows, and business processes by integrating digital technologies. From the perspective of transaction cost theory, digital technologies can reduce search, coordination, monitoring, and contracting costs by improving information transparency and the speed of communication. From the perspective of information asymmetry theory, data-based monitoring and real-time information systems can reduce the gap between management and production units, improving production planning and labour allocation.

The resource-based view and resource orchestration theory further suggest that digital technologies create value only when firms combine them with complementary resources. Digital infrastructure, skilled employees, organizational routines, managerial capabilities, and absorptive capacity are required to transform digital inputs into productivity outcomes (Cohen & Levinthal, 1990; Milgrom & Roberts, 1990; Bloom et al., 2012). This theoretical logic is consistent with the productivity J-curve argument, which states that the benefits of general-purpose technologies may appear gradually because firms must accumulate intangible complementary capital before measurable productivity gains emerge (Brynjolfsson et al., 2021).

Green innovation refers to technological and organizational innovations that reduce environmental damage, improve resource efficiency, and support sustainable production. From the perspective of sustainable development theory, firms are expected not only to improve economic performance but also to internalize environmental constraints into production and innovation decisions. Green innovation can affect labour productivity through cleaner processes, energy-saving technologies, waste reduction, and the reorganization of production routines.

The Porter Hypothesis provides an additional explanation for the productivity implications of green innovation. According to its weak form, environmental pressure and green-oriented innovation activities can stimulate technological upgrading, which may partly offset compliance costs and improve production efficiency (Porter & van der Linde, 1995; Ambec et al., 2013; Dechezleprêtre et al., 2017). In the context of digital transformation, digital technologies can facilitate green innovation by improving environmental monitoring, data-based energy management, and process optimization. Therefore, green innovation may serve as a mediating mechanism between digital transformation and labour productivity. Recent firm-level evidence on digital transformation and green innovation (Sun & Guo, 2022; Wang & Zhong, 2024) confirms the existence of a link between digitalization and investment in green innovation.

Regional heterogeneity can be interpreted through location theory and regional development theory. Firms do not transform digitally in an in-

stitutional and spatial vacuum. The productivity effect of digital transformation depends on complementary regional conditions, including digital infrastructure, skilled labour supply, marketization, industrial agglomeration, and access to innovation services. According to location theory, the spatial distribution of production and innovation activities is shaped by infrastructure, factor endowments, transaction costs, and agglomeration economies. Therefore, the same level of firm-level digital transformation may generate different productivity outcomes across regions.

Methodology and Data

This study uses an unbalanced panel of Chinese A-share listed companies from 2007 to 2023. Financial firms are excluded because their balance-sheet structures, regulatory environment, and labour productivity measurement differ from non-financial firms. ST and *ST firms are also excluded because their abnormal operating conditions may distort the empirical results. Observations with missing values in core variables are removed. To reduce the influence of outliers, continuous variables are winsorized at the 1st and 99th percentiles. The final sample contains 57,993 firm-year observations.

The dependent variable is corporate labour productivity ($\ln_LDSCL$), measured as the natural logarithm of operating revenue per employee. This indicator captures the operating output generated by each employee and is widely used in firm-level productivity research when direct physical output is not comparable across industries.

$$\ln_LDSCL_it = \ln(\text{Operating revenue_it} / \text{Number of employees_it}) \quad (1)$$

The core explanatory variable is the Digital Transformation Index (DTI). Following the textual-analysis approach in accounting, finance, and Chinese digital transformation studies, the index is constructed by counting the frequency of keywords related to artificial intelligence, big data, cloud computing, blockchain, digital platforms, industrial internet, and other digital technologies in firms' annual reports, and then scaling this frequency by the total number of words in the report (Loughran & McDonald, 2016; Yuan et al., 2021).

$$DTI_it = \text{Digital keyword frequency_it} / \text{Total words in annual report_it} \quad (2)$$

The mechanism variable is green innovation (SQZL), measured by the number of granted green patents, including green invention patents and green utility model patents. Because patent counts are highly skewed, the variable is log-transformed after adding one. This measure is consistent with the literature using patent data to evaluate firm-level innovation output (Hall et al., 2005; Popp, 2002).

$$SQZL_it = \ln(1 + \text{Granted green patents_it}) \quad (3)$$

Control variables include leverage (Lev), cash flow, board size (Board), the proportion of independent directors (Independent), and ownership balance (Balance2). These controls capture financial risk, internal financing capacity, corporate governance structure, supervisory independence, and ownership checks and balances.

The empirical strategy includes five steps. First, descriptive statistics and Pearson correlations are reported. Second, baseline regressions are estimated. Third, lagged DTI specifications are used as robustness tests and as a partial response to reverse causality. Fourth, mediation models test whether green innovation is a channel between digital transformation and labour productivity. Fifth, subgroup regressions are used to examine industry and regional heterogeneity.

Model (4) estimates the unconditional association between digital transformation and labour productivity:

$$\ln_LDSCL_it = \alpha_0 + \alpha_1 \cdot DTI_it + \varepsilon_it \quad (4)$$

Model (5) adds firm-level control variables:

$$\ln_LDSCL_it = \beta_0 + \beta_1 \cdot DTI_it + \beta_2 \cdot \text{Controls_it} + \varepsilon_it \quad (5)$$

Model (6) is the preferred specification and includes firm and year fixed effects:

$$\ln_LDSCL_it = \gamma_0 + \gamma_1 \cdot DTI_it + \gamma_2 \cdot \text{Controls_it} + \mu_i + \lambda_t + \varepsilon_it \quad (6)$$

To partially address reverse causality and delayed effects, lagged specifications are estimated:

$$\ln_LDSCL_it = \delta_0 + \delta_1 \cdot DTI_i,t-k + \delta_2 \cdot \text{Controls_it} + \mu_i + \lambda_t + \varepsilon_it, k = 1, 2 \quad (7)$$

The mediating role of green innovation is tested using the following equations:

$$SQZL_it = \theta_0 + \theta_1 DTI_it + \theta_2 \text{Controls_it} + \mu_i + \lambda_t + \varepsilon_it \quad (8)$$

$$\ln_LDSCL_it = \rho_0 + \rho_1 DTI_it + \rho_2 SQZL_it + \rho_3 \text{Controls_it} + \mu_i + \lambda_t + \varepsilon_it \quad (9)$$

In these equations, i denotes firm and t denotes year. μ_i represents firm fixed effects, λ_t represents year fixed effects, and ε_it is the error term. Standard errors are clustered at the firm level to account for within-firm serial correlation and heteroskedasticity (Petersen, 2009; Wooldridge, 2010).

Empirical Results and Analysis

Table 1 reports descriptive statistics. The mean of $\ln_LDSCL$ is 13.823 with a standard deviation of 0.949, indicating meaningful variation in labour productivity across listed firms. The mean value of DTI is 0.009 and the maximum is 0.362, suggesting

that the overall degree of digital transformation remains uneven across firms. The control variables are within plausible ranges for non-financial listed companies after winsorization.

Correlation Analysis

Table 2 shows the Pearson correlation coefficients of the main variables. The correlation between DTI and $\ln_LDSCL$ is positive and statistically significant ($r = 0.013$, $p < 0.01$), but the magnitude is very small. Therefore, the correlation result should be interpreted only as preliminary evidence of a positive association, not as evidence of a strong economic effect. The correlations among control variables do not suggest severe multicollinearity.

Baseline Regression Analysis

Table 3 reports the baseline regression results. Model (1) estimates the unconditional relationship between DTI and labour productivity. Model (2) adds firm-level controls. Model (3) is the preferred specification with firm and year fixed effects. In Model (3), the coefficient of DTI is 0.818 and statistically significant at the 1 % level. These results suggest a positive association between digital transformation and labour productivity. However, given the small unconditional correlation reported in Table 2, the economic magnitude of this relationship should be interpreted cautiously.

Endogeneity and Robustness Tests: Lagged Effects

A potential concern is reverse causality: more productive firms may be more capable of invest-

ing in digital transformation. To partially address this issue, Table 4 uses one-period and two-period lagged DTI variables. This approach improves the temporal ordering of the analysis, although it cannot fully eliminate endogeneity.

The coefficients of DTI_L1 and DTI_L2 are 0.684 and 0.698, respectively, and both are significant at the 5 % level. This finding suggests that the positive association between digital transformation and labour productivity is not limited to the contemporaneous specification. Nevertheless, lagged regressions should be interpreted as supportive robustness evidence rather than definitive proof of causality.

Mechanism Test: The Mediating Role of Green Innovation

The proposed mechanism is that digital transformation may support green innovation by improving environmental monitoring, energy-management precision, and process optimization. Green innovation may then improve labour productivity through resource savings, cleaner production routines, and technological upgrading. This logic is consistent with the weak form of the Porter Hypothesis.

In Model (2), the coefficient of DTI in the green innovation equation is positive and significant, indicating that firms with higher digital transformation tend to report more green innovation outputs. In Model (3), SQZL is positively associated with labour productivity, while the coefficient of DTI declines slightly from 0.818 to 0.811 after SQZL is included. This pattern is consistent with partial mediation. However, the reduction in the DTI coefficient is small, which

Table 1

Descriptive Statistics of Main Variables

Variables	Mean	Standard deviation	Min	Max	P ₁	P ₉₉	Skew.	Kurt.
$\ln_LDSCL$	13.823	.949	4.727	20.139	11.795	16.575	.594	5.238
DTI	.009	.019	0	.362	0	.096	6.423	61.783
Lev	.442	.337	.016	14.810	.072	.929	23.727	948.002
Cash flow	.021	.086	-.318	.339	-.160	.228	-.042	2.959
Board	2.266	.169	1.792	2.773	1.792	2.773	-.360	4.391
Independent	.364	.051	0	.800	.300	.545	1.540	7.334
Balance2	.534	.564	0	4.000	.022	2.459	1.596	6.047

Note: Continuous variables are winsorized at the 1st and 99th percentiles. Source: compiled by the authors.

Table 2

Pearson Correlation Matrix

	$\ln_LDSCL$	DTI	Lev	Cash Flow	Board	Independent	Balance2
$\ln_LDSCL$	1	—	—	—	—	—	—
DTI	0.013***	1	—	—	—	—	—
Lev	0.066***	-0.052***	1	—	—	—	—
Cash flow	-0.055***	0.018***	0.046***	1	—	—	—
Board	-0.001	-0.088***	0.075***	-.029***	1	—	—
Independent	0.016***	0.102***	0.020***	0.169***	-0.495***	1	—
Balance2	-0.063***	0.139***	0.031***	0.233***	-0.052***	0.097***	1

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: compiled by the authors.

Table 3

Baseline Regression: Digital Transformation and Labour Productivity

	(1)	(2)	(3)
	ln_LDSC	ln_LDSC	ln_LDSC
DTI	0.648*** (0.2112)	1.176*** (0.2134)	0.818*** (0.2623)
Lev	—	0.197*** (0.0117)	0.00883 (0.0126)
Cash flow	—	−0.543*** (0.0477)	0.575*** (0.0576)
Board	—	0.0304 (0.0268)	−0.0121 (0.0341)
Independent	—	0.536*** (0.0911)	−0.0581 (0.1084)
Balance2	—	−0.0999*** (0.0072)	−0.000347 (0.0106)
_cons	13.82*** (0.0044)	13.53*** (0.0822)	13.85*** (0.1042)
Firm FE	No	No	Yes
Year FE	No	No	Yes
N	57,993	57,993	57,978
F	9.426***	114.778***	17.923***
R2	0.0002	0.0117	0.7335

Note: Standard errors clustered at the firm level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: compiled by the authors.

Table 5

Mediation Test: Green Innovation as a Mechanism

	(1)	(2)	(3)
	ln_LDSC	SQZL	ln_LDSC
SQZL	—	—	0.000300** (0.0001)
DTI	0.818*** (0.2623)	23.22** (10.3934)	0.811*** (0.2620)
Lev	0.00883 (0.0126)	−1.071* (0.6190)	0.00916 (0.0127)
Cash flow	0.575*** (0.0576)	−4.880** (2.2646)	0.576*** (0.0576)
Board	−0.0121 (0.0341)	−3.876* (2.3140)	−0.0109 (0.0342)
Independent	−0.0581 (0.1084)	−15.65* (8.1159)	−0.0534 (0.1084)
Balance2	−0.000347 (0.0106)	0.341 (0.4025)	−0.000449 (0.0106)
_cons	13.85*** (0.1042)	21.40*** (7.2416)	13.84*** (0.1042)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	57,978	57,978	57,978
F	17.923***	3.714***	16.235***
R2	0.7335	0.6043	0.7335

Note: Standard errors clustered at the firm level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: compiled by the authors.

Table 4

Robustness Test Using Lagged Digital Transformation Indicators

	(1)	(2)	(3)
	Non-lag	Lag 1	Lag 2
DTI	0.818*** (0.2623)	—	—
DTI_L1	—	0.684** (0.2841)	—
DTI_L2	—	—	0.698** (0.3075)
Lev	0.00883 (0.0126)	−0.00500 (0.0240)	−0.00482 (0.0225)
Cash flow	0.575*** (0.0576)	0.653*** (0.0627)	0.632*** (0.0671)
Board	−0.0121 (0.0341)	−0.000479 (0.0387)	−0.00329 (0.0381)
Independent	−0.0581 (0.1084)	−0.0137 (0.1138)	0.00997 (0.1148)
Balance2	−0.000347 (0.0106)	−0.00256 (0.0118)	0.00288 (0.0120)
Constant	13.85*** (0.1042)	13.84*** (0.1151)	13.87*** (0.1140)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	57,978	51,622	45,885
F	17.923***	19.042***	15.750***
R2	0.7335	0.7483	0.7581

Note: $X(t-1) = DTI_L1$, $X(t-2) = DTI_L2$, $Y(t) = \ln_LDSC$. Standard errors clustered at the firm level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: compiled by the authors.

means that green innovation is a present but limited mechanism rather than the dominant channel.

Industry Heterogeneity Analysis

Industrial structure may condition the productivity implications of digital transformation. Based on the industrial classification standard of the China Securities Regulatory Commission, the sample is divided into high-tech and non-high-tech industries. Table 6 reports subgroup regressions.

The coefficient of DTI is statistically significant only in the non-high-tech subsample. This suggests that traditional and non-high-tech firms may obtain larger marginal benefits from basic digitalization because their initial levels of informatization and automation are lower. In contrast, high-tech firms may already operate closer to the technological frontier, so additional digital transformation may have weaker short-term productivity implications. Adjustment costs and the productivity J-curve may also weaken the immediate observable effect of digital upgrading in high-tech sectors.

Regional Heterogeneity Analysis

To examine whether regional conditions moderate the relationship between digital transformation and

Table 6

Regression Results by Industry Heterogeneity

	(1)	(2)
	High-tech industry	Non-high-tech industry
DTI	-0.172 (0.5352)	7.613*** (1.6559)
Lev	-0.114 (0.0914)	0.144 (0.1108)
Cash flow	0.781*** (0.0897)	0.892*** (0.1184)
Board	0.0271 (0.0697)	-0.00294 (0.1223)
Independent	0.197 (0.1648)	-0.0875 (0.2889)
Balance2	0.0265 (0.0224)	0.00358 (0.0388)
_cons	13.55*** (0.1956)	13.81*** (0.3414)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	21,772	16,988
F	13.824***	12.731***
R2	0.7720	0.7520

Note: Standard errors clustered at the firm level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: compiled by the authors.

labour productivity, the sample is divided into eastern, western, and central regions according to firms' registered locations. Table 7 reports the results.

The coefficient of DTI is positive and statistically significant only in the eastern region. In the central and western regions, the coefficients are positive but statistically insignificant. This pattern indicates that the productivity-related association of digital transformation depends on complementary regional conditions. Eastern China has relatively stronger digital infrastructure, deeper labour markets for digital talent, more developed business services, and higher marketization. These conditions may help firms convert digital inputs into measurable productivity improvements. In central and western regions, weaker digital ecosystems and limited complementary assets may reduce the conversion efficiency of digital transformation.

Discussion and Policy Recommendations

The findings should be interpreted in a cautious and conditional manner. The empirical results do not support the claim that digital transformation greatly or automatically improves labour productivity for all firms. Instead, they show a statistically significant but economically moderate association whose strength varies across industries and regions.

The results support the importance of complementary assets. Digital transformation requires skilled employees, management capabilities, pro-

Table 7

Regression Results by Region

	(1)	(2)	(3)
	East	West	Central
DTI	2.828*** (0.7903)	0.587 (1.9595)	2.605 (1.9673)
Lev	0.189* (0.1062)	-0.0852 (0.1861)	-0.445*** (0.1213)
Cash flow	0.836*** (0.0902)	0.804*** (0.1580)	1.113*** (0.1781)
Board	-0.0271 (0.0948)	-0.0245 (0.1475)	0.0873 (0.1191)
Independent	-0.0635 (0.2236)	0.0953 (0.3868)	0.0713 (0.2550)
Balance2	0.0222 (0.0243)	0.0126 (0.0617)	0.0578 (0.0421)
_cons	13.80*** (0.2706)	13.63*** (0.4243)	13.82*** (0.3112)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	26,432	6,638	7,647
F	16.214***	4.851***	10.482***
R2	0.7557	0.7290	0.7891

Note: Standard errors clustered at the firm level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: compiled by the authors.

cess redesign, and organizational learning. Policies that subsidize digital equipment alone may be insufficient if firms lack complementary capabilities. Training programmes, digital management consulting, and support for organizational upgrading may be necessary to translate digital adoption into labour productivity gains.

The partial mediation results imply that green innovation can be one channel through which digital transformation is connected with productivity, but the mechanism is limited in magnitude. Policy instruments should therefore promote the integration of digital and green technologies, including digital energy management, environmental monitoring platforms, cleaner production systems, and green patent commercialization. However, these policies should avoid assuming that green innovation is the only or dominant productivity channel.

The regional results suggest that differentiated digital economy policies are required. In eastern China, the policy priority may be to deepen advanced digital applications and support higher-quality digital-green integration. In central and western regions, firm-level subsidies should be combined with regional investment in digital infrastructure, digital service markets, skilled labour attraction, and innovation ecosystems. Without these complementary conditions, digital transformation may remain symbolic and may not generate clear productivity outcomes.

The stronger association in non-high-tech industries suggests that traditional sectors may have larger catch-up potential. Targeted support for digital upgrading in manufacturing, logistics, and traditional services may generate meaningful productivity improvements, particularly where digital adoption starts from a low base.

Conclusions

This study examined the relationship between digital transformation, green innovation, and corporate labour productivity using panel data from Chinese A-share listed companies from 2007 to 2023. The analysis combined text-based measurement of digital transformation, fixed-effects panel regressions, lagged specifications, mediation tests, and heterogeneity analysis.

The study showed that digital transformation is positively associated with corporate labour productivity. The coefficient remains positive after adding firm and year fixed effects and in lagged specifications. However, the magnitude of the relationship should be interpreted cautiously. The results do not imply that digital transformation automatically or substantially improves labour productivity in all firms; rather, they indicate a statistically robust but economically moderate association.

It is important that green innovation plays a partial mediating role in the relationship between digital transformation and labour productivity. Digital transformation is associated with more green inno-

vation outputs, and green innovation is positively related to labour productivity. Nevertheless, the mediation effect is limited in magnitude, suggesting that green innovation is one mechanism rather than the dominant channel.

A regional study found that the productivity-related association of digital transformation is heterogeneous across industries and regions. The association is more evident in non-high-tech industries and in eastern China, while it is statistically weaker in high-tech industries and in central and western regions. This finding suggests that digital transformation requires complementary conditions, including digital infrastructure, skilled labour, market competition, and regional innovation ecosystems.

This study has several limitations: the Digital Transformation Index is based on annual report text and may capture firms' disclosure intensity rather than actual digital investment; although fixed effects and lagged specifications are used, potential endogeneity cannot be fully eliminated; labour productivity is measured by operating revenue per employee, which may be affected by price changes and industry-specific revenue structures.

Future research may combine textual indicators with direct digital investment data, use stronger identification strategies such as instrumental variables or quasi-natural experiments, and further examine regional policy environments that condition the productivity effects of digital transformation.

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