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Impact of digital transformation on green production: Evidence from China

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ABSTRACT

In the global context of development transformation, digital transformation (DT) has emerged as a prevalent practice among international corporations, facilitating the simultaneous enhancement of economic growth. However, limited research on how digital transformation affects green production, especially at a micro level, poses risks by impeding the understanding of strategies for balancing economic growth and environmental sustainability. This study addresses a critical research gap by elucidating the influence of digitization on green total factor productivity (GTFP). We based our findings on a sample of 280 listed non-financial firms from 2007 to 2021 and computed core variables through text analysis and the super-SBM model. The data analysis using fixed effects models, correlation analysis, instrumental variable approach, and difference-in-differences method. The findings underscore the positive impact of DT on enhancing firms' green innovation, investment efficiency, and internal control, consequently significantly elevating the level of GTFP. Additionally, it was observed that normal DT contributes to the sustainable long-term improvement of a firm's GTFP, whereas excessive DT exhibits a positive impact on short-term GTFP. This study's insights into the positive impact of DT on GTFP serve to guide enterprises and policymakers in navigating a transition towards high-quality development, facilitating a balanced approach that fosters environmental conservation alongside economic growth in both emerging and global contexts.

1. Introduction

The unprecedented rapid growth of the global economy has been accompanied by enormous pressures on the environment and led to the depletion of precious natural resources, resulting in unsustainable economic growth [1,2]. The '*2022 International Energy Agency's Carbon Dioxide Emissions Report*' reveals that global carbon dioxide emissions from energy combustion and industrial processes surged by 0.9 % in 2022, reaching a record high of 36.8 billion metric tons. Additionally, data from the *Global Energy Statistics Yearbook (GESY)* depict a persistent growth trend in global energy consumption, totaling 604.04 EJ in 2022 (Fig. 1). In response to prevalent environmental challenges in emerging economies, many developing nations are embracing green production, emphasizing the harmonization of economic growth, resource utilization, and ecological preservation. Conceptually, green production signifies an essential metric for assessing corporates' enhancement of product quality and production efficiency while ensuring strides toward sustainable development [3]. Therefore, fostering green productivity growth is widely regarded as a pivotal topic in the new stage of economic development, garnering significant attention from policymakers and scholars.

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Against the backdrop of environmental protection and industrial structure upgrading, the digital economy has become an undeniable trajectory [4]. According to the *'2023 Global Digital Economy Development Index Report'*, the TIMG (Technology, Infrastructure, Market, Governance) index average score increased from 45.33 in 2013 to 57.01 in 2021, underscoring the significant growth potential of the digital economy. DT is increasingly recognized as a pivotal pathway towards sustainable development within the industrial sector, with digital technologies driving corporate competitiveness [5]. Consequently, fostering digital transformation has emerged as a critical imperative for developing countries striving to attain innovation-driven growth. While previous studies have primarily relied on macro-level data, significant correlations with firm-level research have surfaced. It is anticipated that digital transformation will positively influence corporate sustainability [6–8], fostering the green evolution of enterprises through the enhancement of information symmetry and the optimization of capital utilization.

Recently, considerable scholars have been devoted to exploring the drivers of green productivity growth. For example, digital transformation entails optimizing operational processes and incorporating digital technologies to reduce reliance on resources [9]. Digital technologies enable firms to streamline operations, cut costs, and enhance the utilization of human capital, thus fostering an efficient management-oriented production framework [10]. Additionally, digital transformation facilitates the integration of monitoring tools and practices, enabling companies to effectively address information asymmetries impacting green innovation inputs and financing constraints. However, current research on digital transformation predominantly focuses on the impact on specific dimensions, such as energy efficiency [11,12] or environmental aspects [9], overlooking the combined influence of digital transformation on holistic corporate greening development. The adoption of green total factor productivity (GTFP) as a key metric for green production, given its comprehensive evaluation framework spanning economic, environmental, and social dimensions [13–16]. By assessing the overall efficiency of resource utilization and environmental pollutant reduction in the production process, GTFP encourages firms to prioritize waste reduction. This alignment with objectives aimed at mitigating environmental pollution and promoting sustainable development underscores the significance of GTFP [16]. Therefore, the micro-level relationship between digital transformation and GTFP is widely recognized as a critical topic in the new phase of economic development.

In theoretical research, further investigation is needed to understand the impact of digital transformation on firms' GTFP. Firstly, the development of digitalization can alter firms' financing patterns and efficiency [17,18]. Additionally, scholars suggest that digital transformation facilitates the smooth flow of production factors such as capital, technology, and marketing to support innovation activities [19], providing a theoretical framework. The enhancement of firms' digital technologies can effectively alleviate financial constraints and mitigate agency problems to enhance investment efficiency and internal control. Consequently, it reduces environmental pollution, decreases firms' input costs and resource consumption, enhances operational efficiency, strengthens competitiveness, and facilitates firms' achievement of green development. These studies provide important theoretical basis and empirical support for empowering firms' GTFP through digital transformation.

In summary, while existing literature provides valuable insights, consensus remains elusive regarding the interplay between DT and GTFP. Current research often examines this relationship at regional levels, neglecting firm-level analysis. Moreover, there's a dearth of systematic exploration into how DT precisely impacts GTFP, alongside limited consideration of diverse firm and industry characteristics. Additionally, studies predominantly focus on linear or non-linear relationships between DT and GTFP, with scant attention to long-term influence on firms' GTFP. Addressing these gaps, this research aims to elucidate the interactive mechanism between DT and firms' GTFP, uncovering specific pathways shaping firms' sustainable green development under varying firm characteristics and macro-environmental conditions.

This article provides three main contributions. Firstly, our research explores the impact of DT on GTFP at the micro-level, complementing previous research that predominantly focused on the macro-level [20]. Additionally, we decompose GTFP into the Green Efficiency Change Index (GECI) and the Green Technological Progress Index (GTPI) to further investigate how digital transformation specifically influences GTFP. Secondly, we examine the mechanism through which digital transformation affects micro-level green production within corporates, emphasizing its positive influence on corporate GTFP through green innovation, investment efficiency,

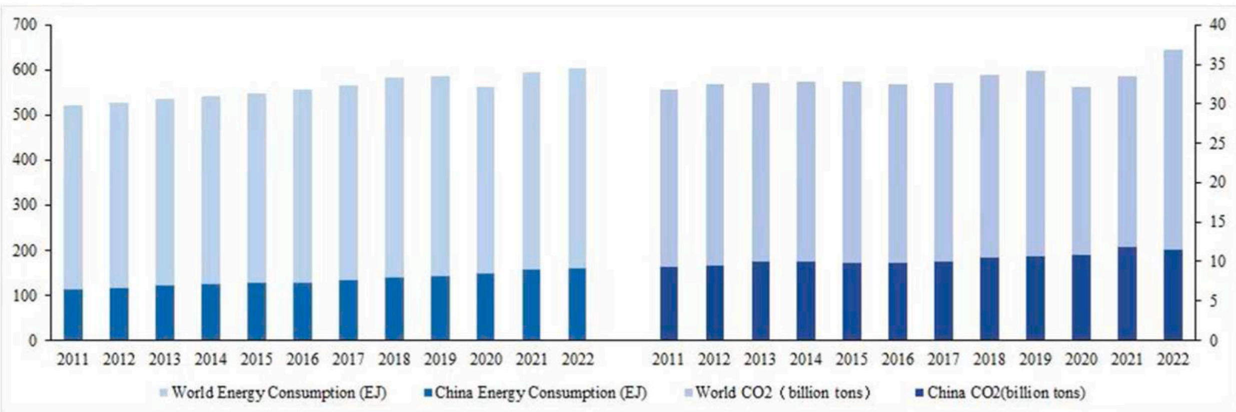


Fig. 1. Carbon dioxide emissions and total energy consumption (2011–2022).

and corporate governance. Thirdly, drawing upon Miles and Snow's [21] framework, we categorize a company's digital transformation into normal and excessive levels. Normal DT embodies a long-term overall strategy, while excessive DT reflects short-term tactical approaches. By distinguishing between normal and excessive levels of digital transformation, we explore their varying impacts on corporate GTFP. This analysis reveals the potential green value inherent in corporate efforts towards digital transformation.

The remainder of this paper is organized as follows. Section 2 presents literature review and Section 2 proposes theoretical hypothesis. Section 4 describes the research methods and models. Section 5 reports the empirical results and additional analysis. Finally, Section 6 concludes and draws some policy implications.

2. Literature view

2.1. *Enterprise green production*

Enterprise green production, emphasizing environmental sustainability and social responsibility, is gaining prominence. As major resource consumers and polluters, companies must reduce their environmental impact [22–24]. By adopting eco-friendly technologies and transformation, they can reduce waste and emissions, protect ecosystems [25]. Lower pollution control costs can enhance profitability and sustainable resource use [26]. Green production also offers economic benefits, such as improved energy efficiency and reduced operational costs [1–3,27,26]. It drives technological innovation and better product design, boosting corporate reputation and attracting environmentally conscious consumers, thereby increasing marketability and providing a competitive edge [4,28].

Previous research has used Environmental Performance Indicators (EPIs) like waste emissions, energy consumption, and resource utilization efficiency to evaluate enterprise green production [7,8,29]. Scholars have also combined green technological innovation with production metrics [9]. Recognizing resource and environmental constraints is crucial in evaluating green production [30]. This study employs Green Total Factor Productivity (GTFP) as a comprehensive indicator to measure the integration of green production and its economic impacts on enterprises [31]. GTFP covers various aspects including resource use, waste emissions, and energy consumption, offering a holistic assessment of enterprise performance from environmental, energy, and economic viewpoints [29,32].

Earlier studies on GTFP have used various methods; for example, Chen and Golley [13] integrated carbon dioxide emissions into production technology using the Directional Distance Function (DDF) and Malmquist-Luenberger (ML) productivity index to estimate GTFP for China's industrial sector. In this study, we address the non-zero slack problem caused by radial and angular deviations by adopting an SBM model inspired by Tone [33], which incorporates undesirable outputs, thus enhancing the analysis of inputs, outputs, and environmental pollution. We integrate this SBM model with Tone's [34] super-efficiency Data Envelopment Analysis (DEA) model for measuring GTFP, improving flexibility, and enabling multidimensional evaluation and weight allocation optimization.

2.2. *Corporate digital transformation and green total factor productivity*

In the context of socioeconomic development, digital transformation has emerged as a critical strategic factor shaping competitiveness, offering significant advantages to firms. By enhancing management capabilities, digital transformation enables companies to better understand market demands, optimize supply chains, and improve production efficiency [35,36]. Furthermore, it serves as an innovation catalyst, effectively addressing market information asymmetry and expediting the innovation process, while digital finance alleviates financing constraints for companies [37], fostering increased research and development (R&D) investment, and leveraging innovation ecosystems to harness external resources for innovation acceleration [4]. Digitization optimizes production processes, reduces labor input, and lowers human resource management costs, thereby stimulating innovation [4]. Moreover, in the global economy, digitization simplifies international trade, attracts foreign investment, and intensifies competition [12], profoundly impacting long-term strategic development for enterprises.

Existing literature exploring the driving factors behind green economic growth primarily focuses on aspects such as resource endowment, industrial clustering, and environmental regulations [3,24]. Digital transformation significantly impacts the transition toward a green economy by presenting both opportunities and challenges for green production growth. Regarding the environmental effects, some researchers argue that DT might lead to increased energy consumption, posing significant challenges to green development [38]. While the application of digital technology in industries can expand economic scale and drive economic growth [11], it's important to consider the Environmental Kuznets Curve (EKC), suggesting that economic development may exacerbate environmental pollution. Digital transformation may increase energy burdens, emissions, and disrupt ecosystems, intensifying environmental issues [39]. Its effectiveness depends on aligning innovation incentives with the development of emerging technologies within a country's institutional framework [37,17]. In developing nations with weak environmental protections, introducing digital technologies may not yield positive economic and environmental impacts [3].

Conversely, major scholars posit that digitalization can enhance environmental performance and propel ecological sustainability [9,18]. As a revolutionary technology, digital technology can facilitate societal sustainable development by boosting energy efficiency within enterprises and reducing pollutant emissions. Xu et al. [12] found that DT significantly enhances clean energy development in enterprises by fostering technological innovation and facilitating bank credit. Li [40] used panel data from Chinese enterprises to highlight the need for synergistic development between digitalization and environmental governance to achieve China's carbon neutrality goals. The positive impact of digitalization on the green economy can be theoretically analyzed through industrial transformation and efficient investment and financing [37,41,42]. Moreover, governmental institutional mechanisms for ecological governance [43] can simultaneously constrain corporate production behaviors and application of new technologies to replace traditional, polluting equipment, fostering a mutually beneficial relationship between the economy and the environment.

In summary, previous research on the potential contributions of digitalization to green production and environmental protection has laid a solid foundation for this study. However, certain gaps remain. Notably, there is insufficient emphasis on the micro-level impact of digital transformation on GTFP. Most studies on the impact of DT on GTFP focus primarily on the macro level [20,44,45]. Furthermore, balancing economic and environmental benefits is crucial. Specifically, it is essential to examine the strategic significance of DT for enterprises and its long-term impact on GTFP, while also analyzing the heterogeneity among different types of enterprises.

This study aims to explore how digitalization enhances GTFP and promotes sustainable development in Chinese listed firms by analyzing their data. Specifically, it examines the potential mechanisms through which digitalization affects GTFP and investigates the heterogeneity among manufacturing firms of different ownership types, regions, and technological levels. Through this research, we aim to fill existing gaps in the literature and provide a viable pathway for global enterprises towards a greener, more economically prosperous, and sustainable future.

3. Theoretical hypothesis

Positioned as a strategic corporate endeavor, green production aims to harmonize environmental attributes with innovation qualities through the development of green technologies and products to mitigate pollution [35,46]. Digital transformation addresses information asymmetry by bridging the gap between enterprises and stakeholders, thereby facilitating alignment between supply and demand in the green innovation market and directly enhancing a company's green innovation capabilities [42]. Elevated levels of green innovation facilitate the flow of innovation factors such as talent, funds, and technology, thereby enhancing their autonomous innovation capabilities and production efficiency [37,47], mitigating pollutant emissions, and advancing the evolution of industrial structures, leading to improvements in GTFP [1,2,27]. Furthermore, based on the economic theory of structural effects, digitalization enables firms to transition their economic structures from heavily polluting manufacturing industries to knowledge-intensive sectors. According to Porter's hypothesis, digital technologies reduce the production costs and surplus value of traditional high-energy-consuming industries, driving corporate innovation, enhancing resource utilization efficiency, and lowering compliance costs. This industrial restructuring promotes green innovation, effectively adjusts the supply-demand relationship, and consequently improves economic performance and catalyzes GTFP [48].

According to the Efficient Market Hypothesis, DT strategies broaden information disclosure channels, effectively enhancing the transparency and liquidity of capital markets, rendering them more efficient and facilitating external funding support, thereby alleviating internal financial pressures [49,50]. Additionally, the application of DT fosters a more dynamic and comprehensive allocation of innovation resources, efficiently managing and utilizing traditional production factors to enhance resource efficiency, correct resource misallocation, and ensure effective investment implementation [24]. While initial investments in digital technologies may temporarily increase emissions due to scale effects, technological advancements and enhanced corporate social responsibility gradually alleviate environmental burdens, promoting environmental performance improvement [42]. Furthermore, Information Efficiency Theory elucidates DT helps alleviate corporate financing constraints, enabling access to more external funding to support green development [51]. Consequently, digitalization effectively mitigates information asymmetry and financing constraints, enhances investment efficiency, enables flexible production adjustments, and reduces resource waste and environmental pollution, ultimately enhancing GTFP.

Research indicates that DT fundamentally transforms business processes and data management by integrating advanced technologies and systems, thereby enhancing the efficiency and accuracy of internal controls, improving risk management, and increasing asset security [1,2,27]; [52]. Digitalization strengthens quality management processes and promotes both internal and external information sharing. According to agency theory, DT helps establish effective interfaces between companies and stakeholders, enhancing the efficiency of agent supervision and reducing information search costs, thereby improving corporate governance ([49]). From the perspective of information asymmetry theory, digital technologies increase transparency and information flow, reducing information asymmetry and thereby improving internal governance [43]. These improvements enable companies to respond more swiftly to changes in policy direction and market demand, facilitating timely and targeted adjustments to green production activities [28]. Thus, DT indirectly enhances GTFP by improving control efficiency and accuracy, strengthening information sharing and feedback, and enabling quicker responses to policy and market changes [16]. Based on the theoretical analysis mentioned above, this research proposes the following hypothesis:

Hypothesis 1. Corporate digital transformation can boost Green Total Factor Productivity (GTFP).

Based on the specific characteristics of individual corporates, each company may have its distinct level of digital transformation. For example, larger-scale companies may require a more extensive adoption of digital technologies. We define the excessive level of digital technology adoption in companies, eliminating the normal level, as the excessive DT. The influence of DT on green production may vary based on the normal and excessive levels of digital technology adoption. Excessive digital transformation entails the production of a substantial number of electronic devices and heightened energy consumption, thereby posing adverse effects on green production. Although limited research has decomposed the adoption of DT into normal and excessive levels, we draw inspiration from the concept of over-investments and under-investments in the field of corporate finance [10]. We anticipate that in the short term, an excessive DT adoption will boost the company GTFP. In contrast, a normal level of DT represents the long-term impact of sustainable digital technology growth, aligning with the overall business strategy as a strategic measure. Thus, we propose the following hypothesis:

Hypothesis 2a. Normal DT positively impacts a firm GTFP in the long term.

Hypothesis 2b. Excessive DT positively impacts a firm GTFP in the short term.

4. Model and variable description

4.1. Basic model

To assess how digital transformation affects corporate GTFP, this study constructed the following econometric model:

$$GTFP_{it} = \alpha_0 + \alpha_1 DT_{it} + \alpha_2 Controls_{it} + \lambda_t + \mu_t + \varepsilon_{it} \tag{1}$$

The regression also controlling for year and firm fixed effects. Standard errors are clustered at the firm level. We are interested in the estimated coefficient of DT. If GTFP decreases (increases), then we expect α1 to be negative (positive), which verifies our hypothesis.

4.2. Variables choosen

Due to the implementation of revised accounting standards in 2007, the comparability of enterprise data during this period is compromised. The sample period under consideration for our analysis spans from 2007 to 2021. All data are collected from the *China Statistical Yearbook* and the *Provincial Statistical Yearbooks*, *China Energy Statistical Yearbook*, *China Statistical Yearbook of Environment*, *China Statistical Yearbook of Science and Technology*, and *China Stock Market and Accounting Research (CSMAR)* database. Firms with missing data, firms in financial industries, and firms with special treatment, including ST (special treatment) and PT (particular transfer), have been eliminated from the sample. All continuous variables are winsorized at the 1 % level for both tails. The final sample contains 2,870 firms with 26824 firm-year observations.

4.3. Variable construction

4.3.1. Dependent variable: green total factor productivity (GTFP)

Building upon prior scholars' research [1,2,27,15,30,45,53], this study integrates the SBM model with the Super-Efficiency Data Envelopment Analysis (Super-SBM model) to measure GTFP. This innovative approach offers heightened flexibility and precision in handling non-convexity, facilitating multidimensional assessments, and optimizing weight allocations. The comprehensive procedure for constructing variables is as follows.

The super-efficient Slacks-based Measure (SBM) model is widely used in GTFP measurement and effectively solves the problem of multiple valid decision units that the standard SBM model cannot address. This study uses the Malmquist production index method to measure the GTFP of enterprises. Under the assumption that all input-output vectors satisfy the non-zero hypothesis, the production possibility set can be defined as follows:

$$P = \left\{ (x, y^d, y^u) \Big/ x_{jtm} \geq \sum_{j=1}^{n} \eta_{it} x_{jtm}, {y_{jtn_1}}^d < \sum_{j=1}^{n} \eta_{jt} {y_{jtn_1}}^d, {y_{jtn_2}}^u \leq \sum_{j=1}^{n} \eta_{jt} {y_{jtn_2}}^u, \sum_{j=1}^{n} \eta_{jt} = 1 \ , \ \eta_{jt} \geq 0 \right\} \tag{2}$$

where M-dimensional input variable $x_{it} = (x_{1it}, \ldots, x_{Mit})$, N1-dimensional desired outputs $y^d_{it} = (y^d_{1it}, \ldots, y^d_{N1it})$, and N2-dimensional undesired outputs $y^u_{it} = (y^u_{1it}, \ldots, y^u_{N2it})$, η is the weight of cross-sectional input and output data, and it is non-negative.

The mathematical form of the GTFP for the super-efficiency SBM model [34] with undesired outputs can be expressed as shown：

$$\min \rho = \frac{\frac{1}{M} \sum_{k=1}^{M} \frac{x}{x_{jk}}}{\frac{1}{N_1 + N_2} \left(\sum_{r_1=1}^{N_1} \frac{y^d}{{y_{jr_1}}^d} + \sum_{r_2=1}^{N_2} \frac{y^u}{{y_{jr_2}}^u} \right)}$$

$$s.t.\ x \geq \sum_{i=1,\neq j}^{n} x_{ki} \eta_i;\ y^d \leq \sum_{i=1,\neq j}^{n} {y_{r_1 i}}^d \eta_i;\ y^u \leq \sum_{i=1,\neq j}^{n} {y_{r2i}}^u \eta_i;\ x \geq x_j\ ;\ y^d \leq {y_j}^d; y^u \leq {y_j}^u;\ \sum_{i=1,\neq j}^{n} \eta_i \tag{3}$$

where p represents the target super efficiency value, η is the weight vector, subscript j is the decision unit.

The super-SBM score as the foundational index to measure the GTFP of listed companies using the Malmquist index. It can be represented as follows:

$$GTFP_t^{t+1} = \frac{1 + S_V^G(x_t, y_t^d, y_t^u;\ y_t^d, -y_t^u)}{1 + S_V^G(x_{t+1}, y_{t+1}^d, y_{t+1}^u;\ {y^d}_{t+1}, -y_{t+1}^u)} \tag{4}$$

The measurement of the Malmquist index can be decomposed into GECI and GTPI. The specific decomposition of the Malmquist index is as follows:

$$GTFP_t^{t+1} = GECI_t^{t+1} \times GTPI_t^{t+1} \tag{5}$$

$$GECI_t^{t+1} = \frac{1 + S_V^t(x_t, y_t^d, y_t^u;\ y^d{}_t, -y_t^u)}{1 + S_V^{t+1}(x_{t+1}, y_{t+1}^d, y_{t+1}^u;\ y^d{}_{t+1}, -y_{t+1}^u)} \tag{6}$$

The input and output indicators for calculating the GTFP are presented in Table 1. This paper employed the Super-SBM method, as delineated in Models (2)–(6), to compute the growth rate of GTFP.

4.3.2. Independent variable: digital transformation (DT)

In this research, we collected and organized the annual reports of all A-share listed companies on the *Shanghai and Shenzhen Stock Exchanges* using Python crawlers. We used the Java PDFbox library to extract text content from these reports and created a data pool for keyword screening. Drawing from a series of classic literature on digital transformation [54]. Finally, we conducted searches, matching, and word frequency counting based on the identified keywords using the data pool extracted from the annual reports of listed companies. The total word frequencies were summed up and the natural logarithm was taken as the standard to measure the degree of corporate digital transformation.

4.3.3. Control variable

Following the usual specification in the research on the *GTFP* [1,2,27]; [16,55,56], we also create a set of control variables, including firm size (*Size*), board size (*Board*), firm listing age (*Age*), largest shareholding ratio (*Top1*), return on total assets (*ROA*), leverage (*Lev*), cash flow ratio (*Liq*), Operating income growth rate *(Growth*), to enhance the empirical results. To reduce the influence of outliers, continuous control variables are treated with a 1 % tail reduction. The definitions of each variable are shown in Table 2.

5. Empirical results

5.1. Descriptive statistics and spatiotemporal variation of variables

Table 3 provides the summary statistics for all variables used in the baseline regression Eq. (1). For the dependent variables, the sample firms' mean (max) values for GTFP, GECI, and GTPI are 0.989 (1.375), 1.001 (1.216), and 0.988 (1.375), respectively. The average for DT is 1.027, respectively. For the control variables, the mean values of Size and Board are 22.33 and 2.153, respectively. A typical firm in our dataset has a Top1 of 35.64, an Age of 2.304, and ROA of 0.04，an Growth of 0.185. The mean Cash and Lev are 0.049 and 2.943, respectively.

To assess multicollinearity among variables, we computed Variance Inflation Factors (VIF), with VIF values of explanatory variables not exceeding 5. Furthermore, Table 4 presents the correlation matrix of all explanatory factors under study. Correlation matrix analysis was conducted to verify the presence of multicollinearity among explanatory factors. The correlation between *Growth* and *DT* was the lowest at 0.004, while the correlation between *Cash* and *ROA* was the highest at 0.389. Hence, based on the results from the correlation matrix and VIF, there is no strong correlation among explanatory variables, indicating the absence of multicollinearity issues.

Fig. 2 illustrates the annual mean trends of *GTFP* and *DT*, revealing a cyclical pattern with an upward trend for *GTFP* and a more pronounced increase for *DT*. Overall, the trends of *DT* and *GTFP* remain consistent over time. Additionally, We employed Python to create a heatmap depicting the mean *GTFP* and *DT* values from 2007 to 2021.

Fig. 3a showcases notable *GTFP* levels achieved by companies across regions. Particularly, *GTFP* demonstrates a gradual decline trend from southeast coast companies towards those in the west and north, with coastal areas showing higher performance compared to northern inland firms. Fig. 3b reveals the continued diffusion of *DT* from developed companies in the east towards central and western regions, presenting an opportunity for economic development in northwestern Chinese companies and contributing to the narrowing of development gaps. Upon examining both figures, a noticeable similarity in the regional distribution of *GTFP* and *DT* among corporations emerges, suggesting a potential correlation.

Table 1
Input and output indicators in the GTFP measurement.

Type	Variable	Definition
Input	Capital input	Ct=(1-δ) × Ct-1+It/Pt
	Labor input	Number of employees
	Energy input	(Company operating costs × Total industry energy input)/Total industry operating costs
Desired output	Enterprise output	Company operating income
Undesired output	SO2 emission	(Company revenue × Industry SO2 emissions)/Total industry revenue
	Other waste emissions	(Company revenue × Industry other waste gas emissions)/Total industry revenue
	Solid waste emissions	(Company revenue × Industry solid waste emissions)/Total industry revenue

Note: The capital input in this table was estimated by employing the perpetual inventory method to assess the capital stock. Let C denote the capital stock, where the base-year capital stock is equal to the total fixed capital formation in the base year divided by 10 %. Let δ denote the depreciation rate, which is set at 5 %. Let It denote fixed asset investment and let Pt denote the provincial fixed asset investment price index. We obtain the mathematical expression for the capital stock as Ct=(1-δ) × Ct-1+It/Pt. Furthermore, in this study, missing energy input and unexpected output data at the firm level were estimated by using industry-level data and other micro-level enterprise data.

Table 2
Variable definitions.

Variable	Abbr.	Definition
Firm size	*Size*	Natural logarithm of total assets
Leverage	*Lev*	Ratio of total liabilities to total assets
Return on total assets	*ROA*	Ratio of net income to total assets
Cash flow ratio	*Cash*	Ratio of net cash flows to current liabilities
Operating income growth rate	*Growth*	Ratio of the difference between the current year's operating revenue and the previous year's operating revenue to the previous year's operating revenue
Board size	*Board*	Natural logarithm of the number of directors on the board
Top1 shareholding	*Top1*	Ratio of shares held by the largest shareholder
Firm listing age	*Age*	Natural logarithm of 1 plus the number of listing years

Table 3
Descriptive statistics.

VARIABLES	Obs	Mean	Std. Dev.	Min	Median	P75	Max
GTFP	26,824	0.989	0.0396	0.702	0.967	1.009	1.375
GECI	26,824	1.001	0.0461	0.809	0.971	1.030	1.216
GTPI	26,824	0.988	0.0331	0.769	0.967	1.007	1.375
DT	26,824	1.027	1.243	0	0	1.792	6.140
Size	26,824	22.33	1.348	18.16	21.39	23.09	27.96
Lev	26,824	2.943	2.355	0.303	1.628	3.246	23.58
ROA	26,824	0.040	0.063	−0.436	0.013	0.068	0.361
Cash	26,824	0.049	0.073	−0.332	0.010	0.091	0.380
Growth	26,824	0.185	0.535	−0.868	−0.0219	0.265	7.671
Board	26,824	2.153	0.200	1.609	2.079	2.197	2.833
Top1	26,824	35.64	15.18	7.932	23.62	46.33	76.44
Age	26,824	2.304	0.721	0.693	1.792	2.890	3.401

Table 4
Correlation matrix.

VARIABLES	DT	Size	Lev	ROA	Cash	Growth	Board	Top1	Age
DT	1.000								
Size	0.163	1.000							
	(0.000)								
Lev	0.006	−0.324	1.000						
	(0.324)	(0.000)							
ROA	0.011	0.031	0.224	1.000					
	(0.071)	(0.000)	(0.000)						
Cash	−0.003	0.049	0.097	0.389	1.000				
	(0.594)	(0.000)	(0.000)	(0.000)					
Growth	−0.004	0.037	−0.049	0.215	0.027	1.000			
	(0.476)	(0.000)	(0.000)	(0.000)	(0.000)				
Board	−0.077	0.215	−0.115	0.025	0.049	−0.012	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.056)			
Top1	−0.073	0.206	−0.027	0.131	0.082	0.033	0.026	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Age	0.034	0.298	−0.219	−0.178	−0.040	−0.021	0.067	−0.118	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	

5.2. The effect of DT on GTFP

We first estimate the baseline model, as shown in *Eq. (1)*, by utilizing the regression model and considering the year and firm fixed effects. Columns (1) in Table 5 is the regression results without adding control variables. We find that the coefficient of corporate GTFP is significantly positive at the 1 % level. Again, the coefficient is statistically significant and positive with the addition of control variables, as shown in Columns (2). The significance is at a 1 % level, showing that *DT* can promote corporate *GTFP*. *DT* can help companies to effectively mitigate information asymmetry and reduce management costs, and thus produce in a more environmentally friendly manner. This result confirms our Hypothesis 1 that *DT* leads to better *GTFP*. Regarding the control variables, the evidence reveals that *Broad* and *Top1* are positively related to *GTFP*, while the effects of *Size* and *Lev* are negative. These results are consistent with those of previous studies [29,30].

To gain further insights into *GTFP,* this paper decomposed it into *GECI* and *GTPI* and carried out regression. Columns (3) and (4) summarize the results for the *GECI* and *GTPI* groups, respectively. The significant positive correlation between *DT* and the GECI suggests digitization significantly contributes to optimizing resource utilization, enhancing production efficiency, and reducing

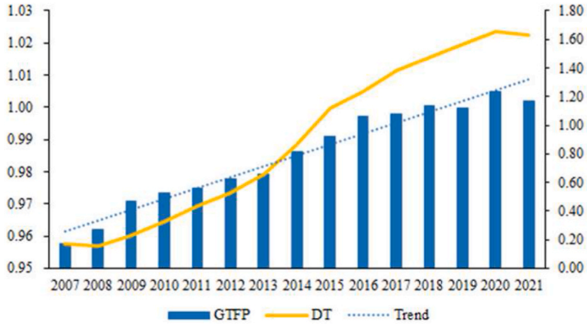
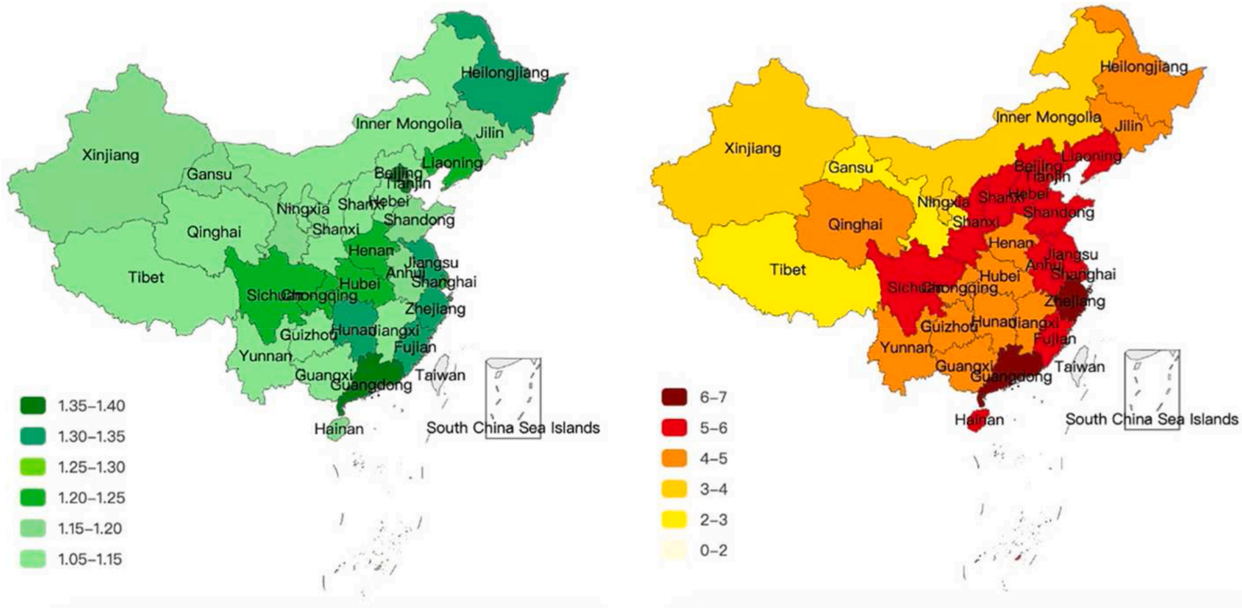


Fig. 2. Temporal variation of DT and GTFP of Chinese listed companies.



a. Spatial distribution of GTFP b. Spatial distribution of DT

Fig. 3. Spatial distribution of China's GTFP and DT over 2007–2021.

environmental pollution within enterprises. Moreover, the adoption of digital technologies can mitigate environmental impacts during production, resulting in decreased emissions and consequently, improved green efficiency. However, the positive effect of DT on the GFPI is not significant. This could be attributed to digitization primarily affecting production and resource utilization efficiency, with a relatively smaller effect on driving green technological progress. Furthermore, other factors such as policy support may also influence green technological progress, potentially reducing the degree of impact exerted by digitization.

5.3. Robustness tests

To further ensure whether the findings are sensitive to different measures of digital transformation, we also replicate the analysis by using two other methods of *DT* index. The first method was proposed by [37]. The DT_1 index is calculated by dividing the total frequency of digitalization-related terms by the length of the MD&A section in the annual report. Another method to address potential biases resulting from the intentional and expected use of keywords in annual reports, we followed the approach proposed by Liu and Tian [28] and computed the DT_2 index to measure the level of digital transformation based on the proportions of software and digital hardware investments in total assets. This approach provides a more intuitive reflection of the level of digital transformation investment made by companies. Columns (2)–(3) in Table 6 show the estimation results with DT_1 and DT_2. The results did not change substantially and were generally consistent with the baseline regression. The impact of corporate digital transformation is still significantly positive.

To alleviate the potential disturbance of endogenous on regression results and to take into account the temporal nature of the impact of digital transformation on a firm's *GTFP*, this article employs the lagged value of the explanatory variable in the regression.

Table 5
Effect of DT on GTFP.

VARIABLES	(1)	(2)	(3)	(4)
	GTFP	*GTFP*	*GECI*	*GPTI*
DT	0.0013***	0.0011***	0.0007*	0.0004
	(6.874)	(3.379)	(1.922)	(1.613)
Size		−0.0053***	−0.0040***	−0.0013***
		(-9.947)	(-7.561)	(-3.854)
Lev		−0.0008***	−0.0006***	−0.0001
		(-4.485)	(-3.548)	(-1.227)
ROA		−0.0082	−0.0080	−0.0012
		(-1.496)	(-1.309)	(-0.285)
Cash		−0.0016	−0.0035	0.0017
		(-0.373)	(-0.716)	(0.478)
Growth		−0.0004	−0.0001	−0.0003
		(-0.803)	(-0.112)	(-0.772)
Board		0.0061***	0.0056**	0.0004
		(2.904)	(2.465)	(0.286)
Top1		0.0001***	0.0001***	0.0000
		(3.162)	(2.739)	(0.522)
Age		0.0016	0.0010	0.0007
		(1.491)	(0.847)	(0.923)
Constant	0.9577***	1.0535***	1.0679***	0.9879***
	(805.24)	(88.235)	(87.659)	(126.66)
Observations	26,824	26,824	26,824	26,824
Number of firms	2,870	2,870	2,870	2,870
Adjusted R-squared	0.113	0.117	0.025	0.116
Year FE	YES	YES	YES	YES
Company FE	YES	YES	YES	YES

Notes: The t-statistics clustered by firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 6
Robustness test.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	GTFP	*GTFP*	*GTFP*	*GTFP*	*GTFP*
DT	0.0011***				0.0011***
	(3.379)				(3.407)
DT1		0.0011**			
		(2.023)			
DT2			0.0010***		
			(3.032)		
LagDT				0.0006*	
				(1.781)	
GDP					−0.0001
					(-0.774)
ER					0.1640
					(0.797)
Observations	26,824	26,144	26,791	22,476	26,824
Number of firms	2,870	2,861	2,869	2,694	2,870
Adjusted R-squared	0.117	0.116	0.117	0.100	0.118
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Company FE	YES	YES	YES	YES	YES

Notes:The t-statistics clustered by firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

The results indicate a statistically significant positive coefficient, as shown in column (4).

Some studies have suggested using regional per capita GDP as a control variable to determine whether there is an Environmental Kuznets Curve (EKC) relationship between economic development level and *GTFP* [1,2,27]. Regions with higher economic development levels may have more advanced infrastructure and resource allocation systems, providing better support conditions for enterprises to effectively undergo digital transformation and implement green production methods. Furthermore, according to the "pollution haven" hypothesis, local governments may lower environmental standards to attract investment, resulting in competition disparities among regions [56]). Less developed regions may tend to lower environmental standards, while more developed regions typically choose to raise environmental standards [3]. We use the natural logarithm of the number of urban environmental legislation as a measure of the impact of local environmental regulation [1,2,27]. Therefore, by controlling for regional economic levels (*GDP*) and environmental regulation (*ER*), it is possible to mitigate the influence of disparities among regions on the relationship between *DT* and *GTFP*, thereby more accurately assessing the impact of digital transformation on *GTFP*. Despite adjusting for regional economic status and environmental regulations, Columns (5) show *DT* still significantly enhances enterprise GTFP, confirming the robustness of the baseline regression results.

5.4. Endogenous problem

Despite incorporating lagged core explanatory variables and substituting explanatory variables in robustness tests, endogenous issues persist in the analysis, particularly the reverse causality problem. This suggests that firms with high levels of *GTFP* are likely to be sustainable environmental companies, enabling them to invest more in digital transformation. This reverse causality creates a feedback loop between digital transformation and *GTFP,* making it difficult to establish a clear cause-and-effect relationship.

To overcome these challenges, we adopted the approach of [2], which utilizes pivotal external events in driving digital transformation to construct the DID test. Specifically, we adopt a quasi-natural experimental research strategy by leveraging the "*Broadband China*" demonstration site digital transformation policy shock [57]. We employed a multi-period DID model as specified in Eq. (7). Our control variables for firm-specific characteristics include all the control variables in the basic regression. The results of the DID model, as presented in column (1) of Table 5, demonstrate a significant increase in GTFP after their respective cities became "Broadband China" demonstration sites.

$$GTFP_{it} = \beta_0 + \beta_1 DID_{it} + \beta_2 Controls_{it} + \lambda_t + \mu_t + \varepsilon_{it} \tag{7}$$

Taking into account the potential bias in treatment group and control group, we also employed the Propensity Score Matching Method (PSM). The matching method uses a logit model to perform a one-to-one nearest-neighbor PSM. Our control variables for firm-specific characteristics include all the control variables in the basic regression. To evaluate the effectiveness of the matching procedure, we conducted equilibrium tests. The results revealed that none of the covariates displayed significant differences, ensuring greater similarity between the treatment and control groups after matching. Column (2) in Table 7 presents the estimated results for the matched firms. The results reveal that the effect of *DT* on GTFP is still significantly positive after excluding the differences in the characteristics between the treatment and control samples, hence further validating our conclusion.

To further mitigate the endogeneity problem, we also used the instrumental variables (IV) approach. Following the approach of Han et al. [4], the paper preliminarily selects the cross-product of the number of fixed telephone lines per 10,000 individuals in each city in 1984 and the nationwide number of internet users in the previous period as the instrumental variable for corporate DT. The 2SLS outcomes in Table 8 display its diagnostics tests. First-stage F-value of 117.73, and both Cragg-Donald Wald F statistics exceed the corresponding Stock-Yogo critical values, allowing us to reject the null hypothesis of weak instrument validity. Moreover, Anderson canonical correlation LM test statistics exhibit p-values below 0.1, indicating the rejection of the hypothesis of inadequate instrument relevance. Additionally, the Hansen-J test p-values are below 0.1. Collectively, from a statistical standpoint, the instrumental variables satisfy the requirements of relevance and exogeneity. In the second stage, the DT coefficient is significant at least at the 10 % level, with the sign consistent with the baseline regression. This indicates that even after adjusting for the potential influence of omitted variables, the positive effect of DT fostering GTFP within firms, particularly in terms of increasing innovation inputs and outputs, remains evident. This further corroborates Hypothesis 1.

5.5. Excess and normal DT

Based on the unique characteristics of each firm, there may exist a normal level of *DT*. The impact of both normal and excessive levels of *DT* on a firm's *GTFP* may vary. To quantify these two types of *DT*, we employ the following model:

$$DT = \xi_0 + \xi_1 Controls_{it} + \lambda_t + \mu_t + \varepsilon_{it} \tag{8}$$

The control variables in Eq. (8) are the same as the main regression. Next, we estimate Eq. (8) to obtain predicted values representing the normal level of *DT* (referred to as "*NORM*") for each company. The residuals from Eq. (8) capture the abnormal level of *DT* (referred to as "*EXCESS*").

Table 7
Endogeneity problem: PSM-DID.

VARIABLES	(1)	(2)
	GTFP	*GTFP*
DID	0.0025***	0.0028*
	(3.064)	(1.721)
Observations	26,824	12,961
Number of firms	2,870	2,724
Adjusted R-squared	0.117	0.097
Controls	YES	YES
Year FE	YES	YES
Company FE	YES	YES

Notes:The t-statistics clustered by firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 8
Endogeneity problem: Instrumental variables approach.

VARIABLES	(1)	(2)
	DT	*GTFP*
IV	0.2164***	
	(2.864)	
DT		0.0215*
		(1.721)
Observations	24,804	24,804
Number of id	2,653	2,653
Adjusted R-squared	0.370	0.123
Controls	YES	YES
Year FE	YES	YES
Company FE	YES	YES

Notes: The t-statistics clustered by firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

We incorporate both current and future periods' *GTFP* to capture the effects of normal and abnormal levels of *DT*. The research findings are presented in Table 9. When using *EXCESS* as the explanatory variable, we observe that the coefficient is significantly positive only for the current period's GTFP. However, in the subsequent period, the coefficient is not statistically significant, indicating that the beyond the normal level of *DT* contributes to short-term performance improvement. Abnormal DT effectiveness diminishes in the long run. For the results using *NORM* as the explanatory variable in columns (4) to (6), the coefficients are not statistically significant for the current $period_t$ but become significantly positive for $periods_{t+1}$ and $periods_{t+2}$. This suggests that *NORM* captures the firms' normal utilization of *DT*, which enhances their long-term performance but may not have an immediate impact on *GTFP*.

5.6. Additional analysis

In our hypothesis development, digital transformation is posited as a strategic business approach aimed at operational transformation. The inherent mechanisms of digital transformation are contingent upon its defining characteristics. Effective digital transformation, thus, augments green innovation, investment efficiency, and internal control systems, consequently enhancing GTFP. Our overarching expectation is for companies to demonstrate enhanced GTFP performance subsequent to digital transformation implementation. To empirically substantiate innovation, investment efficiency, and internal controls as the intrinsic pathways through which digital transformation influences a company's GTFP, we adopt Baron and Kenny's [58] sequential testing methodology to investigate Equation (9).

$$X_{it} = \gamma_0 + \gamma_1 DT_{it} + \gamma_2 Controls_{it} + \lambda_t + \mu_t + \varepsilon_{it}$$

$$GTFP_{it} = \lambda_0 + \phi_1 DT_{it} + \phi_2 X_{it} + \phi_3 Controls_{it} + \lambda_t + \mu_t + \varepsilon_{it} \tag{9}$$

Comprehending the intricate relationship between digital technologies and green innovation requires a nuanced understanding of the co-evolution between digital technology trajectories and firm innovation routines [7,8,35]. DT offers a solution to the innovation dilemma by enhancing innovation efficiency and augmenting the capacity for absorption and transformation [37]. Through digital technologies, firms can swiftly respond to market needs, tap into green demands, adapt product green innovation strategies in real-time, identify environmental market opportunities, and improve overall green innovation efficiency [36,59]. Furthermore, DT can align lenders' risk preferences with the characteristics of corporations' green technology innovation projects, facilitating efficient fund allocation and enhancing digital finance's support for green technology innovation [9]. To further explore the mechanisms underlying green innovation within the DT paradigm, we adopt the ratio of total green patent applications to total patent applications as a metric

Table 9
The effect of normal and excessive DT on firm GTFP.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	$Period_t$	$Period_{t+1}$	$Period_{t+2}$	$Period_t$	$Period_{t+1}$	$Period_{t+2}$
NORM	0.0591***	0.0083*	0.0064*			
	(23.129)	(1.844)	(1.829)			
EXCESS		0.0083*		0.0011***	0.0005	0.0004
		(1.844)		(3.379)	(1.482)	(1.013)
Observations	26,824	23,488	20,643	26,824	23,488	20,643
Number of firms	2,870	2,715	2,627	2,870	2,715	2,627
Adjusted R-squared	0.117	0.106	0.090	0.117	0.106	0.090
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Company FE	YES	YES	YES	YES	YES	YES

Notes: The t-statistics clustered by firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

for assessing firm green innovation.

Table 10 presents the estimation results. Column (1) show that *DT* significantly promotes green innovation (GI) level of firms. The coefficient of *GI* in column (2) is significantly positive at the 5 % level, while the coefficient of *DT* decreases to a certain extent both in value and significance. In other words, the impact of *DT* on *GTFP* is more evident when the innovation level is higher, suggesting that *DT* could help stimulate green innovation to increase firms' *GTFP*.

Previous research has established that *DT* can alleviate financing constraints [51]. The advancement of *DT* facilitates a faster credit approval process and lowers the entry barriers to credit markets; consequently, enterprises can access convenient financing services and diverse funding sources, thereby stimulating their investment activities [11]. Moreover, Information asymmetry often results in external capital sources misvaluing investment projects, leading to a misalignment of investments and inefficient allocation of resources [10]. Given the importance of investment efficiency in corporate productivity, we also explore its impact on the positive relationship between *DT* and *GTFP*. We use the error term of investment model proposed by Richardson [60] using as a proxy for investment efficiency.

In Table 11, columns (1)–(2) show the regression results for the investment efficiency of the full sample of firms. The *DT* regression coefficient in column (2) is positive and significant. The regression coefficients of *DT* and IE in column (2) are significantly positive. This result indicates that investment efficiency enhances the role of DT in promoting *GTFP*.

Digitization can increase information transparency between managers and the board of directors, and thus enable the firm to play its full role as a governance mechanism allowing the board of directors and stakeholders to take decisions[10]. In addition, under effective internal government, corporate managers are more likely to perform social responsibilities more actively, thus helping improve corporate environmental protection investment and sustainability [52]. This viewpoint aligns with the findings of Ha [11], who argue that within a framework of robust internal controls, digital transformation can play a more meaningful role in fostering green innovation. Therefore, sufficient internal supervision can be achieved to delve further into the internal governance (*IG*) mechanism of action between *DT* and *GTFP*, this paper evaluates the decision-making capacity of corporations regarding their production and operational governance by utilizing the *DiBo-China Internal Control Index* as a positive characterization indicator.

We present the findings in Table 12. The results in columns (1)–(2) are significant at the 5 % level and carry the expected signs. In column (1), the coefficient indicates corporates with a higher degree of *DT* has a higher *IC* Index. Then, in columns (2), the coefficient of *IC* is positively significant at 5 % while the coefficients of *DT* are lower than that of basic regression. Thus, the influence of *DT* on improving internal governance within corporations, thereby mitigating unnecessary resource consumption and enhancing green total factor productivity.

5.7. Heterogeneity analysis

5.7.1. SOEs and non-SOEs

Scholars and practitioners have highlighted that ownership influences firms' behavior and performance [1]. From the perspective of green production, SOEs are inefficient in resource allocation and backward in technological innovation because of a lack of incentives [61]. Compared to private enterprises, SOEs can obtain more government support from both fiscal and political aspects. They enjoy implicit or explicit loan guarantees, which allow them to better access external capital [18]. This competitive advantage may lead to a more bureaucratic and inflexible management system in state-owned enterprises, which may lack innovation and flexibility and result in lower green production efficiency [62]. As a result, executives may make inefficient and high-polluting decisions to achieve these objectives. In contrast, the shareholders of non-SOEs tend to establish a more effective incentive and supervision mechanism to enhance the degree of the efficiency of factor production to achieve more low-energy production and innovative incentive mechanisms, which may lead to green production. Based on this exposition, we hypothesize that the impact of the *DT* on *GTFP* varies between SOEs and non-SOEs.

Table 13 presents the effects of the separate estimations for SOEs and non-SOEs. Columns (1) reveal that the impact of DT for SOEs is insignificant, while the estimated coefficients for non-SOEs in columns (2) are significantly positive. These results suggest that digital

Table 10
The role of innovation.

VARIABLES	(7)	(8)
	GI	*GTFP*
DT	0.0224***	0.0010***
	(3.490)	(3.138)
GI		0.0010**
		(1.987)
Observations	26,824	26,824
Number of firms	2,870	2,870
Adjusted R-squared	0.032	0.119
Controls	YES	YES
Year FE	YES	YES
Company FE	YES	YES

Notes: The t-statistics clustered by firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 11
The role of investment efficiency.

VARIABLES	(1)	(2)
	IE	*GTFP*
IE		0.0082***
		(2.627)
DT	0.0020**	0.0009***
	(2.092)	(2.667)
Observations	23,549	23,549
Number of firms	2,718	2,718
Adjusted R-squared	0.134	0.121
Controls	YES	YES
Year FE	YES	YES
Company FE	YES	YES

Notes: The t-statistics clustered by firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 12
The role of internal governance.

VARIABLES	(1)	(2)
	IG	*GTFP*
IG		0.0001**
		(2.136)
DT	0.1540**	0.0007**
	(2.174)	(2.339)
Observations	26,725	26,725
Number of id	2,868	2,868
Adjusted R-squared	0.596	0.121
Controls	YES	YES
year FE	YES	YES
company FE	YES	YES

Notes: The t-statistics clustered by firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

transformation has a more evident impact on promoting the corporate green production efficiency of non-SOEs. Huo and Wang [10] also show that the impact of *DT* on the investment efficiency of private enterprises is more pronounced than that of SOEs. Possible reason is that in the digital era, information becomes more readily accessible and disseminated, encouraging greater collaboration among enterprises and reducing information asymmetry. This, in turn, facilitates more transparent and honest corporate green investment, promoting sustainable corporate business development.

5.7.2. High-tech firms and non-high-tech firms

Intuitively, high-tech firms have a superior innovation resource base and a greater demand for technological innovation research and development [18]. This emphasis on technological innovation can enable high-tech firms to fully leverage their advantages, facilitating digital transformation and accelerating the comprehensive reform of production modes, corporate structures, and business models. Consequently, such efforts can drive improvements in the total factor productivity of high-tech firms [1]. Furthermore, high-tech firms place greater emphasis on sustainability and environmental protection, with a particular focus on sustainability and social responsibility. In this regard, digital transformation can enable companies to adopt more sustainable and environmentally production methods.

Therefore, the impact of *DT* on *GTFP* is expected to be higher for corporations with high-tech firms than non-high-tech firms. To examine this hypothesis, the research samples are divided into high-tech firms and non-high-tech firms according to the dependence of companies on technological innovation by referring to the Guidelines on Industry Classification of Listed Companies (2012 revision). Columns (1) and (2) in Table 14 are based on high-tech and non-high-tech firms, respectively. The research findings indicate that compared to non-high-tech companies, high-tech enterprises are significantly more influenced by the effects of digital transformation, with more pronounced coefficients.

5.7.3. Heterogeneity of geographical areas

Existing research has demonstrated that, in cities with a high level of economic development and infrastructure, the adoption of digital transformation can synergistically enhance the cross-regional flow and agglomeration of factors, resulting in further optimization of corporate internal governance. In order to investigate regional differences in *DT* on *GTFP*, based on previous findings [44], we categorize the sample into companies located in the eastern, central, and western regions of China. The regression results, as presented in Table 15, columns (1) to (3), indicate that *DT* has a significant impact on the *GTFP* of companies in the eastern region at a 1 % level,

Table 13
Heterogeneity analysis: SOEs and non-SOEs.

VARIABLES	SOEs	Non-SOEs
	GTFP	GTFP
DT	0.0007	0.0015***
	(1.476)	(3.187)
Observations	12,489	14,335
Number of firms	1,208	1,958
Adjusted R-squared	0.137	0.090
Controls	YES	YES
Year FE	YES	YES
Company FE	YES	YES

Notes: The t-statistics clustered by firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 14
Heterogeneity analysis: high-techs and non-high-techs.

VARIABLES	High-techs	Non-high-techs
	GTFP	GTFP
DT	0.0014***	0.0008*
	(2.785)	(1.842)
Observations	9,848	16,976
Number of firms	1,254	1,930
Adjusted R-squared	0.105	0.114
Controls	YES	YES
Year FE	YES	YES
Company FE	YES	YES

Notes: The t-statistics clustered by firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

while its effect on companies in the central and western regions is not statistically significant.

This finding suggests that the eastern region's superior digital infrastructure, financial development, and human capital compared to the central and western regions facilitate corporate digital transformation. Its growing Internet popularity attracts talent from other regions, enhancing its human capital structure. However, the central and western regions struggle with acquiring high-level human capital due to the Matthew effect. Additionally, the eastern region benefits from a more supportive policy environment, with greater governmental emphasis on environmental protection and sustainable development, providing policy support for digital transformation and green production.

6. Conclusion

6.1. Discussion

Enterprise green production has attracted significant research attention due to its objective of integrating economic development, resource utilization, and environment preservation. This paper selects Chinese-listed firms from 2007 to 2021 as research samples. Using text analysis techniques and the super-SBM model to construct main variables, we delve into the correlation and underlying

Table 15
Heterogeneity analysis: eastern, central and western regions.

VARIABLES	Eastern	Central	Western
	GTFP	GTFP	GTFP
DT	0.0014***	−0.0002	0.0008
	(3.609)	(-0.218)	(0.860)
Observations	17,944	5,294	3,148
Number of firms	2,027	526	321
Adjusted R-squared	0.115	0.123	0.115
Controls	YES	YES	YES
Year FE	YES	YES	YES
Company FE	YES	YES	YES

Notes: The t-statistics clustered by firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

mechanisms between DT and GTFP. Firstly, we conduct a thorough comparison and discussion of our study's findings with previous research results, elucidating the additional value our study contributes to existing literature.

(1) The main test results show that DT has a significant effect on firms' GTFP. Furthermore, we decompose GTFP into the GECI and GTPI to further examine the specific impact of DT on GTFP. The research demonstrates that digitization optimizes resource use, boosts production efficiency, and cuts environmental pollution. It mainly impacts production and resource use efficiency, with less effect on green technology progress. This is consistent with most literature, indicating that digitization reduces information asymmetry, lowers management costs, and encourages green production. However, some studies suggest that enterprises may need to reallocate factor production during the process of DT. This may squeeze investments in green production, as companies may be more inclined to allocate resources to achieve more direct economic returns. This study responds to these concerns and identifies the following: digitization can more comprehensively coordinate the enterprises' conditions and policy requirements, improve internal governance, and thus significantly mitigate the adverse impact of DT on GTFP.
(2) The mechanism test results indicate that DT promotes GTFP by enhancing green innovation, investment efficiency, and internal governance. This significantly enhances existing literature, emphasizing green innovation as a pivotal driver for sustainable green development, with green production being more intricate and yielding longer-term value compared to other technological innovation processes. Digitization effectively mitigates information asymmetry and financing constraints, boosting investment efficiency and enabling companies to flexibly adjust production to reduce resource waste and environmental pollution. Higher levels of DT enhance information transparency, facilitating decision-making by boards and stakeholders. Moreover, effective internal governance can encourage active fulfillment of social responsibilities, thereby boosting environmental investment and sustainability within the enterprise.
(3) Some scholars have previously found that digital transformation may lead to short-term economic benefits, such as increased production efficiency and reduced labor costs. However, green production often requires long-term investment with less immediate returns, leading companies to prioritize short-term gains over long-term environmental impacts. This study categorizes companies' digital transformation into normal and excessive types. Normal DT reflects a long-term overall green development strategy, while excessive DT reflects short-term, short-sighted behavior to comply with green policies, offering no long-term benefits for the company's green development.

Subsequently, this study conducted several robustness checks by using alternative measurement indicators, lagging explanatory variables, and adding control variables. We also employed PSM-DID and 2SLS methods for endogeneity tests to avoid sample selection bias and potential endogeneity issues from bidirectional causality. All results were consistent with the original findings, confirming the positive impact of digital transformation on firms' green total factor productivity. Lastly, we found that this effect is more pronounced for non-state-owned enterprises, high-tech firms, and companies located in coastal cities, thereby filling a micro-level gap in the research.

6.2. Policy recommendations

Promoting digital transformation and enhancing green production is crucial for manufacturing enterprises to advance industrial upgrading and support low-carbon, high-quality development. This paper provides several recommendations to achieve this goal, aiming to guide and motivate enterprises to increase green total factor productivity (GTFP) and effectively realize a sustainable strategy for economic and ecological development.

Firstly, enterprises should fully recognize digital transformation as a value-driven investment. For instance, Siemens have leveraged advanced data analytics and automation technologies to markedly enhance production efficiency and minimize waste. Manufacturers' strategic investment in digital technologies not only boosts production efficiency but also underpins green innovation, thereby enhancing overall competitiveness and supporting the achievement of the "dual carbon" goals. Viewing digitization as an investment in value rather than a cost is imperative. Companies like Tesla exemplify this approach by diligently adopting new development concepts, actively accelerating green transformation, and fulfilling their environmental and social responsibilities. Furthermore, digital transformation can improve internal governance efficiency, enhance decision-making transparency, and elevate management standards, thereby demonstrating comprehensive capabilities for sustainable development.

Secondly, government departments should enhance current digital policy frameworks and develop comprehensive long-term strategic plans for digital transformation. These plans should articulate clear digital objectives and pathways tailored to various industries. Germany's Industry 4.0 strategy exemplifies a detailed roadmap for integrating digital technologies across multiple sectors, thereby fostering cross-regional digital synergy. Policymakers must fully acknowledge the dual drivers of digitalization and sustainable production. By formulating scientifically sound policies aimed at reducing resource consumption and environmental pollution, governments can incentivize and support enterprises in leveraging digital technologies to boost production efficiency and environmental outcomes. The Chinese government's implementation of smart manufacturing policies serves as a notable example of this dual approach.

Thirdly, effectively leveraging both government intervention and market mechanisms is essential. Targeted funds and tax incentives can catalyze green technology innovation and energy conservation initiatives amid digital transformation efforts. For instance, the European Unions Horizon 2020 program has provided substantial funding for green technology projects, thereby promoting the integration of digital solutions in manufacturing. Furthermore, governments can proactively attract foreign investment to foster the development of green industries, thereby enhancing green total factor productivity (GTFP). The success of Singapore's

Economic Development Board (EDB) in drawing significant foreign investment into green technologies exemplifies this approach, significantly strengthening the nation's green production capabilities.

6.3. Limitations

In summary, while this paper addresses a gap in existing research regarding the impact of digitalization on green total factor productivity (GTFP), several questions remain unresolved, suggesting avenues for future investigation. Firstly, our findings are derived from a single country. It would be beneficial to examine additional emerging markets to validate these results. Secondly, as an initial exploration, this study employs a linear framework to quantitatively analyze the relationship between green finance development and green productivity. However, recent research has increasingly recognized the non-linearity in the interplay between economic factors and environmental outcomes [53,63]. Thirdly, although this study examines the influence of digital transformation on GTFP, it does not differentiate the impacts of various modes of digitalization on GTFP due to data limitations. Future research should address these gaps to provide a more comprehensive understanding of the dynamics at play.

Ethics statement

This study did not require ethics committee review and/or approval because it did not involve human or animal participation or the collection of sensitive personal information.

Informed consent is not required for this study because this study typically uses publicly available secondary data, such as published statistics, data from public databases, etc. These data are anonymized and are fully disclosed and shared.

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Xiantao Wang: Writing – original draft, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation. **Xiaofan Shi:** Writing – review & editing, Visualization, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] H. Wu, Y. Hao, S. Ren, How do environmental regulation and environmental decentralization affect green total factor energy efficiency: evidence from China, Energy Econ. 91 (2022) 104880.
[2] J. Wu, Q. Xia, Z. Li, Green innovation and enterprise green total factor productivity at a micro level: a perspective of technical distance, J. Clean. Prod. 344 (2022) 131070.
[3] R. Xie, Y. Yuan, J. Huang, Different types of environmental regulations and heterogeneous influence on "green" productivity: evidence from China, Ecol. Econ. 132 (2017) 104–112.
[4] D. Han, Y. Ding, Z. Shi, Y. He, The impact of digital economy on total factor carbon productivity: the threshold effect of technology accumulation, Environ. Sci. Pollut. Res. 29 (2022) 55691–55706.
[5] H. Zhai, M. Yang, K.C. Chan, Does digital transformation enhance a firm's performance? Evidence from China, Technol. Soc. 68 (2022) 101841.
[6] Fernández-Portillo Antonio, Manuel Almodóvar-González, Ricardo Hernández-Mogollón, Impact of ICT development on economic growth. A study of OECD European Union countries, Technol. Soc. 63 (2020) 101420.
[7] A. Usman, I. Ozturk, A. Hassan, The effect of ICT on energy consumption and economic growth in South Asian economies: an empirical analysis, Telematics Inf. 58 (2021) 101537.
[8] O. Usman, P.T. Iorember, G. Jelilov, A. Isik, G.N. Ike, S.A. Sarkodie, Towards mitigating ecological degradation in G-7 countries: accounting for economic effect dynamics, renewable energy consumption, and innovation, Heliyon 7 (2021) e08592.
[9] X. Hao, Y. Li, S. Ren, H. Wu, Y. Hao, The role of digitalization on green economic growth: does industrial structure optimization and green innovation matter? J. Environ. Manag. 325 (2023) 116504.
[10] P. Huo, L. Wang, Digital economy and business investment efficiency: inhibiting or facilitating? Res. Int. Bus. Finance 63 (2022) 101797.
[11] L.T. Ha, Effects of digitalization on financialization: empirical evidence from European countries, Technol. Soc. 68 (2022) 101851.
[12] Q. Xu, M. Zhong, X. Li, How does digitalization affect energy? International evidence, Energy Econ. 107 (2022) 105879.
[13] S. Chen, J. Golley, Green' productivity growth in China's industrial economy, Energy Econ. 44 (2014) 89–98.
[14] P. Tian, B. Lin, Promoting green productivity growth for China's industrial exports: evidence from a hybrid input-output model, Energy Pol. 111 (2017) 394–402.
[15] X. Zhan, R. Li, X. Liu, Fiscal decentralisation and green total factor productivity in China: SBM-GML and IV model approaches, Front. Environ. Sci. 10 (2022) 989194.
[16] Z. Zhao, J. Yan, The impact of investor sentiment on firms' green total factor productivity—facilitator or inhibitor? Environ. Sci. Pollut. Control Ser. 30 (2023) 70303–70314.
[17] D. Bai, J. Hu, M. Irfan, M. Hu, Unleashing the impact of ecological civilization pilot policies on green technology innovation: evidence from a novel SC-DID model, Energy Econ. 125 (2023) 106813.
[18] Z. Li, N. Li, H. Wen, Digital economy and environmental quality: evidence from 217 cities in China, Sustainability 13 (2021) 8058.

[19] H. Blichfeldt, R. Faullant, Performance effects of digital technology adoption and product and service innovation–a process industry perspective, Technovation 105 (2021) 102275.
[20] Y. Lyu, W. Wang, Y. Wu, J. Zhang, How does digital economy affect green total factor productivity? Evidence from China, Sci. Total Environ. 857 (2023) 159428.
[21] R.E. Miles, C.C. Snow, A.D. Meyer, Organizational strategy, structure and process, Acad. Manag. Rev. (3) (1978) 546–562.
[22] T.D. Lowe, I. Lorenzoni, Danger is all around: eliciting expert perceptions for managing climate change through a mental models approach, Global Environ. Change 17 (2007) 131–146.
[23] L. Zhu, Y. Hao, Z. Lu, H. Wu, Q. Ran, Do economic activities cause air pollution? Evidence from China's major cities, Sustain. Cities Soc. 49 (2019) 101593.
[24] Q. Ran, X. Yang, H. Yan, Natural resource consumption and industrial green transformation: does the digital economy matter? Resour. Pol. 81 (2023) 103396.
[25] J.A.G. Junior, C.M. Busso, S.C.O. Gobbo, H. Carreão, Making the links among environmental protection, process safety, and industry 4.0, Process Saf. Environ. Protect. 117 (2018) 372–382.
[26] B. Lin, R. Tan, Ecological total-factor energy efficiency of China's energy intensive industries, Ecol. Indicat. 70 (2016) 480–497.
[27] K. Wu, Y. Fu, D. Kong, Does the digital transformation of corporates affect stock price crash risk? Finance Res. Lett. 48 (2022) 102888.
[28] F. Liu, G. Tian, Does information technology replace employment? Evidence based on China's listed companies, Finance Econ. 376 (2019) 95–107.
[29] D. Liu, X. Zhu, Y. Wang, China's agricultural green total factor productivity based on carbon emission: an analysis of evolution trend and influencing factors, J. Clean. Prod. 278 (2021) 123692.
[30] Z. Cheng, W. Jin, Agglomeration economy and the growth of green total-factor productivity in Chinese Industry, Soc. Econ. Plann. Sci. 83 (2022) 101003.
[31] S. Zhong, J. Li, X. Chen, A multi-hierarchy meta-frontier approach for measuring green total factor productivity: an application of pig breeding in China, Soc. Econ. Plann. Sci. 81 (2022) 101152.
[32] O. Usman, P.T. Iorember, O. Ozkan, A. Alola, Dampening energy security-related uncertainties in the United States: the role of green energy-technology investment and operation of transnational corporations, Energy 289 (2024) 130006.
[33] K.A. Tone, A slacks-based measure of super-efficiency in data envelopment analysis, Eur. J. Oper. Res. 143 (2002) 32–41.
[34] K. Tone, Dealing with Undesirable Outputs in DEA: a Slacks-Based Measure (SBM) Approach, vol. 1, GRIPS Discussion Papers, 2015.
[35] T. Ciarli, M. Kenney, S. Massini, Digital technologies, innovation, and skills: emerging trajectories and challenges, Res. Pol. 50 (2021) 104289.
[36] T. Boone, R. Ganeshan, A. Jain, Forecasting sales in the supply chain: consumer analytics in the big data era, Int. J. Forecast. 35 (2019) 170–180.
[37] C. Zhuo, J. Chen, Can digital transformation overcome the corporate innovation dilemma: effect, mechanism and effective boundary, Technol. Forecast. Soc. Change 190 (2023) 122378.
[38] S. Ren, Y. Hao, L. Xu, H. Wu, N. Ba, Digitalization and energy: how does internet development affect China's energy consumption? Energy Econ. 98 (2021) 105220.
[39] H. Wen, C.C. Lee, Z. Song, Digitalization and environment: how does ICT affect corporate environmental performance? Environ. Sci. Pollut. Control Ser. 39 (2021) 54826–54841.
[40] L. Li, Digital transformation and sustainable performance: the moderating role of market turbulence, Ind. Market. Manag. 104 (2022) 28–37.
[41] L. Xue, Q. Zhang, X. Zhang, Can digital transformation promote green technology innovation? Sustainability 14 (2022) 7497.
[42] D. Zhang, Can digital finance empowerment reduce extreme ESG hypocrite resistance to improve green innovation? Energy Econ. 125 (2023) 106756.
[43] R. Manita, N. Elommal, P. Baudier, The digital transformation of external audit and its impact on corporate governance, Technol. Forecast. Soc. Change 150 (2020) 119751.
[44] Q. Gao, C. Cheng, G. Sun, The impact of digital inclusive finance on agricultural green total factor productivity: evidence from China, Frontiers in Ecology and Evolution 10 (2022) 905644.
[45] Y. Liu, Y. Yang, H. Li, Digital economy development, industrial structure upgrading and green total factor productivity: empirical evidence from China's cities, Int. J. Environ. Res. Publ. Health 19 (2022) 2414.
[46] Y. Yan, P. Shao, Enterprise digital transformation, COVID-19 and innovation persistence: evidence from China, Appl. Econ. Lett. (2024) 1–6.
[47] C. Feng, X. Yang, S. Afshan, M. Irfan, Can renewable energy technology innovation promote mineral resources' green utilization efficiency? Novel insights from regional development inequality, Resour. Pol. 82 (2023) 103449.
[48] D. Song, W. Zhu, D. Hai, Can firm digitalization promote green technological innovation? An examination based on listed companies in heavy pollution industries, J. Finance Econ. 48 (2022) 34–48.
[49] N. Shroff, R.S. Verdi, G. Yu, Information environment and the investment decisions of multinational corporations, Account. Rev. 89 (2014) 759–790.
[50] L. Zhang, H. Sun, T. Pu, H. Sun, Z. Chen, Do green finance and hi-tech innovation facilitate sustainable development? Evidence from the Yangtze River Economic Belt, Econ. Anal. Pol. 81 (2024) 1430–1442.
[51] G. Xu, G. Li, P. Sun, Inefficient investment and digital transformation: what is the role of financing constraints? Finance Res. Lett. 51 (2023) 103429.
[52] L. Yang, H. Qin, Q. Gan, Internal control quality, corporate environmental protection investment and finance performance: an empirical study of China's a-share heavy pollution industry, Int. J. Environ. Res. Publ. Health 17 (2020) 6082.
[53] Y. Chen, J. Miao, Z. Zhu, Measuring green total factor productivity of China's agricultural sector: a three-stage SBM-DEA model with non-point source pollution and CO2 emissions, J. Clean. Prod. 318 (2021) 128543.
[54] C. Chen, L. Zhu, H. Zhong, Practical innovation of Chinese corporates from digital survival view, Journal of Management Sciences in China 22 (2019) 1–8.
[55] C.C. Lee, How does green finance affect green total factor productivity? Evidence from China, Energy Econ. 107 (2022) 105863.
[56] B. Guo, K. Chen, Does multi-goal policy affect agricultural land efficiency? A quasi-natural experiment based on the natural resource conservation and intensification pilot scheme, Appl. Geogr. 161 (2023) 103141.
[57] T. Zhao, Z. Zhang, S. Liang, Digital economy, entrepreneurship, and high-quality economic Development：Empirical evidence from urban China, Journal of Management World 36 (2020) 65–76.
[58] R.M. Baron, D.A. Kenny, The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations, J. Personality Soc. Psychol. 51 (1986) 1173.
[59] M. Matarazzo, L. Penco, G. Profumo, Digital transformation and customer value creation in Made in Italy SMEs: a dynamic capabilities perspective, J. Bus. Res. 123 (2021) 642–656.
[60] S. Richardson, Over-investment of free cash flow, Rev. Account. Stud. 11 (2006) 159–189.
[61] O. Kini, R. Williams, Tournament incentives, firm risk, and corporate policies,", J. Financ. Econ. 103 (2012) 350–376.
[62] J. DeVaro, Strategic promotion tournaments and worker performance, Strat. Manag. J. 27 (2006) 721–740.
[63] C. Chang, J. Wen, M. Dong, Does government ideology affect environmental pollution? New evidence from instrumental variable quantile regression estimations, Energy Pol. 113 (2018) 386–400.