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Digital Transformation and Green Total Factor Productivity of Heavily Polluting Enterprises: The Mediating Role of M&A Activity and the Moderating Role of Green Innovation

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KEYWORDS

Corporate green total factor productivity ;
Digital transformation;
M&A activity;
Corporate green innovation;
Mediating effect;
Moderating effect;

ABSTRACT

Data, as a novel factor of production, brings new opportunities for enterprise development. Using a sample of Chinese heavily polluting listed companies, this study measured corporate green total factor productivity (GTFP) by employing the Super-SBM Malmquist index and explored the underlying mechanism through which digital transformation affects GTFP. This study employs an OLS benchmark regression model to investigate the impact of corporate digital transformation on green total factor productivity (GTFP). Additionally, it constructs mediation and moderation effect models to examine the mechanism through which digital transformation affects GTFP, specifically assessing the mediating role of M&A activity and the moderating role of green innovation. The research results indicate that digital transformation has a positive promoting effect on corporate green total factor productivity. M&A activity plays a partial mediating role between the two, meaning that the impact of digital transformation on corporate green total factor productivity is indirectly generated through M&A activity. Corporate green innovation plays a positive moderating role between the two, meaning that the higher the level of corporate green innovation, the more significant the promoting effect of digital transformation on corporate green total factor productivity. The research results remain valid after considering robustness tests such as variable substitution, model transformation, Sobel-Goodman, and Bootstrap methods. Heterogeneity analysis reveals that the positive effect of digital transformation on corporate green total factor productivity (GTFP) is significantly amplified under three conditions: in non-state-owned enterprises, in regions with superior business environments, and in firms with higher information transparency. For the mediation mechanism, M&A activity exhibits partial mediation in non-state-owned firms and in high-index business environments, but transitions to complete mediation in low-index contexts. Correspondingly, the moderating effect of green innovation is markedly stronger under these same conditions. These contingent findings delineate critical boundary conditions, thereby extending theories of digital transformation and corporate sustainability, while providing empirically grounded insights for regulatory policymakers and corporate managers of heavily polluting enterprises.

INTRODUCTION

In China's rapid economic growth, environmental constraints have emerged as a critical barrier to sustainable development. Enhancing green total factor productivity (GTFP) is crucial for driving industrial transformation. Heavily polluting industries while vital to the economy, account for over 40% of industrial emissions, posing significant ecological challenges. Their green transformation is therefore essential for achieving the "dual carbon" goals and promoting high-quality economic development. Although policies encourage synergy between green innovation and digital

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transformation to support industrial upgrading, these enterprises still face obstacles such as low resource efficiency and high compliance costs. Hence, investigating how digital transformation affects GTFP—and its mechanisms and heterogeneity—holds both theoretical and practical relevance for addressing transformation challenges in these sectors.

This study examines how digital transformation influences GTFP among heavily polluting A-share listed firms in China, focusing on the mediating role of M&A activity and the moderating role of green innovation. The contributions are threefold. First, it enriches the literature on digital transformation and GTFP by empirically demonstrating a positive relationship and introducing the super-efficiency SBM-Malmquist index to quantify effects and uncover underlying mechanisms. Second, it extends understanding of the indirect channels through which digital transformation promotes GTFP, showing that M&A activity acts as a partial mediator—digital transformation boosts GTFP both directly and by stimulating M&A. Third, it identifies green innovation as a positive moderator, indicating that stronger green innovation amplifies the GTFP-enhancing effect of digital transformation, clarifying how technological and environmental strategies interact in heavy polluters. Finally, heterogeneity analyses reveal that the relationship varies with firm ownership, regional business environment, and information transparency, offering both theoretical boundary conditions and practical guidance for managers and policymakers in advancing the green transition of heavy-polluting industries.

1.Literature Review

Scholarly research on corporate digital transformation has yielded substantial findings, focusing on two core areas: First, conceptual connotations and measurement methodologies, with quantification achieved via dummy variables [3], expert scoring [4], textual analysis [5,6], and digital asset proportion [7,8]. Second, economic effects, where digital transformation is shown to impact financial performance [9], green innovation [12], production efficiency [14,15], and supply chain management [19], among other dimensions.

For heavily polluting enterprises, digital transformation is both a response to external pressures and a strategic imperative for high-quality development [21]. Existing studies on the digital transformation-green total factor productivity (GTFP) nexus cover multiple levels. At the macro level, digital economy development and digital village construction have been proven to promote TFP and agricultural GTFP, respectively [22,25], with positive spatial spillovers observed [23,24]. At the regional level, significant heterogeneity exists—digital transformation's GTFP-enhancing effect is more pronounced in eastern China [26], and may exacerbate regional disparities [27]. A U-shaped relationship between digitization and urban GTFP is also identified, constrained by geographic and institutional factors [36].

At the micro level, digital technologies boost productivity by reshaping operational processes and mitigating information asymmetries [28-30]. Theoretically, human-machine collaboration and digital tools drive efficiency gains [31,32]; empirically, digital transformation enhances corporate GTFP through supply chain optimization and green innovation [33,34], with virtual simulation technology adoption reducing R&D costs in manufacturing [37]. Digital finance also promotes GTFP via technological innovation and entrepreneurship, with China's GTFP forming a development pattern centered on Beijing, Shanghai, and Guangdong [38].

However, the digital transformation-GTFP relationship is not uniformly positive. Potential pitfalls include TFP growth hindrance from over-reliance on AI [39], short-term ineffectiveness of digital technologies [40], and resource misallocation from excessive digitization [41].

In summary, existing research reveals the complex nature of digital transformation's impact on GTFP but leaves gaps: insufficient focus on heavily polluting enterprises, and inadequate exploration of specific mechanisms and heterogeneous effects. Investigating this relationship in heavily polluting enterprises is therefore significant, as it broadens the economic consequence discussion of digital transformation and enriches GTFP literature. This study thus focuses on three core questions: the relationship between digital transformation and GTFP in heavily polluting enterprises, the underlying mechanisms, and heterogeneous effects across enterprise types and regions.

2.Research Hypotheses

2.1. Digital Transformation and Corporate Green Total Factor Productivity

First, per the information transmission effect, information asymmetry and incomplete information easily lead to enterprise investment misjudgments [43]. Digital technologies reduce multiple costs (e.g. search, verification) [44], enhance enterprises' informatization capabilities [49], and help them optimize production decisions and reduce resource waste, thereby boosting GTFP [51,52].

Second, based on knowledge spillover theory, data technologies enable enterprises to accurately identify resource needs, promote environmental protection equipment upgrades [53], and curb strategic false disclosures to gain green premiums [55]. They also optimize lifecycle resource use and reshape resource allocation [56,58], improving green innovation efficiency and GTFP.

Third, resource allocation theory holds that digital technology embedded in core processes reshapes business functions and drives production paradigm transformation [61], improving resource allocation efficiency. For resource-intensive enterprises with severe misallocation issues, it enhances information sharing and resource integration [63], thus boosting GTFP. In summary, this study proposes:

H1: Digital transformation can significantly enhance corporate green total factor productivity.

2.2. The Mediating Mechanism of M&A Activity Level

Digital transformation (DT) directly enhances green production, but its full potential hinges on firms' ability to integrate internal/external resources. Grounded in Resource-Based View and Dynamic Capabilities Theory, mergers and acquisitions (M&A) serve as strategic tools for firms to rapidly acquire heterogeneous resources and reconfigure competitive competencies, thereby indirectly promoting green total factor productivity (GTFP) through enhanced M&A activity.

M&A fuels GTFP by optimizing resource allocation, expanding economies of scale, and institutional optimization. It accelerates green technology accumulation, innovation capacity building, and embeds green innovation into production systems, driving fundamental GTFP improvement. High M&A activity enables firms to embed deeper into M&A-constructed networks, efficiently accessing/integrating information, technology, capital, and market resources, enriching knowledge bases, and facilitating creative recombination of green knowledge to form new tech combinations, thus advancing green transformation.

DT reduces M&A transaction costs via data mining, expands decision-making information sources, and deepens value excavation, lowering search costs. It enhances risk-return assessment during M&A execution/supervision, improves green governance efficiency, curbs opportunistic behavior, and boosts firms' competitiveness in M&A markets by elevating management efficiency and legitimacy, further promoting M&A activity. Ultimately, increased M&A activity enables firms to acquire advanced green technologies/management experience, enhancing absorptive capacity for green transformation technologies and forming unique heterogeneous knowledge structures to empower GTFP improvement. This study hypothesizes that DT indirectly promotes GTFP through enhanced M&A activity.

H2: M&A activity level plays a mediating role between digital transformation and corporate green total factor productivity.

2.3. The Moderating Effect of Corporate Green Technology Innovation

Green technology innovation refers not only to new products or processes beneficial to environmental protection [92] but also encompasses systematic changes such as green management and green supply chain optimization [93-95]. Research finds that improvements in green technology efficiency and green innovation compensation are key to promoting GTFP [96, 97]. Applying clean production technologies saves energy and curbs pollution at the source, while using end-of-pipe treatment technologies improves pollutant treatment capacity and energy utilization efficiency [98], directly enhancing green technology efficiency. Green innovation can improve production processes, achieve product differentiation, and through isolation mechanisms and technology spillovers, bring enterprises competitive advantages combining both economic and environmental benefits [99].

Synergistic effects exist between green innovation and digital transformation. Hao et al. (2023), among others, indicate that digital transformation can enhance an enterprise's GTFP [51]. However, digital transformation itself is complex and highly uncertain, and its impact on GTFP depends on the enterprise's internal capabilities. Jacobides et al. (2018) find that weaker technological innovation capabilities lead to inefficient economic outcomes from digital transformation [100]. This implies that the positive impact of digital transformation on GTFP may not be uniform and largely depends on whether the enterprise possesses the corresponding absorptive and transformative capacity. Firstly, based on absorptive capacity theory, enterprises with higher levels of green innovation often possess stronger technological absorption and resource integration capabilities [101, 102], enabling them to more effectively apply digital technologies such as the Internet of Things and big data to energy saving, emission reduction, and cleaner production processes, thereby amplifying the positive effects of digital transformation. Secondly, based on environmental enablement theory, green innovation has positive externalities and is susceptible to free-riding and opportunistic behavior threats. Digital transformation technologies can effectively prevent such moral hazards [103, 104], ensuring the sustainability of green collaborative innovation, thus creating a more stable and incentive-compatible innovation environment for digital transformation to enhance GTFP. Therefore, in enterprises with high levels of green innovation, digital transformation can integrate more deeply with existing green technological foundations, management systems, and strategic orientations, creating synergistic effects [105, 106], and more significantly optimizing resource utilization efficiency, reducing energy consumption, and ultimately improving GTFP. Conversely, enterprises with low levels of green innovation may lack the technological capability or implementation pathways to fully realize the potential benefits of digital transformation due to weak green knowledge bases. In summary, green innovation plays an important moderating role in the impact of digital transformation on corporate GTFP, strengthening the enhancing effect by optimizing resource allocation, improving management efficiency, promoting technological innovation, and enhancing market image. Based on this, this study proposes the following hypothesis:

H3: Green technology innovation positively moderates the impact of digital transformation on corporate green total factor productivity.

The research framework of this paper is shown in Figure 1.

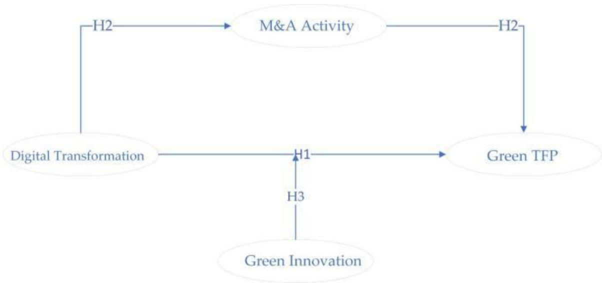

Fig.1. Research framework

3. Model Specification

3.1. Sample and Data

The sample comprises merger and acquisition (M&A) transactions involving Chinese A-share listed companies in heavily polluting industries from 2010 to 2019. Firm-level data are primarily sourced from the CSMAR and WIND databases. Following the methodology of Pan, Liu, and Qiu et al. (2019) [107], firms in industries B06, B07, B08, B09, C17, C19, C22, C25, C26, C28, C29, C30, C31, C32, and D44 are classified as heavily polluting. The data processing procedure includes: (1) excluding firms in the financial and insurance sectors; (2) removing samples labeled as ST or PT; (3) dropping observations with asset-liability ratios less than 0 or greater than 1; (4) excluding related-party transactions; (5) removing deals with transaction values below RMB 1 million; and (6) eliminating observations with missing key financial data. After these filters, the final sample comprises 2,931 observations. To mitigate outlier effects, all continuous variables are winsorised at the 1% level. Data processing and analysis are conducted using STATA 18.0.

3.2.Variable Descriptions

3.2.1.Dependent Variable

Corporate Green Total Factor Productivity ($GTFP_{i,t}$).Following Zhan, Li, and Liu et al. (2022) [108], corporate Green Total Factor Productivity (GTFP) is measured using the Malmquist-Luenberger (ML) index, which is derived from a super-efficiency Slack-Based Measure (SBM) model that incorporates undesirable outputs. The specific input and output variables are constructed as follows:(1) Input Variables: include labor, capital, intermediate inputs, and energy consumption.Labor: measured by the number of employees at the end of the fiscal year. Capital: represented by the firm's fixed capital stock, calculated using the perpetual inventory method. Intermediate Inputs: comprising operating costs, selling, administrative, and financial expenses. Energy: proxied by the product of the industrial electricity consumption in the firm's host city and the ratio of the firm's employees to the city's total industrial employment. (2) Desirable Output: is measured by the firm's operating revenue. (3) Undesirable Outputs: are represented by industrial waste emissions, specifically sulfur dioxide (SO_2) emissions, wastewater discharge, and soot/dust emissions. Each is estimated as the product of the corresponding city-level industrial emission and the ratio of the firm's employees to the city's total industrial employment.

The SBM-Malmquist index decomposes a firm's green productivity into technical efficiency change (EC) and technological change (TC). Matrices of efficiency and technological change differentials are then constructed from the average values of pairwise firm comparisons.

Assuming the existence of multiple decision-making units , each decision-making unit comprises three vectors: inputs DMU_k (k=1,2,..,K) , desirable outputs, and undesirable outputs, which are represented in matrix form as: $X=(x_1,\ldots,x_n)\in R^{m\times n}$, $Y^g=(y_1^{\,g},\ldots,y_n^{\,g})\in R^{S_1\times n}$ and $Y^b=(y_1^{\,b},\ldots,y_n^{\,b})\in R^{S_2\times n}, X>0, Y^g>0, Y^b>0$. Following the approach of Chung, Färe, Grosskopf, et al. (1997) [109], the directional distance function is defined as:

$$\vec{D}_0(x,y,b;g)=\sup\{\beta:(y,b)+\beta g\in p(x)\} \quad (1)$$

Where, g is the direction vector, indicating the preference for desirable over undesirable outputs. $g=(y,-b);\beta$ is the value of the directional distance function. Furthermore, we solve for the directional distance function of decision-making units (DMUs) in period t via the linear programming formulation given in Eq. (2):

$$\overrightarrow{D_0^t}(x^t,y^t,b^t;y^t,-b^t)=\max\beta$$

$$\text{s.t.}\begin{cases}\sum_{k=1}^{K}\omega_k^t x_{kn}^t \ge x_{kn}^t, & n=1,2,\ldots,N;\\ \sum_{k=1}^{K}\omega_k^t y_{ks}^t \ge (1+\beta)y_{ks}^t, & s=1,2,\ldots,S;\\ \sum_{k=1}^{K}\omega_k^t b_{km}^t \ge (1+\beta)b_{km}^t, & m=1,2,\ldots,M;\\ \omega_k^t, & k=1,2,\ldots,K;\end{cases} \quad (2)$$

Based on the directional distance function, the Malmquist-Luenberger (ML) productivity index from period t to period t+1 can be derived as follows:

$$ML_t^{t+1}=\left\{\frac{\left[1+D_0^t(x^t,y^t,b^t;g^t)\right]}{\left[1+D_0^t(x^{t+1},y^{t+1},b^{t+1};g^{t+1})\right]}\times\frac{\left[1+D_0^{t+1}(x^t,y^t,b^t;g^t)\right]}{\left[1+D_0^{t+1}(x^{t+1},y^{t+1},b^{t+1};g^{t+1})\right]}\right\}^{\frac{1}{2}} \quad (3)$$

If ML>0, it indicates that green total factor productivity (GTFP) shows an upward trend from period t to period t+1; otherwise, it exhibits a downward trend. Specifically, the ML productivity index can be further decomposed into the green technical efficiency change index (ML_EFFCH) and the green technological progress change index (ML_TECH). The former reflects the contribution of improvements in technical efficiency to GTFP, while the latter represents the contribution of shifts in the production frontier to productivity. Their specific expressions are as follows:

$$ML\_EFFCH_t^{t+1}=\frac{\left[1+D_0^{t+1}(x^t,y^t,b^t;g^t)\right]}{\left[1+D_0^{t+1}(x^{t+1},y^{t+1},b^{t+1};g^{t+1})\right]} \quad (4)$$

$$ML\_TECH_t^{t+1}=\left\{\frac{\left[1+D_0^{t+1}(x^t,y^t,b^t;g^t)\right]}{\left[1+D_0^t(x^t,y^t,b^t;g^t)\right]}\times\frac{\left[1+D_0^{t+1}(x^{t+1},y^{t+1},b^{t+1};g^{t+1})\right]}{\left[1+D_0^t(x^{t+1},y^{t+1},b^{t+1};g^{t+1})\right]}\right\}^{\frac{1}{2}} \quad (5)$$

Following these steps, the obtained ML index is converted into Green Total Factor Productivity (GTFP). The growth trend of the average GTFP for the sample firms is shown in Figure 2.

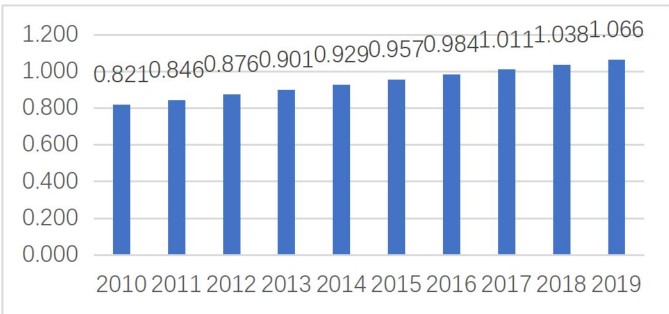

Fig.2. Trend of Average Green Total Factor Productivity in Heavily Polluting Enterprises

3.2.2.Explanatory Variable: Digital Transformation($DCG_{i,t}$)

The degree of corporate digital transformation is measured by the proportion of digital-technology-related intangible assets to total intangible assets. Following the approach of Zhang, Li, and Xing (2021) [7], this metric is constructed using the detailed breakdown of year-end intangible assets disclosed in the notes to the financial statements. Specifically, items related to digital technologies-such as networks, software, intelligent platforms, client-side systems, and management systems-are identified and aggregated. The ratio of this digital-technology-related portion to the total book value of intangible assets serves as the proxy.

3.2.3.Mediating Variable

M&A Activity($SMA_{i,t}$)following Zhang, Song, and Liu (2023) [110] and Zhang, Yao, and Du (2021) [111], this variable is measured by the number of merger and acquisition (M&A) deals completed by sample firm *i* in year *t*.

Corporate Innovation($RD_{i,t}$)following the methodologies of Beladi et al. (2022) and Xue et al. (2023) [112,113], we measure corporate innovation using the natural logarithm of the total count of invention patents, utility models, and design patents plus one (ln(total patents + 1)).

3.2.4.Control Variables

Drawing on established literature, this study controls for a set of firm- and region-level characteristics, including firm size, leverage, board independence, board size, ownership concentration, property rights, and the business environment index. Detailed definitions of these variables are provided in Table 1.

3.3.Model Specification

To test Hypotheses 1, 2, and 3, Models (6) through (9) are constructed as follows:

$$\begin{aligned} GTFP_{i,t} &= \alpha_0 + \alpha_1 DCG_{i,t} + \alpha_2 Size_{i,t} + \alpha_3 Lev_{i,t} \\ &+ \alpha_4 Indep_{i,t} + \alpha_5 Board_{i,t} + \alpha_6 ShareTop_{i,t} \\ &+ \alpha_7 Board_{i,t} + \alpha_8 ShareTop_{i,t} + \alpha_9 Envir_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{6}$$

$$\begin{aligned} SMA_{i,t} &= \beta_0 + \beta_1 DCG_{i,t} + \beta_2 Size_{i,t} + \beta_3 Lev_{i,t} \\ &+ \beta_4 Indep_{i,t} + \beta_5 Board_{i,t} + \beta_6 ShareTop_{i,t} \\ &+ \beta_7 Board_{i,t} + \beta_8 ShareTop_{i,t} + \beta_9 Envir_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{7}$$

$$\begin{aligned} GTFP_{i,t} &= \chi_0 + \chi_1 DCG_{i,t} + \chi_2 SMA_{i,t} + \chi_3 Size_{i,t} \\ &+ \chi_4 Lev_{i,t} + \chi_5 Indep_{i,t} + \chi_6 Board_{i,t} + \chi_7 ShareTop_{i,t} \\ &+ \chi_8 Board_{i,t} + \chi_9 ShareTop_{i,t} + \chi_{10} Envir_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{8}$$

$$\begin{aligned} GTFP_{i,t} &= \delta_0 + \delta_1 DCG_{i,t} + \delta_2 RD_{i,t} + \delta_3 DCG_{i,t} \times RD_{i,t} \\ &+ \delta_4 Size_{i,t} + \delta_5 Lev_{i,t} + \delta_6 Indep_{i,t} + \delta_7 Board_{i,t} \\ &+ \delta_8 ShareTop_{i,t} + \delta_9 Board_{i,t} + \alpha_{10} ShareTop_{i,t} \\ &+ \delta_{11} Envir_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{9}$$

$$\begin{aligned} GTFP_{i,t} &= \eta_0 + \eta_1 DCG_{i,t} + \eta_2 GRD_{i,t} + \eta_3 DCG_{i,t} \times GRD_{i,t} \\ &+ \eta_4 Size_{i,t} + \eta_5 Lev_{i,t} + \eta_6 Indep_{i,t} + \eta_7 Board_{i,t} \\ &+ \eta_8 ShareTop_{i,t} + \eta_9 Board_{i,t} + \eta_{10} ShareTop_{i,t} \\ &+ \eta_{11} Envir_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{10}$$

Among these, Model (6) tests the positive impact of corporate digital transformation on green total factor productivity (GTFP). Building on Model (6), Models (7) and (8) examine the mediating effect of M&A activity. Models (9) and (10) test the moderating effects of firm innovation and green innovation, respectively. Dependent Variable $GTFP_{i,t}$ represents corporate green total factor productivity (GTFP); Explanatory Variable $DCG_{i,t}$ represents the degree of corporate digital transformation; Mediating Variable $SMA_{i,t}$ represents M&A activity; Moderating Variable $RD_{i,t}$, $GRD_{i,t}$ respectively represent corporate innovation and corporate green innovation; Control variables include: firm size $Size_{i,t}$, Financial Leverage $Lev_{i,t}$, Board Independence $Indep_{i,t}$, Board Size $Board_{i,t}$, Ownership Concentration $Share_{i,t}$, Ownership Nature $State_{i,t}$ Environment Index $Envir_{i,t}$; $Industry$ represents industry fixed effects; $Year$ represents fixed effects; $\varepsilon_{i,t}$ represents the random error term.

3.4.Model Specification

(I) Descriptive Statistics of Key Variables

This study's sample comprises 2,931 observations. Table 2 reports the mean, standard deviation, median, maximum, and minimum values for the key variables. Green Total

Factor Productivity($GTFP_{i,t}$)has a mean of 0.950 and a median of 0.951, indicating a roughly symmetric distribution. Its values range from 0.800 to 1.092, with a standard deviation of 0.080, suggesting limited variation in GTFP across sample firms. Digital Transformation($DCG_{i,t}$)shows a mean of 0.047 and a median of 0.002, with a standard deviation of 0.160. This indicates a generally low level of digital adoption among most firms, while a few outliers exhibit significantly higher levels (maximum = 1), resulting in a pronounced right-skewed distribution. M&A Activity(has a mean of 1.176 and a median of 1, implying that most firms undertake few M&A transactions. However, the maximum value reaches 34, and the standard deviation is 1.913, reflecting highly active M&A engagements by a small subset of firms and a strongly right-skewed distribution. Corporate Innovation($RD_{i,t}$)presents a mean of 1.075 and a median of 0, revealing that half of the sample firms report no R&D investment. The wide range (maximum = 8.280) and substantial standard deviation (1.866) highlight a highly uneven distribution of R&D expenditure, with a minority of firms investing significantly above the average. Firm Size ($Size_{i,t}$)has a mean of 22.47 and a standard deviation of 1.402, indicating a relatively concentrated distribution. Financial Leverage($Lev_{i,t}$)shows a mean of 0.519, close to its median of 0.521, suggesting a moderate level of indebtedness among sample firms. Regarding board characteristics, Board Independence ($Indep_{i,t}$) has a mean (value) of 37.3%,Board Size ($Board_{i,t}$) averages 8.831 members, which is in line with typical corporate governance structures. Ownership Concentration, ($ShareTop_{i,t}$)measured by the shareholding ratio of the largest shareholder, shows a mean of 34.4% and a maximum of 90%, indicating highly concentrated ownership in a portion of the sample firms. According to the results for Ownership Nature, 5($State_{i,t}$)53.8% of the sample firms are state-owned, suggesting a balanced composition. The Environment Index ($Envir_{i,t}$)has a mean value of 0.496, suggesting that approximately half of the sample firms face a certain degree of regulatory pressure in their business environment.

(II) Correlation Analysis of Main Variables

This study employs Pearson correlation coefficients to test the correlations among variables, with the results presented in Table 3. Green Total Factor Productivity ($GTFP_{i,t}$) shows a significantly positive correlation with Digital Transformation ($DCG_{i,t}$) (r=0.079, p<0.01) and with M&A Activity ($SMA_{i,t}$) (r=0.195, p<0.01). GTFP is also significantly positively correlated with Corporate Innovation ($RD_{i,t}$) and Corporate Green Innovation ($GRD_{i,t}$) (r=0.183, p<0.01; r=0.217, p<0.01), suggesting a synergistic effect of technology-driven factors on corporate green total factor productivity. Firm Size ($Size_{i,t}$) is significantly positively correlated with ($GTFP_{i,t}$) (r=0.178, p<0.01), whereas Financial Leverage () is significantly negatively correlated with $GTFP_{i,t}$ (r=-0.165, p<0.01), reflecting the constraining effect of financial structure on innovation. Ownership Nature ($State_{i,t}$) is significantly negatively correlated with $GTFP_{i,t}$ (r=-0.197, p<0.01), indicating that state-owned enterprises exhibit weaker green total factor productivity. Among the control variables, Board Size ($Board_{i,t}$) shows a significantly negative correlation (r=-0.106, p<0.01), while Board Independence $Indep_{i,t}$ shows a significantly positive correlation (r=0.099, p<0.01), reflecting the differential impacts of governance structure. The Environmental Index($Envir_{i,t}$) shows a weakly positive correlation with (r=0.047, p<0.05), suggesting that policy pressure from the operating environment may stimulate innovation. Furthermore, all inter-variable correlation coefficients are below 0.5, and Variance Inflation Factor

(VIF) tests indicate no severe multicollinearity issues, meeting the requirements for subsequent regression analysis.

3.5.Multicollinearity Test

Table 4 presents the results of the Variance Inflation Factor (VIF) test. The VIF values for all variables range from 1.03 to 1.58, with a mean VIF of 1.21, which is well below the conventional threshold of 10. This indicates the absence of severe multicollinearity in the model. Furthermore, the tolerance values (1/VIF) all exceed 0.6 (the minimum being 0.634), providing additional confirmation of the independence among the explanatory variables.

3.6.Regression Analysis

1. Baseline Regression Analysis

This study estimates the baseline model, with results presented in Table 5. Column (1) reports the baseline regression results for the impact of corporate digital transformation on Green Total Factor Productivity (GTFP). The estimated coefficient for digital transformation is 0.039 and is statistically significant at the 1% level (t = 4.27). This indicates that for heavily polluting enterprises, a one-percentage-point increase in the degree of digital transformation is associated with a 0.039-percentage-point increase in GTFP. This finding suggests that enhanced digital capability significantly promotes GTFP, providing initial support for Hypothesis H1.Columns (2) through (6) progressively introduce control variables. Although the coefficient for digital transformation declines slightly (from 0.039 to 0.028), it remains statistically significant at the 1% level (with t-statistics all greater than 3.28). This demonstrates the robust positive effect of digital transformation on GTFP, strongly supporting Hypothesis 1.Regarding the control variables in Column (6): Firm Size (Size) exerts a significant positive influence on GTFP (coefficient = 0.019, t = 17.90), suggesting that economies of scale may provide resource support for green productivity. Financial Leverage (Lev) shows a significant negative effect (coefficient = -0.074, t = -11.35), indicating that high debt levels may constrain GTFP. Board Independence (Indep) has a significant positive impact (coefficient = 0.079, t = 2.96), implying that improved corporate governance aids GTFP. The Nature of Property Rights (State) exhibits a significant negative influence (coefficient = -0.029, t = -9.99), which suggests that non-state-owned enterprises (private firms) tend to achieve higher levels of GTFP.

2. Tests for Mediating and Moderating Effects

Following the three-step mediation test procedure proposed by Wen et al. (2014), the total effect of digital transformation on Green Total Factor Productivity (GTFP) is shown in Column (8) of Table 6. The total effect of the core explanatory variable (DCG) on GTFP is 0.028 (t=3.29), which is statistically significant at the 1% level, satisfying the first step of the mediation test. Column (1) of Table 6 examines the impact of digital transformation on the mediating variable, M&A activity (SM). The results show that the coefficient of DCG on SM is 0.958 (t = 3.25), significant at the 1% level, indicating that digital transformation significantly enhances M&A activity (supporting the path DCG → SM). In Column (2) of Table 6, the coefficient of SM on GTFP is 0.005 (t = 6.93), also significant at the 1% level, confirming that M&A activity significantly promotes GTFP (supporting the path SM → GTFP). The mediating effect is calculated as 0.00479 (0.958 × 0.005), accounting for 17.1% (0.00479 ÷ 0.028) of the total effect. The coefficient for the direct effect of DCG on GTFP is 0.023 (t = 2.72), significant at the 1% level, suggesting that a partial mediation may exist. Given that the total effect equals the sum of the mediating and direct effects (0.00479 + 0.023 ≈ 0.028), the results confirm a significant partial mediation effect, thereby supporting Hypothesis 2. Column (3) of Table 6 reports the regression results for Hypothesis 3. Column (3) introduces the interaction term between corporate innovation and digital transformation to test its moderating effect. The result shows that the estimated coefficient for on Green Total Factor Productivity is 0.012 and is statistically insignificant. This indicates that the level of corporate innovation does not significantly motivate or enhance the promoting effect of digital transformation on corporate green innovation. Column (4) introduces the interaction term between green innovation and digital transformation to test the moderating effect of green innovation. The result shows that the estimated coefficient for on GTFP is 0.033, which is statistically significant at the 5% level (t = 2.51). This indicates that a higher level of green innovation strengthens the positive impact of digital transformation on GTFP, thereby supporting Hypothesis 3b.

3.7.Robustness Test

To examine the robustness of our conclusions, this study conducts the following robustness checks.

1. Robustness Test: Alternative Variable Measures

To ensure the robustness of the baseline regression results, this study employs alternative measures for the key variables. Following the approach of Wu, Hu, and Lin et al. (2021) as well as Zhang and Du (2023) [31], Columns (1) and (2) in Table 7 utilize an alternative proxy for digital transformation. This proxy is constructed by using Python's web scraping functionality to identify and count feature words related to digital transformation in firms' annual financial reports. The search covers five key technology categories: Artificial Intelligence, Blockchain, Cloud Computing, Big Data, and Digital Technology Applications. A higher frequency of these feature words indicates a greater degree of corporate digital transformation. Furthermore, to address the right-skewed distribution of the raw word frequency data, we apply a logarithmic transformation by taking the natural logarithm of the word count plus one (ln(word frequency + 1)).The results in Columns (1) and (2) show that the estimated coefficients for are 0.037 (t = 14.81) and 0.027 (t = 11.10), respectively, both statistically significant at the 1% level. This provides further robust support for Hypothesis 1.

2. Robustness Test: Alternative Model Specification

Column (3) employs a Tobit model for estimation. The regression results show that the estimated coefficients for are 0.039 (t = 4.27) and 0.028 (t = 3.28), respectively, both statistically significant at the 1% level. This finding provides further support for Hypothesis 1.

3. Sobel-Goodman Mediation Test

The Sobel-Goodman method is applied to test the significance of the mediating effect of M&A activity. As presented in Table 8, the Sobel test results show that the estimated value of the indirect effect is 0.005 (z = 3.771), with a p-value less than 0.01, indicating that the mediating effect of M&A activity is statistically significant. The Aroian test yields highly consistent results (z = 3.744, p = 0.000), providing further support for the significance of the mediating effect. Similarly, the Goodman test result, with a slightly higher z-value (z = 3.799, p = 0.000), also confirms a significant indirect effect. The decomposition of the total effect into direct and indirect effects shows p-values less than 0.01 and satisfies the relationship: Total Effect = Direct Effect + Indirect Effect (0.023 + 0.005 $\approx$ 0.028).

4. Bootstrap Test

The Bootstrap method, by employing repeated resampling, helps reduce reliance on the normality assumption and enhances the reliability of the results. Table 9 presents the results for the mediating effect of M&A activity using the Bootstrap method with 1,000 resampling repetitions. The results show that the indirect effect of the independent variable $DCG_{i,t}$ on the dependent variable $GTFP_{i,t}$ through the mediator $SMA_{i,t}$ is 0.005, with a Bootstrap standard error of 0.002, a z-value of 3.09 (p = 0.002), and a 95% confidence interval of [0.002, 0.008]. This indicates a significant indirect effect whose confidence interval does not contain zero, thereby confirming the presence of a mediating effect. Meanwhile, after controlling for the mediator, the direct effect of $DCG_{i,t}$ on $GTFP_{i,t}$ is 0.023 (Bootstrap standard error = 0.008, z = 2.80, p = 0.005), with a 95% confidence interval of [0.007, 0.039], indicating that the direct effect is also statistically significant.

These results are highly consistent with the findings from the earlier Sobel test (indirect effect = 0.005, direct effect = 0.023), further supporting the robustness of the conclusion. As both the direct and indirect effects are significant and point in the same direction (both positive), this suggests that $SMA_{i,t}$ plays a partial mediating role in the relationship between $DCG_{i,t}$ and $GTFP_{i,t}$. That is, $DCG_{i,t}$ influences $GTFP_{i,t}$ both indirectly through $SMA_{i,t}$ and also has a direct positive effect on it. While the Bootstrap method enhances result reliability by reducing dependency on the normality assumption, future research could further increase the number of resampling repetitions to improve the precision of interval estimates and examine the adequacy of control variables to ensure model completeness.

3.8.Heterogeneity Analysis

1. Heterogeneity by Ownership Type Compared to private enterprises, state-owned enterprises (SOEs) tend to adopt a more conservative approach toward M&A decisions. Heavily polluting firms with different property rights face varying degrees of government intervention and bear different policy burdens, which may lead to heterogeneous effects of digital transformation on their Green Total Factor

Productivity (GTFP). This study splits the sample into two subsamples—SOEs and non-SOEs—and separately examines the relationship between digital transformation and GTFP, as well as the mediating role of M&A activity and the moderating role of green innovation. The results are presented in Table 10. Columns (1) to (4) in Table 10 report results for the SOE subsample. The estimated coefficients for digital transformation $DCG_{i,t}$ are 0.019, 0.409, 0.016, and 0.021, respectively, none of which are statistically significant. Columns (5) to (8) present results for the non-SOE subsample. Here, the estimated coefficients for $DCG_{i,t}$ are 0.033, 1.220, 0.028, and 0.029, respectively, all significant at the 1% level. In Column (7), the coefficient for M&A activity $SMA_{i,t}$ is 0.004, significant at the 1% level. In Column (8), the coefficient for the interaction term $DCG_{i,t} \times GRD_{i,t}$ is 0.049, significant at the 5% level. The results clearly indicate that digital transformation has a more pronounced and significant positive effect on GTFP in non-state-owned heavily polluting enterprises, whereas its effect on state-owned counterparts is insignificant. Furthermore, the mediating effect of M&A activity and the moderating effect of green innovation are both significant and effective specifically within the non-SOE subsample.

2.Heterogeneity by Business Environment Index. Drawing on the empirical analysis of Kopka and Grashof (2022) [114], whether digital transformation can reduce energy consumption is highly contingent upon local contextual factors. When a firm operates in a region with a higher business environment index, it typically exhibits more advanced management practices and technological capabilities. The motivation for M&A in such contexts is often driven by strategic goals related to technology acquisition and market power enhancement. The progressive deepening of enterprise digitalization accelerates technological empowerment, which optimizes M&A processes, elevates corporate green total factor productivity (GTFP), and helps narrow the technological gap between regions with superior and inferior business environments. To test the differential effects of digital transformation, M&A activity, and green innovation on the GTFP of heavily polluting enterprises across regions with varying business environment indices, this study utilizes the business environment index from the China Provincial Business Environment Index Report 2017 as the benchmark. The sample is divided into two groups-firms in regions with a higher-than-average business environment index and those with a lower-than-average index. The results are presented in Table 11.A comparison between Column (1) and Column (5) in Table 11 reveals that the estimated coefficient for digital transformation $DCG_{i,t}$ in Column (1) is 0.037 (t = 2.90, p < 0.01), which is notably larger than the coefficient of 0.020 (t = 1.70, p < 0.10) in Column (5). This finding indicates that digital transformation exerts a more pronounced positive effect on GTFP for heavily polluting enterprises located in regions with a superior business environment. Examining the mediating role of M&A activity by comparing Columns (2)-(3) with Columns (6)-(7) shows that, with the exception of Column (7), the coefficients for $DCG_{i,t}$ are significantly positive. This pattern suggests that M&A activity plays a partial mediating role in high-index regions, whereas it appears to function as a complete mediator in low-index regions. Finally, a comparison of the moderating effect between Column (4) and Column (8) demonstrates that the estimated coefficient for the interaction term $DCG_{i,t} \times GRD_{i,t}$ is statistically significant only for the high-index group. This result implies that the moderating effect of green innovation is effective exclusively under conditions of a more favorable business environment.

3. Heterogeneity by Information Transparency

M&A activity and green innovation initiatives inherently involve risk and uncertainty. Firms with lower information transparency face greater financing constraints due to the associated informational asymmetry. Conversely, firms with higher transparency can effectively convey objective and comprehensive information about their M&A and innovation activities to the external market. In such a high-transparency context, investors can clearly assess the firm and make timely investment decisions, thereby providing crucial funding support [115]. Following existing literature, this study employs the modified Jones model to measure corporate information transparency. After taking the absolute value of the calculated measure, the sample is split at the median into two groups—high and low information transparency—for subgroup regression analysis. The results are presented in Table 12.

In Columns (1) to (4) of Table 12, which correspond to the high-transparency group, the estimated coefficients for digital transformation $DCG_{i,t}$ are 0.045, 0.904, 0.040, and 0.053, respectively, all statistically significant at the 1% level. In Column (3), the coefficient for M&A activity $SMA_{i,t}$ is 0.005 (significant at the 1% level), confirming its mediating role. However, in Column (4), the coefficient for the interaction term $DCG_{i,t} \times GRD_{i,t}$ is 0.013 and statistically insignificant. These results indicate that for firms with higher information transparency, digital transformation significantly enhances GTFP, M&A activity serves as a mediator in this relationship, but the moderating effect of green innovation is not observed. Turning to the low-transparency group, in Column (5), the coefficient for $DCG_{i,t}$ is 0.012 and insignificant, suggesting that digital transformation does not significantly promote GTFP when information transparency is low. Interestingly, Column (8) reveals that although the coefficient for $DCG_{i,t}$ itself is insignificant, the coefficient for the interaction term $DCG_{i,t} \times GRD_{i,t}$ is significant. This finding implies that under the influence of green innovation, digital transformation can exert a positive effect on GTFP even in low-transparency firms.

4.Results Conclusions

4.1.Main Findings

As a central feature of the digital economy, digital transformation is playing an increasingly significant role in enhancing total factor productivity within heavily polluting enterprises. This study, based on a sample of Chinese listed companies in heavily polluting industries from 2010 to 2019, investigates the impact of digital transformation on corporate green total factor productivity (GTFP), as well as the mediating role of M&A activity and the moderating role of green innovation. The key findings are as follows: First, the degree of corporate digital transformation exerts a significant positive effect on GTFP. Deeper digital adoption is associated with higher levels of green productivity. Second, M&A activity plays a partial mediating role in this relationship. The positive impact of digital transformation on GTFP is partially and indirectly channeled through enhanced M&A activity. Third, green innovation acts as a positive moderator. Specifically, a higher level of green innovation amplifies the positive effect of digital transformation on GTFP. Finally, these core results exhibit significant heterogeneity across firm ownership, regional business environment, and information transparency. The positive effect of digital transformation on GTFP is more pronounced—and both the partial mediation of M&A activity and the moderation of green innovation hold—for firms that are non-state-owned, operate in regions with a superior business environment, or maintain higher information transparency. In contrast, the effect is statistically insignificant for state-owned enterprises. In regions with a lower business environment index, digital transformation still promotes GTFP, but the effect size is significantly smaller than in high-index regions; here, M&A activity appears to function as a complete mediator, while the moderating effect of green innovation is absent. For firms with lower information transparency, digital transformation alone does not significantly promote GTFP; however, in the presence of green innovation, it exerts a positive influence on GTFP.

4.2.Implications

From a practical standpoint, the conclusions of this study offer valuable empirical evidence and policy insights for corporate decision-makers and government regulators. For corporate decision-makers, the implications are threefold.

To begin with, heavily polluting enterprises should intensify their digital transformation efforts. This can be achieved by adopting advanced digital technologies-such as artificial intelligence and blockchain-and by investing in digital skills training for employees. These steps can enhance overall information competency and the practical application of digital tools, thereby boosting GTFP. Furthermore, attention should be paid to M&A activity. Firms should foster the coordinated development of digital transformation and M&A strategy, leveraging digitalization to facilitate transactions, reduce associated costs, optimize resource allocation, and improve post-merger integration-all contributing to higher GTFP. Lastly, it is crucial to refine incentive mechanisms for green innovation. By promoting the synergistic development of digital transformation and green innovation, companies can fully harness the potential of digitalization to advance GTFP. This involves incentivizing in-house R&D capabilities to drive improvements in green productivity. For government regulators, two main courses of action are suggested. Firstly, relevant authorities can formulate and implement supportive policies for corporate digital transformation, including fiscal subsidies and financial support. Creating a favorable policy environment will encourage greater investment in digital technologies. Secondly, regulators should strengthen supervision and guidance over corporate M&A activities and green innovation initiatives to ensure compliant operations. Simultaneously, policy formulation must account for the heterogeneous effects stemming from differences in firm ownership, regional business environment, and information transparency. Moreover, while encouraging M&A and green innovation, policies should emphasize sustainable development to mitigate potential adverse environmental and social impacts.

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Attachment 1

Tab.1. Description of Main Variables

Variable Category	Variable Name	Symbol	Definition
Dependent Variable	Green Total Factor Productivity	$GTFP_{i,t}$	Enterprise green total factor productivity, calculated using ML method
Explanatory Variable	Digital Transformation	$DCG_{i,t}$	Measured by the proportion of intangible assets related to digital technology
Mediating Variable	M&A Activity	$SMA_{i,t}$	Number of mergers and acquisitions of firm *i* in year *t*
Moderating Variable	corporate Innovation	$RD_{i,t}$	Measured by the logarithm of (total number of invention patents, utility models, and design patents + 1)
	corporate Green Innovation	$GRD_{i,t}$	
Control Variable	Firm Size	$Size_{i,t}$	Logarithm of (total assets + 1)
	Financial Leverage	$Lev_{i,t}$	Ratio of liabilities to total assets
	Board Independence	$Indep_{i,t}$	Proportion of independent directors in the total number of board members
	Board Size	$Board_{i,t}$	Total number of board members
	Ownership Concentration	$ShareTop_{i,t}$	Shareholding ratio of the largest shareholder
	Ownership Nature	$State_{i,t}$	Dummy variable: 1 for state-controlled firms, 0 otherwise
	Environment Index	$Envir_{i,t}$	Dummy variable: 1 if above national average index, 0 otherwise

Attachment 2

Tab.2. Descriptive Statistics of Key Variables

Variable	Mean	Max	S.D.	Med	Min
$GTFP_{i,t}$	0.950	1.092	0.0800	0.951	0.800
$DCG_{i,t}$	0.047	1	0.160	0.002	0
$SMA_{i,t}$	1.176	34	1.913	1	0
$RD_{i,t}$	1.075	8.280	1.866	0	0
$GRD_{i,t}$	0.753	5.357	1.058	0	0
$Size_{i,t}$	22.47	26.50	1.402	22.41	15.60
$Lev_{i,t}$	0.519	1.897	0.228	0.521	0.00710
$Indep_{i,t}$	0.373	0.714	0.0579	0.333	0
$Board_{i,t}$	8.831	18	1.748	9	0
$ShareTop_{i,t}$	0.344	0.900	0.150	0.320	0.0263
$State_{i,t}$	0.538	1	0.499	1	0
$Envir_{i,t}$	0.496	1	0.500	0	0

Attachment 3

Tab.3. Correlation Matrix of Key Variables

变量	$GTFP_{i,t}$	$DCG_{i,t}$	$SMA_{i,t}$	$RD_{i,t}$	$GRD_{i,t}$	$Size_{i,t}$	$Lev_{i,t}$	$Indep_{i,t}$	$Board_{i,t}$	$ShareTop_{i,t}$	$State_{i,t}$	$Envir_{i,t}$
$GTFP_{i,t}$	1											
$DCG_{i,t}$	0.079***	1										
$SMA_{i,t}$	0.195***	0.103***	1									
$RD_{i,t}$	0.183***	-0.047*	0.0320	1								
$GRD_{i,t}$	0.217***	-0.088***	0.047*	0.405***	1							
$Size_{i,t}$	0.178***	-0.016	0.094***	0.237***	0.237***	1						
$Lev_{i,t}$	-0.165***	-0.001	0.0270	-0.0180	-0.0180	0.303***	1					
$Indep_{i,t}$	0.099***	0.042*	0.038*	0.0100	0.0100	0.00400	-0.00400	1				
$Board_{i,t}$	-0.106***	-0.009	-0.054**	0.086***	0.086***	0.254***	0.109***	-0.347***	1			
$ShareTop_{i,t}$	-0.062***	-0.069***	-0.044*	0.066***	0.066***	0.260***	0.088***	-0.0170	0.040*	1		
$State_{i,t}$	-0.197***	-0.101***	-0.208***	0.038*	0.038*	0.211***	0.181***	0.00600	0.199***	0.206***	1	
$Envir_{i,t}$	0.047*	0.010	0.098***	0.0270	0.0270	-0.085***	-0.120***	-0.0110	-0.053**	-0.058**	-0.147***	1

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The same applies to the following tables.

Attachment 4

Tab.4. Multicollinearity Test

Variable	VIF	1/VIF
$Size_{i,t}$	1.58	0.633956
$GRD_{i,t}$	1.45	0.689360
$Board_{i,t}$	1.28	0.784052
$RD_{i,t}$	1.21	0.826579
$State_{i,t}$	1.20	0.834306
$Indep_{i,t}$	1.16	0.862243
$Lev_{i,t}$	1.14	0.874843
$ShareTop_{i,t}$	1.11	0.900847
$SMA_{i,t}$	1.09	0.919525
$Envir_{i,t}$	1.05	0.956876
$DCG_{i,t}$	1.03	0.969450
Mean VIF	1.21	

Attachment 5

Tab.5. Baseline Regression Results

变量	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$GTFP_{i,t}$							
$DCG_{i,t}$	0.039***	0.041***	0.041***	0.039***	0.040***	0.036***	0.028***	0.028***
	(4.27)	(4.50)	(4.67)	(4.47)	(4.58)	(4.19)	(3.28)	(3.29)
$Size_{i,t}$		0.010***	0.014***	0.014***	0.016***	0.018***	0.019***	0.019***
		(9.92)	(13.69)	(13.72)	(15.17)	(16.33)	(17.37)	(17.90)
$Lev_{i,t}$			-0.085***	-0.085***	-0.083***	-0.083***	-0.075***	-0.074***
			(-13.07)	(-13.10)	(-12.96)	(-12.97)	(-11.85)	(-11.35)
$Indep_{i,t}$				0.129***	0.064**	0.059**	0.079***	0.079***
				(5.34)	(2.48)	(2.32)	(3.12)	(2.96)
$Board_{i,t}$					-0.006***	-0.006***	-0.005***	-0.005***
					(-7.07)	(-7.34)	(-5.58)	(-5.44)
$ShareTop_{i,t}$						-0.060***	-0.044***	-0.044***
						(-6.22)	(-4.58)	(-4.48)
$State_{i,t}$							-0.030***	-0.029***
							(-10.24)	(-9.99)
$Envir_{i,t}$								0.002
								(0.74)
截距	0.948***	0.717***	0.667***	0.620***	0.655***	0.641***	0.607***	0.605***
	(617.57)	(30.79)	(29.05)	(25.26)	(26.38)	(25.87)	(24.70)	(24.63)
Year	YES	YES	YES	YES	YES	YES	YES	YES
样本量	2,931	2,931	2 931	2 931	2 931	2 931	2 931	2 931
R-squared	0.006	0.038	0.092	0.100	0.115	0.127	0.157	0.157

Robust t-statistics in parentheses， *** p<0.01, ** p<0.05, * p<0.1(the same below).

Attachment 6

Tab.6. Results of the Mediating and Moderating Effect Tests

Variable	Mediating Effect		Moderating Effect	
	(1) $SMA_{i,t}$	(2) $GTFP_{i,t}$	(3) $GTFP_{i,t}$	(4) $GTFP_{i,t}$
$DCG_{i,t}$	0.958***	0.023***	0.021**	0.022**
	(3.25)	(2.72)	(2.36)	(2.40)
$SMA_{i,t}$		0.005***		
		(6.97)		
$RD_{i,t}$			0.005***	
			(6.68)	
$DCG_{i,t} \times RD_{i,t}$			0.012	
			(1.56)	
$GRD_{i,t}$				0.011***
				(7.48)
$DCG_{i,t} \times GRD_{i,t}$				0.033**
				(2.51)
$Size_{i,t}$	0.211***	0.018***	0.005***	0.005***
	(5.58)	(16.36)	(6.94)	(6.96)
$Lev_{i,t}$	0.302*	-0.076***	0.016***	0.014***
	(1.78)	(-12.08)	(14.40)	(11.49)
$Indep_{i,t}$	0.715	0.075***	-0.071***	-0.072***
	(1.28)	(3.01)	(-11.39)	(-11.48)
$Board_{i,t}$	-0.046**	-0.005***	0.072***	0.076***
	(-1.98)	(-5.34)	(2.89)	(3.08)
$ShareTop_{i,t}$	-0.400	-0.042***	-0.005***	-0.005***
	(-1.49)	(-4.38)	(-5.75)	(-5.68)
$State_{i,t}$	-0.815***	-0.025***	-0.042***	-0.041***
	(-10.01)	(-8.55)	(-4.50)	(-4.44)
$Envir_{i,t}$	0.304***	0.000	-0.025***	-0.026***
	(4.27)	(0.17)	(-8.59)	(-8.84)
intercept	-3.205***	0.622***	-0.000	-0.001
	(-3.81)	(25.22)	(-0.02)	(-0.35)
sample size	2 931	2 931	2,931	2 931
R-squared	0.080	0.171	0.188	0.194

Attachment 7

Tab.7. Robustness Tests for the Baseline Mode

Variable	Alternative Explanatory Variable		TOBIT Model Specification	
	(1) $GTFP_{i,t}$	(2) $GTFP_{i,t}$	(3) $GTFP_{i,t}$	(4) $GTFP_{i,t}$
$DCG_{i,t}$	0.037***	0.027***	0.039***	0.028***
	(14.87)	(11.10)	(4.27)	(3.28)
$Size_{i,t}$		0.017***		0.019***
		(15.99)		(17.41)
$Lev_{i,t}$		-0.070***		-0.074***
		(-11.23)		(-11.76)
$Indep_{i,t}$		0.062**		0.079***
		(2.49)		(3.14)
$Board_{i,t}$		-0.004***		-0.005***
		(-5.04)		(-5.57)
$ShareTop_{i,t}$		-0.041***		-0.044***

		(-4.40)		(-4.57)
$State_{i,t}$		-0.026***		-0.029***
		(-8.95)		(-10.11)
$Envir_{i,t}$		0.001		0.002
		(0.41)		(0.74)
Constant	0.940***	0.634***	0.948***	0.605***
	(604.81)	(25.98)	(617.80)	(24.51)
Number of Observations	2,931	2 931	2 931	2 931
R^2/Log likelihood	0.070	0.188	3255.232	3497.054

Attachment 8

Tab.8. Sobel-Goodman Mediation Test

	Est	Std_err	z	P> ∣ z ∣
Sobel	0.005	0.001	3.771	0.000
Aroian	0.005	0.001	3.744	0.000
Goodman	0.005	0.001	3.799	0.000
Path a ： $DCG_{i,t} \rightarrow SMA_{i,t}$	0.958	0.214	4.484	0.000
Path b: $SMA_{i,t} \rightarrow GTFP_{i,t}$	0.005	0.001	6.969	0.000
Indirect effect: a×b	0.005	0.001	3.771	0.000
Direct effect	0.023	0.009	2.717	0.007
Total effect	0.028	0.009	3.278	0.001

Attachment 9

Tab.9. Bootstrap Test

	Coef.	Std.	z	P> ∣ z ∣	Normal-based [95% conf. interval]	
Indirect effect	0.005	0.002	3.09	0.002	0.002	0.008
Direct effect	0.023	0.008	2.80	0.005	0.007	0.039

Attachment 10

Tab.10. Heterogeneity Analysis Results by Ownership Type

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	State-owned				Non-state-owned			
	$GTFP_{i,t}$	$SMA_{i,t}$	$GTFP_{i,t}$	$GTFP_{i,t}$	$GTFP_{i,t}$	$SMA_{i,t}$	$GTFP_{i,t}$	$GTFP_{i,t}$
$DCG_{i,t}$	0.019	0.409	0.016	0.021	0.033***	1.220***	0.028***	0.029***
	(1.32)	(1.58)	(1.14)	(1.32)	(3.06)	(3.71)	(2.56)	(2.58)
$SMA_{i,t}$			0.006***				0.004***	
			(4.71)				(5.07)	
$GRD_{i,t}$				0.016***				0.007***
				(7.95)				(3.08)
$DCG_{i,t} \times GRD_{i,t}$				0.017				0.049**
				(0.93)				(2.51)

$Size_{i,t}$	0.018***	0.129***	0.017***	0.012***	0.020***	0.310	0.018***	0.017***
	(12.18)	(4.75)	(11.61)	(6.96)	(12.31)	(6.38)	(11.37)	(9.88)
$Lev_{i,t}$	-0.076***	-0.095	-0.075***	-0.069***	-0.072***	0.660**	-0.075***	-0.070***
	(-8.28)	(-0.57)	(-8.26)	(-7.66)	(-8.18)	(2.46)	(-8.58)	(-7.92)
$Indep_{i,t}$	0.072**	-0.036	0.072**	0.067**	0.110***	2.411*	0.099	0.118***
	(2.26)	(-0.06)	(2.28)	(2.15)	(2.60)	(1.87)	(2.36)	(2.82)
$Board_{i,t}$	-0.006***	-0.027	-0.006***	-0.006***	-0.002	-0.042	-0.002	-0.002
	(-5.61)	(-1.42)	(-5.47)	(-6.20)	(-1.41)	(-0.87)	(-1.31)	(-1.29)
$ShareTop_{i,t}$	-0.049***	-0.799***	-0.044***	-0.049***	-0.035**	0.161	-0.036**	-0.036**
	(-3.89)	(-3.47)	(-3.49)	(-3.98)	(-2.42)	(0.36)	(-2.49)	(-2.47)
$Envir_{i,t}$	-0.001	0.223***	-0.003	-0.006*	0.006	0.370***	0.004	0.007*
	(-0.39)	(3.32)	(-0.78)	(-1.75)	(1.44)	(2.91)	(1.05)	(1.63)
Constant	0.609***	-1.630***	0.619***	0.747***	0.549***	-6.448***	0.578***	0.597***
	(18.60)	(-2.74)	(19.01)	(20.40)	(13.79)	(-5.32)	(14.50)	(14.40)
Number of Observations	1 578	1,578	1578	1578	1353	1353	1353	1353
R^2	0.120	0.026	0.132	0.161	0.132	0.061	0.148	0.147

Attachment 11

Tab.11. Heterogeneity Analysis Results by Business

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	superior business environment				inferior business environment			
	$GTFP_{i,t}$	$SMA_{i,t}$	$GTFP_{i,t}$	$GTFP_{i,t}$	$GTFP_{i,t}$	$SMA_{i,t}$	$GTFP_{i,t}$	$GTFP_{i,t}$
$DCG_{i,t}$	0.037***	1.039***	0.033***	0.026*	0.020*	0.700***	0.014	0.026**
	(2.90)	(2.73)	(2.59)	(1.89)	(1.70)	(3.21)	(1.21)	(2.11)
$SMA_{i,t}$			0.004***				0.008***	
			(4.57)				(6.01)	
$GRD_{i,t}$				0.007***				0.017***
				(3.11)				(7.93)
$DCG_{i,t} \times GRD_{i,t}$				0.077***				0.002
				(3.61)				(0.15)
$Size_{i,t}$	0.019***	0.384***	0.018***	0.016***	0.019***	0.069**	0.018***	0.013***
	(11.82)	(8.00)	(10.71)	(8.84)	(12.69)	(2.44)	(12.43)	(8.19)
$Lev_{i,t}$	-0.086***	0.488*	-0.087***	-0.081***	-0.064***	0.036	-0.065***	-0.061***
	(-9.06)	(1.73)	(-9.32)	(-8.59)	(-7.46)	(0.22)	(-7.59)	(-7.18)
$Indep_{i,t}$	0.031	-0.165	0.032	0.022	0.105***	1.133*	0.096***	0.112***
	(0.81)	(-0.14)	(0.84)	(0.58)	(3.08)	(1.77)	(2.84)	(3.33)
$Board_{i,t}$	-0.008***	-0.092**	-0.008***	-0.008***	-0.003***	-0.002	-0.003***	-0.003***
	(-5.59)	(-2.18)	(-5.36)	(-5.72)	(-2.78)	(-0.09)	(-2.80)	(-3.07)
$ShareTop_{i,t}$	-0.045***	0.241	-0.046***	-0.047***	-0.048***	-0.868***	-0.041***	-0.017***
	(-3.53)	(0.63)	(-3.63)	(-3.71)	(-3.30)	(-3.17)	(-2.83)	(-3.27)
$State_{i,t}$	-0.029***	-0.959***	-0.025***	-0.031***	-0.028***	-0.673***	-0.022***	-0.026***
	(-7.03)	(-7.76)	(-6.02)	(-7.50)	(-6.72)	(-8.64)	(-5.31)	(-6.31)
Constant	0.655***	-6.280***	0.680***	0.725***	0.572***	-0.299	0.575***	0.684***
	(17.36)	(-5.59)	(17.96)	(17.57)	(17.32)	(-0.48)	(17.60)	(19.36)

Number of Observations	1453	1,453	1453	1,453	1478	1478	1478	1478
R^2	0.168	0.095	0.180	0.186	0.1511	0.077	0.172	0.190

Attachment 12

Tab.12. Terogeneity Analysis Results by Information Transparency

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	higher information transparency				lower information transparency			
	$GTFP_{i,t}$	$SMA_{i,t}$	$GTFP_{i,t}$	$GTFP_{i,t}$	$GTFP_{i,t}$	$SMA_{i,t}$	$GTFP_{i,t}$	$GTFP_{i,t}$
$DCG_{i,t}$	0.045***	0.904***	0.040***	0.053***	0.012	0.951***	0.007	0.005
	(3.70)	(2.71)	(3.33)	(4.09)	(1.04)	(3.65)	(0.56)	(0.40)
$SMA_{i,t}$			0.005***				0.006***	
			(5.58)				(5.03)	
$GRD_{i,t}$				0.015***				0.008***
				(7.06)				(3.69)
$DCG_{i,t} \times GRD_{i,t}$				0.013				0.045**
				(0.67)				(2.51)
$Size_{i,t}$	0.017***	0.313***	0.015***	0.011***	0.021***	0.128***	0.020***	0.018***
	(10.10)	(6.83)	(9.08)	(5.96)	(14.44)	(4.08)	(13.93)	(11.29)
$Lev_{i,t}$	-0.081***	0.374	-0.083***	-0.071***	-0.069***	0.195	-0.070***	-0.068***
	(-8.44)	(1.42)	(-8.72)	(-7.51)	(-8.19)	(1.06)	(-8.40)	(-8.12)
$Indep_{i,t}$	0.043	0.937	0.038	0.052	0.111***	0.711	0.106***	0.108***
	(1.17)	(0.93)	(1.05)	(1.44)	(3.20)	(0.94)	(3.10)	(3.15)
$Board_{i,t}$	-0.005***	-0.063*	-0.005***	-0.005***	-0.004	-0.029	-0.004***	-0.004***
	(-4.09)	(-1.84)	(-3.87)	(-4.43)	(-3.62)	(-1.10)	(-3.50)	(-3.76)
$ShareTop_{i,t}$	-0.028**	0.159	-0.029**	-0.026**	-0.059***	-1.073***	-0.052***	-0.062***
	(-2.11)	(0.44)	(-2.20)	(-2.01)	(-4.31)	(-3.58)	(-3.85)	(-4.53)
$State_{i,t}$	-0.028***	-0.986***	-0.023***	-0.029***	-0.030***	-0.644***	-0.026***	-0.030***
	(-6.87)	(-8.75)	(-5.54)	(-7.20)	(-7.14)	(-7.11)	(-6.14)	(-7.26)
$Envir_{i,t}$	-0.002	0.359***	-0.004	-0.003	0.007*	0.228***	0.006	0.005
	(-0.61)	(3.40)	(-1.11)	(-0.91)	(1.80)	(2.65)	(1.46)	(1.35)
Constant	0.661***	-5.450***	0.689***	0.777***	0.555***	-1.399**	0.564***	0.618***
	(17.39)	(-5.23)	(18.15)	(19.01)	(17.08)	(-1.97)	(17.47)	(17.41)
Number of Observations	1,510	1,510	1,510	1,510	1421	1421	1421	1421
R^2	0.135	0.096	0.153	0.168	0.191	0.079	0.206	0.207