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Microeconomic Effects of Digital Transformation on Total Factor Productivity: Moderating Effects and Mechanisms

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Abstract

This study examines the impact of digital transformation on the total factor productivity (TFP) of Chinese listed companies. Using a firm-level panel dataset from 2007 to 2024 and applying the Levinsohn–Petrin method to estimate TFP, we find that digital transformation significantly enhances firm productivity. Both Digital Technology Application (DTA) and Underlying Technologies (UT) contribute positively to TFP, with the effect of UT being more pronounced. Heterogeneity analysis indicates that the productivity-boosting effect of digital transformation is stronger in firms with higher market value, greater industry competition, and those outside high-pollution industries (HPEs). Mechanism analysis shows that digital transformation promotes TFP through innovation, human capital optimization, cost reduction, and operational efficiency. Moreover, external macro factors such as digital infrastructure, intellectual property protection and marketization further moderate this relationship. Finally, the influence of DT on TFP shows a threshold effect related to profitability fluctuations and cash flow conditions. Our findings provide robust empirical evidence on how digital transformation reshapes firm-level productivity dynamics and highlight the key conditions under which it yields optimal economic returns.

Keywords: digital transformation; total factor productivity; high-pollution enterprises; human capital structure

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1. Introduction

In recent years, China's economic development landscape has undergone significant transformations. Domestically, traditional drivers of economic growth, such as demographic dividends and urbanization, have shown a diminishing marginal contribution to growth, while the negative effects of conventional fiscal and monetary regulation methods have continued to intensify. Internationally, the aftermath of the 2008 financial crisis persists, with globalization facing mounting challenges, rising geopolitical tensions, and a surge in trade protectionism. International economic, trade, technological, and educational exchanges have suffered setbacks, global industrial chains are under pressure to adjust, and growing uncertainties have further heightened the downward pressure on China's economy. From both global and domestic perspectives, economic growth is increasingly driven by the digital economy. In today's volatile global environment, the digital economy is widely regarded as an emerging trend. According to the Global Digital Economy White Paper (2023) [1], "The digital economy scale of the United States, China, and Germany is $17.2 trillion, $7.5 trillion, and $2.9 trillion, respectively, ranking them as the top three globally, with

each accounting for more than 40% of their GDP." The digital economy has become a major force propelling global growth and a critical sector for national development worldwide.

Given the challenging domestic and global environment, China faces an urgent need to improve quality, enhance efficiency, strengthen economic capacity, boost TFP, and accelerate the establishment of a modern economic framework. As the Chinese economy expands, enterprises are also growing in scale. However, many still struggle with internal issues such as structural imbalances and inadequate development quality. The key to China's economic transformation and upgrading lies in changing enterprise behavior and enabling successful transformation. Enterprise efficiency reflects the effectiveness and quality of economic growth. The digital economy offers new growth opportunities and creates favorable conditions for digital transformation. At the enterprise level, digital transformation is a crucial driver of the digital economy's broader development. It leverages data and digital technologies to transform business processes and operations, aiming to fundamentally enhance performance and competitiveness. Digital transformation is a dynamic process that requires continuous optimization of resource allocation. It shifts enterprises away from the traditional resource-dominant industrial development model toward a path more aligned with the development concepts of the new era, leading them into a new stage of growth. Through digital transformation, enterprises can strengthen their competitiveness in an increasingly fierce market environment.

From a theoretical perspective, the relationship between digital transformation and productivity can be explained through several established frameworks. Endogenous growth theory highlights innovation and technological progress as central drivers of long-term TFP growth. The resource-based view (RBV) regards digital technologies as strategic resources that enhance firms' dynamic capabilities. Human capital theory emphasizes how skill upgrading contributes to productivity improvements, while transaction cost and agency theories suggest that digitalization reduces information asymmetry, lowers coordination costs, and enhances governance efficiency. Together, these perspectives imply that digital transformation may influence TFP through multiple mechanisms, including innovation enhancement, human capital optimization, cost reduction, and operational efficiency.

Currently, an increasing number of enterprises are undertaking digital transformation, leveraging digital technologies to upgrade their business models and organizational structures. This raises several important questions: Can digital transformation improve production efficiency? Through what mechanisms does it affect TFP? Do its effects differ significantly across enterprises with varying regional and firm-specific characteristics? While existing studies provide valuable insights, they remain fragmented. Some focus only on single mechanisms (e.g., innovation), while others rely primarily on macro-level data, limiting their ability to capture firm-level heterogeneity. This leaves several critical gaps unaddressed, motivating a comprehensive framework and firm-level empirical investigation. Clarifying the impact of digital transformation on enterprise TFP and adjusting policies accordingly is essential for promoting the transition from old to new growth drivers and for optimizing resource allocation. In response to these questions, this paper investigates how digital transformation affects enterprise TFP, focusing on both its overall impact and the internal mechanisms that drive this relationship. Specifically, it explores whether and how digital transformation improves innovation capability, optimizes human capital structure, enhances cost efficiency, and promotes operational efficiency. Moreover, it examines how the productivity effects of digital transformation vary across firms with different characteristics and operating environments (See Figure 1). Accordingly, this paper addresses three core research questions: (1) Does digital transformation significantly enhance enterprise TFP? (2) Through which mechanisms—innovation, human capital, cost, and efficiency—does digital transformation exert its influence? (3) Do these effects vary

across different firm characteristics and contexts? The main contributions of this study are threefold. First, it provides comprehensive micro-level evidence on how digital transformation influences enterprise TFP in China, distinguishing between the effects of DTA and UT. Second, it identifies and empirically validates multiple mechanisms—enhancement of innovation capability, optimization of human capital structure, cost reduction, and efficiency improvement—through which digital transformation drives productivity. Notably, this study is the first to uncover that cost reduction, as well as improvements in inventory turnover and fixed asset utilization, serve as critical channels through which digital transformation enhances productivity. Third, it extends the heterogeneity analysis by demonstrating that the productivity-enhancing effects of digital transformation are more pronounced in firms with higher market value, greater industry competition, and in regions characterized by higher levels of marketization and more advanced digital infrastructure. Collectively, these findings contribute novel theoretical and empirical insights into the mechanisms and boundary conditions under which digital transformation promotes firm-level productivity growth.

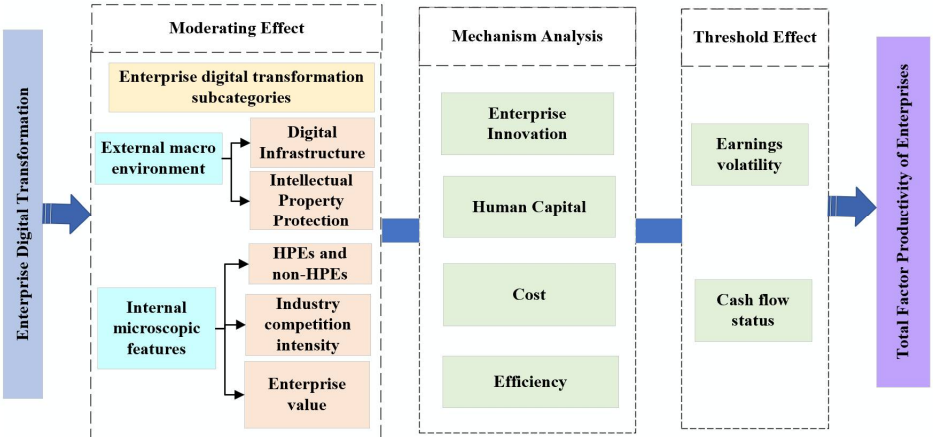


Figure 1. Research framework.

2. Literature Review

With the continuous advancement of digital technologies, academic research on enterprise-level digital transformation has been growing, and related topics have become a popular focus of discussion. Scholars emphasize different aspects of its definition. Gray and Rumpe (2017) [2] suggest that digital transformation entails social, business, and industrial changes driven by information technology, enabling real-time data processing and providing stakeholders with more accurate process and product information. Cennamo et al. (2020) [3] highlight that digital transformation goes beyond traditional backend technology platforms, encompassing changes in strategy, innovation, business processes, and governance. Regarding the driving forces of digital transformation, scholars generally classify them into external and internal factors. External factors refer to environmental conditions such as policy adjustments and market changes faced by enterprises, which can be further divided into policy-level and market-level influences [4,5]. In response to shifts in the external environment, enterprises may adjust their investment, operational, and development strategies, undertaking digital transformation either proactively or reactively. Internal factors refer to an enterprise's own conditions or motivations, including management-level and organizational-level drivers [6,7], which reflect its endogenous drive for innovation and efficiency improvement. At the management level, these include leadership's digital vision and decision-making orientation, while at the organizational level, they encompass resource allocation, employee skills, and cultural readiness for change.

The organizational impacts of digital transformation can be examined from multiple dimensions, creating comprehensive value for enterprises. Economically, it fosters complementarities between digital technologies and labor skills, generating higher value returns that significantly influence both economic and workforce development [8,9]. In governance, the transformation process enhances stakeholder protection mechanisms, reduces internal corruption risks, and mitigates credit vulnerabilities through synergistic interactions with financial inclusion systems [10,11]. From an innovation perspective, digital transformation promotes green innovation by strengthening corporate social responsibility initiatives and upgrading organizational knowledge and resource infrastructures. These improvements support sustainable innovation outcomes and address environmental challenges by enhancing technological capabilities [12,13].

Among these effects, the impact of digital transformation on enterprise TFP is one of its key microeconomic dimensions. Zhou and Wan (2023) [14] found that when an enterprise's digital level increases by one standard deviation, its TFP can rise by 3.73%, and this growth effect is persistent. Tao et al. (2023) [15] showed that, from the perspective of supply chain resilience, digital transformation in downstream firms indirectly enhances the productivity of upstream partners through improved data transmission, demand forecasting, and coordination efficiency. Guo et al. (2023) [16] suggested that, through management myopia and the digital paradox, digital transformation can boost enterprise TFP while also diminishing performance. Ding et al. (2024) [17] highlighted the mediating role of ESG in the relationship between digital transformation and enterprise TFP. Wu et al. (2023) [18] noted that digital transformation promotes TFP through three channels: financial stability, innovation, and information transparency. The effects of digital transformation in specific industries have also drawn particular attention, with the manufacturing sector being a major focus. Zhao et al. (2021) [19] conducted a comparative study of manufacturing and service industries, finding that digital transformation reduces costs, optimizes human capital, fosters innovation, and supports TFP in both sectors. Tang et al. (2024) [20] examined cultural tourism enterprises and found that digital transformation has become a key driver of TFP in this industry. Other scholars have also shown that digital transformation can improve both green TFP and carbon TFP [21,22]. Recent work cautions that intangible accumulation does not automatically translate into productivity gains. Using cross-country firm data, Nakatani (2024) [23] documents a negative association between intangible assets and TFP in China, plausibly linked to the surge of registered intangibles that may not reflect commensurate productive capabilities. This echoes Hu et al. (2017) [24], who show that China's recent patent boom features quantity outpacing quality. Our study helps reconcile these findings by distinguishing digital transformation (adoption and effective use) from the mere stock of intangibles on financial statements. We show that the productivity payoff to digitalization is conditional: it strengthens when marketization and IP protection are higher and when competitive pressure is stronger—contexts where digital investments are more likely to be implemented well and protected from dissipation. A review of the literature reveals that, although existing studies examine the relationship between digital transformation and enterprise TFP from various perspectives, they often lack comprehensive mechanism analysis and systematic investigation. Moreover, the differential effects of digital transformation across different types of enterprises remain underexplored. To address this gap, this paper makes three main contributions. First, it empirically examines the overall effect of digital transformation on enterprise TFP, distinguishing the impacts of DTA and UT. Second, it identifies the internal mechanisms through which digital transformation enhances TFP—specifically via innovation, human capital structure, cost control, and operational efficiency—using a mediation framework and formal statistical testing. Third, it conducts a focused heterogeneity analysis, showing how the effect of digital transformation

varies by firm characteristics such as market value, industry competition, and pollution intensity, as well as by external environmental conditions like digital infrastructure and intellectual property protection.

3. Theoretical Analysis and Research Hypotheses

3.1. Digital Transformation and TFP of Enterprises

Digital transformation should be viewed as a complex adaptive system in which multiple internal mechanisms—innovation, human capital restructuring, cost reduction, and efficiency gains—interact dynamically to shape productivity outcomes. From the perspective of endogenous growth theory, digital transformation enhances innovation by improving information flows, reducing mismatches in R&D inputs, and enabling knowledge spillovers, thereby strengthening the accumulation of technological progress. Consistent with human capital theory, digital transformation reshapes labor demand by increasing the need for digitally skilled employees, improving the overall quality of the workforce and amplifying innovation capacity. Drawing on transaction cost economics, digital transformation reduces operating, financial, and coordination costs through digital platforms and real-time monitoring, thereby freeing resources for productive investment. Finally, from the lens of the resource-based view and dynamic capability theory, digital transformation enhances efficiency by optimizing inventory management, increasing asset utilization, and enabling more flexible organizational responses to market demand. Importantly, these mechanisms are not independent; rather, they are mutually reinforcing. For example, greater innovation raises the demand for high-skilled labor, improved human capital enhances the effectiveness of digital tools, and cost savings allow firms to reinvest in efficiency-enhancing technologies. This systemic and path-dependent interaction underscores that the effect of digital transformation on TFP should be understood not as the result of a single pathway, but as the co-evolution of organizational, technological, and behavioral components. Based on this, we posit Hypothesis 1:

Hypothesis 1. *Digital transformation increases firms' total factor productivity.*

3.2. Transmission Mechanism

3.2.1. Enterprise Innovation Effect

Digital transformation optimizes the allocation of innovation resources. From an agency-theory perspective, it mitigates information asymmetry between principals (shareholders) and agents (managers and employees) through real-time reporting, digital dashboards, granular project tracking, and audit trails, which improve monitoring and incentive alignment, reduce slack and moral hazard in R&D, and channel funds toward higher-return projects. By enabling timely and accurate access to market and customer information, digital transformation further promotes more effective innovation decision-making [25]. Moreover, substantial reductions in information transmission and coordination costs lower intermediation and depreciation expenses during the innovation process, thereby reducing research and development expenditures for a given output [26].

Digital transformation also strengthens cooperation within and beyond the firm, facilitating knowledge recombination and resource sharing that boost innovation output: by lowering communication costs and removing barriers between departments and across enterprises, it promotes collaboration and complementarities between businesses and academic institutions [27], while relaxing geographic constraints on joint R&D and encouraging regional innovation cooperation [28]. As a result, knowledge barriers between departments, enterprises, and regions are effectively dismantled, expanding the boundaries and scope of enterprise innovation [29]. Innovation activities, in turn, transform

production processes and management models, leading to the accumulation of knowledge capital—such as patents, brands, and organizational culture—that enhances the productivity of existing material and human resources, thereby boosting TFP [30]. On factor demand, technological change shifts tasks toward greater skill intensity [31]. On capital inputs, technological advancements continually lower the prices (user cost) of advanced machinery and equipment, allowing enterprises to acquire more capital at reduced cost [32], fostering economies of scale and enhancing production efficiency [33]. Furthermore, improved governance and richer data help prioritize high-return projects and allocate remaining resources more rationally, increasing overall resource utilization efficiency.

Hypothesis 2a. *Digital transformation enhances TFP by improving enterprise innovation capacity.*

3.2.2. Human Capital Structure Effect

Digital transformation in enterprises requires the deployment of more advanced software and hardware. To effectively utilize these tools in production, operations, and management, firms must recruit a greater number of highly skilled technical professionals; employees with higher education levels are better equipped to master cutting-edge technologies, thereby enhancing the enterprise's human capital structure [34]. As production, operations, and management move toward greater intelligence and automation, the demand for low-skilled workers declines and the need for highly skilled, highly educated talent grows, driving organizational upgrading and the creation of more high-tech departments and specialized roles. Crucially, the presence of graduate and highly educated employees generates knowledge spillovers within teams and across units, improving the efficiency of lower-skilled workers and amplifying the returns to digital tools [35].

Optimizing the human capital structure effectively enhances labor productivity: employees with a bachelor's degree or higher are better able to operate advanced technological equipment, thereby improving production efficiency [36]. Compared with workers of lower educational attainment, higher-educated employees exhibit stronger multi-functional adaptability, enabling them to handle both specialized and general tasks; this flexibility reduces redundancy in human resource allocation and contributes to gains in TFP [37]. By elevating absorptive capacity and the effective use of digital technologies, a more skilled workforce also supports higher innovation output and deeper adoption quality.

Hypothesis 2b. *Digital transformation enhances enterprise TFP by optimizing the human capital structure.*

3.2.3. Cost Effect

From a theoretical perspective, the cost-effect of digital transformation can be understood through the lens of transaction cost economics and agency theory. Digital technologies reduce coordination and information costs by improving real-time communication, lowering monitoring frictions, and enhancing transparency [38]. This not only decreases operating and administrative expenses but also mitigates agency costs by improving decision quality and reducing managerial slack. For example, digital platforms and advanced management systems minimize raw material waste, improve process efficiency, and reduce the probability of costly decision-making errors [39]. In addition to operating costs, digital transformation also lowers financial costs. More stable and transparent operating outcomes signal reduced business risk, thereby improving firms' creditworthiness in the eyes of external investors and lenders. As perceived risk declines, financial institutions are more inclined to offer financing at favorable terms, such as lower interest rates, which indirectly reduces the cost of capital. Furthermore, digital technologies—such as real-time cash flow

monitoring, digital payment platforms, and smart financial systems—optimize capital allocation, lower transaction fees, and reduce precautionary liquidity needs [40]. Persistently high cost levels can crowd out resources for R&D and equipment upgrades, or lead to overly conservative strategies, both of which constrain long-term productivity [41,42]. Thus, curbing both operational and financial costs is not merely a short-term benefit, but a critical pathway for sustaining total factor productivity over the long run [43].

Hypothesis 2c. *Digital transformation enhances enterprise TFP by lowering costs.*

3.2.4. Efficiency Effect

The efficiency-enhancing role of digital transformation can be understood through the lens of dynamic capability theory and the resource-based view. Dynamic capability theory emphasizes that firms improve performance not only by acquiring resources, but also by reconfiguring and redeploying them in response to environmental change [44]. Digital transformation provides the tools for such reconfiguration by enabling firms to optimize both short-term operating cycles and long-term capital deployment. From the RBV perspective, improved efficiency in asset utilization and inventory management constitutes a valuable and difficult-to-imitate capability that strengthens competitive advantage.

At the operational level, digital technologies improve inventory turnover through real-time monitoring, automated replenishment, and AI-based demand forecasting. These tools reduce mismatches between supply and demand, lower excess stock, and release working capital, thereby enhancing agility and mitigating risks associated with storage, obsolescence, and procurement shocks [45,46]. In parallel, digital transformation improves fixed asset utilization by facilitating predictive maintenance, digital twin simulations, and asset performance analytics. These practices extend asset lifecycles, reduce idle capacity, and increase capital productivity, while simultaneously lowering depreciation costs and minimizing delays from equipment failures [47,48].

Crucially, these two dimensions of efficiency do not operate in isolation. Improved inventory management reduces operational slack, while enhanced asset utilization amplifies returns from existing capital. Their synergistic interaction creates a complementary efficiency system that strengthens firms' ability to reallocate freed resources toward innovation and growth-oriented activities. In this way, digital transformation not only improves short-term efficiency but also establishes a foundation for sustained gains in total factor productivity.

Hypothesis 2d. *Digital transformation promotes TFP by improving operational efficiency.*

3.3. Heterogeneity Analysis

To unpack how and when digitalization lifts productivity, we proceed in three parts. First, we distinguish Underlying Technologies (AI, big data, blockchain, cloud) from Digital Technology Applications embedded in operations. Second, we assess external moderators—digital infrastructure, intellectual property protection, and marketization. Third, we examine internal moderators—pollution intensity, product-market competition, and firm valuation—that shape firms' ability to convert digital inputs into TFP gains.

3.3.1. Subcategories of Enterprise Digital Transformation

UT—artificial intelligence, big data, blockchain, and cloud computing—are general-purpose digital technologies that expand a firm's frontier of data, computation, and connectivity. As general-purpose technologies, they exhibit scalability, non-rivalry, and strong complementarities with organization and human capital, creating option value for new products, processes, and business models and generating broad knowledge

spillovers across units and time [33,44,49,50]. By contrast, DTA refers to embedding those foundations into specific workflows (e.g., enterprise systems, supply-chain digitization, analytics-in-use). Such applications primarily yield local process improvements—faster information flows, tighter cost control, and better asset and inventory utilization—with returns that can be sizable but often subject to diminishing marginal gains within bounded routines [3,14,39,51,52]. Taken together, theory suggests that UT should lift TFP not only directly (through automation and data-driven decisions) but also indirectly by enabling complementary organizational changes and subsequent application layers; the resulting network and learning effects can compound over time and across use cases, plausibly delivering a larger aggregate productivity impulse than any single application domain.

Hypothesis 3a. *Both UT and DTA increase firm TFP, and the productivity effect is stronger for UT than for DTA.*

3.3.2. External Macro Environment

Digital infrastructure—broadband networks, backbone fiber, data centers, cloud access—acts as a general-purpose, enabling infrastructure that complements firm-level digital transformation. In regions with denser, faster, and more reliable networks, the marginal return to digital transformation rises because (i) latency and bandwidth constraints fall, lowering coordination and information-processing costs; (ii) data generation, storage, and sharing become cheaper and timelier, strengthening analytics, automation, and AI deployment; and (iii) interoperability across partners expands, amplifying supply-chain spillovers and platform effects. These mechanisms align with evidence that better digital infrastructure improves knowledge flows, supply-chain efficiency, and the conversion of digital adoption into performance gains [50,53–56].

Formally, we treat digital infrastructure as a regional moderator that conditions the DT–TFP link. Operationally, digital infrastructure is proxied by broadband access ports per capita at the provincial level (with a robustness proxy given by minimum distance to the nearest optical-fiber backbone city). Where digital infrastructure is high, firms face lower frictions integrating cloud services, IoT/ERP systems, and data-driven routines; where digital infrastructure is weak, identical digital transformation efforts confront bottlenecks (unstable connectivity, limited throughput), muting productivity payoffs—even with comparable internal capabilities.

Hypothesis 3b. *Digital infrastructure plays a positive regulatory role in the impact of digital transformation on TFP.*

Stronger intellectual property protection increases the appropriability of returns from digital transformation by safeguarding software, algorithms, data assets, and digitally enabled process innovations, thereby lowering imitation risk, curbing free-riding, and supporting licensing/contracting needed to scale digital use [44,57]. In environments with weak intellectual property protection, firms anticipate leakage of digital know-how and data, underinvest in complementary capabilities, and limit external data sharing; where intellectual property protection is stronger—proxied by city/provincial court rulings and related indices—firms face clearer enforcement, more predictable payoffs, and greater incentives to embed and exploit digital tools, with documented links to innovation investment and commercialization in China [50,58–60]. Thus, the same level of digital adoption should translate into larger productivity gains when intellectual property protection is robust.

Hypothesis 3c. *Intellectual property protection plays a positive regulatory role in the impact of digital transformation on TFP.*

Greater marketization—where resource allocation, entry–exit, and pricing are guided more by market forces than administrative intervention—should strengthen the productivity payoff of digital transformation. In market-oriented regions, stronger competition and harder budget constraints intensify selection on managerial quality and technology fit, pushing firms to deploy digital tools in ways that raise efficiency rather than merely signaling adoption [5,61]. Deeper factor-market development and fewer distortions also ease the reallocation that digital transformation requires—hiring digitally skilled labor, outsourcing noncore functions, and scaling data-intensive processes—while clearer property rights and contracting environments reduce transaction costs in digital ecosystems, from platform participation to data sharing [3,62]. Empirically, China's provincial marketization differences—measured by the China Marketization Index—capture precisely these institutional features [63]. Therefore, the same level of digital adoption should translate into larger gains in total factor productivity where market mechanisms are stronger.

Hypothesis 3d. *Marketization plays a positive regulatory role in the impact of digital transformation on TFP.*

3.3.3. Internal Micro Characteristics

In heavily polluting industries, stringent environmental compliance, capital-intensive production, and rigid legacy processes divert managerial attention and financial resources toward meeting regulatory mandates, dampening the organizational change and complementary investments that make digital tools productive [64,65]. High fixed-asset intensity also limits the scope for rapid process reconfiguration and reduces the short-run elasticity of operations to information and analytics. By contrast, firms in non-high-polluting industries—often more service- or knowledge-intensive—exhibit greater process modularity, lower compliance drag, and higher returns to data, software, and organizational recombination, allowing digital technologies to translate more readily into efficiency gains and learning effects [34,51]. Hence, digital transformation should yield larger productivity improvements outside heavy-pollution sectors.

Hypothesis 3e. *The positive impact of digital transformation on total factor productivity is stronger for companies operating in non-high-polluting industries.*

Competitive pressure raises the marginal value of information, speed, and process innovation: firms in tight markets face stronger incentives to adopt and effectively implement digital tools for rapid sensing, decision-making, and cost/quality improvements, while weakly competitive markets permit slack and dilute execution discipline [49]. Competition also amplifies learning-by-doing and selection: firms that combine digital technologies with complementary organizational changes survive and expand, whereas laggards exit, increasing the observed productivity payoff to digitalization [66,67]. Moreover, digital transformation enables timely product and service differentiation, data-driven pricing, and agile supply-chain coordination that are especially valuable where rivals are numerous and customer switching costs are low [68]. Consequently, stronger product-market competition should intensify the productivity gains from digital transformation.

Hypothesis 3f. *The positive impact of digital transformation on total factor productivity is stronger for companies operating in highly competitive product markets.*

Higher-valued firms typically enjoy superior access to external finance, stronger investor monitoring, and richer intangible endowments (capabilities, brand, data), which lower adoption frictions and enable complementary organizational change—conditions un-

der which digital technologies yield larger productivity gains [49,51,69]. Market valuation also reflects credible growth options and managerial commitment, supporting multi-year digital programs and talent acquisition that turn technology into sustained efficiency and innovation improvements [32]. Further, financially healthier firms are better positioned to absorb short-term adjustment costs and operational risks during transformation, reinforcing the realized TFP payoff [70].

Hypothesis 3g. *The positive impact of digital transformation on total factor productivity is stronger for companies with high enterprise value.*

4. Study Design

4.1. Model Setup

To examine whether digital transformation can enhance enterprises' TFP, this study develops Model (1) drawing on the frameworks of Tao et al. (2023) [15] and Huang et al. (2023) [50]:

$$TFP_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \rho X_{i,t} + \mu_i + \delta_t + \gamma_s + \eta_c + \varepsilon_{i,t} \quad (1)$$

where $TFP_{i,t}$ represents the TFP of enterprise i in year t. In the empirical specifications, we take the natural logarithm of TFP as the dependent variable. $DT_{i,t}$ is the core explanatory variable. $X_{i,t}$ represents control variables. To mitigate potential omitted variable bias, we incorporate multiple layers of fixed effects across our empirical models. Firm fixed effects control for unobservable time-invariant firm characteristics such as managerial ability, corporate culture, or long-term strategic orientation. μ_i, δ_t, γ_s and η_c represent the industry fixed effects, time fixed effects, industry fixed effects (at the 4 digit industrial classification level) and city fixed effects, respectively. Year fixed effects capture macroeconomic shocks and secular trends in digital infrastructure development—such as the increasing penetration of mobile phones, internet access, and nationwide digital governance reforms—that may influence all firms over time. In our baseline regression, we additionally include industry and city fixed effects to account for technological heterogeneity across sectors and regional differences in infrastructure and policy environments.

This study employs a moderation effect model to analyze the differences in the impact of digital transformation on the TFP of different types of enterprises.

$$TFP_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \alpha_2 Z_{i,t} + \alpha_3 DT_{i,t} \times Z_{i,t} + \rho X_{i,t} + \mu_i + \delta_t + \gamma_s + \eta_c + \varepsilon_{i,t} \quad (2)$$

Model (2) is based on Model (1) with the addition of two variables. One is the moderator variable $Z_{i,t}$, and the other is the interaction term $DT_{i,t} \times Z_{i,t}$, which reflects how the impact of digital transformation on enterprise TFP is moderated by $Z_{i,t}$. The moderator vector $Z_{i,t}$ comprises six constructs that condition the productivity effects of digital transformation: (i) a heavily polluting industry indicator (HP = 1 if the industry is listed in the official heavy-pollution catalogue; 0 otherwise); (ii) digital infrastructure, proxied by broadband access ports per capita at theprovincial level; (iii) intellectual property protection (IPP), measured by a provincial -level IP protection index based on counts of IP-related court rulings; (iv) product-market competition, measured by the sales-based Herfindahl–Hirschman Index at the four-digit industry–year level and inverse-coded so that larger values indicate stronger competition; (v) regional marketization, captured by the provincial China Marketization Index; and (vi) firm valuation, proxied by Tobin's Q, defined as (market value of equity + book value of debt)/total assets (market value of equity + book value of debt)/total assets.

4.2. Variable Selection and Data Sources

(1) Dependent Variable: TFP of Enterprises. We estimate TFP primarily using the Gandhi–Navarro–Rivers (GNR) production-function approach and treat five alternative estimators—ordinary least squares, firm fixed effects, generalized method of moments, Olley–Pakes (OP), and Levinsohn–Petrin (LP)—as robustness checks reported in the Appendix A. GNR identifies output elasticities from the firm's first-order optimality conditions for flexible inputs, thereby avoiding the strong monotonicity/invertibility assumptions required by control-function methods and mitigating simultaneity and selection concerns that affect ordinary least squares and fixed-effects estimates. OP and LP remain informative benchmarks: OP uses investment as a proxy for unobserved productivity (which can drop observations with zero investment), whereas LP uses intermediate inputs and thus eases sample-selection concerns. In all specifications, we adopt a Cobb–Douglas production function; we provide the full estimation steps for GNR, OP, LP, and generalized method of moments, together with mathematical derivations and diagnostics, in Appendix A. All variables are drawn from the China Stock Market and Accounting Research (CSMAR) database.

(2) Explanatory Variable: Degree of Digital Transformation of Enterprises. Building on the work of Wu et al. (2021) [52], this paper employs text analysis to measure the degree of digital transformation. The process involves three steps, using both Python (version 3.10) and Java (version 17) tools for calculation. Step 1: Employ Python web scraping tools and the Java PDFBox library to collect and extract text data from annual reports. The extracted text serves as the corpus for keyword frequency analysis. Step 2: Based on existing literature and policy reports, select keywords related to digital transformation for analysis. Specifically, these keywords are categorized into two groups: DTA and UT. DTA refers to the practical application of digital technologies, while UT includes Artificial Intelligence Technology (AIT), Big Data Technology (BDT), Blockchain Technology (BT), and Cloud Computing Technology (CCT). The specific terms are shown in Figure 2. During keyword matching, it is important to note that if a digital transformation-related term is preceded by a negation word such as "no," "not," or "none," it should be excluded from the statistics. Step 3: Using the annual report text corpus, classify and extract the frequency of digital transformation-related keywords and perform statistical analysis. The classified frequency data are then aggregated to construct panel data on enterprise digital transformation. We construct five sub-indicators to measure digital transformation: one indicator for DTA and four indicators for UT—namely AIT, BDT, BT, and CCT. These five standardized sub-indicators are aggregated into a composite index, which serves as the main explanatory variable in the empirical analysis. In conducting heterogeneity analysis, we further break down the technologies applied in digital transformation by different keyword frequency composition dimensions and perform regression analysis for each category of technology (See Figure 2).

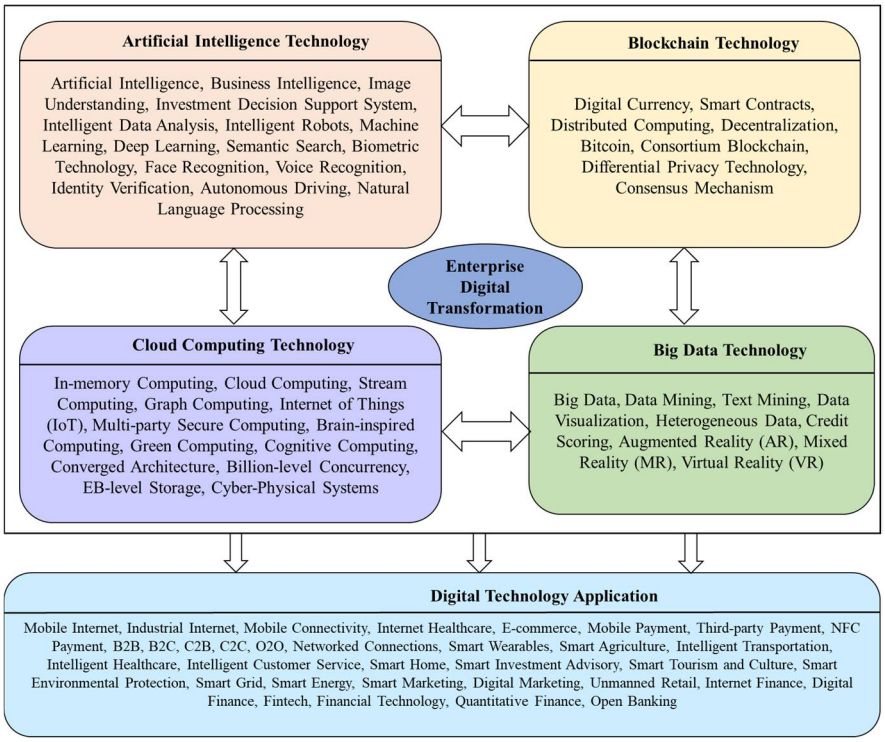


Figure 2. Annual Report Text Extraction Fields for Enterprise Digital Transformation.

The level of enterprise digital transformation has exhibited a year-on-year upward trend, particularly driven by the growing application of DTA such as AIT, BDT, and CCT. Using text analysis, this study measures the digital transformation level of each company and then calculates the annual average digital transformation level for Chinese listed companies.

(3) Control Variables. Based on the studies of Huang et al. (2023) [50] and Wu et al. (2021) [52], the following control variables are selected: firm age (AGE), firm size (SIZE), leverage ratio (LEV), ratio of intangible assets (IAR), ownership concentration (TOP10), revenue growth rate (ORG), current ratio (CR) and proportion of independent directors (INDE).

This study uses A-share listed companies from the Shanghai and Shenzhen Stock Exchanges for the period 2007–2024. Consistent with existing literature, we exclude firms designated as "Special Treatment" (ST) or "Particular Transfer" (PT) due to financial irregularities or delisting risks. We also exclude financial firms and observations with missing key variables. After these filtering steps, our final unbalanced panel dataset comprises 51,458 firm-year observations, covering 5401 unique A-share listed companies. This broad and representative sample enables us to capture firm-level heterogeneity across industries, ownership structures, and regions. Patent data is obtained from the China Research Data Services platform, which provides full-text annual reports and patent records. Firm-level financial indicators such as total assets and liabilities are sourced from the Wind Economic Database. Detailed definitions of all variables used in this study are provided in Table A1 of the Appendix A. Table 1 presents the pairwise correlations among the key variables. DT is positively and significantly correlated with TFP, suggesting that firms with higher levels of digital adoption tend to have better productivity outcomes. SIZE also shows a positive correlation with both DT and TFP, indicating that larger firms are more likely to undergo digital transformation and achieve higher productivity. The IAR is negatively correlated with TFP, reflecting the possibility that asset-heavy firms may be less flexible or

efficient in leveraging digital tools. Importantly, the magnitudes of these correlations are moderate, and no strong multicollinearity is observed among the independent variables.

Table 1. Bivariate Correlation Matrix.

Variables	LEV	AGE	SIZE	IAR	TOP10	ORG	CR	INDE
LEV	1.0000							
AGE	0.1305 **	1.0000						
SIZE	0.4596 ***	0.1621 **	1.0000					
IAR	0.0764	−0.0544	0.0567	1.0000				
TOP10	−0.1026	−0.1885 **	0.1823 *	0.0010	1.0000			
ORG	0.0353	−0.0475	0.0518	−0.0733	0.1091	1.0000		
CR	−0.6413 ***	−0.1106	−0.3094 ***	−0.2522 ***	0.1090	−0.0394	1.0000	
INDE	−0.0197	0.0051	0.0176	−0.0652	0.0336	−0.0018	0.0273	1.0000

Note: This table reports pairwise Pearson correlation coefficients among key control variables. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

5. Empirical Analysis

5.1. Baseline Regression Analysis

To clarify identification, we structure Table 2 so that the estimating variation is always within a firm over time, while the fixed effects (FE) in each column progressively purge broader sources of confounding. All columns include firm FE (removing time-invariant firm heterogeneity) and year FE (absorbing nationwide shocks). Column (1) is the within-firm baseline. Column (2) adds industry FE, which captures persistent sectoral differences in technology intensity, regulation, and market structure that could otherwise load onto the DT coefficient. Column (3) instead adds city FE, absorbing persistent local factors (infrastructure, policy stance, demand conditions). Column (4) includes both industry and city FE in addition to firm and year FE, our preferred specification, jointly purging sectoral and locational heterogeneity. This sequencing serves two purposes: (i) it demonstrates that the DT coefficient is stable in sign and magnitude as controls become more stringent—hence robust to alternative FE environments; and (ii) it keeps the model parsimonious and avoids over-conditioning or collinearity while making clear what variation identifies β in each column. Importantly, adding industry/city FE is informative in our data because a nontrivial share of firms switches industry or city over the sample, so these FE are not mechanically collinear with firm FE. Our findings are consistent with previous studies: Tao et al. (2023) [15] found that the digital transformation of upstream listed companies can indirectly improve the production efficiency of downstream partners through supply chain spillover effects, while Zhao et al. (2021) [19] reported that digital transformation in both manufacturing and service industries can effectively enhance corporate productivity (see Table 2). The difference from Nakatani (2024) [23] (and the broader literature informed by Hu et al., 2017 [24]) reflects our distinct measurement of digital transformation and the boundary conditions under which it generates productivity gains. Our DT measures emphasize the use of digital tools (text/expert indices) and capability building (digital patenting). The DT–TFP link is stronger where institutional quality (marketization, IP protection) and competition are higher—environments that facilitate selection, protect data assets, and discipline implementation. In settings characterized by rapid accumulation of low-quality intangibles (as noted by Hu et al., 2017 [24]), or weaker institutions (as in Nakatani (2024) for China averages [23]), digital investments may not materialize into productivity.

Table 2. Regression results of digital transformation on enterprise TFP.

	(1) TFP	(2) TFP	(3) TFP	(4) TFP
DT	0.0035 ***	0.0030 ***	0.0035 ***	0.0031 ***
	(5.79)	(5.64)	(5.99)	(5.85)
LEV	−0.0096 **	−0.0106 **	−0.0092 **	−0.0104 **
	(−2.01)	(−2.32)	(−1.98)	(−2.32)
AGE	0.0331 ***	0.0338 ***	0.0349 ***	0.0362 ***
	(3.89)	(4.17)	(4.14)	(4.52)
SIZE	0.0686 ***	0.0687 ***	0.0690 ***	0.0689 ***
	(51.64)	(53.71)	(53.63)	(55.00)
IAR	−0.1084 ***	−0.1022 ***	−0.1141 ***	−0.1097 ***
	(−6.38)	(−6.33)	(−7.17)	(−7.13)
TOP10	0.0001	0.0002 **	0.0001 *	0.0002 **
	(1.63)	(2.01)	(1.70)	(2.11)
ORG	0.0288 ***	0.0288 ***	0.0290 ***	0.0290 ***
	(38.91)	(39.45)	(38.36)	(38.99)
INDE	−0.0001	−0.0001	−0.0001	−0.0001
	(−0.83)	(−0.78)	(−0.93)	(−0.85)
Constant	1.5185 ***	1.4694 ***	1.5495 ***	1.4872 ***
	(71.40)	(48.04)	(40.47)	(33.54)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	N	Y	N	Y
City FE	N	N	Y	Y
N	51,458	51,458	51,458	51,458
R^2	0.5967	0.6089	0.6155	0.6261

Note: (1) The values in parentheses are *t*-values, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the individual level. The same applies to all subsequent tables. (2) Unless otherwise specified, all regressions in this paper control for firm, year, industry, and city fixed effects.

5.2. Robustness Checks

(1) Replacement of Dependent Variable: In the baseline analysis, we compute total factor productivity (TFP) using the Gandhi–Navarro–Rivers (GNR) estimator and re-estimate Equation (1) with this measure. For robustness, we also construct TFP with five alternative methods—ordinary least squares, firm fixed effects, generalized method of moments, Olley–Pakes, and Levinsohn–Petrin—and re-run Equation (1) using each alternative TFP. The estimated coefficients on digital transformation remain similar in sign and significance across specifications; full results are reported in Table A2. To ensure our findings are not driven by a single proxy, we replace the baseline text-frequency measure with three widely used alternatives. First, following Qi et al. (2020) [71], we use the share of digital-related intangible assets in total intangible assets, which captures capitalized investments in software, databases, proprietary digital technologies, and other codified capabilities—thereby mitigating the rhetorical bias inherent in keyword counts. Second, drawing on Zhao et al. (2021) [19], we employ a composite digital transformation index for manufacturing firms constructed from text analysis and expert scoring, blending semantic information with domain assessments to better reflect substantive transformation. Third, consistent with Huang et al. (2023) [50], we use the number of digital-technology patent applications as an outcome-anchored proxy for digital capability building. (2) Exclusion of Municipalities Directly Under the Central Government: Municipalities such as Beijing, Shanghai, Chongqing, and Tianjin have economic scales comparable to certain provinces and distinct political statuses. Their institutional development and governance structures differ from those of prefecture-level cities, which could influence the generalizability of our

findings. To ensure sample comparability, we excluded listed companies headquartered in these municipalities, retaining only those located in prefecture-level cities. (3) Shortening the Sample Period: The baseline regression initially covered the period from 2007 to 2024. To mitigate potential distortions arising from major external shocks—specifically, the 2008 global financial crisis and the COVID-19 pandemic starting in 2020—we restricted the sample period to 2009–2019 and re-estimated the model. This adjustment ensures that the estimated relationship between digital transformation and TFP is not confounded by these extraordinary macroeconomic events, thereby enhancing the robustness and credibility of the empirical results. (4) Adjustment of Clustering Level: The baseline regression clustered standard errors at the individual level. Following Tao et al. (2023) [15], we additionally clustered standard errors at the industry–time level, which offers a more robust approach by mitigating the effects of heteroscedasticity and autocorrelation on statistical inference (See Table A3).

5.3. Endogeneity Test

We find that digital transformation promotes the improvement of TFP in Chinese listed companies. However, firms with higher TFP may be more inclined to undertake digital transformation, suggesting the potential presence of reverse causality in the baseline regression. Moreover, while TFP is influenced by multiple factors and we have controlled for several variables that may affect it, the possibility of omitted variable bias cannot be fully ruled out. Therefore, endogeneity issues may exist in the relationship between digital transformation and TFP.

(1) Instrumental Variables Method. In studies on the digital economy and digital transformation, many scholars have employed early telecommunications data as an instrumental variable [72,73]. Following this literature, we first use provincial fixed-line telephone penetration to construct an IV, as historical communication infrastructure is highly correlated with digital adoption yet plausibly exogenous to firm-level productivity shocks in the post-2007 period. Specifically, we combine the logarithm of fixed-line telephones per 100 people in 1984 with the logarithm of internet broadband access ports from 2006 to 2018 [50]. The rationale is twofold: (i) fixed-line penetration captures long-term regional communication endowments that exogenously shaped later digital development (relevance), and (ii) conditional on firm, region, and year fixed effects, historical infrastructure is unlikely to be directly correlated with contemporaneous firm-level productivity shocks (exclusion). In the baseline IV specification, we adopt the approach of "one instrumental variable corresponds to one endogenous variable", so there is no over-identification in the model. As shown in column (1) of Table A4, the first-stage regression confirms strong relevance (F-statistic = 21.81), and the Cragg–Donald Wald F-statistic and Kleibergen–Paap rk LM statistic both indicate the absence of weak-instrument or identification problems. The second-stage regression (column (2)) shows that digital transformation significantly improves TFP, with a coefficient of 0.4975 ($p < 0.01$, 95% CI [0.1509, 0.8441]).

To further strengthen identification, we introduce two additional instruments. First, we use the minimum distance between a firm's prefecture-level city and the nearest optical-fiber backbone city, a predetermined geographic feature that reflects the ease of accessing high-quality digital infrastructure. Regions closer to backbone nodes enjoyed earlier and cheaper access to network resources, affecting firms' propensity to adopt digital technologies, while this distance has no direct link to firm-level productivity shocks. Table A4 (column (3)) reports that the first-stage coefficient is significantly negative (-0.0008, $t = -12.78$), with a first-stage F-statistic of 30.93, a Cragg–Donald Wald F-statistic of 163.241 (above the Stock–Yogo threshold of 16.38), and a Kleibergen–Paap rk LM statistic of 163.052 ***. The second stage confirms that digital transformation remains

significantly positive for TFP (*coef.* = 0.0209, *t* = 3.97). Second, we employ the average digital transformation level of other firms in the same industry (ADIG) to capture industry-wide technological diffusion and peer effects. As shown in Table A4 (column (5)), the first stage is very strong (*coef.* = 0.4934, *t* = 21.78; *F*-statistic = 474.43; Cragg–Donald Wald *F* = 474.432; Kleibergen–Paap rk *LM* = 253.981 ***), and the second stage again yields a positive and significant coefficient for digital transformation (*coef.* = 0.0152, *t* = 4.27). These results confirm that both distance and ADIG serve as valid instruments, and their estimates are highly consistent with the baseline findings.

(2) Policy Shock (DID). We further exploit the staggered establishment of National Big Data Comprehensive Pilot Zones as a quasi-natural experiment, treating it as an exogenous shock to firms' digital transformation opportunities. These pilot zones, initiated in selected provinces and cities, provided enhanced data infrastructure, governance frameworks, and supportive services that substantially lowered firms' costs of digital adoption. Firms located in pilot regions constitute the treatment group, while those outside serve as controls. The DID regression in Table A5 (column (1)) shows that the policy significantly promoted the productivity-enhancing effect of digital transformation, with the DID coefficient estimated at 0.0026 (*t* = 2.75). Conceptually, DID helps mitigate endogeneity by leveraging firm fixed effects to difference out time-invariant unobservable (e.g., persistent managerial quality or long-run capabilities) and year fixed effects to absorb common time shocks (e.g., macro cycles and industry-wide technology trends).

(3) Heckman Two-Step Method. Finally, we address potential sample selection bias using the Heckman two-step procedure. After controlling for the inverse Mills ratio (*IMR* = −0.1301, *t* = −10.32), the coefficient of digital transformation remains significantly positive (0.0248, *t* = 7.09), as reported in Table A5 (column (2)).

Taken together, the results from multiple complementary strategies—including historical telecommunications penetration, geographic proximity to backbone infrastructure, industry-level digitalization spillovers, exogenous policy shocks, and sample-selection correction—all consistently show that digital transformation exerts a significant and robust positive impact on firms' TFP. These findings alleviate endogeneity concerns and reinforce the causal interpretation of our results.

5.4. Heterogeneity Analysis Test

5.4.1. Heterogeneity Analysis—Subcategories of Enterprise Digital Transformation

In constructing the measure of enterprise digital transformation, we selected relevant word frequencies from two perspectives: DTA and UT. For technology application, we used word frequencies from the DTA dimension, while for UT, we selected word frequencies from the AIT, BDT, BT, and CCT dimensions. To distinguish the effects of different types of technologies on enterprise TFP, we took the logarithm (after adding 1) of the word frequency for each of the five dimensions—DTA, AIT, BDT, BT, and CCT. In addition, we summed the data for the four UT indicators (AIT, BDT, BT, and CCT) and then took the logarithm of the sum to construct a composite UT indicator, which reflects the development level of an enterprise's underlying technologies. In this study, we conducted regression analyses using DTA, UT, AIT, BDT, BT, and CCT as explanatory variables. The results show that both DTA and UT significantly enhance enterprise TFP. A comparison of their coefficients and significance levels indicates that UT exerts a stronger influence on productivity than DTA. While UT comprises the fundamental and core technologies that underpin digital transformation, serving as its technological foundation (see Table A6).

5.4.2. Heterogeneity Analysis—External Macro Environment

China is vast, with pronounced geographic differences between the north and south as well as the east and west. These regions vary significantly in economic development, infrastructure, and institutional maturity, which in turn shape enterprise operations and decision-making. As a result, geographical location and regional characteristics exert a lasting and profound influence on micro-enterprises. Following the empirical strategy, this section applies Model (2), which incorporates interaction terms to test the moderating effects of external macro-environmental factors on the relationship between digital transformation and TFP. Heterogeneity analysis of the external macro environment not only clarifies the influence of regional differences but also offers valuable insights for local governments in formulating effective policies to promote digital transformation and enhance the TFP of local enterprises. From a systems perspective, these regional disparities reflect variations in local innovation ecosystems, industrial structures, and government interventions. Even with nationwide investment in digital infrastructure, differences in local absorptive capacity and policy implementation create unique boundary conditions for the effectiveness of digital transformation.

(1) Digital Infrastructure. Significant disparities in digital infrastructure exist across China's provinces, affecting the initiation, pace, and effectiveness of enterprise digital transformation. Following Huang et al. (2023) [50], this study uses the per capita number of internet broadband access ports as an indicator of digital infrastructure, treating it as a moderating variable. We focus on the coefficient magnitude and significance of the interaction term DTDINF and find that stronger digital infrastructure amplifies the positive effect of digital transformation on TFP. Well-developed digital infrastructure provides the essential conditions for transformation, improving information processing speed and data analysis capacity, facilitating smoother communication, and enabling timely resource sharing, which collectively enhance decision-making efficiency. Moreover, firms in regions with advanced infrastructure are more likely to integrate emerging digital technologies into production and operations, optimizing management processes and uncovering new growth opportunities [54]. In contrast, firms in regions with underdeveloped infrastructure face obstacles such as limited access to advanced technologies and insufficient funding for digital innovation. Enhanced infrastructure also improves supply chain management efficiency, strengthens customer relationship maintenance [53], and enables employees to adopt and master digital technologies more quickly, thereby improving productivity. Thus, digital infrastructure is a critical factor shaping the productivity impact of digital transformation, with well-developed systems amplifying its positive effects [55]. However, infrastructure alone is insufficient; effectiveness also depends on regional system-level features such as industrial clustering, university–industry linkages, and proactive local government policies. Provinces with robust technology ecosystems (e.g., Guangdong, Zhejiang) tend to convert infrastructure investment into firm-level productivity gains more effectively, whereas regions with weaker innovation ecosystems may underutilize digital infrastructure despite comparable hardware inputs.

(2) Intellectual Property Protection (IPP). IPP is vital for fostering innovation and driving economic growth [57]. Digital transformation depends on advanced digital technologies, which are often easier to imitate or replicate than other forms of technology, making IPP particularly critical in this context [44]. The willingness of enterprises to pursue digital transformation is frequently influenced by the strength of local IPP. Following Shen and Huang (2019) [58], this study measures IPP levels in Chinese cities using the number of IP-related case rulings in local courts. Our results show that the impact of digital transformation on TFP is more pronounced in regions with stronger IPP [60]. Robust IPP provides a stable external innovation environment, reduces the risk of patent misappropriation [59],

and enables firms to form stable expectations of returns from digital transformation, thereby motivating continuous investment in research and experimental development. Strong IPP also facilitates the effective application and commercialization of patents, accelerating the conversion of digital transformation outcomes into productive forces [74]. From a systems theory perspective, IPP serves as a regulatory infrastructure that shapes firm behavior and innovation trajectories. In regions with weak IPP, even technologically capable firms may underinvest in digital transformation due to higher perceived risks of imitation and lower expected returns on innovation. By contrast, strong IPP regimes function as institutional enablers, safeguarding intangible assets, stabilizing long-term expectations, and amplifying the positive link between digital transformation and TFP (see Table A7).

(3) Marketization Index (MI). Marketization reflects the extent to which resource allocation and enterprise behavior are governed by market mechanisms rather than administrative intervention. Regions with higher marketization are characterized by fairer competition, more efficient factor flows, and stronger institutional support, creating an enabling environment for transformation and innovation. Following Wang et al. (2025) [75], this study adopts the provincial marketization index to measure regional marketization. The empirical results show that the interaction term between digital transformation and marketization (DIMI) is significantly positive, indicating that the productivity-enhancing effect of digital transformation is stronger in provinces with higher marketization. This highlights institutional quality as a boundary condition: in highly marketized regions, competitive pressure and flexible resource allocation amplify the benefits of digital initiatives, whereas in less marketized regions, weak governance and distorted allocation constrain firms from fully leveraging digital tools.

5.4.3. Heterogeneity Analysis—Internal Micro Characteristics

Building on the analysis of external macro-environmental factors, this section turns to the role of internal micro-level characteristics in shaping the relationship between digital transformation and TFP. These characteristics reflect firm-specific conditions—such as industry attributes, competitive positioning, and financial standing—that influence both the capacity and incentives for digital transformation. Following the empirical strategy, we apply Model (2), incorporating relevant interaction terms to test the moderating effects of internal characteristics on the impact of digital transformation on TFP.

(1) HPEs and Non-HPEs. Following Zhang et al. (2022) [76], A-share listed companies are classified into high-pollution enterprises (HPEs) and non-HPEs. The results show that digital transformation enhances production efficiency in both groups, but the effect is more pronounced among non-HPEs. HPEs are subject to strict environmental regulations that constrain financing options and delay the approval of new investment projects, thereby limiting the intensity and continuity of digital transformation. More importantly, environmental regulation acts as a systemic boundary condition that shapes the internal transformation process. Regulatory pressures can create feedback loops in which compliance demands consume resources and managerial attention, reducing the firm's capacity to pursue complex, long-term initiatives such as digital transformation. Consequently, digital maturity develops more slowly, and the resulting productivity gains are limited. In contrast, non-HPEs face fewer institutional constraints and enjoy greater strategic flexibility in adopting and implementing digital transformation. As Zhao et al. (2024) [65] note, these firms are better positioned to restructure organizational processes and fully capture the benefits of digital initiatives. Industry characteristics further explain this heterogeneity: in non-HPEs, particularly in the service sector, digital transformation is closely integrated with core business functions and directly contributes to productivity improvements [34], whereas in HPEs, production efficiency relies more heavily on physical

assets and heavy machinery [64], making digital transformation more of a supporting than a transformative force. Overall, the difference in effectiveness between HPEs and non-HPEs reflects not only policy and financial constraints but also systemic interactions between external institutional pressures and internal transformation capacity, which limit the full realization of digital transformation's productivity potential in HPEs.

(2) Industry Competition Intensity. The level of competition among enterprises varies across industries and can significantly influence both the decision-making process and the effectiveness of digital transformation. To quantify competition, we use the Herfindahl–Hirschman Index (HHI), a widely adopted measure of industry concentration. The HHI is introduced as a moderating variable in Model (2), with the interaction term DTHHI as the primary variable of interest. Regression results show a significantly positive coefficient for DTHHI, indicating that industry competition exerts a strong positive moderating effect on the relationship between digital transformation and firm TFP. Specifically, as competition intensifies, the productivity-enhancing effect of digital transformation becomes more pronounced. In highly competitive industries, digital transformation plays a greater role in driving productivity improvements. Facing intense market rivalry, firms are compelled to adopt high-risk, high-return strategic decisions to maintain their competitive advantage [66]. Under resource constraints, fierce competition incentivizes firms to pursue digital transformation as a means of discovering new growth opportunities [28]. Digital transformation also enables firms to differentiate their products and services, emphasizing unique features and advantages [68], while enhancing their capacity to respond rapidly to market and policy changes through real-time data collection and analysis [67]. Consequently, the greater the industry competition, the stronger the positive impact of digital transformation on TFP.

(3) Enterprise Market Value. A firm's market value reflects investors' expectations regarding its current performance and future growth prospects, often measured by Tobin's Q ratio. Regression results show a significantly positive coefficient for the interaction term DTTQ, indicating that digital transformation has a stronger effect on the TFP of firms with higher market value. This finding can be explained from three perspectives. First, a higher market value not only signals strong investor confidence in a firm's current position but also suggests an optimistic outlook for its future development. Such firms typically enjoy stable cash flows and broader financing channels, enabling them to secure capital market support more easily [69]. Second, firms with higher market value generally possess greater capabilities for digital transformation, including stronger talent pools and more advanced digital technology foundations, which allow them to integrate digital solutions into production processes more rapidly, thereby enhancing TFP [32]. Third, these firms tend to exhibit higher risk tolerance and a stronger inclination toward long-term strategic planning, enabling them to implement digital transformation initiatives more effectively and sustain their productivity gains over time [65] (see Table A8).

6. Further Analysis

6.1. Mechanism Analysis

This section adopts a systems thinking perspective to examine how digital transformation enhances TFP through multiple, interrelated mechanisms. Innovation, human capital upgrading, cost control, and efficiency improvements are not isolated drivers but are dynamically interconnected within a reinforcing structure. For example, innovation stimulated by digital transformation increases the demand for advanced human capital, while skilled personnel enhance the application and absorption of digital tools, thereby fueling further innovation. Similarly, cost savings generated through digital transformation can be reinvested to support efficiency-enhancing processes, creating a virtuous cycle.

Recognizing these feedback dynamics provides deeper insight into the cumulative and systemic nature of digital transformation's impact on firm performance.

Based on the theoretical analysis, we empirically test the mechanisms from four dimensions: innovation, human capital structure, cost, and efficiency. Therefore, based on Model (1), we introduce the following Models (3) and (4):

$$Mediator_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \rho X_{i,t} + \mu_i + \delta_t + \gamma_s + \eta_c + \varepsilon_{i,t} \quad (3)$$

$$TFP_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \alpha_2 Mediator_{i,t} + \rho X_{i,t} + \mu_i + \delta_t + \gamma_s + \eta_c + \varepsilon_{i,t} \quad (4)$$

where $Mediator_{i,t}$ is the mediating variable. In Model (3), our primary focus is on the magnitude and significance of α_1. In Model (4), we examine whether the inclusion of the mediator weakens the direct effect of digital transformation on TFP. We place particular emphasis on the coefficient α_2, which captures the mediating effect.

In order to empirically test the four hypothesized mechanisms, we construct a set of mediator variables that capture distinct but interrelated dimensions of firm performance enhancement. Innovation capability (Innovate) is measured as the natural logarithm of one plus the number of patent applications in a given year, following Jiang et al. (2020) [77] and Cao et al. (2023) [78], which provides a direct, quantitative indicator of a firm's technological output and innovation intensity, and is widely adopted in the literature as a timely proxy for innovative performance [79,80]. Human capital structure (HC) is measured by the proportion of employees holding a bachelor's degree or higher, reflecting the educational attainment and skill composition of the workforce; this indicator captures the extent to which a firm's labor force is equipped to absorb and apply advanced technologies, consistent with Huang et al. (2023) [50], Zhao et al. (2021) [19], and Qureshi (2023) [81]. Cost efficiency (CER) is proxied by the ratio of total operating costs to total operating revenue, reflecting the firm's capacity to control operating expenditures relative to income generation; lower values indicate more effective cost management, consistent with the approach of Hulten (2001) [82] and Griliches (2009) [83]. Operational efficiency is captured by two complementary turnover measures: fixed asset turnover (FAT), calculated as operating revenue divided by the average net value of fixed assets, and inventory turnover (ITR), calculated as operating revenue divided by the average inventory; the former reflects the utilization efficiency of capital-intensive resources, while the latter measures the speed with which inventory is converted into sales, following Brynjolfsson and Hitt (1998) [51], Caves et al. (1982) [84], and Teng et al. (2024) [85].

6.1.1. Innovation Capability Improvement Mechanism

Regression results in Columns (1) and (2) of Table 3 indicate that digital transformation has a significant positive effect on firms' innovation capability, and that innovation capability, in turn, is significantly and positively associated with TFP. This finding supports the argument that digital technologies enhance a firm's absorptive capacity and facilitate the integration of innovation resources [78,86]. Moreover, as Brynjolfsson and Hitt (2000) [49] note, digital transformation can generate sustained productivity gains by enabling organizational change and fostering the development of new products and processes. The Sobel (1982) test yields a z-value of 19.38 ($p < 0.01$), confirming a statistically significant indirect effect of digital transformation on TFP through innovation capability [87]. This result provides robust empirical support for Hypothesis 2a, highlighting innovation capability as a key pathway through which digital transformation promotes firm-level productivity improvements.

Table 3. Mechanism Analysis - Innovation and Human Capital Structure.

	(1)	(2)	(3)	(4)
	Innovation Capability Improvement Mechanism		**Human Capital Structure Optimization Mechanism**	
	Innovate	**TFP**	**HC**	**TFP**
DIG	0.0229 **	0.0035 ***	0.0085 ***	0.0033 ***
	(2.16)	(5.72)	(5.45)	(5.61)
Innovate		0.0013 ***		
		(2.66)		
HC				0.0191 ***
				(3.17)
LEV	−0.2747 ***	−0.0087 *	−0.0379 ***	−0.0089 *
	(−3.89)	(−1.81)	(−3.74)	(−1.86)
AGE	0.0735	0.0320 ***	−0.0842 ***	0.0347 ***
	(0.49)	(3.75)	(−3.88)	(4.09)
SIZE	0.5076 ***	0.0679 ***	0.0126 ***	0.0684 ***
	(23.86)	(49.11)	(4.05)	(51.26)
IAR	1.0173 ***	−0.1088 ***	−0.1462 ***	−0.1057 ***
	(3.59)	(−6.38)	(−3.48)	(−6.25)
TOP10	0.0003	0.0001	0.0003	0.0001
	(0.22)	(1.64)	(1.57)	(1.54)
ORG	−0.0040	0.0289 ***	0.0028 *	0.0287 ***
	(−0.35)	(38.97)	(1.74)	(38.89)
INDE	−0.0005	−0.0001	−0.0004	−0.0001
	(−0.27)	(−0.83)	(−1.46)	(−0.77)
Constant	−2.5363 ***	1.5240 ***	0.2896 ***	1.5130 ***
	(−6.59)	(71.09)	(5.41)	(71.51)
Fixed effects	Y	Y	Y	Y
N	51,111	51,111	51,457	51,457
R^2	0.3469	0.5984	0.2265	0.5975
Sobel *z*	19.38 ***		8.581 ***	

Note: The values in parentheses are *t*-values, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.1.2. Human Capital Structure Optimization Mechanism

Regression results in Columns (3) and (4) of Table 3 show that digital transformation significantly improves firms' human capital structure, measured by the proportion of highly educated employees, and that a more optimized human capital structure is positively associated with TFP. This finding is consistent with the view that digital transformation reshapes skill requirements, increasing the demand for advanced cognitive and technical capabilities that enhance productivity [31,81]. The Sobel (1982) test yields a *z*-value of 8.581 ($p < 0.01$), confirming a statistically significant mediating effect of human capital in the digital transformation–TFP relationship [87]. These results provide empirical support for Hypothesis 2b, suggesting that improvements in workforce quality constitute an important channel through which digital transformation drives productivity gains.

6.1.3. Cost Reduction Mechanism

Regression results in Columns (1) and (2) of Table 4 show that digital transformation significantly reduces the cost-to-revenue ratio, and that lower costs are associated with higher TFP. This finding aligns with the argument that technology adoption can improve cost efficiency by streamlining processes and reducing resource waste [82,83]. The Sobel (1982) test yields a *z*-value of −5.886 ($p < 0.01$), confirming a statistically significant mediating effect of cost reduction in the digital transformation–TFP relationship [87]. These

results provide empirical support for Hypothesis 2c, indicating that cost savings represent an important pathway through which digital transformation enhances firm productivity.

Table 4. Mechanism Analysis - Cost and Efficiency.

	(1)	(2)	(3)	(4)	(5)	(6)
	Cost Reduction Mechanism		**Operational Efficiency Improvement Mechanism**			
	CER	**TFP**	**FAT**	**TFP**	**ITR**	**TFP**
DIG	−0.0006 **	0.0036 ***	1.0552 ***	0.0024 ***	1.2428 ***	0.0033 ***
	(−2.38)	(6.06)	(3.90)	(4.30)	(2.59)	(5.57)
CER		0.1830 ***				
		(12.84)				
FAT				0.0010 ***		
				(21.27)		
ITR						0.0001 ***
						(6.94)
LEV	−0.0245 ***	−0.0051	−1.2952	−0.0080 *	−1.8749	−0.0091 *
	(−10.03)	(−1.09)	(−0.76)	(−1.78)	(−0.71)	(−1.93)
AGE	0.0009	0.0329 ***	−2.7458	0.0361 ***	−7.1243 *	0.0343 ***
	(0.32)	(3.94)	(−0.94)	(4.44)	(−1.67)	(4.05)
SIZE	0.0002	0.0686 ***	0.2430	0.0683 ***	0.1727	0.0685 ***
	(0.26)	(52.79)	(0.45)	(54.23)	(0.20)	(51.77)
IAR	−0.0129	−0.1061 ***	−38.6956 ***	−0.0688 ***	−14.4908	−0.1066 ***
	(−1.62)	(−6.37)	(−7.06)	(−4.28)	(−1.06)	(−6.30)
TOP10	0.0002 ***	0.0001	−0.0095	0.0001 *	0.0351	0.0001
	(4.95)	(1.26)	(−0.34)	(1.77)	(0.66)	(1.50)
ORG	0.0079 ***	0.0273 ***	3.4215 ***	0.0253 ***	2.8822 ***	0.0284 ***
	(17.26)	(37.44)	(10.93)	(36.62)	(5.07)	(38.70)
INDE	−0.0001 ***	−0.0001	0.0300	−0.0001	0.0796	−0.0001
	(−2.68)	(−0.57)	(0.90)	(−1.22)	(0.97)	(−0.92)
Constant	0.9866 ***	1.3380 ***	9.4648	1.5090 ***	20.1059 *	1.5159 ***
	(132.24)	(52.20)	(1.37)	(74.96)	(1.79)	(71.57)
Fixed effects	Y	Y	Y	Y	Y	Y
N	51,457	51,457	51,451	51,451	51,451	51,451
R^2	0.1494	0.6026	0.0312	0.6444	0.0072	0.5998
Sobel *z*	−5.886 ***		31.27 ***		7.91 ***	

Note: The values in parentheses are *t*-values, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.1.4. Operational Efficiency Improvement Mechanism

Regression results in Columns (3)–(6) of Table 4 indicate that digital transformation significantly increases both fixed asset turnover and inventory turnover, and that higher values of these indicators are positively associated with TFP. This finding is consistent with prior research showing that digital technologies enhance resource utilization efficiency and accelerate capital turnover [51,85]. The Sobel (1982) test yields *z*-values of 31.27 ($p < 0.01$) and 7.91 ($p < 0.05$) for the fixed asset turnover and inventory turnover models, respectively, confirming significant mediating effects [87]. These results provide empirical support for Hypothesis 2d, suggesting that operational efficiency improvements constitute an important channel through which digital transformation promotes productivity growth.

6.2. Threshold Effect Test

The effect of DT on productivity enhancement may require specific conditions to be met. In this study, we adopt a threshold effect model to identify the critical values existing in the DT process.

$$\begin{aligned} TFP_{i,t} = \gamma_0 + \gamma_1 DT_t \times I(Threshold_{i,t} \ll \theta) \\ +\gamma_2 DT_t \times I(Threshold_{i,t} > \theta) + \rho Controls_{i,t} + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{5}$$

where *Threshold* is the threshold variable, and I is the indicator function. If the condition inside the parentheses is satisfied, I is assigned a value of 1; if the condition is not met, I is assigned a value of 0. Model (3) represents a single threshold model. Based on this model, further double and triple threshold models can be constructed, which would help capture multiple turning points that may occur during the DT process.

This paper selects profit volatility and cash flow status as threshold variables. First, the effect of digital transformation on productivity is related to the profit volatility of the enterprise. More stable profitability can enhance the effectiveness of digital transformation. This paper uses the three-year volatility of return on assets (ROA) to measure profit volatility. ROA refers to the ratio of earnings before interest and taxes (EBIT) to total assets, and the three-year volatility is calculated as the standard deviation from year $t-2$ to year t. This method effectively reflects the stability of a company's profitability over a specific period. Higher profit volatility means that the company's profit level is less stable. We use profit volatility as the threshold variable to examine whether there is a threshold effect in the impact of digital transformation on the TFP of enterprises. Second, cash flow status is crucial for the daily operations of a company. If a company lacks sufficient cash flow, digital transformation will be difficult to implement and may not lead to improvements in productivity. This paper uses the ratio of net cash flow from operating activities to total assets to measure cash flow status. The larger this ratio, the more abundant the company's cash flow. We use cash flow status as the threshold variable to analyze whether there is a threshold effect in the impact of digital transformation on productivity.

To conduct the threshold effect analysis, it is first necessary to determine the number of threshold variables and the specific threshold values. The regression results show that when TFP of enterprises is used as the dependent variable, profit volatility only passes the single threshold test, indicating that there is a single threshold effect of profit volatility in the impact of digital transformation on TFP. Similarly, cash flow status also passes only the single threshold test, indicating that there is a single threshold effect of cash flow status on the impact of digital transformation on TFP. The threshold effect test results for profit volatility and cash flow status are shown in Table 5.

Table 5. Threshold effect test results.

Variable	Threshold Type	F-Statistic	*p*-Statistic	Threshold Value	95% Confidence Interval	Critical Value		
						0.1	0.05	0.01
PV	Single Threshold	36.13 ***	0.0014	0.0304	[0.0212, 0.0245]	18.1029	21.3194	31.2363
CFS	Single Threshold	28.17 ***	0.0000	0.0683	[0.0589, 0.0657]	12.9675	15.0382	20.1741

Note: The values in parentheses are *t*-values, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.2.1. Profit Volatility

The impact of digital transformation on the TFP of enterprises varies with the level of profit volatility. Specifically, when a company's profit volatility is less than or equal to 0.0304, digital transformation significantly improves the company's TFP. However, when a company's profit volatility surpasses 0.0304, the positive effect of digital transformation becomes insignificant. Therefore, the productivity-enhancing effect of digital transfor-

mation on enterprises only becomes apparent when the profit level is relatively stable. First, when profit volatility is high, company management often prioritizes improving profitability rather than focusing on long-term digital transformation goals. Management tends to allocate resources to short-term objectives rather than to long-term strategies like digital transformation, which require sustained investment. In contrast, stable profitability boosts management's confidence in digital transformation strategies, enabling them to persist with the implementation of these long-term development plans [74]. Second, digital transformation requires not only advanced technologies but also continuous financial investment. Stable profitability provides sufficient funds for enterprises, ensuring the smooth implementation of digital strategic formation strategies. If profitability is unstable, the company's digital transformation strategy may face internal resistance and difficulties in execution, which could lead to interruptions or abandonment of the transformation process [88].

6.2.2. Cash Flow Status

When a company's cash flow status is less than or equal to 0.0683, the effect of digital transformation is not significant. But, when the company's cash flow status exceeds 0.0683, digital transformation significantly promotes TFP. This indicates that sufficient cash flow ensures the smooth implementation of digital transformation strategies. Conversely, when a company lacks sufficient cash flow, digital transformation cannot effectively enhance TFP. In the initial phases of digital transformation, firms often face significant upfront costs, such as expenses for acquiring digital equipment, upgrading software, and training employees in new digital skills [42]. Without sufficient cash flow, these expenditures may be unsustainable, thus affecting the smooth progress of the transformation. Moreover, during the implementation of digital transformation, companies may face many unforeseen risks. Sufficient cash flow ensures that daily operations are not disrupted. Digital transformation is a complex and lengthy process, and the risk of failure is high [40]. When cash flow is insufficient, a company may be forced to halt or delay its digital transformation. Additionally, as the pace of technological upgrades accelerates, companies need adequate cash flow to keep up with equipment updates and technology maintenance [89] (see Table 6).

Table 6. Threshold effect regression results.

	(1)	(2)
	TFP	**TFP**
DT	0.0311 ***	
(PV $\leq$ 0.0304)	(6.28)	
DT	−0.0047	
(PV > 0.0304)	(−0.61)	
DT		−0.0026
(CFS $\leq$ 0.0683)		(−0.33)
DT		0.0352 ***
(CFS > 0.0683)		(4.86)
Controls	Y	Y
Constant	4.6738 ***	4.6527 ***
	(72.95)	(58.28)
Firm/Year FE	Y	Y
Industry/City FE	Y	Y
N	15,674	12,082
R^2	0.7039	0.5741

Note: The values in parentheses are *t*-values, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

7. Conclusions and Policy Implications

This paper empirically investigates the impact of digital transformation on TF at the firm level, while exploring both internal transmission mechanisms and external moderating factors. The main findings are as follows: (1) digital transformation significantly enhances TFP, with both DTA and UT positively contributing to productivity. The effect of DTA is more pronounced. (2) External macro-environmental factors condition digital transformation effectiveness. A well-developed digital infrastructure and a robust IPP environment significantly strengthen the productivity-enhancing effect of digital transformation. (3) Firm-level characteristics exert important moderating influences. Industry competition intensifies the relationship, while the impact of digital transformation is stronger in non-HPEs and in firms with higher market valuations. (4) Digital transformation promotes TFP through multiple internal mechanisms, including innovation-driven upgrading, optimization of human capital structure, cost control, and efficiency gains. (5) The threshold effect of profit volatility and cash flow status on digital transformation. In the process of digital transformation promoting the TFP of enterprises, profit volatility has a significant impact on its effect and presents a single threshold effect. In addition, a good cash flow status is a key factor to ensure the smooth implementation of digital transformation. Enterprises must ensure that the cash flow status reaches a specific threshold value to promote the improvement of TFP.

Based on the empirical findings, we offer the following targeted recommendations for policymakers and firm managers: (1) For Policymakers: ① Continue promoting digital transformation through differentiated support measures. Firms in capital-intensive, high-pollution, or highly competitive sectors may face greater challenges in transformation and require tailored incentives such as tax breaks, subsidies, or public-private pilot programs. ② Strengthen enterprise innovation and digital capability building. Public policies should support R&D tax credits, digital skill training programs, and access to enabling technologies, especially for small and medium-sized enterprises. ③ Improve the digital ecosystem by investing in public infrastructure—such as 5G networks, data centers, and smart logistics—and by enhancing institutional safeguards, particularly in intellectual property protection, data security, and digital standards enforcement, fostering market-oriented environments that facilitate effective digital adoption. (2) For Enterprise Managers: ① Align digital strategies with internal readiness. Before initiating digital transformation, firms should assess their financial and human resource capacities to ensure sustained investment across technology, systems, and people. ② Focus on core productivity drivers. Firms should prioritize digital investments that directly enhance innovation, optimize workforce structure, reduce operating costs, and improve asset utilization. ③ Tailor digital transformation to firm-specific conditions. There is no one-size-fits-all approach; firms should adapt their transformation paths to match their industry environment, digital maturity, and strategic objectives. ④ Strengthen collaboration within digital supply chains. Leveraging digital tools for coordination, data sharing, and integration with upstream and downstream partners can generate network-based productivity gains and shared innovation benefits.

8. Research Limitations and Future Directions

Measurement of digital transformation. Our core variable is constructed from annual-report text, which can emphasize "talk" over "action" and may not fully capture implementation depth or effectiveness. In the revision, we supplement the text-based index with additional proxies (e.g., digital-related intangible-asset shares, digital-technology patenting, and a policy-shock DID), but residual measurement error may persist. Future research should pair disclosure-based indicators with operational evidence—such as ERP/IoT de-

ployment and usage logs, execution of digital capital expenditure, software license/cloud usage telemetry, and third-party audit information—and adopt quality-adjusted innovation measures to better map capabilities to outcomes.

Mediation analysis and identification. Our mediation tests initially relied on the Sobel approach, which assumes no unobserved confounding between the mediator and the outcome—an assumption that is strong in firm-level settings and may be violated. In the revision, we complement the analysis with more robust mediation strategies (structural equation modeling with bootstrapped indirect effects and an instrumental-variables approach to the mediator) and explicitly acknowledge that causal mediation hinges on partially untestable assumptions. Future work should incorporate sensitivity analyses for mediator–outcome confounding, exploit quasi-experimental mediator shocks (e.g., staggered policy rollouts or infrastructure upgrades), and consider panel-based mediation frameworks to mitigate bias.

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Abbreviations

The following abbreviations are used in this manuscript:

TFP	Total Factor Productivity
HPE	High-Pollution Enterprise
IPP	Intellectual Property Protection
HC	Human Capital
HHI	Herfindahl-Hirschman Index

Appendix A. Methodological Derivations for TFP Estimation

TFP is a micro-level concept at the firm level. However, due to data limitations, early studies focused on estimating TFP at the macro level. With the increasing availability of micro-level enterprise data, firm-level TFP estimation has attracted growing attention. In the process of fitting the production function, input factors cannot fully explain total output, leading to a residual productivity term—namely TFP. It reflects improvements in production efficiency driven by technological progress and institutional optimization.

To estimate TFP, the production function is specified as a Cobb–Douglas production function.

$$Y_{it} = A_{it} L_{it}^{\alpha} K_{it}^{\beta} \tag{A1}$$

where A_{it} denotes TFP, K_{it} represents capital input, and L_{it} denotes labor input. Taking the logarithm of Equation (A1) yields the following linear form:

$$y_{it} = \alpha l_{it} + \beta k_{it} + u_{it} \tag{A2}$$

The logarithmic form of A_{it} is incorporated into u_{it}. Direct estimation of Equation (A2) using OLS would result in sample selection bias and simultaneity bias. To maximize profits, firms adjust input factors in real time based on current production conditions, leading to correlation between the error term and the regressors. Therefore, OLS is not suitable for direct estimation. Marschak and Andrews (1944) [90] suggest that this issue can be addressed by decomposing u_{it}.

$$y_{it} = \alpha l_{it} + \beta k_{it} + \varpi_{it} + e_{it} \tag{A3}$$

The error term u_{it} is decomposed into two components: ϖ_{it} and e_{it}. Here, ϖ_{it} captures the portion of the error that reflects the firm's adjustment of input factors in response to its current production conditions, while e_{it} represents the true random error. Currently, various methods have been developed to address this issue.

① Fixed Effects Estimation Method. For panel data, using a firm fixed effects model can effectively address endogeneity arising from unobserved heterogeneity across firms. However, this method is only applicable to panel datasets and cannot capture information contained in time variation, nor can it fully identify the parameters to be estimated. Moreover, applying a fixed effects model requires the assumption that ϖ_{it} is time-invariant, which is difficult to satisfy in real-world scenarios.

② OP Method. To address the limitations of the fixed effects estimation method, Olley and Pakes (1992) [91] proposed a consistent semiparametric estimator. Specifically, they assume that firms adjust their investment strategies based on current production conditions, and that unobserved productivity can be proxied by the firm's current investment. The core idea of the OP method is to establish a functional relationship between capital stock and investment.

$$K_{it+1} = (1 - \delta)K_{it} + I_{it} \tag{A4}$$

Let I_{it} and K_{it+1} denote the firm's current investment and capital stock, respectively. Equation (A4) implies an orthogonal relationship between the two. This formulation requires the assumption that firms' expectations of future ϖ are significantly and positively correlated with their current investment decisions. Based on this, the following optimal investment function can be established:

$$i_{it} = i_\iota(\varpi, k_{it}) \tag{A5}$$

Taking the inverse of Equation (A5) and assuming $h() = i^{-1}()$, the unobservable productivity term ϖ can be expressed as:

$$\varpi_{it} = h_\iota(i_{it}, k_{it}) \tag{A6}$$

Substituting Equation (A6) into the production function yields:

$$y_{ii} = \beta \cdot l_{ii} + \gamma \cdot k_{ii} + h_i(i_{ii}, k_{ii}) + e_{ii} \tag{A7}$$

Let ϕ_{it} be defined as:

$$\phi_{it} = \gamma \cdot k_{it} + h_\iota(i_{it}, k_{it}) \tag{A8}$$

Equation (A8) shows that it consists of two components: capital stock and investment. Define the estimated value of $\phi_{it_}$ it as $\widetilde{\varnothing}_{it}$. In the first step, estimate y_{it} as follows:

$$y_{it} = \beta \cdot l_{it} + \phi_{it} + e_{it} \tag{A9}$$

Directly estimate Equation (A9) to obtain a consistent and unbiased estimate of the coefficient on l_{it}. The key of this step lies in estimating $\widetilde{\varnothing}_{it}$, which is defined by the following equation:

$$V_{it} = y_{it} - \hat{\beta} \cdot l_{it} \tag{A10}$$

Estimate the following equation:

$$V_{it} = \gamma \cdot k_{it} + g(\phi_{i-1} - \gamma k_{it-1}) + \mu_{it} + e_{it} \tag{A11}$$

In this equation, $g(\cdot)$ is a function of ϕ_{i-1} and k_{it-1}. Equation (A11) is estimated using higher-order polynomials of ϕ_{i-1} and k_{it-1}. Since both k_{it} and k_{it-1} appear in Equation (A10), nonlinear least squares must be used. After estimating all the coefficients in Equation (A11), the logarithmic value of the residual is obtained by fitting Equation (A1), thereby yielding the log value of TFP.

③ LP method: The OP method requires a monotonic relationship between current investment and total output, which leads to the exclusion of firms with zero investment in the current period. To address this issue, Levinsohn and Petrin (2003) [92] proposed replacing investment with intermediate input as the proxy variable. Data on intermediate inputs are generally more accessible than investment data. The LP method also provides several ways to test the validity of the selected proxy, thereby expanding the range of viable proxy variables. As a result, the LP method offers greater flexibility in proxy selection.

④ GMM method: Blundell and Bond (1998) [93] suggested incorporating instrumental variables into the production function to address endogeneity problems. The lagged values of explanatory variables can serve as instruments. However, the GMM method has two main drawbacks. First, ϖ may be influenced by both short-term and long-term factors. Second, GMM models require transformations such as differencing and lagging, which demand long time-series data. The following fixed effects model is specified:

$$\varpi_{it} = \varpi_i + v_{it} \tag{A12}$$

Take the first difference of Equation (A12).

$$\Delta y_{it} = \alpha_L \Delta l_{it} + \alpha_M \Delta m_{it} + \alpha_K \Delta k_{it} + \Delta v_{it} \tag{A13}$$

The two-period lagged terms are considered the optimal instrumental variables. Serial correlation in v_{it} may cause current technology shocks to correlate with past input factors. The following model is specified:

$$v_{it} = \rho v_{it-1} + \eta_{it} \tag{A14}$$

Substituting into model (A13), we obtain:

$$y_{it-1} - \beta l_{it-1} - \gamma k_{it-1} - \varpi_i = v_{it-1} \tag{A15}$$

The production function is expressed as:

$$y_i = \varpi_t(1-\rho) + \rho y_{it-1} + \beta l_{it} + \gamma k_{it} - \rho\beta l_{it-1} - \rho\gamma k_{it-1} + \eta_{it} \tag{A16}$$

By applying first-differencing to eliminate fixed effects:

$$\Delta y_{it} = \rho \Delta y_{it-1} - \beta \Delta l_{it} + \gamma k_{it} - \rho\beta \Delta l_{it-1} + \rho\gamma \Delta k_{it-1} + \Delta\eta_{it} \tag{A17}$$

Use y_{it-2} as an instrumental variable to estimate the parameter ρ.

⑤ GNR method: When both labor and intermediate materials are treated as static input factors, the ACF method requires additional conditions to estimate a Cobb–Douglas–type gross-output production function. Gandhi et al. (2020) [94] address this issue by adding share-regression equations for static inputs. Doraszelski and Jaumandreu (2013) [95] and Grieco et al. (2016) [96] also estimate production functions by imposing first-order condition (FOC) restrictions for static inputs; however, the former requires information on factor prices, and the latter is not applicable to the Cobb–Douglas functional form.

Let the wage (labor price) be (W_t), the price of intermediate materials be (P_t^M), and normalize the output price to 1. The firm's problem is:

$$\underset{L_u, M_u}{max} \ (K_{it})^{\beta_k} (L_{it})^{\beta_l} (M_{it})^{\beta_m} e^{\omega_{it}} - W_t L_{it} - P_t^M M_{it} \tag{A18}$$

Taking the first-order condition with respect to intermediate materials (M_{it}) yields:

$$\beta_m (K_{it})^{\beta_k} (L_{it})^{\beta_l} (M_{it})^{\beta_m - 1} e^{\omega_{it}} = P_t^M \tag{A19}$$

Multiplying both sides by (M_{it}), dividing by (Y_{it}), and taking logarithms gives:

$$\ln s_{it}^M = \ln \beta_m - \varepsilon_{it} \tag{A20}$$

where ($s_{it}^M = P_t^M M_{it} / Y_{it}$) is the share of intermediate-materials expenditure in gross output. Since (ε_{it}) is an error term with zero mean, ordinary least squares (OLS) on the above share equation yields estimates ($\hat{\beta}_m$) and ($\hat{\varepsilon}_{it}$). Given arbitrary values for (β_k) and (β_l), productivity can be written as

$$\omega_{it}(\beta_k, \beta_l) = \gamma_{it} - \beta_k k_{it} - \beta_l l_{it} - \hat{\beta}_m m_{it} - \hat{\varepsilon}_{ii} \tag{A21}$$

Invoking the model setup, The production function can be re-expressed as

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \hat{\beta}_m m_{it} + g\left(y_{it-1} - \beta_k k_{it-1} - \beta_l l_{i-1} - \hat{\beta}_m m_{i-1} - \hat{\varepsilon}_{i+1}\right) + \xi_{it} + \hat{\varepsilon}_{it} \tag{A22}$$

where $g(\cdot)$ is approximated by a high-order polynomial. Using the "structural" relationships implied by firms' input choices and the evolution of productivity, we construct moment conditions $E\left[(\xi_{it} + \hat{\varepsilon}_{it}) Z_{it}^{CNR}\right] = 0$ and estimate ($\hat{\beta}_k$) and ($\hat{\beta}_l$) by GMM, where the instrument set is

$$Z_{it}{}^{GNR} = \left\{k_{it}, k_{it-1}, l_{it-1}\right\} \tag{A23}$$

In summary, the GNR method does not require a monotonic relationship between investment (as in OP) or materials (as in ACF/LP) and productivity. Compared with proxy-variable approaches, GNR therefore relies on **fewer** assumptions. However, like proxy methods, GNR requires separating the disturbance term via the share-regression equation in order to form valid moments for estimation.

Table A1. Variable Definitions.

Variable	Definition
TFP	Total Factor Productivity, calculated using the LP method.
DT	Digital Transformation Index, constructed based on text mining of annual reports.
LEV	Leverage ratio, defined as total liabilities/total assets.
AGE	Firm age, measured as the number of years since establishment.
SIZE	Firm size, measured as the natural logarithm of total assets.
IAR	Intangible assets ratio, calculated as intangible assets/total assets.
TOP10	Ownership concentration, measured as the shareholding ratio of the top 10 shareholders.
ORG	Ownership type dummy, equals 1 if the firm is state-owned, 0 otherwise.
INDE	Proportion of independent directors on the board.
Innovate	Innovation capacity, measured as ln(1 + number of patent applications).
HC	Human capital structure, measured as the proportion of employees with a bachelor's degree or above.
CER	Cost efficiency, proxied by the ratio of total operating cost to revenue.
FAT	Inventory turnover ratio, used to capture operational efficiency.
ITR	Fixed asset turnover ratio, also used to capture operational efficiency.
HHI	Industry competition level, measured using the Herfindahl–Hirschman Index (HHI).
DINF	Digital infrastructure, proxied by the number of broadband access ports per capita in each province.
IPP	Intellectual property protection, measured by the number of IP-related case rulings in local courts.
MI	Marketization index, from China's provincial marketization index database
HPE	High-polluting enterprise dummy variable, equals 1 if firm is classified as HPE, 0 otherwise.
TQ	Tobin's Q, used as a proxy for firm market value.

Table A2. Robustness test—replacing the explained variables.

	(1) TFP_OP	(2) TFP_LP	(3) TFP_OLS	(4) TFP_FE	(5) TFP_GMM
DT	0.0032 ***	0.0022 *	0.0022 ***	0.0020 ***	0.0049 ***
	(3.92)	(1.66)	(4.59)	(4.38)	(4.90)
LEV	−0.0210 ***	−0.3210 ***	−0.0031	−0.0013	−0.0307 ***
	(−3.43)	(−29.87)	(−0.77)	(−0.34)	(−4.14)
AGE	0.0419 ***	−0.0134	0.0344 ***	0.0334 ***	0.0394 ***
	(3.71)	(−0.71)	(4.87)	(4.93)	(2.88)
SIZE	0.0611 ***	0.0240 ***	0.0708 ***	0.0718 ***	0.0580 ***
	(35.66)	(9.37)	(64.21)	(67.49)	(27.52)
IAR	−0.1880 ***	0.0698 *	−0.0628 ***	−0.0487 ***	−0.2549 ***
	(−8.38)	(1.67)	(−4.47)	(−3.56)	(−9.03)
TOP10	0.0001	0.0005 ***	0.0001	0.0001	0.0002
	(1.04)	(2.77)	(1.24)	(1.20)	(1.26)
ORG	0.0373 ***	0.0227 ***	0.0233 ***	0.0217 ***	0.0449 ***
	(38.00)	(11.66)	(38.02)	(37.15)	(38.08)
CR	−0.0001	−0.0000	−0.0001	−0.0001	−0.0001
	(−0.49)	(−0.07)	(−1.04)	(−1.13)	(−0.31)
INDE	1.2569 ***	0.2386 ***	1.6721 ***	1.7321 ***	1.1230 ***
	(43.62)	(5.08)	(95.19)	(103.37)	(32.19)
ROE	0.0032 ***	0.0022 *	0.0022 ***	0.0020 ***	0.0049 ***
	(3.92)	(1.66)	(4.59)	(4.38)	(4.90)
Constant	−0.0210 ***	−0.3210 ***	−0.0031	−0.0013	−0.0307 ***
	(−3.43)	(−29.87)	(−0.77)	(−0.34)	(−4.14)
Firm/Year FE	Y	Y	Y	Y	Y
Industry/City FE	Y	Y	Y	Y	Y
N	51,458	51,335	51,458	51,458	51,458
R^2	0.4830	0.1589	0.6842	0.7036	0.3989

Note: The values in parentheses are *t*-values, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3. Robustness test—replacing the explained variables, eliminating municipality data, shortening the sample period, and adjusting the clustering level.

	(1) TFP	(2) TFP	(3) TFP	(4) TFP	(5) TFP	(6) TFP
DT1	0.0124 ***					
	(3.14)					
DT2		0.2003 ***				
		(3.93)				
			0.0007 ***			
			(2.66)			
DT				0.0043 ***	0.0036 ***	0.0035 ***
				(6.43)	(5.07)	(9.24)
LEV	−0.0091 *	−0.0096 **	−0.0106 ***	−0.0131 **	−0.0097	−0.0096 ***
	(−1.90)	(−2.01)	(−6.52)	(−2.49)	(−1.63)	(−3.24)
AGE	0.0316 ***	0.0326 ***	0.0356 ***	0.0273 ***	0.0291 **	0.0331 ***
	(3.66)	(3.82)	(10.69)	(2.89)	(2.56)	(6.88)
SIZE	0.0695 ***	0.0687 ***	0.0694 ***	0.0680 ***	0.0666 ***	0.0686 ***
	(51.86)	(51.40)	(164.07)	(45.90)	(37.30)	(81.19)
IAR	−0.1015 ***	−0.1094 ***	−0.1099 ***	−0.1087 ***	−0.0907 ***	−0.1084 ***
	(−5.94)	(−6.43)	(−17.62)	(−5.62)	(−4.34)	(−11.33)
TOP10	0.0001	0.0001	0.0001 ***	0.0002 *	0.0001	0.0001 ***
	(1.42)	(1.63)	(4.78)	(1.82)	(0.90)	(2.93)
ORG	0.0288 ***	0.0288 ***	0.0291 ***	0.0285 ***	0.0279 ***	0.0288 ***
	(38.71)	(38.81)	(65.51)	(33.38)	(30.34)	(32.73)
INDE	−0.0001	−0.0001	−0.0001 *	−0.0000	−0.0000	−0.0001
	(−1.00)	(−0.95)	(−1.72)	(−0.42)	(−0.36)	(−1.34)
Constant	1.5171 ***	1.5200 ***	1.4898 ***	1.5331 ***	1.5391 ***	1.5057 ***
	(70.30)	(70.98)	(34.21)	(65.89)	(50.78)	(92.61)
Firm/Year FE	Y	Y	Y	Y	Y	Y
Industry/City FE	Y	Y	Y	Y	Y	Y
N	50,125	50,675	51,434	41,495	26,948	51,130
R^2	0.5978	0.5966	0.6252	0.6027	0.5819	0.9032

Note: The values in parentheses are *t*-values, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4. Endogeneity test—instrumental variables.

	(1) DT	(2) TFP	(3) DT	(4) TFP	(5) DIG	(6) TFP
Telephone	0.0474 ***					
	(3.84)					
Distance			−0.0008 ***			
			(−12.78)			
ADIG					0.4934 ***	
					(21.78)	
DT		−0.0433 **		0.0209 ***	−0.0744	0.0152 ***
		(−2.18)		(3.97)	(−1.40)	(4.27)
LEV	−0.0401 ***	−0.0115 ***	−0.1131 ***	0.0334 ***	−0.1434	−0.0089 *
	(−1.50)	(−5.24)	(−4.45)	(18.47)	(−1.15)	(−1.86)
AGE	−0.1893 ***	0.0242 ***	−0.1488 ***	0.0080 ***	0.2253 ***	0.0355 ***
	(−3.41)	(4.27)	(−8.65)	(5.86)	(14.87)	(4.13)
SIZE	0.2343 ***	0.0796 ***	0.1507 ***	0.0740 ***	0.1113 ***	0.0659 ***
	(35.27)	(17.00)	(34.97)	(86.41)	(0.59)	(40.42)

Table A4. *Cont.*

	(1) DT	(2) TFP	(3) DT	(4) TFP	(5) DIG	(6) TFP
IAR	−0.0776	−0.1122 ***	0.1515 ***	−0.1513 ***	−0.0047 ***	−0.1073 ***
	(−0.76)	(−14.05)	(1.52)	(−22.57)	(−4.54)	(−6.26)
TOP10	−0.0054 ***	−0.0001	−0.0040 ***	0.0005 ***	0.0079	0.0002 **
	(−10.80)	(−1.08)	(−11.60)	(16.85)	(0.94)	(2.33)
ORG	0.0067	0.0291 ***	0.0151	0.0261 ***	0.2202 ***	0.0287 ***
	(0.88)	(49.07)	(1.38)	(35.31)	(35.76)	(38.55)
INDE	−0.0042 ***	−0.0003 ***	0.0029 ***	−0.0006 ***	−0.0042 ***	−0.00003
	(−4.69)	(−2.59)	(3.31)	(−9.18)	(−3.12)	(−0.31)
Firm/Year FE	Y	Y	Y	Y	Y	Y
Industry/City FE	Y	Y	Y	Y	Y	Y
N	51,099	51,099	45,951	45,951	51,035	51,035
R^2		0.1274		0.6620		0.4351
F-statistic	14.72 ***		30.93 ***		474.43 ***	
Cragg-Donald Wald F statistic		34.719 [12.41]		163.241 [16.38]		474.432 [16.38]
Kleibergen-Paap rk LM statistic		16.342 ***		163.052 ***		253.981 ***

Note: The values in parentheses are *t*-values, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5. Endogeneity test—DID and Heckman two-step method.

	(1) TFP	(2) TFP
DID	0.0026 ***	
	(2.75)	
DT		0.0248 ***
		(7.09)
IMR		−0.1301
		(−10.32)
LEV	−0.0081 ***	−0.1053
	(−4.64)	(−0.94)
AGE	0.0379 ***	0.2912 ***
	(10.67)	(5.01)
SIZE	0.0709 ***	0.4953 ***
	(163.11)	(32.86)
IAR	−0.1179 ***	−1.4122 ***
	(−17.78)	(−8.67)
TOP10	0.0001 ***	0.0009 *
	(3.46)	(1.85)
ORG	0.0290 ***	0.2238 ***
	(60.71)	(28.15)
INDE	−0.0001 **	0.0008
	(−2.34)	(0.67)
Constant	1.5042 ***	1.5055 ***
	(146.44)	(120.29)
Firm/Year FE	Y	Y
Industry/City FE	Y	Y
N	45,951	51,458
R^2	0.6050	0.9038

Note: The values in parentheses are *t*-values, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6. Heterogeneity Analysis—Categories of DT in Enterprises.

	(1) TFP	(2) TFP
DTA	0.0025 ***	
	(3.83)	
UT		0.0041 ***
		(6.28)
LEV	−0.0098 **	−0.0096 **
	(−2.04)	(−2.01)
AGE	0.0327 ***	0.0330 ***
	(3.83)	(3.88)
SIZE	0.0689 ***	0.0688 ***
	(52.00)	(51.75)
IAR	−0.1084 ***	−0.1081 ***
	(−6.38)	(−6.37)
TOP10	0.0001	0.0001
	(1.58)	(1.52)
ORG	0.0288 ***	0.0288 ***
	(38.99)	(38.86)
INDE	−0.0001	−0.0001
	(−0.90)	(−0.86)
Constant	1.5187 ***	1.5179 ***
	(71.24)	(71.42)
Firm/Year FE	Y	Y
Industry/City FE	Y	Y
N	51,458	51,458
R^2	0.5959	0.5968

Note: The values in parentheses are *t*-values, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7. Heterogeneity Test—External Macro Environment.

	(1) TFP	(2) TFP	(3) TFP
DTDINF	0.0070 ***		
	(2.88)		
DINF	−0.0171 ***		
	(−3.20)		
DTIPP		0.0135 ***	
		(4.29)	
IPP		−0.0086	
		(−0.74)	
DIMI			0.0007 ***
			(3.05)
MI			−0.0004
			(−0.35)
DT	0.0009	0.0140 ***	0.0107 ***
	(1.11)	(5.58)	(4.27)
LEV	−0.0077 *	−0.0086 *	−0.0012
	(−1.68)	(−1.78)	(−0.25)
AGE	0.0121 ***	0.0347 ***	0.0303 ***
	(3.69)	(4.06)	(3.51)
SIZE	0.0680 ***	0.0687 ***	0.0680 ***
	(53.16)	(51.64)	(49.45)
IAR	−0.0995 ***	−0.1053 ***	−0.1034 ***
	(−6.12)	(−6.13)	(−6.18)

Table A7. *Cont.*

	(1) TFP	(2) TFP	(3) TFP
TOP10	0.0001 *	0.0001	0.0001
	(1.68)	(1.62)	(1.35)
ORG	0.0291 ***	0.0288 ***	0.0281 ***
	(39.69)	(38.62)	(38.22)
INDE	−0.0001	−0.0001	−0.0001
	(−1.08)	(−0.71)	(−1.11)
Constant	1.5234 ***	1.5075 ***	1.5261 ***
	(59.98)	(65.77)	(64.71)
Firm/Year FE	Y	Y	Y
Industry/City FE	Y	Y	Y
N	50,669	50,842	49,348
R^2	0.6035	0.5976	0.6077

Note: The values in parentheses are *t*-values, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8. Heterogeneity Test—Internal Micro Characteristics.

	(1) TFP	(2) TFP	(3) TFP
DTHP	−0.0021 ***		
	(−3.88)		
HP	−0.0001		
	(−0.05)		
DTHHI		0.0029 **	
		(2.24)	
HHI		−0.0044 *	
		(−1.65)	
DTTQ			0.0003 ***
			(2.60)
TQ			−0.0001 ***
			(−3.61)
DT	0.0039 ***	0.0031 ***	0.0024 ***
	(12.90)	(9.18)	(3.63)
LEV	−0.0099 ***	−0.0097 ***	−0.0065
	(−6.12)	(−5.99)	(−1.39)
AGE	0.0333 ***	0.0329 ***	0.0340 ***
	(9.98)	(9.85)	(4.01)
SIZE	0.0686 ***	0.0686 ***	0.0684 ***
	(169.11)	(169.20)	(52.08)
IAR	−0.1083 ***	−0.1087 ***	−0.1069 ***
	(−17.51)	(−17.59)	(−6.27)
TOP10	0.0001 ***	0.0001 ***	0.0001
	(4.38)	(4.35)	(1.49)
ORG	0.0288 ***	0.0288 ***	0.0285 ***
	(63.22)	(63.13)	(37.93)
INDE	−0.0001	−0.0001	−0.0001
	(−1.54)	(−1.53)	(−0.70)
Constant	1.5181 ***	1.5196 ***	1.5191 ***
	(175.75)	(175.42)	(71.92)
Firm/Year FE	Y	Y	Y
Industry/City FE	Y	Y	Y
N	51,415	51,447	50,530
R^2	0.5969	0.5967	0.5928

Note: The values in parentheses are *t*-values, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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