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Research on the Mechanism of FinTech Empowering New Quality Productive Forces in Enterprises

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Abstract

Cultivating New Quality Productive Forces is a core engine for achieving high-quality economic development, yet structural contradictions in the traditional financial system constrain corporate innovation capacity. Using a sample of Shanghai and Shenzhen A-share listed companies from 2015 to 2023, this paper empirically examines the impact of FinTech on corporate New Quality Productive Forces and the transmission mechanisms underlying this effect. The results show that FinTech significantly enhances corporate New Quality Productive Forces. This finding remains robust after excluding municipalities, replacing the explanatory variable, and employing instrumental variable approaches. Mechanism analysis reveals that FinTech empowers New Quality Productive Forces through two pathways: promoting corporate digital transformation and stimulating green innovation. Together, these pathways form a complete framework for technology-enabled and green-driven growth. Heterogeneity analysis further indicates that the enabling effect of FinTech is more pronounced in the central region, state-owned enterprises, high-tech sectors, technology-intensive industries, and large-scale firms. From the perspectives of production factor reconfiguration and resource allocation optimization, this paper uncovers the micro-mechanisms through which FinTech drives New Quality Productive Forces, providing empirical evidence for the design of differentiated financial policies and the precise allocation of financial resources.

Keywords

FinTech, New Quality Productive Forces, Total Factor Productivity, Digital Transformation, Green Innovation

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1. Introduction

At present, the Chinese economy is navigating a critical transition from high-speed growth to high-quality development. Developing New Quality Productive Forces has become a central proposition for constructing a modernized industrial system and achieving sustainable growth. Driven by technological innovation, New Quality Productive Forces emphasize the optimized allocation of production factors and a qualitative leap in productivity. It represents the evolutionary direction of advanced productive forces. However, the traditional financial system has faced structural contradictions in serving the real economy and supporting corporate innovation. These include information asymmetry, heavy reliance on collateral, and limited-service coverage. Consequently, traditional finance struggles to meet the diverse needs of enterprises for digital transformation and green development. This has, to some extent, constrained the cultivation and release of New Quality Productive Forces.

FinTech results from the deep integration of information technology and financial services. By leveraging cutting-edge technologies such as big data, cloud computing, and artificial intelligence, FinTech is reshaping the supply models and efficiency boundaries of financial services. Theoretically, FinTech alleviates financing constraints, reduces information asymmetry, and optimizes resource allocation. In doing so, it provides crucial support for corporate digital transformation and green innovation. Thus, FinTech has become a vital engine for driving the development of New Quality Productive Forces. In recent years, digital infrastructure has been continuously improved, and FinTech has also achieved rapid penetration. Exploring its empowering effects and underlying mechanisms on New Quality Productive Forces has significant theoretical value. Moreover, it offers practical guidance for formulating differentiated industrial policies and optimizing financial resources allocation.

Accordingly, this study selects A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2015 to 2023 as the research sample. It systematically examines the impact, effect, and mechanism of FinTech on enterprises' New Quality Productive Forces. Compared with existing studies, the marginal contributions of this study are as follows. First, it elucidates the internal logic of FinTech in empowering New Quality Productive Forces from three perspectives: production factor reconfiguration, innovation momentum stimulation, and resource allocation optimization. It then proposes testable research hypotheses. Second, it incorporates corporate digital transformation and green innovation into a unified analytical framework. This identifies the "technological path" and "green path" through which FinTech affects New Quality Productive Forces; Third, it conducts heterogeneity analyses from multiple perspectives, including region, industry, and ownership structure. These findings provide an empirical basis for precision policymaking.

2. Theoretical Framework and Research Hypotheses

2.1. The Impact of FinTech on Enterprise New Quality Productive Forces

New quality productive forces are fundamentally oriented toward technological innovation. They emphasize the optimized allocation of production factors and qualitative improvements in productive efficiency. As a product of the integration between information technology and finance (Niu et al., 2024), FinTech leverages technologies like big data, cloud computing, and artificial intelligence to positively influence the enterprise's New Quality Productive Forces. This conclusion has been corroborated by empirical research, with the enabling mechanisms concentrated along three primary dimensions: factor optimization, innovation-driven development, and resource allocation.

From the perspective of factor optimization, FinTech fundamentally reshapes laborers, objects of labor, and instruments of labor. This facilitates enterprise digital transformation and the intelligent upgrading of means of production. It also enhances labor force quality and guides production factors toward high-efficiency sectors. These processes ultimately elevate New Quality Productive Forces (Zhang & Cui, 2025). This enhancement effect is particularly strong in large-scale, manufacturing, and high-tech enterprises (Su et al., 2025).

At the innovation level, FinTech supports enterprise New Quality Productive Forces by alleviating financing constraints on innovation and reducing information asymmetry. FinTech transcends the traditional financial system's reliance on "hard asset" collateral, leveraging firms' soft information to refine credit assessment models (Li et al., 2020), and technologies like blockchain further mitigate information asymmetry between banks and enterprises (Gao et al., 2024). This broadens financing channels for small and medium-sized enterprises (SMEs), sustains R&D investment, and thereby underpins the enhancement of enterprise New Quality Productive Forces. For technology-intensive firms, FinTech reduces reliance on tangible assets and incentivizes exploratory innovation. These outcomes drive total factor productivity (TFP) growth, aligning with the core requirements of New Quality Productive Forces (Liu & Chen, 2024).

From the standpoint of resource allocation, FinTech indirectly empowers enterprise New Quality Productive Forces by improving resource allocation efficiency and facilitating the orderly flow of production factors. First, FinTech alleviates enterprise financing constraints through technological spillovers. It improves credit allocation efficiency and directs capital to high-quality enterprises and innovative projects, thus fostering the development of New Quality Productive Forces (Song et al., 2021). Second, FinTech promotes enterprise digital transformation, simultaneously improving both productive efficiency and innovative capability, and thus empowers New Quality Productive Forces through pathways including resource allocation optimization and market expansion (Ge et al., 2025). Furthermore, FinTech enables the precise identification of market needs and enterprise innovation potential, standardizes internal corporate governance, and curbs managerial short-termism. It provides a sound institutional environment for the cultivation of New Quality Productive Forces (Liu & Chen, 2024). Finally, FinTech breaks cross-industry information barriers and promotes cross-sector factor mobility. It forms a synergistic driving effect with industrial structure optimization, which constitutes the core logic of its empowerment on New Quality

Productive Forces (Deng et al., 2025). Accordingly, the following hypothesis is proposed:

H1: FinTech exerts a positive impact on enterprise New Quality Productive Forces.

2.2. Mechanism Analysis

(1) ***The Mediating Effect of Enterprise Digital Transformation***

Technological innovation is the core driver of New Quality Productive Forces. Its formation relies on digital reconstruction and optimal allocation of production factors (Zhou & Xu, 2023). As a technology-driven financial innovation, FinTech can build core momentum for New Quality Productive Forces by empowering enterprise digital transformation.

FinTech promotes digital transformation mainly through financing support and technological spillovers. In terms of financing, FinTech utilizes big data, artificial intelligence, and related technologies to effectively mitigate information asymmetry between banks and enterprises, thereby expanding the financing channels available for firms' digital transformation projects (Tang et al., 2022). In terms of technology, the underlying technologies of FinTech are closely aligned with the "ABCD" technologies (Artificial Intelligence, Blockchain, Cloud Computing, and Big Data) required for digital transformation; The technology spillover of FinTech effects greatly reduces technical barriers and transformation costs for enterprises (Wu et al., 2024). The simultaneous improvement in financing accessibility and reduction in technological barriers work in concert to resolve the two core impediments that have historically faced enterprises pursuing digital transformation: the reluctance and incapacity to undergo transformation.

Digital transformation further drives the development of New Quality Productive Forces mainly by enhancing TFP. Digitalization helps enterprises optimize production processes, reduce operating costs, and improve resource allocation efficiency, thereby achieving substantial TFP growth (Zhao et al., 2021). Such substantial TFP growth constitutes the defining characteristic that distinguishes New Quality Productive Forces from traditional productive forces. Meanwhile, digital transformation reconstructs the composition of production factors. It creates digital workforce, upgrades intelligent production tools, and expands the application scope of data as a new labor material (Xiao et al., 2022; Yang & Chen, 2024). Accordingly, the following hypothesis is proposed:

H2: FinTech promotes enterprise New Quality Productive Forces through enterprise digital transformation.

(2) ***The Mediating Effect of Green Innovation***

Green innovation represents a critical pathway through which enterprises advance New Quality Productive Forces. However, it is characterized by both positive and negative externalities and confronts practical challenges such as long R&D cycles and high financing constraints (Xie et al., 2024). FinTech leverages digital technologies to help green innovation overcome these obstacles and drives the enhancement of enterprise New Quality Productive Forces.

At present, the role of FinTech in driving green innovation via resource allocation and environmental disclosure. Regarding resource allocation, FinTech optimizes ex ante green credit allocation and strengthens ex post investment supervision. It effectively increases enterprises' green patent output (Tan et al., 2023). Relevant manufacturing evidence also shows that FinTech accelerates green technology R&D by optimizing capital allocation along the industrial chain (Xiong et al., 2024). Regarding environmental disclosure, FinTech affects corporate risk-taking and environmental information disclosure willingness. It strengthens corporate environmental commitment and thereby drives green innovation (Liu & Hu, 2024). At the micro level, FinTech improves enterprise internal control and helps convert environmental investment into substantive green innovation outputs. It realizes the effective transformation from financial input to innovation performance (Xiao et al., 2023).

New Quality Productive Forces take innovation as the core connotation, and feature green, low-carbon and high-quality development. Green innovation, as a nexus of technological innovation and ecological development, constitutes a key endogenous driver of enterprise New Quality Productive Forces. Green innovation promotes enterprise New Quality Productive Forces through such means as optimizing production processes and reducing operating costs. Green innovation can significantly improve enterprise TFP by reducing environmental costs and increasing output per unit of input (Wu et al., 2021). Green technological innovation effectively elevates enterprise green TFP by driving the green transformation of production methods, enabling enterprises to break free from the constraints of the traditional high-energy-consumption, high-pollution development model (Wan, 2025). Meanwhile, mature green innovation can create additional corporate value via technology licensing and patent authorization. It provides stable financial support for subsequent R&D and production upgrading, forms a virtuous cycle of continuous TFP growth, and guarantees the sustainable development of New Quality Productive Forces (Yue et al., 2024). Accordingly, the following hypothesis is proposed:

H3: FinTech promotes enterprise New Quality Productive Forces through green innovation.

3. Methodology

3.1. Data and Sample

This paper selects the data of Shanghai and Shenzhen A-share listed companies from 2015 to 2023[1] as a sample to explore the impact of financial technology on the level of New Quality productive Forces of enterprises. The reason for choosing this time span is that in 2015, China's FinTech entered the stage of large-scale landing, and this interval covers the complete cycle of policy implementation and

[1]The new quality metric will be formally proposed in September 2023, and intensive policy implementation after 2024 may be subject to expectation bias, so ending the sample period in 2023 may improve the reliability and Consistency of the estimates.

technology iteration, which can achieve both data availability and the timeliness of intermediary mechanism transmission. Among them, the financial data of listed companies were obtained from the annual reports of enterprises on the Juchao Consulting website and the WIND database, and the original data come from the China Stock Market & Accounting Research (CSMAR) database. The data related to the development level of financial technology come from the website of Baidu Index and the Digital Finance Research Centre of Peking University, and the green innovation data come from the green patent information published by the State Intellectual Property Office (SIPO).In this paper, the company stock code and fiscal year are used as the matching identifiers of enterprise microdata to integrate the enterprise data; and the provincial fintech index is matched to the corresponding enterprises by the province-year of the enterprise's registered place; the green patent data is aligned with the stock code and the year of the patent application to the enterprise annual observation, and the number of green patents applied by the enterprise in the current year is aggregated to the corresponding year, so as to complete the matching and integration of the multi-source data.

In order to ensure the data quality, this paper refers to the conventional practice in the previous literature, initially selects 39,012 observations of A-share listed companies in Shanghai and Shenzhen from 2015 to 2023 as the original samples, and screens them according to the following steps: firms in the financial industry, firms designated as ST or *ST, and firms with missing key variables were excluded to ensure data integrity; in addition, all micro-level continuous variables were winsorized at the 1st and 99th percentiles to reduce the impact of outliers. Finally, 28,010 valid observations are obtained for subsequent empirical analyses.

3.2. Variable Selection and Explanation

(1) *Core Explanatory Variable*: *FinTech*

Scholars mainly adopt three mainstream approaches to measure the development level of FinTech. First, the Peking University Digital Inclusive Finance Index (Guo et al., 2020), which relies on transaction data from Ant Group to characterize regional FinTech development from multiple dimensions (Huang et al., 2023). Second, the text mining method constructs a FinTech index based on the frequency of relevant keywords in news reports (Guo et al., 2019). Third, the scale and quantity of regional FinTech enterprises are used to reflect local FinTech development (Song et al., 2021). Among them, the first and third methods are more applicable to macro-level analysis at the national and provincial levels. The traditional text mining approach, by contrast, relies on news release frequency and cannot accurately capture the actual demand and application of FinTech among market participants. Accordingly, following Sheng and Fan (2020), this study adopts the Baidu Search Index to measure regional FinTech development. This method effectively overcomes the limitations of conventional text mining and is well-suited to the micro research context of exploring how FinTech empowers firms' New Quality Productive Forces.

The specific measurement procedure is as follows. First, referring to existing literature, FinTech-related keywords are selected from four dimensions: (1) basic technology dimension: big data, cloud computing, artificial intelligence, blockchain, and biometric recognition; (2) payment infrastructure dimension: online payment, mobile payment, and third-party payment; (3) financial intermediary service dimension: online lending, internet financing, online microcredit, online banking, e-banking, open banking, internet-only banking, and direct banking; (4) direct nomenclature dimension: internet finance and FinTech. Subsequently, keyword indices are aggregated according to the four dimensions above, and the entropy weight method is applied for objective weighting. The calculated weights of each dimension are 0.2114, 0.2779, 0.1806 and 0.3302 respectively. Finally, a comprehensive regional FinTech development index is synthesized through weighted summation, which is taken as the core measurement indicator of FinTech in this paper.

(2) ***Dependent Variable*: *New Quality Productive Forces***

As the core driving force for high-quality economic development, cultivating and enhancing New Quality Productive Forces is pivotal for enterprises to undergo transformation, upgrade their industrial structure, and pursue green development. Referring to the research of Song et al. (2024), this article constructs a new composite New Quality Productive Forces index based on the two-factor productivity theory, which overcomes the limitation of relying on only one dimension of R&D investment to measure the level of innovation. The index system is based on two fundamental factors: Labour and means of production and is then divided into four sub-dimensions: living labour, materialised labour, hard technology and soft technology. Since the New Quality Productive Forces includes not only R&D inputs but also top production, factor allocation and firm performance, an index measured with multiple indices can comprehensively characterise the core features and thus differs from a single index reflecting only R&D intensity. The approach consists of analysing the entropy values of the indicators, assigning different weights to each indicator for a comprehensive assessment and multiplying the results by 100 for standardisation. The evaluation system for the individual productivity indicators of the new quality companies is shown in Table 1.

Table 1. Enterprise new quality productive forces indicator system.

Variable	Component	Subfactors	Indicator	Indicator value description	Weight (%)
New Quality Productive Forces	Labor	Living Labor	R&D Staff Salary Percentage	R&D expenses-salary and remuneration/operating revenue	28
			R&D Staff Percentage	Number of R&D personnel/Number of employees	4
			Highly educated people Percentage	Number of undergraduates and above/Number of employees	3

Continued

		Proportion of fixed assets	Fixed assets/Total assets	2
	Materialized Labor (Labor Objects)	Manufacturing cost ratio	(Subtotal of cash outflows from operating activities + Fixed assets depreciation + Amortization of intangible assets + Provision for impairment − Cash paid for purchasing goods and receiving labor payments-Wages paid to and for employees)/(Subtotal of cash outflows from operating activities + Fixed assets Depreciation + Amortization of intangible assets + Provision for impairment)	1
Production Tools	Hard Technology	Proportion of R&D depreciation and amortization	R&D expenses-depreciation and amortization/operating revenue	27
		R&D lease expense ratio	R&D expenses-Lease fee/operating revenue	2
		R&D direct investment ratio	R&D expenses-Direct input/operating revenue	28
		Intangible assets Percentage	Intangible assets/Total assets	3
	Soft Technology	Total Asset Turnover Ratio	Operating income/Average total assets	1
		Equity multiplier inverse	Owners' equity/Total assets	1

(3) *Mediating Variables: Digital Transformation and Green Innovation*

Following Wu et al. (2021), we measure corporate digital transformation using a text-mining approach. Specifically, we use a structured keyword dictionary covering five dimensions: artificial intelligence, big data, cloud computing, blockchain, and digital technology applications. Using Python-based web crawling techniques, we calculate the frequency of these keywords in the full text of annual reports of A-share listed companies. The baseline proxy variable for corporate digital transformation (*Digital_transformation*) is then constructed as the natural logarithm of one plus the total keyword count. The rationale for this measurement stems from the nature of the annual report. As a legally mandated disclosure document, the annual report is prepared by management with due diligence and systematically reflects the firm's strategic priorities and resource allocation. When a firm substantively advances its digital transformation, related technical terms naturally appear with high frequency in the annual report text. Conversely, a firm lacking such practices would not extensively use these terms. Hence, variation in keyword frequency across annual reports effectively captures cross-firm heterogeneity in digital transformation intensity.

Nevertheless, the absolute word frequency measure may be influenced by firm-level differences in information disclosure styles. Firms with a higher propensity for disclosure tend to produce longer annual reports. Consequently, even when their underlying digital transformation levels are comparable, the absolute keyword count may be inflated by greater text volume, leading to estimation bias. To address this concern, we further standardize keyword frequency by annual report length, constructing an alternative measure for robustness checks in the subsequent mechanism analysis. Following Zhou et al. (2024), we extract the total number of characters in the "Management Discussion and Analysis" (MD&A) section of each listed firm's annual report. We then compute the density of digital transformation keywords per 10,000 characters of MD & A text and take the natural logarithm to obtain the alternative measure. The MD & A section is selected as the length benchmark for two main reasons. First, this section primarily presents the firm's operating conditions and strategic plans, making it the most informative textual segment regarding digital transformation. Second, the length of the MD & A section is predominantly constrained by accounting standards and disclosure regulations rather than by firms' voluntary disclosure practices. This property allows for a more reliable identification of keyword density variation driven by strategic emphasis on digital transformation.

Green Innovation. To accurately measure corporate green innovation, we follow Tao et al. (2021) and adopt the perspective of green patent output, using the number of green invention patent applications of listed companies as the proxy variable. We focus on green invention patents rather than utility model patents because the former are subject to more stringent examination criteria and embody higher innovation quality. Thus, they better reflect a firm's substantive breakthroughs in green technology. Given that this indicator contains many zero values and exhibits a right-skewed distribution, we take the natural logarithm of (one plus the number of green invention patent applications) to obtain the measure of corporate green innovation (*Green_innovation*).

(4) *Controlling Variables*

Table 2. Descriptive statistics.

Variable Name	Variable Symbol	Observed Value	Mean	Standard Deviation	Minimum	Median	Maximum
New Quality Productive Forces	New_Quality_Productivity	28,010	2.864	0.719	1.203	2.715	5.849
Financial Technology	FinTech	28,010	5.488	0.779	3.740	5.354	7.369
Digital Transformation	Digital_transformation	28,010	1.746	1.415	0.000	1.609	5.220
Green Innovation	Green_innovation	28,010	0.828	1.098	0.000	0.000	4.500
Firm Size	Size	28,010	13.044	1.251	9.962	12.825	17.082
Board Size	BoardSize	28,010	8.340	1.614	0.000	9.000	18.000
Age	age	28,010	10.370	7.949	1.000	8.000	34.000
Fixed Assets (%)	fixasset	28,010	19.926	14.576	0.184	16.746	66.927

Continued

Debt-to-Asset Ratio (%)	Lev	28,010	38.659	18.913	5.523	37.525	91.100
Profitability (%)	Roa	28,010	4.105	6.028	−28.675	4.181	20.914
Proportion of Independent Directors (%)	indep	28,010	37.793	5.237	33.330	36.360	57.140
Top 10 Shareholders Shareholding ratio (%)	top10	28,010	59.945	15.056	24.060	61.180	94.910

Referring to previous literature, this paper controls for the firm-level factors that may have a significant impact on firm innovation: Size (the natural logarithm of the firm's total assets), age (the time span of the firm's establishment), Lev (the ratio of total liabilities to total assets), and Roa (the ratio of net profit to total assets), fixasset (the ratio of fixed assets to total assets), BoardSize (number of directors), indep (the ratio of the number of independent directors to the total number of board members of the enterprise), top10 (the ratio of the number of shares held by the top 10 shareholders of the enterprise to the total number of shares of the enterprise). The specific data is shown in **Table 2**.

As can be seen from **Table 2**, the level of New Quality Productive Forces of enterprises, the level of financial technology, and the degree of digital transformation and green innovation in different provinces and years show large differences, and the variables are basically within a reasonable range, which can provide a good sample distribution basis for the study based on panel data.

3.3. Empirical Model

Based on the previous theoretical analysis, to explore the relationship between FinTech and the New Quality Productive Forces of enterprises, this paper uses panel data from A-share listings on the Shanghai and Shenzhen stock markets to construct the following model:

$$\mathrm{New}P_{i,t} = \alpha_0 + \alpha_1 FinTech_{i,t} + \sum \alpha_m \mathrm{Control}_{i,t} + \lambda_{k\times t} + \mu_t + \theta_i + \varepsilon_{i,t} \quad (1)$$

Here, i and t represent firm and year respectively, and k represents province. The explanatory variable $\mathrm{New}P$ stands for firms' New Quality Productive Forces, FinTech indicates FinTech, and Control denotes the other control variables in the model. In order to effectively control the inherent characteristics at the industry level, the common shocks at the time level, and the heterogeneous shocks in different provinces in different years, with reference to the fixed-effects setting method of Li et al. (2020), this paper, in the benchmark regression simultaneously controls for industry fixed effects (θ_i), year fixed effects (μ_t) and province-year interaction fixed effects ($\lambda_{k\times t}$) to maximally mitigate omitted variable bias and ensure the robustness of the estimation results. $\varepsilon_{i,t}$ is a random perturbation term. This paper does not include firm fixed effects, since the core explanatory variable is measured at the municipal level, and province-year interactive fixed effects have been incorporated to sufficiently account for heterogeneity, thereby preventing the core explanatory information from being overly absorbed. All regressions report robust standard errors clustered at the firm level to account for potential serial correlation and heteroskedasticity within firms.

4. Empirical Analysis

4.1. Benchmark Regression

Table 3 presents the baseline regression results examining the effect of FinTech on firms' New Quality Productive Forces. Column (1) controls only for industry, year, and province-year interaction fixed effects, and the coefficient of FinTech is significantly positive at the 1% level, indicating that FinTech development has a significant positive contribution to firms' New Quality Productive Forces. Column (2) introduces enterprise-level control variables, and the results show that the coefficient of FinTech is significantly 0.352. In economic terms, this means that a one-unit increase in FinTech index is associated with a 0.352-unit increase in New Quality Productive Forces in firms, confirming the robustness of the baseline conclusions. The results indicate that FinTech can significantly promote the New Quality Productive Forces level of enterprises. By optimizing factor allocation and resource efficiency, FinTech supports corporate technological innovation and internal governance. These results confirm Hypothesis H1.

Table 3. Baseline regression results.

VARIABLES	(1)	(2)
	New_Quality_Productivity	New_Quality_Productivity
lnFinTech	0.221***	0.352***
	(2.908)	(4.867)
fixasset		1.195***
		(20.653)
Lev		−0.203***
		(−4.371)
Roa		−0.327***
		(−2.725)
indep		0.144
		(1.030)
Size		0.030***
		(3.788)
top10		−0.219***
		(−4.162)
BoardSize		0.008
		(1.428)

Continued

age		−0.005***
		(−4.729)
Constant	1.653***	0.466
	(3.965)	(1.127)
Observations	28,010	28,010
R-squared	0.201	0.239
Industry FE	YES	YES
Year FE	YES	YES
Province-year FE	YES	YES

Note: t statistics in parentheses, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Same as below.

4.2. Robustness Tests

To further verify the reliability of the baseline estimates, we conduct four additional robustness checks, the results of which are reported in **Table 4**. First, we exclude firms headquartered in the four directly administered municipalities—Beijing, Shanghai, Tianjin, and Chongqing—on the grounds that these cities differ systematically from other regions in terms of policy resources, economic structure, and firm composition, and their inclusion may introduce systematic bias into the estimates. Following Luo et al. (2016), re-estimating the model on the restricted sample yields a coefficient of 0.371 on the key explanatory variable, which remains statistically significant at the 1% level (column (1)).

Second, we address potential concerns regarding the measurement of the dependent variable by replacing the baseline measure of New Quality Productive Forces with an alternative proxy for firm-level productivity. Following the approach proposed by Yang (2015), we adopt total factor productivity estimated via the Olley-Pakes method (TFP_OP) as an alternative dependent variable. Re-estimating the baseline specification with this measure yields a coefficient of 0.252, which is statistically significant at the 5% level (column (2)). The positive and significant effect of FinTech remains consistent with our baseline finding, confirming that the core relationship is robust to alternative definitions of productivity.

Third, we replace the baseline measure of FinTech with an alternative indicator constructed using machine learning methods, following the approach of Huang et al. (2023). Re-estimating the model with this alternative measure produces a coefficient of 0.029, significant at the 1% level (column (3)), consistent with the baseline finding.

Fourth, standard errors are re-clustered at the province level to account for potential within-province correlation in the error term, given that firms operating in the same province are likely subject to similar macroeconomic conditions, regional policy environments, and institutional contexts. The coefficient on the key explanatory variable is 0.352 and remains significant at the 5% level (column (4)).

Fifth, we augment the baseline specification with industry-by-year fixed effects to absorb unobserved time-varying industry-level factors that might otherwise confound the estimates. The coefficient on the key explanatory variable is 0.346, statistically significant at the 1% level (column (5)). Across all four checks, the direction, magnitude, and statistical significance of the core estimates remain broadly stable, supporting the robustness of the baseline results.

Table 4. Robustness tests.

	(1)	(2)	(3)	(4)	(5)
	Excl. Municipalities	Alternative Dependent Variable	Alternative Independent Variable	Province-Level Clustering	Industry × Year FE
lnFinTech	0.371***	0.252**	0.029***	0.352**	0.346***
	(4.918)	(1.960)	(4.273)	(2.670)	(4.816)
Constant	0.548	5.495***	2.336***	0.466	0.513
	(1.349)	(7.820)	(20.430)	(0.591)	(1.247)
Controls	YES	YES	YES	YES	YES
Observations	22,404	27,467	28,010	28,010	27,962
R-squared	0.241	0.292	0.239	0.239	0.257
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Province × Year FE	YES	YES	YES	YES	YES

Table 5. Oster omitted variable bias test.

Method	Decision Rule	Estimated Value	Test Result
Method 1	$\delta > 1$	−3.09	Pass
Method 2	[0.209, 0.491]	0.466	Pass

Although the baseline regressions include a comprehensive set of firm-level controls and multi-dimensional fixed effects, the possibility that unobserved confounders may still affect the consistency of the estimates cannot be entirely ruled out. To quantify the potential influence of omitted variables, we employ the bias-correction framework proposed by Oster (2019), implementing two complementary methods. In Method 1, we set the R-squared of the hypothetical fully specified model, R_{0max}, equal to 1.3 times the baseline R-squared ($R_{0max} = 1.3 \times 0.239 = 0.311$), impose the null of $\beta = 0$, and solve for δ—the ratio of the influence of unobserved variables to that of the observed controls. A value of $\delta > 1$ indicates that omitted variables would need to exert a disproportionately large effect, relative to the included controls, to drive the estimated coefficient to zero, suggesting that omitted variable bias is unlikely to be a serious concern. Method 2 instead fixes $\delta = 1$ (i.e., assumes that unobserved variables are at most as important as observed ones) and the same R_{0max}, and recovers the bias-adjusted coefficient estimate β^*; if β^* falls within the 95% confidence interval of the baseline estimate, the result is deemed robust. As reported in **Table 5**, both methods pass the respective diagnostic criteria, further alleviating concerns about omitted variable bias.

4.3. Endogeneity Tests

The baseline estimates may be subject to endogeneity arising from two sources: reverse causality, whereby firms with higher New Quality Productive Forces may attract greater FinTech adoption and omitted variable bias from unobserved firm or regional characteristics correlated with both FinTech development and productivity. To address these concerns, we employ an instrumental variable (IV) approach combined with two-stage least squares (2SLS) estimation, drawing on two distinct instruments.

The first instrument follows Tang et al. (2020) and uses the one-period lagged value of FinTech (L.lnFinTech) as an instrument. The relevance condition is met because current FinTech development is strongly correlated with its own lagged value. The exclusion restriction is satisfied on the grounds that the lagged measure is predetermined relative to current firm behavior and cannot be directly influenced by contemporaneous New Quality Productive Forces outcomes. The first-stage coefficient on L.lnFinTech is positive and significant at the 1% level (column (1)), confirming instrument strength; the second-stage coefficient on the instrumented FinTech variable is also positive and significant at the 1% level (column (2)).

The second instrument exploits geographic variation in digital infrastructure access by constructing an interaction between each firm's city-level distance to the nearest backbone cable hub city and year indicators. The Eight-Vertical-Eight-Horizontal backbone fiber-optic network constitutes the foundational architecture of China's telecommunications infrastructure and forms the basis for regional digital infrastructure development (Wang et al., 2023). Cities located closer to backbone hubs face lower construction costs and more favorable conditions for digital infrastructure deployment, leading to faster and more widespread FinTech adoption. Crucially, the geographic distance between a city and the nearest backbone hub is a historically fixed geographic attribute that predates and is independent of contemporary financial or economic activity (Chao et al., 2024) and has no direct channel to affect firm-level New Quality Productive Forces other than through FinTech. Interacting this cross-sectional distance measure with year indicators introduces the time-series variation needed to identify FinTech's causal effect while preserving the instrument's exogeneity. The first-stage results confirm that proximity to backbone hubs is associated with significantly higher FinTech development (column (3), significant at the 1% level), and the second-stage coefficient remains positive and significant at the 1% level (column (4)). The Kleibergen-Paap (KP) Wald F-statistics and KP rank LM statistics reported at the bottom of **Table 6** both comfortably pass the standard thresholds for instrument strength and under-identification, respectively, validating the choice of instruments.

Table 6. Endogeneity tests.

	(1)	(2)	(3)	(4)
	lnFinTech	New Quality Productive Forces	lnFinTech	New Quality Productive Forces
lnFinTech		0.369***		0.424***
		(4.095)		(3.520)
L.lnFinTech	0.757***			
	(18.880)			
Distance × Year			−0.000***	
			(−36.492)	
Controls	YES	YES	YES	YES
Observations	23,697	23,697	28,010	28,010
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Province × Year FE	YES	YES	YES	YES
KP Wald F	356.458		1,331.664	
KP RK LM	576.410		668.029	

4.4. Heterogeneity Tests

The benchmark regression analysis presented earlier confirms the core hypothesis of this paper: that FinTech can have a significant positive impact on enterprises' New Quality Productive Forces (H1). However, China's economic development is characterized by significant imbalances, with substantial differences in resource endowments, institutional environments, and technological foundations among enterprises across different regions, industries, and micro-level characteristics. Consequently, the enabling effect of FinTech on enterprises' New Quality Productive Forces is inevitably profoundly influenced by these heterogeneous factors. To further reveal the boundary conditions and context-dependence of FinTech's mechanism of action, this paper conducts an in-depth heterogeneity analysis across five dimensions: regional heterogeneity, regional innovation heterogeneity, ownership heterogeneity, industry heterogeneity, and firm size heterogeneity.

(1) ***Analysis of Regional Heterogeneity***

China's eastern, central, and western regions exhibit marked gradients in the concentration of financial resources, the development of digital infrastructure, and the stage of industrial structure evolution (Guo et al., 2020). To examine how these macro-regional characteristics influence the enabling effect of FinTech, this paper divides the sample enterprises into three subsamples based on their registered locations—eastern, central, and western—and conducts regression analyses for each subsample.

The empirical results (**Table 7**) indicate that the positive impact of FinTech on enterprises' New Quality Productive Forces exhibits significant regional heterogeneity. Specifically, the effect of FinTech is strongest in the central region, where the coefficient of the core explanatory variable, lnFinTech, reaches 0.734 and is statistically significant at the 1% level. The underlying logic of this result lies in the fact that the central region is currently at a critical stage of absorbing industrial transfers from the eastern region while accelerating industrial upgrading and technological transformation, leading to an extremely strong demand for capital and technology. The deep integration of FinTech can effectively break down the geographical and informational barriers of traditional finance, significantly alleviating the financing constraints of enterprises in the central region and thereby fully unleashing their potential for technological innovation and productivity improvement (Song et al., 2021).

Table 7. Regional heterogeneity test of fintech's impact on enterprises' new quality productive forces.

	(1)	(2)	(3)
	Eastern Region	Central Region	Western Region
lnFinTech	0.238*	0.734***	0.312***
	(1.746)	(5.374)	(2.905)
Constant	1.004	−1.230*	0.864
	(1.267)	(−1.668)	(1.520)
Controls	YES	YES	YES
Observations	20,821	4119	3055
R-squared	0.246	0.250	0.346
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Province-year FE	YES	YES	YES

The positive effect of FinTech in the western region ranks second, with a coefficient of 0.312 (significant at the 1% level). Although the western region also faces strong demand for capital, constraints such as a relatively lagging institutional environment, a weak industrial foundation, and underdeveloped digital infrastructure create friction in the implementation of FinTech's "technological spillover" and "resource allocation" effects, resulting in a weaker enabling impact compared to the central region. In contrast, the positive effect in the eastern region is relatively weaker, with a coefficient of 0.238 (significant only at the 10% level). This is primarily because the eastern region already possesses a highly developed financial system, ample traditional financial resources, and a high baseline level of enterprise digitalization and New Quality Productive Forces. According to the law of diminishing marginal returns, the marginal improvement potential that FinTech can bring to the eastern region is relatively limited (Tang et al., 2020).

(2) ***Analysis of Heterogeneity across Innovative Regions***

The core of New Quality Productive Forces lies in technological innovation, and regional innovation policies often provide enterprises with a favorable external environment. Based on the list of "Pilot Innovative Industrial Clusters" published by the Ministry of Science and Technology, this study constructs a city-level difference-in-differences (DID) dummy variable for pilot innovative industrial cluster status and interacts it with the FinTech index. The rules for defining the pilot attributes of innovative industrial clusters are as follows: adopt the list of pilot cities of national innovative industrial clusters officially announced by the Ministry of Science and Technology, and match the city where the enterprise is registered with the pilot list one by one; construct a city-level dummy variable, which assigns a value of 1 if the enterprise is registered in a pilot city and 0 if it is not a pilot city.

The regression results (**Table 8**, column (1)) show that the coefficient of the interaction term (c.lnFinTech × Innovation Region) is 0.012 and is positive at the 1% significance level. This indicates that if a firm is located in a pilot city of an innovative industrial cluster, the positive effect of FinTech on its New Quality Productive Forces is significantly enhanced. Policies for innovative industrial clusters not only provide tax incentives and fiscal subsidies but, more importantly, foster collaboration among industry, academia, and research institutions, accelerating knowledge spillovers and technology sharing. In such a highly concentrated innovation ecosystem, the targeted capital allocation and digital transformation support provided by FinTech can be more efficiently converted into enterprises' green innovation outcomes and improvements in total factor productivity, thereby forming a dual-drive synergy combining FinTech with industrial cluster policies.

(3) ***Analysis of Heterogeneity in Ownership Type***

Under China's distinctive property rights system, the nature of property rights is a key factor influencing enterprises' access to resources and strategic decision-making. This study introduces an interaction term for ownership type to test this hypothesis. The results show that the interaction coefficient is 0.024 and is significant at the 1% level (Column (2)). This implies that ownership type (SOE = 1, non-SOE = 0) significantly amplifies the positive effect of FinTech, indicating that the positive impact of FinTech on New Quality Productive Forces is more pronounced in state-owned enterprises (SOEs).

This finding can be explained from the following perspectives. First, SOEs often undertake policy-driven tasks such as major national technological breakthroughs, serving as lead entities in industrial chains, and facilitating green and low-carbon transitions. Consequently, their funding needs for fostering New Quality Productive Forces are substantial and concentrated. Second, SOEs typically possess more standardized internal governance structures and stronger data asset accumulation. This enables FinTech institutions to utilize big data and artificial intelligence technologies more accurately to create credit profiles for these enterprises, thereby precisely matching their massive funding needs during digital transformation. Finally, the resource capacity and policy advantages of SOEs allow them to more effectively convert the capital and technological dividends brought by FinTech into tangible green innovation outputs (Xiao et al., 2023), thereby amplifying the enabling effects of FinTech.

(4) ***Analysis of Industry-Specific Heterogeneity***

There are fundamental differences in factor intensity and technology life cycles across industries, which determine their varying sensitivity to FinTech. This paper examines heterogeneity from two dimensions: high-tech industries and technology-intensive industries. Following Bai (2022), we determine the industry codes of high-tech listed companies based on the National Bureau of Statistics' Classification of High-Tech Industries (Manufacturing) (2013) and Classification of High-Tech Industries (Services) (2013). Drawing on the methodology of Yin et al. (2018), we classify all sample industries into three categories—technology-intensive, asset-intensive, and labor-intensive—based on the intensity of production factors, in accordance with the China Securities Regulatory Commission's 2012 industry classification standards.

a) Heterogeneity of the High-Tech Industry

Empirical results show that the coefficient of the high-tech industry interaction term is 0.053 and is significant at the 1% level (Column (3)). High-tech enterprises exhibit typical characteristics such as "high R&D investment, high innovation risk, a high proportion of intangible assets, and a lack of traditional collateral" (Li et al., 2020). Under the traditional financial system, such enterprises often face severe credit rationing and financing constraints. Leveraging big data risk control and blockchain technology, FinTech has effectively broken free from the reliance on "hard asset" collateral. By mining "soft information" such as intellectual property and operational cash flows, FinTech has significantly reduced information asymmetry between banks and enterprises. Consequently, FinTech can provide high-tech enterprises with financial support that is highly tailored to their R&D cycles and high-risk characteristics, thereby playing a more critical "timely assistance" role in the cultivation of New Quality Productive Forces.

b) Heterogeneity of Technology-Intensive Industries

Furthermore, the interaction coefficient for technology-intensive industries is as high as 0.067 and is also statistically significant at the 1% level (Column (4)). Technology-intensive industries rely heavily on continuous equipment upgrades, intelligent production transformation, and investment in knowledge-based factors. As discussed under Hypothesis H2, the underlying technologies of FinTech (e.g., artificial intelligence and cloud computing) are highly aligned with those required for corporate digital transformation (Wu et al., 2024). In technology-intensive industries, FinTech not only fulfills the financial function of "capital supply" but also serves as an enabler through "technological spillovers." It effectively meets the capital needs for enterprises' intelligent transformation, reduces transformation costs, and accelerates the concentration of production factors in high-efficiency sectors, thereby providing a powerful driving force for the leap in New Quality Productive Forces.

(5) ***Analysis of Enterprise Scale Heterogeneity***

Enterprise scale is also a critical factor determining the efficiency of resource allocation. To avoid endogenous disturbances caused by dynamic changes in firm size during the sample period, this paper refers to the methodology of Luo et al. (2024), which measures enterprise scale using total assets in 2007. We divide the sample into a high-scale group and a low-scale group based on the industry median, assigning a value of 1 to large-scale enterprises and 0 to small-scale enterprises.

Regression results show that the coefficient of the enterprise scale interaction term is 0.013 and is significant at the 1% level (Column (5)). This implies that as enterprise scale increases, the positive effect of FinTech on New Quality Productive Forces also strengthens.

Although one of the original objectives of FinTech was to develop inclusive finance and alleviate financing difficulties for small and medium-sized enterprises (SMEs), economies of scale still play a dominant role in driving the complex endeavor of fostering New Quality Productive Forces, which involves deep-seated digital transformation (H2) and systemic green innovation (H3). Large enterprises possess more sophisticated digital infrastructure, richer data resources, and stronger talent pools, enabling them to integrate FinTech services more efficiently and embed them into complex supply chain management and the optimization of green production processes (Wu et al., 2021). Consequently, large enterprises demonstrate a greater comprehensive capacity to absorb the benefits of FinTech and translate them into improvements in total factor productivity.

Table 8. Heterogeneity test.

	(1)	(2)	(3)	(4)	(5)
	Innovative Region	Enterprise Nature	High-Tech Industry	Technology-Intensive	Enterprise Scale
c.lnFinTech#	0.012***	0.024***	0.053***	0.067***	0.013***
	(3.823)	(6.736)	(3.365)	(4.221)	(3.793)
Constant	2.357***	2.520***	2.195***	2.174***	2.646***
	(20.718)	(22.026)	(17.896)	(17.836)	(19.764)
Controls	YES	YES	YES	YES	YES
Observations	28,010	28,010	28,010	28,010	28,010
R-squared	0.238	0.242	0.238	0.239	0.238
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Province-year FE	YES	YES	YES	YES	YES

5. Mechanism Analysis

The baseline empirical analysis confirms that FinTech significantly enhances corporate New Quality Productive Forces. However, the underlying transmission channels remain to be fully elucidated. According to our theoretical framework, FinTech may indirectly drive New Quality Productive Forces through two pathways: promoting corporate digital transformation and stimulating green innovation. To test these hypotheses while addressing potential endogeneity of the mediators, we adopt a two-stage least squares (2SLS) estimation within a mediation framework (Yang et al., 2020; Cui, 2022). Consistent with the baseline specification, we use the contemporaneous FinTech index (lnFinTech) as the instrument for each mediator. The exclusion restriction is plausible because regional FinTech development is largely determined by macro-level factors (e.g., digital infrastructure and financial regulation) and is unlikely to be driven by reverse causality from an individual firm's New Quality Productive Forces.

5.1. Model Specification

The conventional three-step mediation approach relies on the exogeneity assumption of the mediator—i.e., that the mediator is not simultaneously influenced by the outcome variable. In our context, however, a firm's digital transformation and green innovation may be endogenously correlated with its New Quality Productive Forces. Therefore, we use lnFinTech as an instrument for Digital_transformation and Green_innovation to estimate the causal effect of each mediator on New Quality Productive Forces using the following two-stage regressions:

First stage:

$$\text{Mediator}_{i,t} = \beta_0 + \beta_1 \ln \text{Fintech}_{i,t} + \sum \beta_m \text{Controls}_{i,t} + \mu_i + \lambda_t + \epsilon_{i,t}$$

Second stage:

$$\text{New\_Quality\_Productivity}_{i,t} = \gamma_0 + \gamma_1 \widehat{Mediator}_{i,t} + \sum \gamma_m \text{Controls}_{i,t} + \mu_i + \lambda_t + \xi_{i,t}$$

where Mediator alternatively denotes Digital_transformation and Green_innovation, and $\widehat{Mediator}$ is the fitted value from the first stage. All regressions include industry fixed effects (μ_i), year fixed effects (λ_t), and province-year fixed effects.

5.2. Mediating Role of Digital Transformation

Table 9. Mechanism test: mediating role of digital transformation (2SLS).

Variable	(1) First stage	(2) Second stage
	Digital_transformation	New_Quality_Productivity
lnFinTech	11.982***	
	(3.453)	
$\widehat{\text{Digital\_transformation}}$		0.029***
		(2.893)
Controls	YES	YES
Industry/Year/Province-Year FE	YES	YES
Observations	28,010	28,010
Adjusted R-squared	0.238	0.239
Kleibergen-Paap rk LM statistic	12.375	
Kleibergen-Paap rk Wald F statistic	12.099	

We first test whether digital transformation mediates the effect of FinTech on New Quality Productive Forces. **Table 9** reports the 2SLS results.

Column (1) shows that FinTech has a positive and statistically significant effect on digital transformation, with a coefficient of 11.982 ($p < 0.01$). The Kleibergen-Paap rk LM statistic (12.375, $p < 0.01$) rejects the null of under-identification. The Kleibergen-Paap rk Wald F statistic (12.099) is slightly below the Stock-Yogo critical value of 16.38 for 10% maximal IV size (Stock & Yogo, 2005). Nevertheless, as Bound et al. (1995) demonstrate, when the first-stage F-statistic lies between 10 and 20, the finite-sample bias of 2SLS remains acceptable. Moreover, the first-stage coefficient is highly significant, and the second-stage results are robust; therefore, the instrument is considered valid.

Column (2) presents the second-stage results. The fitted value of digital transformation has a positive and significant coefficient (0.029, $p < 0.01$) on New Quality Productive Forces. The indirect effect of FinTech via digital transformation is thus $11.982 \times 0.029 \approx 0.347$, which is comparable to the direct effect (0.352) reported in the baseline regression. This indicates that digital transformation is an important transmission channel through which FinTech enhances New Quality Productive Forces, supporting Hypothesis H2.

5.3. Mediating Role of Green Innovation

We next examine whether green innovation serves as a mediating channel. **Table 10** reports the 2SLS estimates.

Table 10. Mechanism test: mediating role of green innovation (2SLS).

Variable	(1) First stage	(2) Second stage
	Green_innovation	New_Quality_Productivity
lnFinTech	0.505***	
	(8.158)	
$\widehat{Green\_innovation}$		0.695***
		(5.911)
Controls	YES	YES
Industry/Year/Province-Year FE	YES	YES
Observations	28,010	28,010
Adjusted R-squared	0.238	0.239
Kleibergen-Paap rk LM statistic	69.006	
Kleibergen-Paap rk Wald F statistic	67.439	

Column (1) demonstrates that FinTech significantly promotes green innovation, with a coefficient of 0.505 ($p < 0.01$). The Kleibergen-Paap rk LM statistic (69.006, $p < 0.01$) and the weak instrument test (Wald F = 67.439, far above the conventional threshold) confirm the validity of the instrument.

Column (2) reveals that the fitted value of green innovation has a positive and significant coefficient (0.695, $p < 0.01$) on New Quality Productive Forces. The indirect effect is $0.505 \times 0.695 \approx 0.351$, again close to the direct effect reported in the baseline regression (0.352). Hence, green innovation also constitutes a critical mediating pathway, supporting Hypothesis H3.

5.4. Comparison and Integration of the Two Pathways

In summary, FinTech enhances corporate New Quality Productive Forces through two mediating pathways: a technology pathway via digital transformation (indirect effect = 0.347) and a green pathway via green innovation (indirect effect = 0.351). Both indirect effects are quantitatively similar to the direct effect (0.352), suggesting that they jointly form a complete mediation framework.

To ensure that the conclusions regarding the mediating pathway of digital transformation are not driven by the specific absolute word frequency measure, we adopt the keyword density indicator (normalized by the length of the MD&A section) as an alternative measure of digital transformation and re-estimate the two-stage least squares (2SLS) model. The results show that the first-stage coefficient of FinTech on the normalized density indicator is 0.520, significant at the 1% level. The second-stage coefficient of the normalized density indicator on corporate New Quality Productive Forces is 0.673, also significant at the 1% level. The estimated indirect effect is approximately 0.350, which is quantitatively consistent with the baseline indirect effect (0.347). Moreover, the Kleibergen-Paap Wald F statistic is 23.04, exceeding the critical value, indicating that weak instrument bias is not a concern. These findings indicate that the mediating role of digital transformation does not depend on the specific word frequency measure, and that cross-firm differences in information disclosure styles do not materially undermine the core conclusions.

Notably, the estimated effect of green innovation on New Quality Productive Forces (0.695) is substantially larger than the estimated effect of digital transformation (0.029). This difference carries important economic implications: green innovation reduces environmental costs, increases output per unit, and optimizes the allocation of production factors more directly and efficiently, thereby generating a stronger immediate impact on total factor productivity (TFP). In contrast, digital transformation acts primarily as a foundational "enabler"; its effect on New Quality Productive Forces unfolds through a longer transmission chain. The two mechanisms are complementary and mutually reinforcing—digital transformation provides the data infrastructure and intelligent platforms for green innovation, while green innovation directs digital transformation toward sustainable development.

Furthermore, the weak-instrument F-statistic is much higher for the green innovation model (67.439) than for the digital transformation model (12.099), indicating that FinTech explains a larger share of the variation in green innovation. This difference likely reflects that green innovation is more sensitive to financial support, whereas digital transformation is also constrained by firm-specific factors such as internal technological capabilities and organizational structure.

6. Conclusions and Recommendations

Using a sample of A-share listed firms on the Shanghai and Shenzhen stock exchanges from 2015 to 2023, this study empirically investigates the influence of FinTech on corporate New Quality Productive Forces and its underlying mechanisms. The core conclusions are summarized as follows.

First, FinTech exerts a significantly positive effect on New Quality Productive Forces. Benchmark regression results suggest that a one-unit rise in FinTech development level corresponds to an average increase of 0.352 units in firms' New Quality Productive Forces. This finding remains robust after conducting a series of robustness tests and endogeneity treatments. The result implies that FinTech effectively boosts corporate innovation capacity and productivity growth. It achieves this by restructuring production factors, stimulating innovation momentum, and optimizing resource allocation.

Second, heterogeneity analysis confirms that the empowering effect of FinTech presents obvious heterogeneous characteristics across different contexts. Regionally, the effect is the strongest in central China, followed by western China, while the eastern region shows a relatively weaker impact. In terms of firm attributes, state-owned enterprises, high-tech industries, technology-intensive industries and large-scale enterprises gain more prominent benefits from FinTech. In addition, targeted policies for innovative industrial clusters can generate remarkable synergistic effects with FinTech development.

Third, mechanism analysis verifies that FinTech empowers corporate New Quality Productive Forces through two dominant pathways: digital transformation and green innovation. Specifically, FinTech can directly promote the improvement of New Quality Productive Forces. Meanwhile, it also plays an indirect mediating role by accelerating enterprise digital transformation (indirect effect = 0.347) and facilitating green innovation (indirect effect = 0.351). The indirect effects of the two pathways are comparable in magnitude to the direct effect. Together, they form a complete analytical framework for the empowerment mechanism of FinTech.

Considering the above conclusions, this study puts forward targeted policy implications. First, governments should further improve FinTech digital infrastructure and deepen the integration of digital technology and financial services. More financial and technological resources should be allocated to central and western regions to narrow the regional digital development gap. Second, authorities ought to optimize supporting institutional arrangements of FinTech to better support corporate digital transformation. Financial institutions are encouraged to launch differentiated digital financing products according to industrial characteristics. This can lower the transformation barriers and solve the dilemma that restricts SMEs from digital upgrading. Third, a sound green FinTech service system should be established. Big data and blockchain technology can be adopted to strengthen environmental information disclosure and green project identification. This helps channel more financial resources into green innovation fields. Fourth, policymakers should adhere to targeted and differentiated policy design. Classified FinTech development plans should be formulated for state-owned and private enterprises, as well as high-tech and traditional industries. Such differentiated arrangements can fully release the policy dividends of FinTech and maximize its economic benefits.

Authors' Contributions

Yinxin Ding, Xinyi Cui, and Guo Chen contributed equally to this work and should be regarded as co-second authors. All authors have read and approved the final manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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