



FinTech, heterogeneous innovation, and firm total factor productivity

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ABSTRACT

FinTech, as a technology-driven financial innovation, is an important engine for deepening supply-side structural reform in finance and enhancing the capacity of financial services for the real economy. Against the backdrop of advancing innovation-driven development, this study uses micro data on listed firms from 2000 to 2023 to examine how FinTech improves firm total factor productivity (TFP) from the perspective of heterogeneous innovation behaviors. The results show that FinTech significantly increases firm TFP. This conclusion remains robust after addressing endogeneity concerns and conducting multiple robustness tests. The mechanism analysis indicates that FinTech promotes firm heterogeneous innovation (incremental and breakthrough innovation), in turn enhancing TFP. Breakthrough innovation contributes more to TFP at the margin. The heterogeneity analysis further reveals that the impact of FinTech on TFP is stronger for manufacturing and large-scale firms, as well as for firms with low bargaining power in supply chains or higher levels of digital transformation. These findings underscore the role of FinTech in easing information frictions and reallocating knowledge and financial resources toward innovation with higher productivity payoffs, thereby linking financial digitalization to firm-level knowledge creation and diffusion.

Introduction

Financial Technology (FinTech), underpinned by artificial intelligence (AI), blockchain, cloud computing, and big data, has experienced leapfrogging growth. By the end of 2024, global activity and investment were clustered around cross-border payments, crypto-related solutions, and AI-enabled applications. The United States and the United Kingdom remained the two most active investment hubs, while the United Arab Emirates (led by Dubai) benefited from strategic economic transformation and posted strong FinTech expansion. In Asia, Singapore and Hong Kong continued to be among the most dynamic markets, particularly in crypto and cross-border payments. China's FinTech trajectory converged with global trends in AI deployment and data-security practices, yet displayed distinctive strengths in overseas scaling, regulatory technology, and talent development. Taken together, these patterns highlight a competitive, knowledge-intensive landscape in which institutional design, human capital, and data governance shape FinTech diffusion and market outcomes. In recent years, scholars have conducted multidimensional explorations of FinTech. At the national level, Umar et al. (2025) found that FinTech can reduce energy intensity and promote renewable energy adoption in some European countries, with

technological innovation and artificial intelligence playing positive moderating roles. At the urban level, Singh et al. (2025), focusing on urban slums in India, demonstrated that FinTech reduces transaction costs and enhances asset management capabilities, thereby increasing the utilization of productive credit. At the corporate level, Khan and Ahmad (2025) revealed that FinTech alleviates corporate credit constraints by mitigating information asymmetry, with this positive externality being more pronounced in developing countries. In the digital economy era, investigating how FinTech enhances firm total factor productivity (TFP) helps us understand how it optimizes business models, strengthens competitiveness, improves product and service quality, and better meets market demand, thereby driving high-quality firm growth. A growing literature documents the effects of FinTech on TFP, but most studies foreground FinTech's financial attributes, emphasizing channels such as financing constraints, information asymmetry, and default risk (He et al., 2023; Song et al., 2021). Li et al. (2025) showed that regional FinTech development promotes technological innovation, in turn raising TFP. Their innovation proxy, however, is patent quantity; therefore, it is unclear whether the gains stem from entry into new technological domains or from intensification within existing fields. Closer to our approach, Yan et al. (2025) focused

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on corporate green technologies and found that FinTech and environmental-protection taxation jointly expand the boundaries of green innovation. [Byun et al. \(2021\)](#) distinguished breakthrough from incremental innovation. Conceptually consistent with the former, [Acemoglu et al. \(2022\)](#) classified innovation as radical versus incremental. They measured breakthrough innovation through patents in new technology domains and incremental innovation through patents in existing domains. Therefore, differing from previous mechanistic analyses, this study examines the role of FinTech in corporate production efficiency from the perspectives of radical and incremental innovation, thereby enriching research in the field of FinTech.

This study explicates how FinTech affects TFP through the mediating channels of heterogeneous innovation, specifically breakthrough and incremental innovation. We proceed in three steps. First, we test whether FinTech raises firm-level TFP. Second, we examine heterogeneous innovation responses by adopting the classification and measurement established by [Verhoeven et al. \(2016\)](#), [Balsmeier et al. \(2017\)](#), and [Byun et al. \(2021\)](#), distinguishing breakthrough innovation (entry into new technological domains) from incremental innovation (intensification within existing domains). Third, we assess the relative contribution of each pathway by testing whether the productivity effect of breakthrough innovation exceeds that of incremental innovation.

This study has two main contributions. First, in terms of research content, it departs from traditional mechanism analyses (e.g., financing constraints, information asymmetry, and technological innovation) and focuses on heterogeneous innovation. We link FinTech to firm productivity through heterogeneous innovation, examining whether FinTech raises TFP by fostering heterogeneous innovation and, further, which type of innovation delivers the larger productivity gain. Unlike the taxonomies in [Dong et al. \(2025\)](#) and [Collins and Morris \(2025\)](#), we directly partition firms' technological innovation into breakthrough and incremental categories, collectively referred to as heterogeneous innovation. Following [Byun et al. \(2021\)](#), we operationalize breakthrough and incremental innovation using patent data on Chinese listed firms to measure each firm's heterogeneous innovation capability. Second, we apply a four-step mediation model to explore how FinTech empowers heterogeneous innovation and enhances TFP, mitigating the potential endogeneity of the traditional three-step approach. We further adopt a double/debiased machine learning (DDML) framework with random forest, LASSO, and gradient boosting algorithms to confirm robustness.

Literature review and research hypotheses

FinTech and firm TFP

TFP denotes the portion of output growth that is not explained by observed factor inputs (e.g., capital and labor), the so-called Solow residual. Improvements in TFP primarily reflect more efficient resource allocation and technological progress. High productivity thus signals not only strong innovative capacity, but also adaptive capability in dynamic markets, enabling firms to respond swiftly to shifts in demand and to deliver higher-quality products and services, which are foundations of sustained competitive advantage ([Brynjolfsson et al., 2025](#)). Additionally, high productivity is associated with superior allocation and more efficient use of production factors, which lowers operating costs and strengthens market competitiveness ([Prato, 2025](#)). Moreover, productivity gains typically depend on a skilled and specialized workforce; such labor exhibits strong technological adaptability and rapidly assimilates new production methods and process innovations, further enhancing firm competitiveness and long-run viability ([Kalyani et al., 2025](#); [Moon et al., 2023](#)). FinTech possesses the dual attributes of finance and technology. From the financial perspective, scholars have found that FinTech can enhance firm TFP by, for instance, alleviating financing constraints and reducing information asymmetry ([Khan & Ahmad, 2025](#)), improving labor resource allocation efficiency ([Ang et al., 2024](#)), and enhancing information and resource allocation effects ([Luo et al.,](#)

[2022](#)). Contrary to the mainstream view, [Hmoud et al. \(2025\)](#), based on data from Jordan and Palestine, found that the rapid development of FinTech may reduce capital allocation efficiency. A potential explanation is that FinTech development intensifies competition in the lending market, leading to distortions in risk pricing and causing some capital to flow to projects that are not the most efficient. From the perspective of its technological attribute, [Manu et al. \(2025\)](#) found that innovation output can amplify the promotional effect of FinTech on the circular economy. [Li et al. \(2020\)](#) found that FinTech can enhance the innovation effect of tax rebates, thereby promoting corporate innovation and driving high-quality development of the real economy. [Wang et al. \(2021\)](#) discovered that FinTech can increase the TFP of commercial banks, and the magnitude of this enabling effect varies with their applied technological capabilities. [Huang et al. \(2025\)](#), by constructing a multi-sector endogenous growth model, found that FinTech can increase regional R&D investment, thereby promoting regional economic growth. [Osei-Assibey Bonsu et al. \(2025\)](#) found that FinTech helps promote green innovation in manufacturing firms, which is conducive to achieving high-quality development, and that this enabling effect is stronger in China than in India. Based on the analysis of the above two aspects, this study proposes:

Hypothesis 1. FinTech enhances firm TFP.

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Incremental innovation builds on existing technologies, with diminishing marginal returns arising from repeated efforts within the same domain ([Akcigit & Kerr, 2018](#)). Conversely, breakthrough innovation opens new technological domains, reshapes economic structures, and catalyzes follow-on innovations ([Acemoglu et al., 2022](#)), thereby serving as the primary engine of structural upgrading and high-quality growth. Although both forms of innovation raise productivity, their effects differ, with the marginal contribution of breakthrough innovation typically being larger ([Acemoglu et al., 2022](#)). Consistent with this view, [Shen et al. \(2023\)](#) exploited network infrastructure construction as an exogenous shock, demonstrating that it facilitates breakthrough innovation, expands firms' innovation boundaries, and elevates productivity. At the macro level, sustained innovation improves national TFP, while efficient resource allocation amplifies the productivity payoff from breakthrough discovery ([Feder, 2018](#)).

Regarding incremental innovation, FinTech promotes innovation through several channels: it increases the volume of green technology patenting ([Chen et al., 2024](#)), relaxes financing constraints and strengthens firms' innovative capacity ([Guo et al., 2025](#)), and interacts with financial regulation to raise regional marketization, indirectly stimulating innovation quantity ([Zheng et al., 2023](#)). For breakthrough innovation, FinTech induces structural change and technological substitution in financial services ([Broby, 2021](#)) and supports localized breakthrough business models, such as mobile finance, P2P lending, and crowdfunding ([Anshari et al., 2020](#)). Theoretically, the FinTech ecosystem exerts disruptive effects on financial intermediation and delineates future trajectories for breakthrough innovation systems ([Palmié et al., 2020](#)). Based on the above, this study proposes:

Hypothesis 2. FinTech promotes heterogeneous innovation, which, in turn, increases firm TFP, with breakthrough innovation exerting a stronger effect.

Research design

Data sources and description

We assembled an unbalanced panel of 3,697 Chinese listed firms over 2000–2023. Patent information and prefecture-level counts of FinTech firms were obtained, respectively, from the China National Intellectual Property Administration (CNIPA) and CNRDS. Firm-level

financial and governance data were drawn from CSMAR, and city-level covariates were compiled from the National Bureau of Statistics and the *China City Statistical Yearbook*. We excluded ST and *ST firms to retain normally operating listed companies, dropped observations with missing values on key variables, and winsorized all continuous variables at the 1 % level in both tails.

Variable construction

(1) Dependent variable. Our dependent variable was firm-level TFP. In the baseline analysis, we estimated TFP using the Olley–Pakes (OP) and Levinsohn–Petrin (LP) procedures, denoted by TFP_OP and TFP_LP, respectively. For robustness, we additionally computed TFP via OLS, firm fixed effects (FE), and GMM, yielding TFP_OLS, TFP_FE, and TFP_GMM for subsequent checks. Annual averages of all five measures are reported in Fig. 1.

(2) Core independent variable. Our core independent variable was the firm-level FinTech development index (*FinTech*). Following the methodology of Li et al. (2020), we constructed this index through textual analysis of listed firms’ annual reports using Python. The detailed keyword dictionary used for identification is provided in Table 1. The construction process consisted of the following steps: ① Text Extraction: We extracted all textual content from the main body of each firm’s annual report, excluding headers, footers, and appendices. ② Dictionary Construction and Segmentation: A comprehensive FinTech keyword dictionary was compiled, encompassing terms across three technological dimensions: artificial intelligence, blockchain, cloud computing, big data, online transformation, and mobile transformation. This custom dictionary was integrated into the Jieba Chinese word segmentation library to ensure accurate identification of relevant terms. ③ Text Processing and Frequency Count: After segmenting the text, we removed standard stop words and then counted the frequency of all FinTech-related keywords appearing in each report. ④ Index Calculation: The firm-level FinTech development index for a given year was calculated as the natural logarithm of one plus the total annual FinTech keyword frequency. To facilitate robustness checks, we also collected city-level FinTech development metrics, defined as the number of newly registered FinTech firms in the city where the firm is headquartered and the cumulative number of registered FinTech firms in that city. Both city-level FinTech variables were similarly log-transformed after adding one.

(3) Mechanism variables. We captured firms’ heterogeneous innovation using patent outputs. Following Shen et al. (2023) and Byun et al. (2021), we excluded design patents and retained invention and

Table 1
FinTech keywords.

Dimension	FinTech keywords
Artificial intelligence	Artificial intelligence, robotics, machine learning, deep learning, neural networks, facial recognition, biometric recognition, voice recognition, pattern recognition, image recognition, facial payment, virtual reality, augmented reality, knowledge graph, intelligent transformation, smart deposits, smart teller services, intelligent finance, smart banking outlets, intelligent credit services, smart-oriented, smart banking, intelligent marketing, intelligent, intelligent systems, intelligent risk control, intelligent finance, automation, natural language processing.
Blockchain	Blockchain, distributed ledger, supply chain, Internet of Things, proximity, quantum, quantum communication, quantum encryption, digital currency, cryptocurrency.
Cloud computing	Distributed, distributed storage, distributed computing, distributed architecture, distributed database, financial cloud, trusted computing, cloud adoption, private cloud, virtualization, privacy-preserving computing, cloud-based, cloud services, cloud service platform, cloud transformation, cloud computing, cloud architecture, cloud platform, cloud system, cloud disaster recovery.
Big data	Big data, big data analytics, big data services, big data technology, big data modeling, big data mining, data storage, data excavation, data governance, data centers, digitalization, digital transformation, digital economy, digital identity, digital ecosystem, digital credit cards, digital banking, digital business models.
Online transformation	E-commerce, digitalization, electronic finance, electronic channels, electronic commerce, electronic payment, internet, internet finance, financial technology, digital technology, networking, online finance, online wealth management, online financing, online consumer loans, online banking, online payment, web-based, online transactions, online payments, internet banking, online, web-based.
Mobile transformation	Scenario-based approach, scenario-based finance, application programming interface (API), open platform, open banking, open ecosystems, software development platforms, mobile banking, mobile payments, QR code payments, mobile e-commerce, mobile internet, mobile finance, mobile payments, digital payments, mobile applications, application interfaces, direct banking.

utility-model patents only. Using the International Patent Classification (IPC) at the four-digit level, we proceeded as follows. For each firm and year t , we first constructed the firm’s existing technology set from all IPC four-digit codes observed up to year $t - 1$. We then compared the IPC codes of newly applied-for patents in year t with this set. Patents whose IPC four-digit codes did not appear in the existing set were classified as breakthrough innovation (entry into a

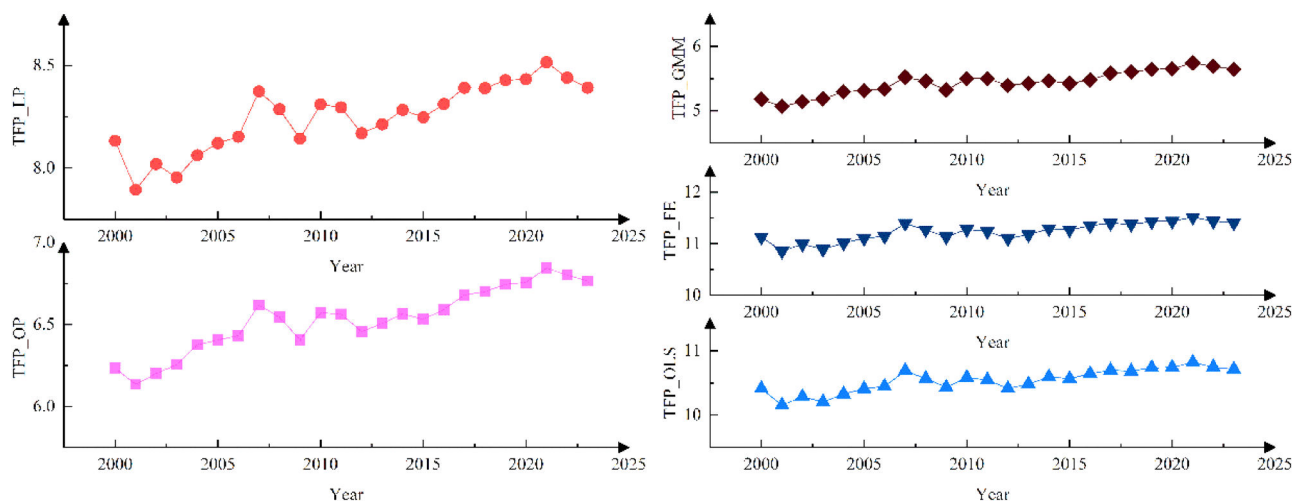


Fig. 1. Comparison of TFP estimation results.

new technology field), while those whose codes did appear were classified as incremental innovation (activity within an existing field). Based on this classification, we calculated the number of new technology field patents (*lnNew_patent*) and existing technology field patents (*lnKnown_patent*) annually to measure breakthrough and *incremental* innovation, respectively. Because heterogeneous innovation is typically associated with stronger positive externalities, we emphasized its productivity effects by adding two complementary indicators: intertemporal technological similarity (*Similarity*) and the number of newly added IPC codes (*lnNew_IPC*). *Similarity* measures the degree of overlap between the technological space of patents in year *t* and that in year *t* - 1. A lower value indicates greater divergence, suggesting more significant expansion in the innovation trajectory (Byun et al., 2021). The formula is as follows:

$$Similarity_{i,t} = \frac{T_{i,t}T'_{i,t-1}}{(T_{i,t}T'_{i,t})^{1/2}(T_{i,t-1}T'_{i,t-1})^{1/2}} \tag{1}$$

Where $T_{i,t}$ denotes the technological space distribution vector of firm *i* in year *t*. $T_i = (X_{i,1}, X_{i,2}, \dots, X_{i,k})$, $X_{i,k}$ represents the ratio of the number of type-*k* patent applications to the total number of patent applications by firm *i*. Consistent with Byun et al. (2021), *Similarity* captures incremental innovation, while *lnNew_IPC* captures breakthrough innovation.

(4) Control variables. To mitigate omitted variable bias, we included a set of control variables. These include firm age (*Age*), board size (*Boardsize*), firm market value (*TobinQ*), industry concentration (*HHI_A*), ownership concentration (*Shrcr1*), price-to-book ratio (*PB*), level of economic development (*lnGDP*), and industrial structure (*Industrystructure*). Descriptive statistics for all relevant variables are reported in Table 2.

Model specification

To examine the impact of FinTech on firms' TFP, this study constructed the following baseline regression model:

$$TFP_{it} = \beta_0 + \beta_1 FinTech_{it} + \sum \beta_n Controls_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{2}$$

Where subscripts *i* and *t* denote firm and year, respectively. TFP represents the total factor productivity of firm *i* in year *t*, measured using both the OP and LP methods. *FinTech* indicates the level of financial

technology development for firm *i* in year *t*. *Controls* denotes the set of control variables. μ_i , γ_t , and ε_{it} represent firm fixed effects, time fixed effects, and the random disturbance term, respectively. Robust standard errors were employed to address potential heteroskedasticity in standard error estimation. The coefficient of interest was β_1 . A significantly positive β_1 suggests that FinTech enhances firms' TFP.

Empirical analysis

Baseline regression results

Building on the established premise that FinTech fosters firm performance via TFP gains (Gaibulloev et al., 2025), we estimated the baseline regression model to formally assess the role of FinTech in enhancing TFP. Table 3 reports the estimated effect of FinTech on firm

Table 3
Baseline regression results.

	(1) <i>TFP_OP</i>	(2) <i>TFP_LP</i>	(3) <i>TFP_LP</i>	(4) <i>TFP_LP</i>
<i>FinTech</i>	0.0379*** (0.0074)	0.0388*** (0.0080)	0.0595*** (0.0088)	0.0611*** (0.0096)
<i>Age</i>		0.5078*** (0.0914)		0.7152*** (0.1058)
<i>Boardsize</i>		0.1284*** (0.0438)		0.2031*** (0.0493)
<i>TobinQ</i>		0.0104 (0.0076)		0.0084 (0.0089)
<i>lnGDP</i>		0.1182*** (0.0450)		0.1385*** (0.0518)
<i>Industrystructure</i>		0.4127** (0.1809)		0.3721* (0.2128)
<i>HHI_A</i>		0.1038 (0.0691)		0.1063 (0.0729)
<i>Shrcr1</i>		0.0007 (0.0010)		0.0013 (0.0012)
<i>PB</i>		0.0007 (0.0039)		-0.0026 (0.0045)
<i>Constant</i>	5.3456*** (0.1040)	2.8601*** (0.5005)	6.8311*** (0.1844)	3.5583*** (0.5715)
<i>Firm FE</i>	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>N</i>	20,357	17,512	20,357	17,512
<i>R²</i>	0.4543	0.4534	0.4651	0.4686

Note: Robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively. Unless otherwise specified, the following tables are the same.

Table 2
Descriptive statistics.

Variable names	Variable	N	Mean	Min	Max	SD
TFP (OP)	<i>TFP_OP</i>	20,357	6.6794	5.0999	8.8455	0.7857
TFP (LP)	<i>TFP_LP</i>	20,357	8.3642	6.4062	11.0944	0.9759
TFP (OLS)	<i>TFP_OLS</i>	20,357	10.6651	8.4004	14.1297	1.2031
TFP (FE)	<i>TFP_FE</i>	20,357	11.3604	8.9664	15.0596	1.2837
TFP (GMM)	<i>TFP_GMM</i>	20,357	5.5790	4.0657	7.5877	0.7164
FinTech	<i>FinTech</i>	20,357	3.5151	0.0000	6.5206	1.4014
Number of newly registered FinTech firms in the current year	<i>lnNewFinTech</i>	13,805	2.8766	0.0000	6.3919	1.8075
Cumulative number of registered FinTech firms	<i>lnTotalFinTech</i>	13,805	4.0682	0.0000	8.0485	2.2205
Number of new patents	<i>lnNew_patent</i>	20,357	1.4880	0.0000	6.3491	0.9252
Interannual patent technological similarity	<i>Similarity</i>	18,888	0.7573	0.0000	0.9998	0.2549
Number of new IPC (international patent classification) categories	<i>lnNew_IPC</i>	20,357	1.3958	0.0000	5.2311	0.8297
Number of existing patents	<i>lnKnown_patent</i>	20,357	2.7140	0.0000	9.5141	1.4395
Firm age	<i>Age</i>	20,357	2.8736	1.7918	3.5264	0.3568
Board size	<i>Boardsize</i>	20,354	2.1221	1.6094	2.7081	0.1987
Tobin's Q	<i>TobinQ</i>	20,180	2.0136	0.8559	7.5561	1.1739
Industry concentration	<i>HHI_A</i>	19,687	0.1734	0.0405	0.9110	0.1435
Ownership concentration	<i>Shrcr1</i>	20,266	33.5551	8.2586	73.5623	14.6448
Price-to-Book ratio (P/B ratio)	<i>PB</i>	20,180	3.4061	0.6012	14.7971	2.5313
Prefecture-level city Per Capita GDP	<i>lnGDP</i>	18,280	11.4831	9.6548	12.2234	0.5700
Industrial structure	<i>Industrystructure</i>	18,280	0.4028	0.1491	0.6452	0.1125

TFP. Columns (1)–(2) use TFP_OP as the dependent variable: Column (1) includes year and firm fixed effects only, while Column (2) augments the baseline with controls. Columns (3)–(4) switch to TFP_LP: Column (3) includes year and firm fixed effects, and Column (4) additionally adds controls. Across all specifications, the FinTech coefficient is positive and statistically significant. The result is invariant to the TFP estimator (OP vs. LP) and to the inclusion of controls, indicating that FinTech robustly raises firm-level productivity and providing empirical support for Hypothesis 1.

Endogeneity treatment

(1) Addressing reverse causality. While FinTech can enhance firms' TFP, firms with higher production efficiency often have stronger technological absorption and financing capabilities, which may, in turn, promote their FinTech development. Therefore, there may be a bidirectional causal relationship between FinTech and TFP, potentially biasing the estimation. To address this issue, we followed the approach of Chong et al. (2013) and constructed two instrumental variables: the average FinTech level of other firms in the same region and industry during the same period (IV1), and the average FinTech level of other firms in the same industry during the same period (IV2). We applied a two-stage least squares (2SLS) regression. Columns (1)–(3) in Table 4 report the results. In the first stage, both IV1 and IV2 are significantly correlated with firm-level FinTech at the 1 % level, supporting the relevance hypothesis. In the second stage, the estimated coefficients of FinTech are 0.0444 and 0.0657, both statistically significant at the 1 % level. Compared with the baseline regression, the coefficients are larger after accounting for reverse causality, suggesting that endogeneity may bias the baseline estimates downward. Under both the OP and LP methods, the Kleibergen–Paap rk LM statistics are approximately 1737.1, and the Hansen J statistics are 0.996 and 0.478, with p-values of 0.318 and 0.490, respectively. This indicates that the instruments are not weak and that the overidentifying restrictions cannot be rejected. Overall, the core finding remains robust; that is, FinTech significantly enhances firms' TFP.

(2) Addressing sample selection bias. FinTech adoption among listed firms is not entirely random and may be influenced by firm-specific characteristics, which could also affect TFP. This raises concerns about sample selection bias. Referring to Yan et al. (2025), this study employed the Heckman two-stage model to correct for and test potential sample selection bias. In the first stage, this study constructed a binary dependent variable indicating whether a firm's FinTech level is above the sample-period average (assigned a value of 1 if above and 0 otherwise). A Probit regression was then conducted

using the set of control variables from the baseline model as independent variables to estimate the inverse Mills ratio (IMR). In the second stage, we included the IMR as a control in the baseline regression. Columns (4) and (5) of Table 4 present the results. Under the OP method (Column 4), the IMR coefficient is -0.0354 and statistically significant. Under the LP method (Column 5), the IMR coefficient is -0.0526 , also statistically significant. In both cases, the FinTech coefficient remains positive and significant at the 1 % level. These results indicate that the core findings of this study remain robust after accounting for sample selection bias. FinTech continues to have a positive effect on firms' TFP.

(3) Consideration of omitted variable bias. To mitigate the potential influence of omitted variables on the baseline regression results, this study conducts a placebo test. Following the approach of Du et al. (2023), we randomly generated fakeFinTech based on the mean and standard deviation of actual FinTech. These variables were then re-estimated in the baseline regression model. This procedure was repeated 1000 times to eliminate the influence of randomness. In theory, the fake FinTech variable should have no effect on firms' TFP (i.e., the coefficient should be zero). Otherwise, it would suggest the presence of omitted variable bias.

Fig. 2 presents the kernel density distributions of the regression coefficients and t-values from 1000 placebo tests. The estimated coefficients and t-values are almost symmetrically distributed around zero and approximately follow a normal distribution. Notably, the coefficient from the baseline regression reported in Column (2) of Table 3 (0.0388) lies outside the distribution of the placebo estimates. This suggests that the positive effect of FinTech on firms' TFP identified in the baseline analysis is unlikely to be driven by unobservable random factors, thereby reinforcing the robustness of the main finding.

Robustness checks

To ensure the robustness of the results, four complementary robustness checks were conducted:

(1) Alternative variable measurements. For the dependent variable TFP, we employed three estimation methods: OLS, FE, and GMM. For the key independent variable, FinTech, we adopted the measurement approach of Song et al. (2021). Specifically, we used the logarithm of the number of newly registered FinTech firms in the cities where firms were located ($\ln NewFinTech$) and the cumulative number of registered FinTech firms ($\ln TotalFinTech$), both log-transformed after adding one. The estimation results in Panel A of Table 5 consistently

Table 4
Instrumental variable and Heckman regression results.

	(1) <i>FinTech</i>	(2) <i>TFP_OP</i>	(3) <i>TFP_LP</i>	(4) <i>TFP_OP</i>	(5) <i>TFP_LP</i>
<i>IV1</i>	0.7582*** (0.0129)				
<i>IV2</i>	0.0631*** (0.0192)				
<i>FinTech</i>		0.0444*** (0.0073)	0.0657*** (0.0082)	0.0332*** (0.0077)	0.0528*** (0.0092)
<i>IMR</i>				-0.0354^* (0.0213)	-0.0526^{**} (0.0245)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes
Kleibergen–Paap rk LM statistic		1737.1090	1737.1090		
Hansen J statistic		0.9960	0.478		
Hansen J statistic P value		0.31840	0.4895		
N	17,512	16,925	16,925	17,512	17,512
R ²	0.8019	0.4533	0.4686	0.4539	0.4695

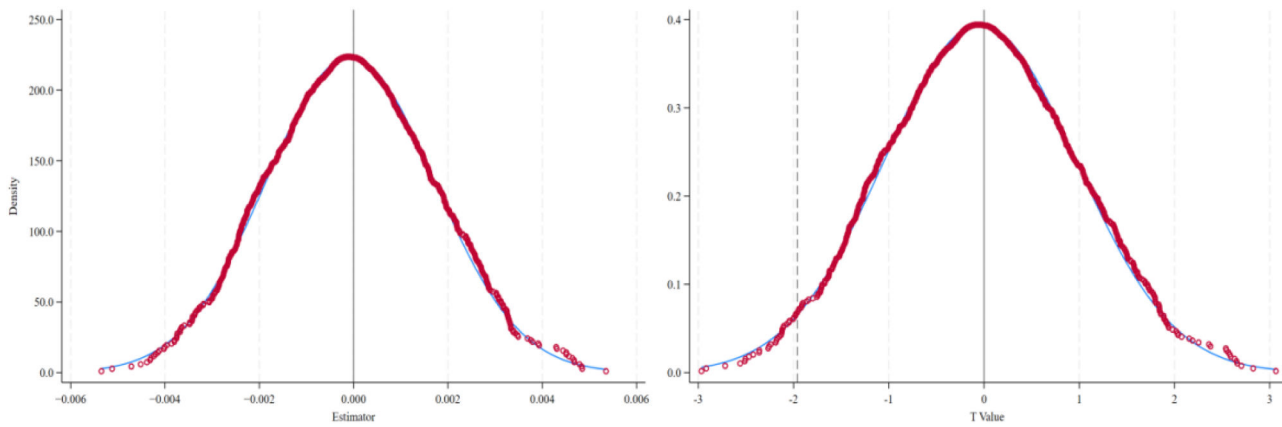


Fig. 2. Placebo test.

Table 5

Robustness checks.

Panel A:	(1)	(2)	(3)	(4)	(5)	(6)
Alternative variable measurements	<i>TFP_OLS</i>	<i>TFP_FE</i>	<i>TFP_GMM</i>	<i>TFP_OLS</i>	<i>TFP_FE</i>	<i>TFP_GMM</i>
<i>lnNewFinTech</i>	0.0220** (0.0099)	0.0233** (0.0105)	0.0125* (0.0069)			
<i>lnTotalFinTech</i>				0.0627*** (0.0203)	0.0663*** (0.0215)	0.0359*** (0.0135)
N	13,250	13,250	13,250	13,250	13,250	13,250
R ²	0.4902	0.4979	0.3152	0.4919	0.4996	0.3163
Panel B:	(1)	(2)	(3)	(4)	(5)	(6)
Inclusion of interaction fixed effects	<i>TFP_OP</i>	<i>TFP_LP</i>	<i>TFP_OP</i>	<i>TFP_LP</i>	<i>TFP_OP</i>	<i>TFP_LP</i>
<i>FinTech</i>	0.0307*** (0.0045)	0.0494*** (0.0048)	0.0370*** (0.0045)	0.0583*** (0.0051)	0.0382*** (0.0046)	0.0614*** (0.0051)
<i>Firm × Year FE</i>	Yes	Yes	No	No	No	No
<i>City × Year FE</i>	No	No	Yes	Yes	No	No
<i>Province × Year FE</i>	No	No	No	No	Yes	Yes
N	16,925	16,925	16,925	16,925	16,925	16,925
Panel C:	(1)	(2)	(3)	(4)	(5)	(6)
Accounting for exogenous policy shocks	<i>TFP_OP</i>	<i>TFP_LP</i>	<i>TFP_OP</i>	<i>TFP_LP</i>	<i>TFP_OP</i>	<i>TFP_LP</i>
<i>FinTech</i>	0.0393*** (0.0080)	0.0610*** (0.0095)	0.0378*** (0.0079)	0.0590*** (0.0094)	0.0382*** (0.0079)	0.0593*** (0.0094)
<i>TechFinanceDID</i>	-0.0222 (0.0298)	0.0046 (0.0345)				
<i>AIDID</i>			0.0060 (0.0117)	0.0117 (0.0132)		
<i>BigDataDID</i>					0.0164 (0.0260)	0.0197 (0.0307)
N	17,509	17,509	17,009	17,009	17,164	17,164
R ²	0.4535	0.4686	0.4092	0.4139	0.4205	0.4283
Panel D:	(1)	(2)	(3)	(4)	(5)	(6)
DDML	Random forest		Lasso regression		Gradient boosting	
<i>FinTech</i>	<i>TFP_OP</i>	<i>TFP_LP</i>	<i>TFP_OP</i>	<i>TFP_LP</i>	<i>TFP_OP</i>	<i>TFP_LP</i>
	0.0289*** (0.0047)	0.0734*** (0.0057)	0.0362*** (0.0044)	0.0656*** (0.0050)	0.0245*** (0.0047)	0.0753*** (0.0057)
N	17,512	17,512	17,512	17,512	17,512	17,512
Controls	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes

show that FinTech significantly improves firms' TFP, confirming the main findings across various measures.

(2) High dimensional fixed effects. We gradually incorporated interaction fixed effects, such as firm × year, city × year, and province × year fixed effects, into the baseline regression model. This allowed us to control for potential omitted variable bias. As shown in Panel B of Table 5, the results remain consistent, providing further support for the core conclusion.

(3) Accounting for exogenous policy shocks. The sample period includes several major policy shocks, including the Tech Finance pilot policy (*TechFinanceDID*), the National AI Innovation Application Pilot Zones (*AIDID*), and the National Big Data Comprehensive Pilot

Zones (*BigDataDID*). To mitigate their potential confounding effects, we sequentially incorporated these policy dummies into the baseline regressions. The results in Panel C of Table 5 show that these policies do not alter the positive effect of FinTech on firms' TFP.

(4) Double/debiased machine learning (DDML). Chernozhukov et al. (2018) argued that parameter estimation with machine learning methods is prone to regularization bias and overfitting, which, in turn, yield biased estimates. To address these issues, the article proposes using Neyman-orthogonal scores together with cross-fitting, an approach known as double or debiased machine learning (DDML). The article further notes that DDML is applicable to a range of settings, including the partially linear model, the

partially linear instrumental variables model, and estimating the average treatment effect. Based on the application of DDML in the estimation of average treatment effects, Yang et al. (2020) find that gradient boosting delivers the best performance and empirically corroborate the Big N audit quality effect. Zhao et al. (2025), employing DDML with support vector machines, random forests, XGBoost, LightGBM, and CatBoost, found that the low-altitude airspace opening policy significantly enhances innovation in the aviation manufacturing sector. However, building on a partially linear DDML framework (Giraldo et al., 2024; Wei & Xia, 2024; Xing et al., 2023), this study estimated the benchmark specification using random forests, LASSO, and gradient boosting to ensure the robustness of the baseline findings. The comparative regressions reveal the relative strengths and weaknesses of the three algorithms and allow a vivid contrast with the baseline estimates (coefficients and significance), providing theoretical and empirical support that DDML outperforms conventional causal estimators, such as OLS. The results in Panel D of Table 5 consistently show that FinTech significantly enhances firms' TFP, again affirming the robustness of the findings.

Mechanism analysis

Ye et al. (2023) argued that enhancing the quality of innovation is imperative to fully leverage the enabling effect of FinTech on the green TFP of firms. To probe the mechanism linking FinTech to firm TFP, we examined two mediators, breakthrough and incremental innovation,

and compared their marginal contributions to productivity. The preceding section developed a theoretical FinTech→heterogeneous innovation→TFP framework; here we subject that mechanism to empirical testing. Considering concerns about the traditional three-step mediation procedure (Aguinis et al., 2017; Pieters, 2017), we implemented a four-step mediation design that helps mitigate endogeneity in the mediator and outcome equations. The model is specified as follows:

$$M_{it} = \gamma_0 + \gamma_1 FinTech_{it} + \sum \gamma_n Controls_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{3}$$

$$TFP_{it} = \delta_0 + \delta_1 M_{it} + \sum \delta_n Controls_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{4}$$

$$TFP_{it} = \varphi_0 + \varphi_1 M_{it} + \varphi_2 FinTech_{it} + \sum \varphi_n Controls_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{5}$$

Where the mediating variables M_{it} include breakthrough innovation and incremental innovation, while other model specifications are consistent with the baseline regression. Unlike existing literature, which typically uses the number of invention patent applications or grants to proxy innovation quality, this study adopts two alternative indicators for breakthrough innovation: the number of patents in new technological fields (*lnNew_patent*) and the number of newly added IPC codes (*lnNew_IPC*). These measures allow for a more comprehensive quality-based classification of firms' technological innovation. The regression results are presented in Table 6, with Columns (1)–(3) corresponding to the above models. Panel A uses *lnNew_patent* to measure breakthrough innovation. Column (1) shows that FinTech significantly enhances

Table 6
FinTech, heterogeneous innovation, and firm TFP.

Panel A:	(1)	(2)	(3)	(4)	(5)
<i>Breakthrough Innovation1</i>	<i>lnNew_patent</i>	<i>TFP_OP</i>	<i>TFP_OP</i>	<i>TFP_LP</i>	<i>TFP_LP</i>
<i>FinTech</i>	0.0517*** (0.0152)		0.0376*** (0.0080)		0.0591*** (0.0095)
<i>lnNew_patent</i>		0.0251*** (0.0044)	0.0241*** (0.0043)	0.0402*** (0.0051)	0.0386*** (0.0051)
Sobel Z	13.9810***			16.3700***	
Bootstrap (1000)	[0.0129, 0.0172]			[0.0187, 0.0250]	
N	17,512	17,512	17,512	17,512	17,512
R ²	0.0208	0.4529	0.4555	0.4677	0.4727
Panel B:	(1)	(2)	(3)	(4)	(5)
<i>Breakthrough Innovation2</i>	<i>lnNew_IPC</i>	<i>TFP_OP</i>	<i>TFP_OP</i>	<i>TFP_LP</i>	<i>TFP_LP</i>
<i>FinTech</i>	0.0519*** (0.0137)		0.0373*** (0.0080)		0.0588*** (0.0095)
<i>lnNew_IPC</i>		0.0296*** (0.0048)	0.0283*** (0.0048)	0.0463*** (0.0057)	0.0443*** (0.0057)
Sobel Z	16.0960***			14.3210***	
Bootstrap (1000)	[0.0129, 0.0174]			[0.0182, 0.0240]	
N	17,512	17,512	17,512	17,512	17,512
R ²	0.0172	0.4531	0.4557	0.4680	0.4729
Panel C:	(1)	(2)	(3)	(4)	(5)
<i>Incremental Innovation1</i>	<i>Similarity</i>	<i>TFP_OP</i>	<i>TFP_OP</i>	<i>TFP_LP</i>	<i>TFP_LP</i>
<i>FinTech</i>	0.0117*** (0.0040)		0.0329*** (0.0081)		0.0548*** (0.0097)
<i>Similarity</i>		0.0335** (0.0171)	0.0305* (0.0170)	0.0457** (0.0193)	0.0408** (0.0192)
Sobel Z	12.4140***			13.4000***	
Bootstrap (1000)	[0.0098, 0.0133]			[0.0148, 0.0196]	
N	16,242	16,242	16,242	16,242	16,242
R ²	0.0307	0.4517	0.4537	0.4651	0.4694
Panel D:	(1)	(2)	(3)	(4)	(5)
<i>Incremental Innovation2</i>	<i>lnKnown_patent</i>	<i>TFP_OP</i>	<i>TFP_OP</i>	<i>TFP_LP</i>	<i>TFP_LP</i>
<i>FinTech</i>	0.0694*** (0.0181)		0.0370*** (0.0080)		0.0581*** (0.0095)
<i>lnKnown_patent</i>		0.0272*** (0.0056)	0.0258*** (0.0056)	0.0451*** (0.0066)	0.0430*** (0.0066)
Sobel Z	25.3020***			26.6760***	
Bootstrap (1000)	[0.0414, 0.0492]			[0.0614, 0.0724]	
N	17,512	17,512	17,512	17,512	17,512
R ²	0.2517	0.4532	0.4557	0.4687	0.4735
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

firms' breakthrough innovation capacity at the 1 % level. Column (2) shows that breakthrough innovation significantly improves firms' TFP at the 1 % level. Column (3) confirms that both FinTech and breakthrough innovation significantly enhance TFP at the 1 % level. Moreover, the Sobel Z-value is statistically significant at the 1 % level, and the 95 % confidence interval of the Bootstrap test (1000 samples) does not include zero, confirming the presence of a mediating effect. Columns (4) and (5) estimate TFP using the LP method. The results remain consistent with those in Columns (2) and (3) and pass both the Sobel and Bootstrap tests. Panel B uses *lnNew_IPC* as the proxy for breakthrough innovation. The regression results suggest that FinTech promotes firm-level TFP through enhanced breakthrough innovation. In contrast to existing literature that relies solely on patent counts or R&D input to characterize technological innovation, this study used intertemporal technological similarity (*Similarity*) and the number of patents in known technological fields (*lnKnown_patent*) as a proxy for incremental innovation. Panel C or D, Column (1) shows that FinTech significantly promotes incremental innovation. Column (2) indicates that incremental innovation significantly enhances firms' TFP. Column (3) shows that both FinTech and incremental innovation significantly improve TFP. The Sobel test statistic is significant, and the Bootstrap confidence interval does not include zero, providing further support for the mediating effect. Columns (4) and (5) report consistent results. Comparing the effects of the two measures of breakthrough innovation and incremental innovation, the indirect effect of breakthrough innovation on TFP is larger than that of incremental innovation on TFP (under the OP method, $(0.0517 \times 0.0251 + 0.0519 \times 0.0296) / 2 > (0.0117 \times 0.0335 + 0.0694 \times 0.0272) / 2$; the same result holds under the LP method), indicating that breakthrough innovation affects firms' TFP more significantly. This finding supports Hypothesis 2.

Heterogeneity analysis

Industry heterogeneity

Prior research shows that FinTech alleviates information asymmetry and improves credit allocation, thereby raising firm TFP (Song et al., 2021). Because manufacturing is both capital- and technology-intensive, it depends more on efficient financial intermediation and should realize larger productivity gains from FinTech. We define *Manufacturing* = 1 for firms in manufacturing industries and 0 otherwise, and estimate the interaction *Manufacturing* × *FinTech* to compare effects across sectors. As reported in Table 7, Column (1), the interaction coefficient is positive and statistically significant, indicating that the productivity effect of FinTech is significantly stronger for manufacturing firms than for non-manufacturing firms. This result suggests that, to advance the strategy of building a strong manufacturing base, manufacturing enterprises and the policies that support them should prioritize FinTech adoption to improve resource allocation and accelerate technological

Table 7
Heterogeneity analysis.

	(1)	(2)	(3)	(4)
	<i>TFP_OP</i>	<i>TFP_OP</i>	<i>TFP_OP</i>	<i>TFP_OP</i>
<i>Manufacturing</i> × <i>FinTech</i>	0.0254* (0.0141)			
<i>Corporate_size</i> × <i>FinTech</i>		0.0193** (0.0084)		
<i>FinTech</i> × <i>SSC</i>			0.1277*** (0.0390)	
<i>FinTech</i> × <i>DT</i>				0.0094** (0.0038)
<i>Controls & Low-order Terms</i>	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes
N	17,512	17,512	15,343	15,624
R ²	0.4561	0.4761	0.4467	0.4591

upgrading.

Firm size heterogeneity

Firms differ in how they translate FinTech into innovation and productivity. Large firms typically maintain more developed markets and dedicated R&D units; their denser technological and collaborative networks facilitate the absorption of information and knowledge spillovers, enabling more effective use of external resources. SMEs, by contrast, rely more on internal knowledge flows, potentially limiting FinTech's productivity leverage. We measured firm size by total assets and defined firms above the industry median as large (assigned a value of 1) and others as small (value of 0). The interaction term *Corporate_size* × *FinTech* was used to assess heterogeneity across firm size. As reported in Table 7, Column (2), the interaction coefficient is positive and significant at the 1 % level, indicating that FinTech's TFP effect is stronger for large firms. These firms should exploit scale advantages and deepen FinTech adoption to enhance production and operational efficiency.

Supply chain bargaining power heterogeneity

A firm's supply chain position shapes its access to resources, information transmission, and influence over transactions. Generally, firms that are upstream or hold key customer or supplier ties possess stronger bargaining power and can better steer resource allocation and industry coordination, potentially amplifying FinTech's TFP effect. Following Wang and Cheng (2025), we measured supply chain bargaining power (SSC) as the average of the shares of purchases from the top five suppliers and sales to the top five customers; a higher SSC implies lower bargaining power. We estimated the interaction *FinTech* × *SSC* to gauge heterogeneity. Contrary to ex ante expectations, Table 7, Column (3) shows a positive coefficient significant at the 1 % level, indicating that FinTech raises TFP more for firms with weaker bargaining power. A plausible mechanism is that such firms face greater exposure to supplier or customer turnover, decoupling, and supply chain disruptions; adopting FinTech helps them improve transparency, credit access, and relational stability, thereby enhancing productivity. This result highlights the developmental value of FinTech for small and micro enterprises embedded in supply chains.

Digital transformation heterogeneity

Digital transformation (DT) captures a firm's ability to adopt, integrate, and reconfigure new-generation information technologies. Higher DT implies stronger foundations in data acquisition, process automation, organizational coordination, and intelligent decision-making capabilities that constitute the technological and institutional infrastructure for FinTech adoption. Following Wu et al. (2021), we measured DT and estimated the interaction *FinTech* × *DT* to assess heterogeneity by digital maturity. As reported in Table 7, Column (4), the interaction coefficient is 0.0094 and significant at the 1 % level, indicating that FinTech's positive effect on TFP is stronger among firms with higher DT. In the digital economy, firms with advanced digital capabilities should leverage this base to scale FinTech solutions, improve product and service efficiency, and contribute to high-quality growth.

Research conclusions and policy implications

Facing the opportunities and challenges resulting from the new wave of digital technologies and productivity transformation, FinTech serves as an important driver in promoting firm technological innovation and, in turn, enhancing operational efficiency. Under the dual goals of advancing high-quality economic development and promoting Chinese-style modernization, this study uses Chinese listed firms from 2000 to 2023 as the research sample to examine the impact of FinTech on firm TFP, its underlying mechanisms, and heterogeneous effects. The main

findings are as follows: FinTech development significantly enhances firm TFP. This conclusion is sustained after addressing potential endogeneity issues arising from reverse causality, sample selection bias, and omitted variables, and conducting robustness checks using double machine learning. The mechanism analysis shows that FinTech promotes firm TFP through heterogeneous innovation, with breakthrough innovation contributing more to TFP at the margin. The TFP-enhancing effect of FinTech is stronger for manufacturing firms, large-scale firms, firms with low SSC, and firms with a high degree of DT.

Based on these findings, the study proposes the following policy recommendations. First, establishing a dynamic regulatory framework and digital inclusion system for the digital age. Policymakers should base their efforts on institutional preparedness and regulatory adaptability, striving to create a FinTech policy environment that balances innovation encouragement with risk control. The core objective is to promote a shift in regulatory approach from static compliance to dynamic inclusiveness, thereby providing institutional safeguards for the application of FinTech in industrial upgrading and technological innovation. Within this framework, enterprises with different characteristics should be guided toward differentiated development paths: manufacturing firms need to deepen the integration of FinTech into production processes to enhance intelligent manufacturing capabilities; larger enterprises should leverage their resource advantages to optimize the application of FinTech in financing structures and transaction costs; companies with low bargaining power in supply chains can use FinTech to improve information transparency and risk resilience; and highly digitalized enterprises should increase their investment in cutting-edge technologies, such as artificial intelligence and blockchain, to achieve synergistic empowerment of technology and institutions. Second, optimizing financial resource allocation to catalyze a technology–industry–finance virtuous cycle. There should be active integration of superior financial resources to build a service system for scientific and technological achievement transformation that covers the entire product lifecycle. Strengthening financial support for key core technologies and disruptive technological breakthroughs is essential to foster new quality productive forces. At the policy implementation level, the government needs to adopt targeted, drip-irrigation-style innovation incentive policies to promote the deep integration of science and technology with financial capital. This will not only catalyze breakthrough innovations in enterprises but also enhance China's voice in global digital financial governance through the construction of an open and collaborative innovation ecosystem. Third, strengthening International Policy Coordination and Enhancing Institutional Openness. Active participation in constructing a global digital financial governance system should be encouraged, promoting international mutual recognition and cooperation in regulatory standards. By establishing cross-border FinTech cooperation mechanisms, support should be provided to help developing countries improve their digital financial infrastructure. Simultaneously, advocacy of inclusive digital principles in multilateral forums will offer practical pathways for emerging economies to promote DT and high-quality development, contributing to the creation of an inclusive and sustainable global innovation ecosystem.

This study also leaves several topics for further research. First, mechanism identification can be further enriched. This study considers only heterogeneous innovation—breakthrough and incremental innovation—particularly focusing on the former. Future research could explore other mechanisms, such as resource allocation efficiency, credit misallocation, and information availability. Second, the dynamic evolution mechanism warrants further investigation. This study examines the relatively static effect of FinTech on firm TFP, lacking analysis of its dynamic effects, such as differences across firm life cycles.

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CRedit authorship contribution statement

Rongrong Wei: Writing – review & editing, Validation, Supervision, Methodology, Data curation, Conceptualization. **Yueming Xia:** Writing – original draft, Visualization, Software, Investigation, Formal analysis.

Declaration of competing interest

All authors of this study declare that they have no conflict of interest. None of the authors is financially or non-financially involved with the organizations being studied in this article.

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