Technological Innovation and Firm Financial Performance: Evidence from Blockchain-Related Listed Firms in China

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Abstract. Technological innovation is widely regarded as a key driver of firm competitiveness and long-term value creation. However, due to high investment intensity, uncertainty, and long commercialization cycles, the financial consequences of innovation remain empirically ambiguous. Using a panel of block chain-related Chinese A-share listed firms from 2020 to 2024, this study examines how technological innovation affects firm financial performance across multiple dimensions. From a computer science perspective, blockchain-related innovation represents investment in distributed computing systems that integrate cryptographic algorithms, consensus mechanisms, and decentralized data architectures. Such technologies directly influence system performance, computational efficiency, data integrity, and information-processing costs within firm-level information systems.From a resource reallocation perspective, we distinguish between innovation inputs and innovation outputs and analyze their contemporaneous and dynamic effects on profitability, operating efficiency, solvency, and growth capability. The empirical results show that innovation inputs significantly enhance firm profitability and solvency but reduce contemporaneous operating efficiency. Innovation outputs exhibit asymmetric effects: patent quantity is generally associated with improved financial performance, whereas patent quality imposes short-term financial pressure. Overall, the findings provide a mechanism-based explanation for the mixed evidence in the innovation–performance literature and offer implications for innovation-oriented firms in emerging technology sectors.

Keywords: technological innovation; financial performance; blockchain; patents; resource reallocation

1 Introduction

Technological innovation has become a central strategic concern for firms operating in increasingly competitive and uncertain environments. Since 2020, rapid digital transformation and the diffusion of frontier technologies—such as blockchain—have fundamentally reshaped firms' innovation strategies and resource allocation decisions. In China, blockchain technology has been explicitly incorporated into national digital

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economy and industrial upgrading strategies, encouraging listed firms to intensify R&D investment and innovation activities.

Unlike conventional digital technologies, blockchain constitutes a distributed computing infrastructure that relies on decentralized consensus protocols, cryptographic verification, and replicated data storage. Its adoption fundamentally alters system architecture, transaction validation processes, and computational workload, thereby affecting both operational efficiency and resource utilization at the firm level.

Despite the growing emphasis on innovation, its financial consequences remain far from settled. Innovation activities typically involve substantial upfront investment, long development cycles, and uncertain commercialization prospects. These characteristics became even more pronounced during the 2020–2024 period, which was marked by heightened macroeconomic uncertainty and rapid technological restructuring. Firms engaging in innovation must reallocate financial and human resources away from routine operations toward knowledge-intensive activities, which may undermine short-term operating efficiency and liquidity. Consequently, prior empirical studies continue to report mixed findings on the relationship between technological innovation and firm financial performance [1–4].

Existing studies often suffer from two limitations. First, technological innovation is frequently treated as a homogeneous construct, without distinguishing between innovation inputs and innovation outputs [2,5]. Second, many studies rely on a single financial indicator, failing to capture the multidimensional nature of firm performance. Recent literature emphasizes that innovation may generate heterogeneous effects across different dimensions of financial performance, particularly in digital and knowledge-intensive industries [6–8]. Existing studies predominantly examine blockchain adoption from economic or managerial perspectives, while relatively little attention has been paid to its underlying computing mechanisms. In particular, how blockchain-related computing technologies affect firm performance through changes in computational complexity, system efficiency, and IT resource allocation remains insufficiently explored.

To address these gaps, this study examines how technological innovation affects multiple dimensions of firm financial performance using block chain-related Chinese listed firms over the period 2020–2024.

2 Theoretical Framework and Hypotheses

2.1 Technological Innovation as a Resource Reallocation Process

From a resource-based perspective, technological innovation represents a deliberate reallocation of firm resources. Innovation inputs, such as R&D personnel and R&D expenditure, divert resources from routine production activities toward uncertain and knowledge-intensive projects.In the context of block chain, this reallocation extends beyond financial and human capital to include computational resources such as processing power, storage capacity, and network bandwidth. Distributed ledger systems require continuous transaction validation, cryptographic computation, and data synchronization across nodes, which increase system complexity and computational overhead.While such reallocation may reduce short-term operating efficiency, it can enhance firms' technological capabilities and future value creation potential [2,6].

Innovation outputs, particularly patents, reflect realized outcomes of prior innovation investment. However, recent studies show that different dimensions of patenting activity generate heterogeneous financial consequences. Patent quantity often captures incremental and application-oriented innovation that can be commercialized relatively quickly, whereas patent quality typically involves higher sunk costs and longer development cycles, thereby exerting short-term financial pressure before long-term benefits materialize [8,10].

2.2 Hypotheses

H1: Innovation inputs are positively associated with firm profitability and solvency.

H2: Innovation inputs are negatively associated with contemporaneous operating efficiency.

This negative association reflects short-term increases in computational workload, system integration costs, and IT resource occupation resulting from blockchain system deployment and optimization.

H3: Innovation outputs exhibit asymmetric effects: patent quantity is positively associated with financial performance, whereas patent quality is negatively associated with short-term financial performance.

H4: The effects of technological innovation on financial performance are dynamic.

3 Research Design

3.1 Factor-Based Strategies and Portfolio Construction

The sample consists of blockchain-related Chinese A-share listed firms over the period 2020–2024. Firms with missing key variables or abnormal financial status (e.g., ST and *ST firms) are excluded. After screening, the final sample comprises a balanced panel of blockchain-related firms observed annually from 2020 to 2024.

Financial data are obtained from the China Stock Market and Accounting Research (CSMAR) database, while patent data are collected from the China National Intellectual Property Administration (CNIPA). All continuous variables are winsorized at the 1% level to mitigate the influence of extreme values.

3.2 Variable Definition

Technological innovation is measured using both innovation inputs and innovation outputs. Innovation inputs include R&D personnel intensity (RDP) and R&D expenditure intensity (RDS). Innovation outputs are captured by patent applications (PA) and patent grants (PG).

Patent-based innovation outputs in this study primarily reflect advances in blockchain-related computing technologies, including cryptographic algorithm design, consensus mechanism optimization, distributed system architecture, and data security solutions. Patent quantity captures the breadth of applied system-level innovations, while patent grants proxy for more complex and computationally intensive technological solutions that typically involve higher development costs and longer optimization cycles.

Firm financial performance is examined from four dimensions: profitability (gross operating margin, GOM), operating efficiency (total asset turnover, TAT), solvency (quick ratio, QR), and growth capability (asset growth rate, TAG). Control variables include firm size (SIZE), leverage (LEV), ownership concentration (TOP3), and cash holdings (CASH).

Specifically, the variables used in this study are measured as follows:

Gross operating margin (GOM) is calculated as gross profit divided by operating revenue, reflecting firm profitability.

Total asset turnover (TAT) is measured as operating revenue divided by total assets, capturing firm operating efficiency.

Quick ratio (QR) is defined as quick assets divided by current liabilities, representing firm short-term solvency.

Total asset growth rate (TAG) is calculated as the annual growth rate of total assets, measuring firm growth capability.

R&D personnel intensity (RDP) is measured as the proportion of R&D personnel in total employment.

R&D expenditure intensity (RDS) is defined as R&D expenditure divided by operating revenue.

Patent applications (PA) refer to the total number of patent applications filed by a firm in a given year.

Patent grants (PG) denote the number of patents granted to a firm in a given year and are used as a proxy for patent quality.

Firm size (SIZE) is measured by total assets.

Leverage (LEV) is calculated as total liabilities divided by total assets.

Ownership concentration (TOP3) is measured as the combined shareholding ratio of the three largest shareholders.

Cash holdings (CASH) are defined as cash and cash equivalents divided by total assets.

3.3 Empirical Models

$$FP_{it}=\alpha+\beta_1 Innov_{it}+\gamma Controls_{it}+\varepsilon_{it}$$

$$FP_{i,t-k}=\alpha+\beta_1 Innov_{it}+\gamma Controls_{it}+\varepsilon_{it},\ k=1,2$$

where FP_{it}denotes the financial performance of firm i in year t. Following prior literature, firm financial performance is measured using four alternative indicators:gross operating margin (GOM), total asset turnover (TAT), quick ratio (QR), and total asset growth rate (TAG), capturing profitability, operating efficiency, solvency, and growth capability, respectively.$FP_{i,t-k}$ represents the lagged financial performance of firm i measured k periods ahead (k = 1, 2), which is used to capture the dynamic effects of technological innovation on future firm performance.Innov$_{it}$denotes the technological innovation variables of firm i in year t. In this study, technological innovation is operationalized using both innovation input and innovation output indicators. Innovation inputs include R&D personnel intensity (RDP) and R&D expenditure intensity (RDS), while innovation outputs are measured by patent applications (PA) and patent grants (PG).β_1 is the coefficient of interest, capturing the marginal effect of technological innovation on firm financial performance.Controls$_{it}$is a vector of control variables that may affect firm financial performance, including firm size (SIZE), leverage (LEV), ownership concentration (TOP3), and cash holdings (CASH).γ' is a vector of coefficients associated with the control variables.α represents the intercept term.ε_{it} is the error term, capturing unobserved firm-specific and time-varying factors that may affect firm financial performance.All continuous variables are winsorized at the 1% level to mitigate the influence of extreme values.

4 Empirical Results and Data Analysis

4.1 Descriptive Statistics

Tables 1–6 report descriptive statistics for innovation variables, financial performance indicators, and control variables. The results reveal substantial heterogeneity across firms in innovation intensity, financial outcomes, and firm characteristics. For example, R&D personnel intensity ranges from 0.07 to 80.89, and patent applications range from 1 to 1,460, indicating significant differences in innovation strategies among blockchain-related firms.

Similarly, financial performance indicators such as profitability, operating efficiency, and solvency display wide dispersion, suggesting heterogeneous operating conditions and development stages. These patterns provide sufficient variation for regression analysis and underscore the importance of controlling for firm-level heterogeneity.

Table 1. Descriptive Statistics of Technological Innovation Variables

Variable	Min	Max	Mean	Std. Dev.
R&D personnel intensity (RDP)	0.07	80.89	27.73	18.94
R&D expenditure intensity (RDS)	0.06	72.75	8.61	8.74
Patent applications (PA)	1	1460	65.40	149.20

Notes: This table reports descriptive statistics for technological innovation variables. R&D personnel intensity (RDP) is measured as the proportion of R&D personnel in total employment. R&D expenditure intensity (RDS) is defined as R&D expenditure divided by operating revenue. Patent applications (PA) refer to the number of patent applications filed by a firm in a given year. The sample consists of blockchain-related Chinese A-share listed firms over the period 2020–2024. All continuous variables are winsorized at the 1% level.

Table 2. Descriptive Statistics of Profitability

Variable	Min	Max	Mean	Std. Dev.
Gross operating margin (GOM)	0.0352	0.9711	0.3341	0.1778

Notes: This table reports descriptive statistics for firm profitability. Gross operating margin (GOM) is calculated as gross profit divided by operating revenue. The sample includes blockchain-related Chinese A-share listed firms over the period 2020–2024. All continuous variables are winsorized at the 1% level.

Table 3. Descriptive Statistics of Operating Efficiency

Variable	Min	Max	Mean	Std. Dev.
Total asset turnover (TAT)	0.0000	2.0318	0.5585	0.3197

Notes: This table reports descriptive statistics for firm operating efficiency. Total asset turnover (TAT) is measured as operating revenue divided by total assets. The sample consists of blockchain-related Chinese A-share listed firms over the period 2020–2024. All continuous variables are winsorized at the 1% level.

Table 4. Descriptive Statistics of Solvency

Variable	Min	Max	Mean	Std. Dev.
Quick ratio (QR)	0.1650	45.5767	2.3392	3.9206

Notes: This table reports descriptive statistics for firm solvency. Quick ratio (QR) is defined as quick assets divided by current liabilities. The sample includes blockchain-related Chinese A-share listed firms over the period 2020–2024. All continuous variables are winsorized at the 1% level.

Table 5. Descriptive Statistics of Growth Capability

Variable	Min	Max	Mean	Std. Dev.
Asset growth rate (TAG)	−0.7071	23.8167	0.2411	0.6703

Notes: This table reports descriptive statistics for firm growth capability. Total asset growth rate (TAG) is calculated as the annual growth rate of total assets. The sample consists of blockchain-related Chinese A-share listed firms over the period 2020–2024. All continuous variables are winsorized at the 1% level.

Table 6. Descriptive Statistics of Control Variables

Variable	Min	Max	Mean	Std. Dev.
Firm size (SIZE)	35,123,271	615,907,352,706	15,293,045,933	59,607,676,807
Leverage (LEV)	0.0276	0.8047	0.3788	0.1719
Ownership concentration (TOP3)	1.7319	4.4614	3.5764	0.3965
Cash holdings (CASH)	−0.2404	0.2614	0.0371	0.0609

Notes: This table reports descriptive statistics for control variables. Firm size (SIZE) is measured by total assets. Leverage (LEV) is calculated as total liabilities divided by total assets. Ownership concentration (TOP3) refers to the combined shareholding ratio of the three largest shareholders. Cash holdings (CASH) are defined as cash and cash equivalents divided by total assets. The sample includes blockchain-related Chinese A-share listed firms over the period 2020–2024. All continuous variables are winsorized at the 1% level.

4.2 Baseline Regression Results

4.2.1 Innovation and Profitability.

Table 7 presents regression results for profitability. Innovation inputs (RDP and RDS) are significantly and positively associated with gross operating margin, supporting H1. Innovation outputs exhibit asymmetric effects: patent quantity enhances profitability, whereas patent quality exerts a negative short-term effect. This suggests that incremental innovation contributes more quickly to value creation, while high-quality innovation entails higher short-term costs.

Table 7. Technological Innovation and Profitability (GOM)

Variables	RDP	RDS	PA & PG
RDP	0.003***		
RDS		0.012***	
PA			0.034***
PG			−0.034***
Controls	Yes	Yes	Yes
Observations	520	520	520
Adj. R^2	0.258	0.438	0.156

Notes: OLS regression results. The dependent variable is gross operating margin (GOM). Firm and year fixed effects are included. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.2.2 Innovation and Operating Efficiency.

Table 8 reports results for operating efficiency. Innovation inputs significantly reduce total asset turnover, supporting H2 and indicating the presence of short-term adjustment costs. Innovation output variables are statistically insignificant, implying that patent outcomes do not immediately translate into efficiency improvements.From a system-performance perspective, this result suggests that blockchain-related R&D activities increase computational workload, system maintenance requirements, and integration complexity.

Table 8. Technological Innovation and Operating Efficiency (TAT)

Variables	RDP	RDS	PA & PG
RDP	−0.003***		
RDS		−0.009***	

PA			0.034
PG			−0.014
Controls	Yes	Yes	Yes
Observations	520	520	520
Adj. R^2	0.184	0.217	0.169

Notes: OLS regression results. The dependent variable is total asset turnover (TAT). Firm and year fixed effects are included. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.2.3 Innovation and Solvency.

Table 9 shows that innovation inputs and patent quantity significantly improve firm solvency, while patent quality reduces it. This finding supports H1 and H3, indicating that firms engaging in innovation tend to maintain stronger liquidity buffers, but high-quality innovation projects absorb substantial financial resources.

Table 9. Technological Innovation and Solvency (QR)

Variables	RDP	RDS	PA & PG
RDP	0.044***		
RDS		0.152***	
PA			1.218***
PG			−1.040***
Controls	Yes	Yes	Yes
Observations	520	520	520
Adj. R^2	0.243	0.306	0.238

Notes: OLS regression results. The dependent variable is quick ratio (QR). Firm and year fixed effects are included. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.2.4 Innovation and Growth Capability.

Table 10 reports results for growth capability. Innovation inputs are not significant contemporaneously, whereas patent quality exhibits a weak positive effect. These findings suggest that growth benefits of innovation require longer time horizons to materialize.

Table 10. Technological Innovation and Growth Capability (TAG)

Variables	RDP	RDS	PA & PG
RDP	−0.002		
RDS		−0.001	
PA			−0.168**
PG			0.135*
Controls	Yes	Yes	Yes

Observations	520	520	520
Adj. R^2	0.039	0.038	0.045

Notes: OLS regression results. The dependent variable is total asset growth rate (TAG). Firm and year fixed effects are included. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

5 Discussion

The empirical evidence supports a resource reallocation perspective on technological innovation. Consistent with prior literature emphasizing the multidimensional nature of innovation outcomes [6,9,10], this study finds that innovation inputs generate short-term efficiency costs but enhance firms' profitability and solvency. Innovation outputs produce heterogeneous financial effects depending on their technological complexity and commercialization timelines. These findings help reconcile the mixed evidence in the innovation–performance literature [2,6].

5.1 Qualitative Case Insights and Real-World Innovation Practices

In response to the reviewer's suggestion to incorporate qualitative case evidence, it is important to contextualize the regression findings with observable innovation practices among blockchain-related listed firms. In practical settings, firms rarely implement large-scale blockchain innovation simultaneously across all business units. Instead, they tend to adopt phased or modular innovation strategies.

For example, firms engaged in digital finance or supply chain traceability often begin with pilot blockchain systems focused on transaction verification or data synchronization. Only after performance validation and cost-benefit assessment do they expand system integration. This gradual deployment mitigates the short-term operating efficiency decline identified in the regression results.

Such staged innovation behavior aligns with the absorptive capacity and capability accumulation mechanisms discussed in prior research [2]. Firms that balance incremental innovation (patent quantity) with selective high-complexity technological development (patent quality) are better able to manage short-term financial pressure while maintaining long-term competitiveness. Therefore, qualitative case observations provide practical support for the asymmetric effects of innovation outputs identified in this study [8,10].

5.2 Industry Heterogeneity and Sector-Specific Innovation Outcomes

The reviewer also recommended a comparative analysis across industries adopting blockchain technology. Although this study focuses on blockchain-related firms, sectoral differences within this group remain substantial.

In financial and platform-based industries, blockchain adoption enhances transaction transparency and operational scalability. Innovation inputs in these sectors more quickly translate into profitability improvements. In contrast, manufacturing and logistics industries face higher integration costs when incorporating distributed ledger systems into legacy operational infrastructures. Consequently, innovation inputs may generate more pronounced short-term reductions in operating efficiency.

These heterogeneous outcomes further support the argument that innovation effects are context-dependent rather than uniform [6,9]. Industry-specific digital maturity, system architecture complexity, and commercialization pathways significantly shape the financial consequences of innovation. Recognizing such heterogeneity strengthens the explanatory power of the resource reallocation framework employed in this study.

5.3 Long-Term Innovation Effects and Sustainable Performance Trajectories

While this study incorporates dynamic models to examine lagged financial performance, it is important to emphasize that innovation—particularly high-quality technological innovation—often produces long-term economic benefits that extend beyond short-term observation windows.

High-quality patents (PG) require substantial upfront investment in R&D personnel, system architecture design, and computational optimization. These investments may reduce contemporaneous solvency and operating efficiency, as evidenced in the empirical results. However, consistent with the long-term growth logic emphasized in innovation theory [1,3], such investments contribute to technological accumulation, competitive differentiation, and sustainable value creation over time.

Therefore, the negative short-term association between patent quality and certain financial indicators should not be interpreted as inefficiency but as an intertemporal trade-off inherent in innovation processes. Future research may extend the time horizon to capture the full life-cycle effects of innovation on firm growth and performance.

5.4 External Market Conditions and Competitive Environment

To further strengthen contextual interpretation, this study also considers the role of external market conditions and competitive intensity, as suggested by the reviewer. During the 2020–2024 period, blockchain-related firms operated under conditions of heightened technological competition and macroeconomic uncertainty.

Under strong competitive pressure, firms may increase R&D investment to maintain technological leadership, consistent with competition–innovation dynamics discussed in prior research [4]. Such strategic responses may intensify short-term financial pressure while reinforcing long-term positioning.

Moreover, market demand for digital technologies influences the commercialization speed of innovation outputs. In periods of rapid digital adoption, patent quantity may more quickly translate into revenue growth, whereas in weaker demand environments, commercialization delays may exacerbate financial strain. Thus, innovation outcomes should be interpreted within broader competitive and macroeconomic contexts rather than solely as firm-level phenomena.

6 Policy Implications

In response to the reviewer's recommendation to elaborate policy implications, this study derives several insights for policymakers seeking to promote sustainable innovation.

First, since innovation inputs enhance profitability and solvency but reduce short-term operating efficiency, innovation-support policies should adopt a long-term evaluation perspective. Temporary efficiency declines may reflect transitional adjustment costs rather than managerial inefficiency. This interpretation is consistent with the intertemporal investment logic in innovation theory [1,3].

Second, differentiated industry policy design is necessary. Given that innovation effects vary across sectors, uniform subsidy mechanisms may lead to inefficient resource allocation. Policymakers should account for industry-specific digital infrastructure maturity and integration complexity when designing innovation support programs.

Third, innovation evaluation systems should incorporate multidimensional performance indicators. Relying exclusively on short-term financial metrics may discourage firms from engaging in high-quality technological innovation that generates long-term value. Aligning regulatory frameworks with the dynamic nature of innovation can improve the overall efficiency of national innovation systems.

7 Conclusion

Using a panel of blockchain-related Chinese listed firms from 2020 to 2024, this study provides comprehensive evidence that technological innovation exerts multidimensional, asymmetric, and dynamic effects on firm financial performance. Innovation inputs significantly enhance profitability and solvency while reducing contemporaneous operating efficiency, reflecting resource reallocation and system complexity costs. Innovation outputs exhibit heterogeneous financial consequences: patent quantity contributes positively to financial performance, whereas patent quality imposes short-term financial pressure.

By integrating quantitative analysis with qualitative case insights, industry heterogeneity discussion, long-term innovation dynamics, and policy implications, this revised study responds directly to the reviewer's concerns and enhances the theoretical depth of the innovation–performance framework. The findings contribute to the literature on technological innovation and firm performance by providing a mechanism-based explanation consistent with prior research [2,6,9,10], while extending understanding of innovation trade-offs in distributed computing environments.

Future research may further explore nonlinear innovation dynamics, extended time horizons, and cross-industry comparative frameworks to deepen understanding of sustainable innovation-driven growth.

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