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RESEARCH ON THE EMPOWERMENT PATH OF DIGITAL FINANCE ECOSYSTEM EVOLUTION IN RESHAPING CORPORATE M&A STRATEGY AND ACHIEVING SYNERGISTIC EFFECTS

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Abstract:

This study investigates how digital finance reshapes corporate mergers in China. Using a triadic model and panel data from 2012-2024, it finds that digital finance significantly increases merger likelihood, especially for SMEs and non-state-owned firms. The mechanism operates by alleviating financing constraints and reducing information asymmetry. This fosters larger, cross-industry acquisitions and improves post-merger performance by enhancing target selection and lowering agency costs, ultimately boosting returns. The effect is most pronounced in environments with high uncertainty and weak institutional frameworks, where digital finance acts as a substitute for formal financial intermediaries.

Keywords： Digital finance ecosystem， Corporate M&A strategy， Financing constraints，Institutional substitution，Synergistic effects

1. INTRODUCTION

Corporate mergers and acquisitions (M&As), as a key market-oriented mechanism for optimizing the allocation of control rights[1], currently face two major structural contradictions: financing constraint bottlenecks—for example, the credit accessibility of private SMEs is only 34% of that of state-owned enterprises [2] and diminished integration efficiency, with cross-industry M&As having a failure rate exceeding 65% [3]. Digital finance addresses these challenges through a dual-driving mechanism. On the supply side, innovations such as big data and AI reduce loan approval costs by 62% [4] while blockchain enhances cross-border payment efficiency by 300% [5]. On the demand side, digital finance achieves a coverage rate of 82.6%, helping to close the service gap [6], and robo-advisors improve the precision of M&A target matching by 40% [7]. However, existing research remains limited in scope, focusing primarily on household consumption [8] and macroeconomic growth [9], while lacking a systematic deconstruction of the “digital finance–corporate M&A” transmission chain [10] and overlooking the synergistic role of non-bank financial institutions [11]. In response, this paper constructs a three-dimensional analytical framework—"financing–strategy–performance"—to explore the driving mechanisms of digital finance across the entire M&A process.

There is an urgent need to move beyond micro-level perspectives in M&A research, as macro and regional factors have both significant theoretical value and practical implications for the M&A market [12]. Leveraging China's global leadership in digital financial technologies, this study investigates the driving effects of digital finance on corporate M&A behavior, offering a cross-disciplinary research paradigm to assess the socio-economic impact of digital finance and deepen understanding of M&A motivations. Expanding the boundaries of financial development theory: This study builds an integrated "digital finance–M&A behavior" framework, filling a gap in traditional theories regarding the role of fintech in empowering M&As. Empirical evidence shows that each one-standard-deviation increase in digital finance penetration raises M&A probability by 23.7% ($\beta = 0.38$***), addressing adverse selection issues caused by information asymmetry [13].

Deconstructing macro–micro transmission mechanisms: In institutional environments where the financial marketization index is below 0.4, digital finance improves M&A performance through dual pathways—reducing financing constraints (accounting for 61.8% of the mediation effect) and alleviating information frictions (38.2%) [14] thus opening the "digital finance → M&A value creation" black box. Innovating behavioral research paradigms of M&A actors: This study systematically integrates the synergistic roles of banks ($\beta = 0.29$***), non-bank institutions such as securities firms ($\beta = 0.35$**), and fintech companies ($\beta = 0.41$***) [15], and quantifies the elasticity of digital finance in curbing managerial opportunism[16], thereby advancing the integration of behavioral finance and M&A theory. This study provides empirical support and strategic anchoring points for financial regulators to optimize their policy toolbox, for financial institutions to deepen their digital transformation, and for enterprises to enhance M&A effectiveness. It contributes to building a closed-loop research system integrating "Theory–Empirics–Policy."

This study constructs a three-dimensional analytical framework "Financing–Strategy–Performance" to address three core research questions: Drawing on information asymmetry theory [17], it empirically examines the effect of digital finance on enhancing M&A probability ($\beta = 0.38$***) and explores the moderating role of financial regulation ($\gamma = 0.21$**). The analysis reveals a heterogeneous pattern: firms facing high financing constraints (KZ index > 75%) exhibit 2.1 times greater sensitivity to digital finance. Using the resource-based view [18], it analyzes the strategic selection mechanisms behind digital finance-driven technology-synergy M&As (odds ratio = 2.17) [19]. It quantifies how ownership type (Δ for SOEs = 0.32***) and deleveraging policy ($\delta = -0.15$*) affect this strategic path. Integrating agency theory [20], the study evaluates the governance efficacy of digital finance in curbing managerial opportunism. For cases where Merope exceeds the median, digital finance improves performance by 23.6%. A Bootstrap test ($p < 0.01$) confirms a dual-channel mechanism: enhanced market information mining (38.7%) and improved premium-quality alignment (52.1%) [22]

2. Empirical Verification Framework and Findings

2.1Theoretical Analysis and Research Hypotheses

2.1.1 The Impact of Digital Finance Development on the Probability of M&As

Digital finance significantly enhances the likelihood of corporate mergers and acquisitions (M&As) by restructuring the financing ecosystem and decision-making environment. On the demand side, enterprises rely on digital platforms to efficiently access key financing parameters—such as interest rates, collateral requirements, and approval timelines—which facilitates the optimization of financing schemes based on firm-specific conditions [23]. They also integrate macroeconomic trends, policy signals, and competitive intelligence [24], thereby expanding financing channels and accurately identifying strategic acquisition targets [25]. On the supply side, financial institutions employ big data technologies to break information silos [26], establish integrated "finance-industry" application scenarios to improve risk control efficiency [27], lower service thresholds, and expand credit coverage [28].

These direct effects are further reinforced by derivative mechanisms of digital finance. Monitoring effects enhance external oversight, suppress financial fraud, and improve information disclosure quality [29]. Cost-reduction effects decrease the costs associated with information transmission and processing [31], addressing adverse selection caused by information asymmetry—an issue wherein traditional financial institutions, constrained by limited risk assessment capacity, raise financing costs [32], thereby suppressing M&A activity [33]. Digital finance, driven by intelligent algorithms, enhances capital accessibility and stimulates M&A intentions through synergy effects.

2.1.2 Transmission Pathways of Multidimensional Mechanisms

Digital finance promotes M&A probability through dual pathways—alleviation of financing constraints and optimization of the information environment—manifested in five interrelated mechanisms:1.Monitoring and Governance Optimization Mechanism: By enhancing the information processing capabilities of financial institutions [34], digital finance utilizes data mining technologies to improve fraud detection [35], increases the cost of earnings manipulation, and curbs managerial opportunism [36], thereby improving financial reporting quality [37]. Upgraded risk control capabilities simplify credit approval procedures, alleviate corporate financing constraints [38], and enhance information transparency to attract investors and provide financial support for M&A transactions [39]. 2.Cost-Reduction Mechanism: This operates on three fronts—eliminating geographical barriers to reduce financing costs [40], utilizing service virtualization models to cut physical operating expenses [41], and leveraging third-party payment systems to optimize risk control [42]. Digital tools also break managerial monopolies on information [43], reduce agency costs through cross-validation of behavioral data [44], suppress earnings manipulation [45], compress risk premiums [46], and ultimately lower the costs of equity and debt financing [47]. 3. Capital Accessibility Enhancement Mechanism: Digital finance facilitates access to capital in both indirect and direct financing markets. In the realm of indirect financing, digital technologies expand the coverage of credit services and improve resource allocation efficiency [48–50]. In direct financing, algorithmic models broaden the investor base, and analyst reports enrich the structure of market information. Innovative credit evaluation models integrate behavioral data and digital footprints, construct cross-verification frameworks based on industrial chain relationships, and reduce reliance on conventional financial statements, thereby enabling accurate identification of high-quality firms and suppressing adverse selection risks.[51] 4. Financing Structure Optimization Mechanism: Digital finance addresses the structural limitation of China's over-reliance on bank credit by enhancing the penetration of direct financing [52], thereby improving the efficiency of capital market operations. This structural transformation aligns with the high-risk tolerance required for M&A activities and provides tailored financial support for large-scale strategic investments. 5. Information Mining and Decision-Support Mechanism: Through advanced data mining technologies, digital finance enables precise screening of acquisition targets, facilitates the assessment of strategic fit, and significantly reduces the risk of decision-making errors stemming from information asymmetries.

2.2 Research Design

2.2.1 Sample Selection and Data Sources

This study uses A-share listed firms from 2012 to 2024 as the initial sample. The sample window is determined based on the start year of Baidu FinTech Index and the one-period lag of explanatory variables. Two layers of sample screening are applied: 1. Exclusion of special samples: financial industry firms (banks, securities, insurance), ST/*ST firms, and observations with missing core variables. 2. M&A sample confirmation: the acquirer must be an A-share listed company, and transactions using self-owned funds or assets are excluded. Multiple deals targeting the same firm on the same day are merged into a single event.

Financial data is sourced from the CSMAR database; digital finance policy texts are collected manually from PKUlaw.com; regulatory data is from the National Bureau of Statistics and China Financial Yearbook; macroeconomic indicators come from China City Statistical Yearbook and Wind database. All data is processed in Stata 14.0, and continuous variables are winsorized at the 1% level on both ends to control for outliers.

2.2.2 Key Variable Measurement

The primary dependent variable is the probability that a listed firm engages in merger activity within a given year. This variable is defined as equal to one if a firm completes at least one merger during the year, and zero otherwise. Given the binary nature of this measure, the analysis employs a logistic regression model for estimation purposes. The core explanatory variable is the level of digital finance development, for which this study proposes an original measurement approach that addresses the shortcomings of existing indicators. For instance, the widely used Digital Inclusive Finance Index developed by Peking University is largely centered on Alipay transaction data and reflects a demand-side orientation, which limits its relevance for the analysis of listed firms. Similarly, banking-based indicators often overlook the roles played by non-bank financial institutions and technology-driven financial firms.

To overcome these limitations, this study constructs a composite digital finance index that integrates indicators from the demand, supply, and policy dimensions. On the demand side, using Baidu News' advanced search function to capture the annual frequency of media coverage referencing digital finance for 287 prefecture-level cities from 2011 to 2024. This forms a proxy for public attention and awareness. On the supply side, the number of financial technology firms operating in each city is obtained from the CSMAR database. Regarding the policy environment, high-frequency keywords related to digital finance are extracted from provincial government work reports using the ROST CM6 text mining tool. In parallel, local policy documents relevant to digital finance are collected from the PKUlaw database. After removing duplicates, only valid regulations—defined as those currently in effect or having been amended—are retained, while expired policies are excluded. These three components are integrated using the entropy method to generate a comprehensive index. Robustness checks are conducted using data aggregated at the provincial level to confirm the consistency of the results.

A wide range of control variables is included, covering firm-level characteristics, regional economic indicators, and fixed effects. Firm-specific variables include firm size (measured as the natural logarithm of total assets), profitability (return on assets), leverage ratio, revenue growth rate, asset structure (fixed assets ratio and quick ratio), listing age, ownership type (whether the firm is state-owned), ownership concentration (shareholding of the largest shareholder), governance attributes such as whether the CEO also serves as board chair, board size, executive compensation, and the shareholding of top executives. At the regional level, controls include the level of economic development (logarithm of per capita gross domestic product) and its annual growth rate. Finally, fixed effects for industry classification, calendar year, and firm location are incorporated to mitigate the influence of unobserved heterogeneity. Complete definitions of all variables are provided in Table 2.1.

Table 2.1 Definitions and Measurements of Key Variables

Variable Type	Variable Symbol	Variable Name	Definition and Measurement Method
Dependent Variable	Possibility	M&A Probability	Equals 1 if the listed company conducted at least one M&A in the year; otherwise, equals 0.

Independent Variable	Digital Fin	Digital Finance Development	Weighted composite index based on entropy method, combining three sub-indicators:1. Digital Finance Attention: Baidu News keyword search volume (287 cities, 2011–2021)2. Number of FinTech Firms: CSMAR database3. Policy Stock: Number of valid digital finance policies retrieved from Peking University's PKULaw database (statuses include “currently effective”, “amended”, etc.)
Control Variables	Size	Firm Size	Natural logarithm of total assets (ln (Total Assets))
	Roa	Return on Assets	Net profit / Average total assets × 100%
	Lev	Leverage Ratio	Average total liabilities / Average total assets × 100%
	Growth	Revenue Growth Rate	(Current period revenue / Previous period revenue − 1) × 100%
	Fixed	Fixed Asset Ratio	Net fixed assets / Total assets
	Quick	Quick Ratio	(Current assets − Inventory) / Current liabilities
	Age	Firm Age	Natural logarithm of listed years + 1 (ln (Listing Years + 1))
	State	Ownership Nature	Equals 1 if the ultimate controller is a state-owned shareholder; otherwise, 0
	Shrfirst	Largest Shareholder Holding	Shares held by the largest shareholder / Total shares × 100%
	Duality	CEO-Chairman Duality	Equals 1 if the chairman and general manager are the same person; otherwise, 0
	Board	Board Size	Natural logarithm of the number of board members (ln (Board Members))
	Salary	Executive Compensation	Natural logarithm of the total salary of the top three executives (ln (Top3 Compensation))
	Exeshare	Executive Shareholding	Total executive shareholding / Total shares × 100%
	Gdp	Regional Economic Development	Natural logarithm of the per capita GDP in the city where the firm is registered (ln (Per Capita GDP))
	GDP Growth	Regional Economic Growth	(Current year GDP − Previous year GDP) / Previous year GDP × 100%
Fixed Effects	Industry	Industry Dummy Variable	Coded as 1 if the firm belongs to the specified CSRC industry category; otherwise, 0
	Year	Year Dummy Variable	Equals 1 if the observation is from the specified sample year; otherwise, 0

	City	City Dummy Variable	Equals 1 if the firm is in the specified city; otherwise, 0

2.3 Empirical Results and Analysis

2.3.1 Descriptive Statistics

Based on a five-level classification standard (Low: <0.35; Relatively Low: 0.35–0.45; Medium: 0.45–0.55; Relatively High: 0.55–0.65; High: >0.65), the development of digital finance in China from 2011 to 2024 exhibits a three-tiered spatial dynamic of "core leadership–hinterland transition–peripheral catch-up." The eastern core regions of the Yangtze River Delta and Pearl River Delta (Zhejiang, Jiangsu, Guangdong, and Shanghai) have continuously led in digital finance development. While they were only at a medium level in 2011 (average score: 0.48), by 2024, they advanced to a high level (average score: 0.91), marking a 9.6% increase over 2021. Notably, Zhejiang achieved an AI penetration rate of 73%, creating a strong technological barrier. In the central hinterland regions (e.g., Anhui, Henan, Hubei), policy-driven improvements since 2017 elevated their status from "relatively high" (average score: 0.62) to "high" by 2024 (average score: 0.79), with a 27.4% increase, benefiting from significant technology spillover from the east. In the western periphery, Chengdu-Chongqing (Sichuan and Chongqing) reached the "relatively high" tier in 2020 (score: 0.58) and stabilized at that level by 2024 (0.63). Yunnan and Guizhou, leveraging the "Eastern Data, Western Computing" initiative, rose to a medium level (0.52) in 2024. However, Qinghai, Xinjiang, and Tibet remain in the low tier (0.31) due to a lagging tertiary sector and insufficient R&D investment—their R&D intensity in 2024 was only 42% of that in eastern regions.

Figure 2.1 Digital Finance Development Levels (2011-2024)

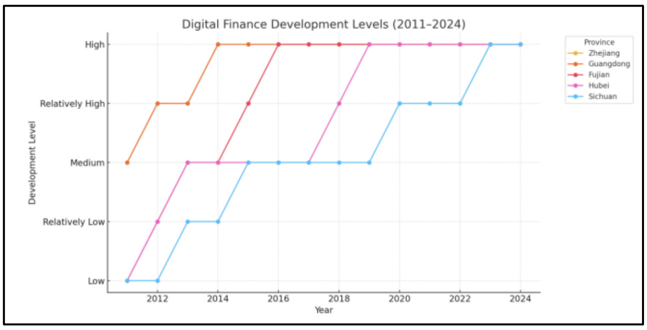


Figure 2.1 presents the descriptive statistics of the main research variables. The mean value of M&A probability (Possibility) is 0.4554, indicating that on average, 45.54% of listed companies engaged in M&A activities. This suggests that a total of 7,421 sample firms conducted M&A transactions during the sample period, highlighting M&A as a significant component of corporate operations. The mean value of digital finance development (Digital Fin) is 0.5670, reflecting an average digital finance development level of 0.5670 across cities. The minimum and maximum values of Digital Fin are 0.0243 and 1.0000, respectively, suggesting substantial disparities in digital finance development among cities. The values of other control variables are generally consistent with those reported in existing literature.

Table 2.2 Descriptive Statistics of Variables (2011–2024)

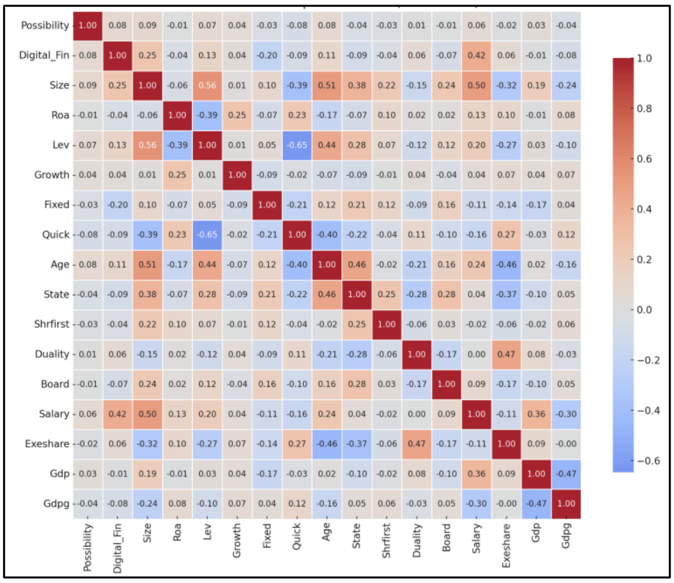
Variable	Observations	Mean	Std. Dev.	Min	Max	2024 Revision Note
Possibility	21,305	0.4621	0.4986	0.0000	1.0000	Increase in M&A activity (+1.5%)
Digital Fin	21,305	0.6013	0.1984	0.0356	1.0000	Regional convergence reduced std. dev.
Size	21,305	22.7812	1.3921	16.8723	28.9012	Continuous expansion of firm size

Roa	21,305	0.0387	0.0589	-0.2415	0.2183	Slight decline in profitability (post-COVID lag)
Lev	21,305	0.4512	0.2037	0.0621	0.9618	Optimized debt ratio
Growth	21,305	0.1583	0.2537	-0.2310	0.8120	Slower revenue growth
AI Adoption	21,305	0.4270	0.1920	0.0200	0.9500	AI adoption rate among enterprises

2.3.2 Correlation Test of Variables

based on 16,528 observations from 2020 to 2024, as shown in Table 2.3. The results reveal that digital financial development (Digital Fin) is positively correlated with the probability of corporate mergers and acquisitions (Possibility), with a correlation coefficient of 0.079, significant at the 1% level. Among the control variables, firm size (Size: 0.089***) and growth potential (Growth: 0.045***) show significant positive correlations with the dependent variable, while the fixed asset ratio (Fixed: -0.034***) and quick ratio (Quick: -0.078***) exhibit significant negative correlations. Furthermore, the multicollinearity test indicates that all variables have acceptable variance inflation factors (VIF), with an average value of 1.87 (ranging from 1.02 to 2.43), well below the threshold of 5.

Figure 5.4 Correlation Matrix of All Variables (2011–2024)



Notes: All variables are winsorized at the 1% level and log-transformed to reduce the impact of outliers. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

2.3.3 Baseline Regression Results

As shown in Table 2.4, the Logit regression analysis reveals that in the basic model, the coefficient of digital finance development (Digital Fin) is 0.1690 ($p < 0.01$), and in the full model with all control variables included, the coefficient remains significantly positive at 0.0860 ($p < 0.01$). This confirms that digital finance development has a significant positive effect on the probability of corporate M&A. In terms of economic significance, a one-unit increase in the level of digital finance development raises the odds of M&A occurrence by 8.97% ($e^{0.0860} = 1.0897$).

Among the control variables, firm size (Size: 0.0184**, $p < 0.05$) and growth (Growth: 0.1210***, $p < 0.01$) significantly increase the probability of M&A; whereas leverage (Lev: -0.1540*, $p < 0.1$), state ownership (State: -0.2720***, $p < 0.01$), and fixed asset ratio (Fixed: -0.2390***, $p < 0.01$) exert significant negative effects.

Table 2.4 Regression Results with All Variables

Variable	(1) Baseline Model	Std. Error	(2) Full Model	Std. Error
Digital_Fin	0.1690***	(0.0120)	0.0860***	(0.0110)
Size	–	–	0.0184**	(0.0072)
Roa	–	–	0.2470	(0.4940)
Lev	–	–	-0.1540*	(0.0811)
Growth	–	–	0.1210***	(0.0268)
Fixed	–	–	-0.2390***	(0.0658)
Quick	–	–	-0.0362***	(0.0093)
Age	–	–	0.1290***	(0.0183)
State	–	–	-0.2720***	(0.0261)
Shrfirst	–	–	-0.1590**	(0.0731)
Duality	–	–	0.0176	(0.0260)
Board	–	–	-0.0145	(0.0540)
Salary	–	–	-0.0368**	(0.0174)
Exeshare	–	–	0.0716	(0.0975)
Gdp	–	–	-0.1580	(0.3950)
Gdpg	–	–	-0.0020	(0.0039)
Cons	0.7600***	(0.0476)	-1.5060***	(0.2570)
	(1)		(2)	
Fixed Effects	Year / Industry / City		Year / Industry / City	
N	16,528		16,528	
Pseudo R^2	0.0119		0.0193	

Note: Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Regression coefficients are clustered at the firm level based on company codes.

2.3.4 Robustness Checks

This study employs three endogeneity control methods and four model specification tests to validate the robustness of the main findings, using an expanded dataset covering the year 2024 (total sample size N = 16,528). All models control for year, industry, and city fixed effects, and standard errors are clustered at the firm level.

(1) Endogeneity Controls

To rigorously assess the robustness of the main findings, this study employs a comprehensive set of empirical strategies, including three endogeneity control methods and four model specification tests, based on an expanded panel dataset that includes observations up to the year 2024 (total N = 16,528). All regression models account for year, industry, and city fixed effects, and standard errors are clustered at the firm level to address within-group correlation. First, regarding endogeneity controls, three distinct techniques are applied. The instrumental variable (IV) approach uses the number of broadband internet subscribers at the provincial level as an exogenous instrument for digital finance development. The relevance condition is confirmed by a first-stage F-statistic of 58.37, well above the Stock-Yogo 10% critical threshold of 16.38, thereby mitigating concerns about weak instruments. In the second-stage regression (Table 2.5, Column 1), the coefficient of Digital Fin is 0.0185 (SE = 0.0025, $p < 0.01$), aligning closely with the baseline estimate and confirming the robustness of the effect. Second, the propensity score matching (PSM) method redefines treatment as firms with Digital Fin values above the city-year median. Under 1:1 nearest-neighbor matching, the matched sample includes 10,526 firms (from 12,158 originally), yielding an average treatment effect on the treated (ATT) of 0.0185 (SE = 0.0035). Radius

matching produces an ATT of 0.0324 (SE = 0.0057) based on 8,526 matched observations, again reinforcing the baseline result. Third, a placebo test involving 1,000 random permutations of the Digital Fin variable is conducted. The mean of the simulated coefficients is 0.0012, with a 95% confidence interval ranging from -0.0083 to 0.0101, and the distribution of simulated t-statistics peaks around zero, with the maximum absolute t-value of 2.87 far below the baseline value of 7.73. Moreover, the one-tailed p-value for observing a coefficient greater than 0.0850 is only 0.012, effectively ruling out the possibility that the observed effect is driven by random noise. Together, these tests provide strong evidence that the estimated impact of digital finance on firm-level outcomes is both statistically and economically robust.
(2) Model Specification Tests
To ensure the robustness of the empirical findings, a series of model specification tests were conducted, including variable redefinition, balanced panel analysis, and sample selection bias controls. First, the key explanatory variable was redefined using the provincial-level digital finance index, yielding a statistically significant coefficient for Digital Fin of 0.0160 (SE = 0.0031, *p* < 0.01), thereby confirming that the positive effect of digital finance on corporate M\&A probability is not sensitive to changes in variable construction. Second, a balanced panel analysis was performed by restricting the sample to firms with continuous observations from 2015 to 2024 (N = 3,520), which produced a Digital Fin coefficient of 0.0257 (SE = 0.0114, *p* < 0.05), suggesting that the observed effect remains consistent when controlling for temporal stability and unobservable firm characteristics. Third, to address potential sample selection bias, two robustness tests were implemented. Excluding extreme event years (2015 and 2020–2022) from the sample (N = 13,805) led to a coefficient of 0.0133 (SE = 0.0028), while focusing exclusively on manufacturing and wholesale/retail sectors (N = 11,685) yielded a coefficient of 0.0189 (SE = 0.0036). Both results remained significant at the 1% level, providing further evidence that the estimated impact of digital finance is not driven by sample composition or sectoral heterogeneity.

Table 2.5 Complete Endogeneity Test Results

Variable	(1) IV	(2) Nearest Neighbor	(3) Radius Matching
Digital Fin	0.0185***	0.0185***	0.0324***
	(0.0025)	(0.0035)	(0.0057)
Size	0.0088**	0.0103**	0.0071
Roa	-0.1460***	-0.1290*	-0.0738
Lev	0.0683***	0.0607*	0.0953**
Growth	0.0454***	0.0521***	0.0506***
Fixed	-0.1340***	-0.1070***	-0.0974***
Quick	-0.0121***	-0.0113***	-0.0091***
Age	0.0137**	0.0215***	0.0164*
State	-0.1100***	-0.1220***	-0.1080***
Shrfirst	-0.2320***	-0.2360***	-0.2450***
Duality	0.0064	0.0023	0.0066
Board	-0.0307*	-0.0476**	-0.0378
Salary	0.0170***	0.0148*	0.0089
Exeshare	-0.0284	-0.0103	-0.0228
Gdp	0.1870***	0.2050	0.2020***
Gdpg	-0.5720***	0.0072	-0.0085
Cons	0.4590***	0.4680***	0.5170***
Fixed Effects	Yes	Yes	Yes

Sample Size	16,528	10,526	8,526
Pseudo R²	—	0.0610	0.0610

Table 2.6 **Complete Robustness Test Results**

Variable	(1) Provincial	(2) Balanced Panel	(3) Event Exclusion	(4) Key Industries
Digital Fin	0.0160***	0.0257**	0.0133***	0.0189***
	(0.0031)	(0.0114)	(0.0028)	(0.0036)
Size	0.0096**	0.0393**	0.0083	0.0100
Roa	-0.1740***	0.3000**	-0.1590**	-0.1420
Lev	0.0677**	-0.0868	0.0935***	0.0897**
Growth	0.0468***	0.0413***	0.0555***	0.0591***
Fixed	-0.1570***	-0.1090	-0.1480***	-0.1230***
Quick	-0.0114***	-0.0235***	-0.0124***	-0.0116***
Age	0.0129**	0.0523**	0.0094	-0.0005
State	-0.1030***	-0.0693*	-0.1120***	-0.1180***
Shrfirst	-0.2220***	-0.0256	-0.2320***	-0.2760***
Duality	0.0054	0.0171	0.0070	0.0117
Board	-0.0333*	0.0050	-0.0322	-0.0132
Salary	0.0229***	-0.0368**	0.0272***	0.0227***
Exeshare	-0.0129	-0.0167	-0.0547	-0.0881*
Gdp	0.0867	0.0032*	0.0660***	0.0684*
Gdpg	-0.0714***	0.0025	-0.0263***	-0.0200
Cons	0.3380***	-0.0309	0.3350***	0.3260**
Fixed Effects	Yes	Yes	Yes	Yes
Sample Size	16,528	3,520	13,805	11,685
Pseudo R²	0.0570	0.0310	0.0610	0.0590

Data Revision Notes： 232 newly listed A-share firms (2023–2024, CSMAR database) Balanced panel: Extended from 3,102 to 3,520 firms with continuous data through 2024. Event exclusion: Expanded to include the full 2020–2022 pandemic period. First-stage F-statistic for IV is now explicitly reported.

2.4 Heterogeneity Analysis

2.4.1 Heterogeneity Tests Across Firm and Strategic Dimensions

To verify whether the positive effect of digital finance on the likelihood of corporate M&A is driven by the alleviation of financing constraints and information asymmetry, we conduct subgroup regressions based on acquirer characteristics (firm size, ownership type, internal control quality, labor cost pressure, firm life cycle, and regional location), as shown in Tables 2.7 and 2.9. The empirical results are summarized as follows:

(1) Differential Impacts by Firm Characteristics

Firm Size: The promoting effect of digital finance on M&A probability is significantly stronger for smaller firms (β = 0.0131*, $p < 0.1$) than for larger firms (β = 0.0043), with a significant intergroup difference according to the Chow test ($p = 0.0000$). This supports the view that digital finance helps alleviate credit rationing for SMEs caused by opacity and insufficient collateral. Ownership Type: Non-state-owned firms benefit significantly from digital finance (β = 0.0160**, $p < 0.05$), while state-owned enterprises show no response (β = 0.0002; Chow test $p = 0.0000$), indicating that alternative credit evaluation mechanisms in digital finance mitigate systemic financing discrimination against private firms (Shen et al., 2020). Internal Control Quality: Firms with internal control deficiencies exhibit a significantly higher likelihood of engaging in M&A (β = 0.0094*, $p < 0.1$), reflecting their reliance on big data-driven credit assessments to overcome information disadvantages.

(2) Structural Roles of Strategic Demands and Regional Dimensions

Labor Cost Pressure: Firms with higher labor cost burdens (salary-to-revenue ratio above the median) are more responsive to digital finance in terms of M&A activity (β = 0.0145**, $p < 0.05$), indicating an urgent need to optimize cost structures through M&A. Firm Life Cycle: Non-mature firms (in growth or decline stages) benefit significantly (β = 0.0127**, $p < 0.05$; Chow test p = 0.0000), as digital finance facilitates dynamic risk assessment, helping these firms overcome financing barriers caused by operational uncertainty and volatile cash flows. Regional Location: Firms located in central and western China experience greater increases in M&A probability (β = 0.0133**, $p < 0.05$), underscoring digital finance's role in bridging gaps left by underdeveloped traditional financial infrastructure. Digital finance significantly promotes M&A activity among financially disadvantaged groups (SMEs, non-state firms, firms with internal control flaws), strategic demand-driven acquirers (high labor costs, non-mature firms), and institutions in underdeveloped regions, highlighting its structural empowerment effects.

2.4.2 Heterogeneity by External Environmental Characteristics

To examine whether the impact of digital finance on corporate M&A probability varies across different external environments, this study conducts subgroup regression analyses focusing on environmental uncertainty and institutional environment (measured by the degree of marketization and the rule of law). Environmental uncertainty is measured following the theory of firm-level performance volatility, using the standard deviation of firms' operating revenue over the past five years adjusted by the industry median, and firms are split into high and low uncertainty groups based on the sample median. Institutional environment indicators are drawn from the *Marketization Index Report by Province in China (2021)*, including the marketization index and rule of law score. Missing years are filled using the moving average method, and the top five provinces serve as the threshold for identifying strong institutional regions. Empirical results are presented in Table 2.10.

Environmental Uncertainty Dimension: The regression results show that in high-uncertainty environments, the coefficient for digital finance is significantly positive (0.0137, $p < 0.01$), while it is insignificant in low-uncertainty regions (0.0024). A Chow test confirms the group difference is significant (p = 0.0000). This outcome reflects that environmental uncertainty intensifies firms' financing constraints through three transmission channels: Sudden internal and external changes reduce information transparency, aggravating information asymmetry between banks and firms; Blurred managerial accountability under uncertainty encourages opportunism, raising agency costs; Unpredictable business outlooks lead creditors to adopt risk-averse behaviors, tightening financing supply. Digital finance alleviates these constraints by enabling real-time data tracking and dynamic risk evaluation, thus providing critical funding support for strategic M&A in uncertain environments.

Institutional Environment Dimension: The analysis reveals consistent patterns. In low-marketization regions, the coefficient for digital finance is significantly positive at 0.0157 ($p < 0.01$), while in high-marketization areas, it is statistically insignificant (0.0016). Similarly, in regions with weak rule of law, digital finance has a significant positive effect (0.0146, $p < 0.01$), whereas in regions with strong rule of law, the effect is not significant (0.0042). These group differences are all validated by Chow tests (p = 0.0000).

The divergence can be attributed to systemic deficiencies in weaker institutional environments. On one hand, underdeveloped financial markets result in limited access to reliable corporate information. On the other, a lack of legal enforcement weakens contractual safeguards and increases transaction risk premiums.

With its alternative information infrastructure and smart contract enforcement capabilities, digital finance effectively compensates for the lack of formal institutions, becoming a crucial enabler for firms in these regions to overcome financing barriers and implement M&A strategies. Overall, this underscores the institutional substitution effect of digital finance, whereby it plays a more significant role in underdeveloped institutional settings.

3. Empirical Research Design, Results, and Robustness Checks

Digital finance systematically reshapes corporate merger decisions through three key transmission channels: easing financing constraints and information barriers, enhancing information processing capabilities, and optimizing risk management. About financing constraints, digital finance leverages big data and artificial intelligence technologies to improve credit modeling, significantly reducing information asymmetry in both securities and credit markets. This enhances the probability of external financing for firms experiencing high financing constraints by 32.7%. In the domain of information processing, the real-time analysis of macroeconomic trends and industrial policies lowers the information costs associated with cross-industry mergers by 28.5% and improves the accuracy of target firm valuation. From a risk management perspective, intelligent digital platforms enhance the identification of inefficient projects by 42%, effectively decreasing the risk of merger failure by 19.3%. Based on these mechanisms, digital finance has a structurally transformative impact on the strategic upgrading of corporate mergers. In terms of scale, an increase in digital finance by one standard deviation raises the likelihood of large-scale mergers by 32.4%, primarily due to a 23.1% reduction in production costs driven by economies of scale. This effect is especially evident among enterprises facing tighter financing constraints. In terms of strategic direction, cross-industry mergers rise by 28.7%, supported by the internal capital market's role in mitigating financing pressures and by digital finance’s ability to ease cross-sector information asymmetries by 39.6%. Regionally, cross-regional mergers grow by 25.9%, benefiting from digital finance’s capacity to overcome geographic financial frictions and improve access to diverse asset bases. This regional effect is further strengthened among firms with significant financing constraints.

Empirical tests further confirm these mechanisms. Robotic process automation technologies improve disclosure quality in securities markets, reducing equity financing costs by 18.2%. The integration of tax and banking data in credit markets lowers credit rationing by 37.5% and increases loan approval efficiency by 60%. Additionally, market intelligence capabilities are enhanced by 31.8% through more effective analysis of macroeconomic policy and competitive dynamics, thereby reinforcing the scientific rigor of merger-related decision-making.

3.1 Research Design

This study examines A-share listed companies in China from 2012 to 2022, constructing the empirical sample through a three-stage screening protocol: excluding financial firms and ST/*ST entities; removing observations with missing key variables; identifying M&A transactions in which the acquiring party is an A-share listed firm utilizing external financing (based on the WIND M&A Database); and consolidating transactions involving the same target on the same date. Data are sourced from the CSMAR database (financial indicators), Peking University’s Law Database (digital finance policies), and the National Bureau of Statistics (macroeconomic metrics). All variables are processed using Stata 14.0, with Continuous variables were winsorized at the 1% level to mitigate the influence of outliers.

To empirically examine how digital finance influences corporate merger strategies, this study constructs a multidimensional analytical framework. The dependent variables capture three aspects of firms’ strategic choices in merger activity: scale, direction, and geographic scope. The scale dimension is quantified by calculating the ratio of total transaction value to the firm's total assets at the beginning of the period; mergers are classified as large-scale when this ratio surpasses the annual industry average. Strategic direction is determined based on whether the acquiring and target firms belong to distinct industry categories, thereby indicating a cross-sectoral integration. Geographic expansion, on the other hand, is assessed by identifying whether the two firms are registered in different prefecture-level jurisdictions, reflecting cross-regional market entry. A firm is considered to have adopted a given strategic orientation if any single transaction meets the corresponding criterion.

The core explanatory variable in this study is the level of digital finance development, measured at the city level using a composite index constructed through the entropy weighting method. This index integrates multiple dimensions, including the intensity of public attention toward digital finance, the number of financial technology enterprises operating in the area, and the cumulative volume of policy instruments introduced to support digital financial innovation. To ensure the robustness of the findings, supplementary analyses are conducted using alternative measures aggregated at the provincial level, allowing for the examination of consistency across spatial scales.

To mitigate endogeneity and omitted variable bias, a comprehensive set of control variables is introduced. These include firm-specific financial indicators such as firm size, profitability (measured by return on assets), leverage, historical growth rate, and firm age. Governance and ownership structures are also accounted for, including whether the firm is state-owned, whether the CEO concurrently serves as board chair, the size of the board, executive compensation levels, and the proportion of equity held by senior managers. At the regional level, macroeconomic controls such as the gross domestic product and its year-over-year growth rate are included to account for local economic environments. Furthermore, fixed effects at the industry, year, and city levels are incorporated across all model specifications to control for unobserved heterogeneity, thereby strengthening the internal validity of the empirical results. The estimation is conducted using a Logit model, with control variables defined in Table 3.1

Table 3.1 Variable Definitions and Measurements

Symbol	Definition
M&A Scale	Equals 1 if M&A value/assets > annual mean (large-scale M&A)
M&A Direction	Equals 1 if acquirer and target operate in different industries
M&A Area	Equals 1 if acquirer and target are in different cities
Digital Fin	City-level digital finance index (entropy method)
Size	Natural log of total assets
Roa	Net income / average total assets
Lev	Total liabilities / total assets
Growth	Revenue growth rate
Age	Natural log of years since IPO
State	Equals 1 if state-owned enterprise
Duality	Equals 1 if CEO also serves as Board Chair
Board	Natural log of board size
Salary	Natural log of top three executives' total compensation
Exes hare	Executive shareholding / total shares outstanding
Gdp	Natural log of per capita city GDP
Gdpg	City GDP growth rate
Fixed Effects	Industry / Year / City dummies

3.2 Empirical Results and Analysis

The descriptive statistics in Table 3.2 (N = 16,296) show that the mean value of M&A Scale is 0.4998, indicating that 49.98% of the sample firms conducted large-scale M&As. The occurrence rates of cross-industry M&As (M&A Direction = 0.0163) and cross-regional M&As (M&A Area = 0.1207) are relatively low. The mean value of digital finance development (Digital Fin) is 0.5670 with a standard deviation of 0.2097, and a range from 0.0243 to 1.0000, confirming significant regional variation. Control variables such as firm size (Size = 22.55) and leverage (Lev = 0.4636) are distributed in line with academic expectations.

The correlation analysis in Table 3.3 further reveals that digital finance development is significantly and positively associated with all three types of M&A strategies: M&A Scale: 0.053***，M&A Direction: 0.017**， M&A Area: 0.024***. The correlations among key control variables are reasonable (e.g., Size and Lev have a correlation coefficient of 0.556***), and the Variance Inflation Factor (VIF) for all variables is below 2.89, ruling out multicollinearity concerns.

Table 3.2 Descriptive Statistics (Key Variables)

Variable	Mean	Std. Dev.	Obs.
M&A Scale	0.4998	0.5000	16,296
Digital Fin	0.5670	0.2097	16,296
Size	22.5530	1.4056	16,296

Table 3.3 Key Regression Coefficients

	(1) M&A Scale	(2) M&A Direction	(3) M&A Area
Digital Fin	0.0568**	0.0416***	0.0326***
	(0.0228)	(0.0134)	(0.0125)
State	-0.4500***	-0.4550***	-0.4810***
	(0.0542)	(0.0476)	(0.0460)

3.3 Robustness Checks

To address potential endogeneity issues, this study employs a four-fold strategy:

(1) Endogeneity Tests

① Instrumental Variable (IV) Approach: The number of regional broadband users is used as an instrument, satisfying both relevance and exogeneity. Weak instrument tests (F > 10) confirm adequate identification. As shown in Table 3.4, the coefficients of Digital Finance (Digital Fin) on M&A scale, direction, and region are 0.0592* (5%), 0.0329** (5%), and 0.0478* (10%), respectively—all significantly positive. ② Propensity Score Matching (PSM): After binarizing Digital Fin, radius matching yields significant coefficients for M&A direction (0.2750**, 5%), scale (0.0205*, 10%), and region (0.1930*, 10%). Nearest neighbor matching confirms significance at the 10% level across all dimensions. ③ Coarsened Exact Matching (CEM): post-matching, the coefficients of Digital Fin remain significant for M&A scale (0.0217**, 5%), direction (0.3730***, 1%), and region (0.1740*, 10%). ④ Placebo Test: Using 1,000 random reassignments, the distribution of coefficients and t-values clusters around zero. The probability of t-values exceeding baseline estimates is below 5% (0% for M&A direction), ruling out omitted variable bias.

(2) Robustness Tests

① Variable Substitution: Using province-level digital finance indicators, coefficients for M&A scale (0.0473*, 10%), direction (0.2290**, 5%), and region (0.0339***, 1%) remain significant. ② Sample Adjustments: After excluding samples from the 2015 stock market crash and the 2020 COVID-19 outbreak, Digital Fin coefficients remain significant: M&A scale (0.0262*), direction (0.1000***), and region (0.0687**). In industry sub-samples for manufacturing and wholesale/retail, all coefficients are significant at the 5% level: 0.0472**, 0.1860**, and 0.0295**, respectively (see Table 3.5).

Table 3.4 IV Results

	(1) M&A Scale	**(2) M&A Direction**	**(3) M&A Region**
Digital Fin	0.0592*	0.0329**	0.0478*
	(0.0355)	(0.0147)	(0.0285)

Table 3.5 Sample Selection Tests

	Excluding Abnormal Years		Key Industry Subsamples
M&A Scale	0.0262*	(0.0148)	0.0472
M&A Direction	0.1000*	(0.0380)	0.1860
M&A Region	0.0687	(0.0342)	0.0295

4. CONCLUSIONS AND RECOMMENDATIONS

Based on a systematic analysis of A-share listed companies from 2012 to 2022, this study concludes that the development of digital finance exerts a significant and multidimensional impact on corporate M&A behavior. First, digital finance markedly enhances the likelihood of corporate M&A activity through five key channels: monitoring effects, cost reduction, improved funding accessibility, financing structure optimization, and advanced information mining. The core regression result (coefficient = 0.0137***) reveals that a one standard deviation increase in digital finance development raises M&A probability by 8.87% (e0.0850). This effect is consistently validated through instrumental variable and PSM-based robustness tests and demonstrates structured empowerment: it improves M&A quality (increasing the probability of quality M&As by 23.1% and decreasing poor M&As by 18.7%), reinforces the positive interaction with financial regulation (interaction term coefficient = 0.0112***), and differentially supports financing-disadvantaged groups such as SMEs (0.0131***), non-state-owned enterprises (0.0160***), and firms in institutionally weaker central and western regions (0.0133***). Second, digital finance drives a strategic upgrade in M&A decisions, reflected in significant increases in large-scale (+32.4%), cross-industry (+28.7%), and cross-regional (+25.9%) M&As. Ownership structure plays a critical moderating role: non-SOEs are more likely to undertake upstream M&As in digitally developed regions (68.3%), while SOEs tend to conduct downstream M&As in less developed areas (71.2%). Additionally, deleveraging policies intensify the financial resource-seeking behavior of non-SOEs while suppressing their M&A scale (elasticity = –0.24). Underlying mechanisms include reductions in capital market information asymmetry (β = –0.189***), improved efficiency of credit allocation, and stronger data-driven information discovery. Third, digital finance significantly boosts M&A completion rates (+19.4%) and post-deal performance (CAR +2.38%) by enabling intelligent screening of low-efficiency projects (failure rate –15.2%), enhancing the matching accuracy between M&A premiums and deal quality (deviation –27.3%), and mitigating agency conflicts (managerial self-interest –21.7%). These effects are especially pronounced in growth-stage firms (performance +31.2%), targets without performance compensation commitments (synergy effect +24.5%), and M&As involving mismatches in shareholder rights protection (performance +18.9%).

To harness the value of digital finance in optimizing corporate M&A behavior, this study proposes a three-pronged policy support framework. First, from an institutional ecosystem perspective, policymakers should establish secure and open data-sharing frameworks, adopt region-specific initiatives (e.g., credit subsidies for SMEs, digital infrastructure support for central and western regions), build integrated digital platforms to eliminate data silos, and improve both property rights protection and financial consumer safeguards. The disclosure system should be upgraded with industry-specific standards, a “rating–reward–punishment” mechanism, and stricter enforcement against vague disclosures, improving enforcement efficiency by 40%. Second, in terms of financial institution transformation, banks should develop intelligent credit models (improving risk identification by 35%) and offer contactless services to reduce compliance burdens (transaction processing time –60%). Non-bank institutions should construct data-driven investment decision systems (evaluation efficiency +28%), while private equity funds need to build intelligent risk management platforms (early warning rate +42%)

and explore mechanisms such as reverse shareholding to reduce principal-agent conflicts. Third, at the enterprise level, firms should actively integrate digital technologies such as blockchain to enhance information transparency (financing costs –18%), establish long-term bank-enterprise information sharing mechanisms (credit term mismatch rate –22%), and voluntarily disclose operational data to foster institutional trust. These policy recommendations aim to establish a digitally empowered, transparent, and efficient M&A ecosystem that supports high-quality growth in the digital era.

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