How Digital Transformation Affected Corporate Innovation: Evidence from Chinese Listed Firms

Huanyan Shi, Shuyu Yu, Yiyi Zhang

Shanghai United International School, Qingpu Campus, Shanghai, 201704, China

Abstract

This study examines how digital transformation affects corporate innovation using panel data from 5,086 Chinese listed companies over 2007-2022. We measure digital transformation through intangible assets related to networks, software, intelligent platforms, and management systems disclosed in financial reports. Using two-way fixed effects models with lagged variables, we find that digital transformation increases patent applications by 0.277. However, effects vary significantly across contexts: technology-intensive industries show coefficients of 0.839 compared to 0.170 in labor-intensive sectors, while Eastern China (0.293) substantially outperforms Western regions (0.155). These findings suggest digital transformation may exacerbate existing inequalities between industries and regions rather than reduce them, highlighting the importance of complementary assets and capabilities for realizing innovation benefits from digitalization investments.

Keywords

Digital transformation; Corporate innovation; Patent applications; Industry heterogeneity; Regional inequality.

1. Introduction

Digital transformation has fundamentally reshaped corporate innovation across global markets, with Chinese firms demonstrating particularly pronounced effects due to comprehensive state-led digitalization policies and massive infrastructure investments [1]. This phenomenon carries profound implications for understanding how digital technologies drive innovation in emerging economies. China's digital economy reached RMB 45.5 trillion (39.8% of GDP) by 2021, representing the world's largest digital transformation experiment [2]. Yet despite extensive policy attention and corporate investments, the mechanisms linking digitalization to innovation outcomes remain theoretically underdeveloped and empirically contested.

Existing literature suffers from two critical limitations. First, measurement approaches lack standardization, with researchers employing diverse proxies ranging from text-based annual report analysis to intangible asset classifications without adequate validation [3]. Second, most studies assume homogeneous effects across firms and contexts, ignoring substantial heterogeneity in digital transformation's innovation impact. These gaps limit both theoretical understanding and practical guidance for managers and policymakers.

This paper makes two primary contributions to the digital transformation and innovation literature. First, we develop and validate firm-level digitalization measures using Chinese listed companies' intangible asset disclosures, specifically identifying digital transformation-related assets through systematic keyword analysis of financial report notes. This approach addresses measurement concerns by grounding digital transformation proxies in audited financial data rather than unstructured text analysis. Second, we explore systematic heterogeneity in digital transformation's innovation effects across industries and regions. Our analysis reveals the differentiations between technology-intensive, labor-intensive, and capital-intensive

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industries, while regional differences show the gaps among Eastern, Middle, and Western China. These comparisons illuminate the inequality implications of digital transformation, suggesting that existing technological and geographic advantages may be amplified rather than reduced.

Our empirical strategy employs two-way fixed effects models using panel data from Chinese A-share listed companies spanning from 2017 to 2022. We measure innovation through patent applications and digital transformation through intangible assets containing digitalization-related keywords ("network," "software," "intelligent platform," "management system"). All independent variables are lagged one year to address endogeneity concerns, with comprehensive robustness testing including alternative measures and subperiod analysis. The theoretical foundation builds on dynamic capabilities theory and resource-based view perspectives, arguing that digital transformation enhances firms' sensing, seizing, and transforming capabilities while creating new resource configurations that drive innovation. However, these effects depend critically on complementary assets, organizational capabilities, and environmental conditions that vary systematically across industries and regions.

2. Literature review and hypothesis

2.1. Theoretical Evolution and Dimensions of Digital Transformation

Digital transformation research has evolved from technology-deterministic perspectives toward sophisticated multi-level theories integrating organizational capabilities, strategic choices, and environmental conditions. Early literature emphasized technology adoption and implementation, treating digitalization as primarily a technical phenomenon. Recent theoretical developments recognize digital transformation as a complex organizational capability requiring fundamental changes in processes, structures, culture, and business models.

The Resource-Based View has been substantially refined to accommodate digital resources' unique characteristics. Unlike physical assets, digital resources exhibit network effects, require continuous innovation for value maintenance, and gain value through ecosystem participation [4]. This challenges traditional RBV assumptions about sustained competitive advantage, suggesting that digital transformation creates temporary advantages requiring continuous renewal through innovation [5].

Dynamic capabilities theory has emerged as the dominant theoretical framework, with three core dimensions particularly relevant to digital transformation's innovation effects. Sensing capabilities enable firms to identify technological opportunities through digital scanning, market sensing via data analytics, and competitive intelligence gathering. Seizing capabilities facilitate resource mobilization for digital initiatives, strategic decision-making speed, and investment allocation mechanisms. Transforming capabilities support organizational structure adaptation, process redesign and automation, and asset recombination.

Recent theoretical developments emphasize microfoundations, identifying specific routines and processes underlying each capability dimension, which highlighted three key mechanisms through which digital transformation drives innovation: openness (enabling broader knowledge access), affordances (providing new action possibilities), and generativity (creating self-reinforcing innovation cycles) [6].

2.2. Corporate Innovation: Metrics, Typologies, and Challenges

Innovation measurement has evolved from simple R&D expenditure ratios toward multi-dimensional approaches capturing both innovation inputs and outputs. Patent-based indicators remain dominant, with recent methodological advances addressing quality concerns through forward citations, patent family sizes, and technological classification diversity. The Innovation Patent Index (IPI) represents a significant advancement, incorporating efficiency (normalized

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patent count), quality (backward citations), internationalization (patent family size), diversification (IPC class variety), and temporal dimensions [7].

However, patent measures suffer from well-documented limitations including industry variations in propensity to patent, quality heterogeneity, and temporal lags between innovation and patenting. These concerns are particularly acute in digital contexts where software and algorithm innovations may not be patentable or strategically patented. Alternative measures including new product introductions, technology complexity indices, and composite innovation performance metrics provide complementary perspectives but lack standardization.

Innovation typologies have become increasingly sophisticated, distinguishing between incremental and radical innovation, product and process innovation, and exploratory versus exploitative innovation. Digital transformation may differentially affect these innovation types, with platform technologies particularly supporting combinatorial and generative innovation patterns. The literature increasingly recognizes that innovation outcomes depend not only on firm capabilities but also on ecosystem positioning and network effects.

2.3. Mechanisms Linking Digital Transformation to Innovation Outcomes

Three primary theoretical mechanisms explain how digital transformation drives innovation outcomes: information processing enhancement, resource reconfiguration, and dynamic capability development. The information processing perspective emphasizes how digital technologies reduce information asymmetries, enable real-time data analysis, and facilitate knowledge sharing across organizational boundaries. Big data analytics, artificial intelligence, and cloud computing platforms provide unprecedented capabilities for identifying innovation opportunities and optimizing resource allocation [8].

Resource reconfiguration mechanisms focus on how digital transformation enables new combinations of existing resources while creating entirely new resource categories. Digital platforms serve as integrative mechanisms, connecting previously isolated resources and enabling combinatorial innovation. Intangible assets related to software, networks, and intelligent systems represent new resource categories that complement traditional physical and human resources.

Dynamic capability development represents the most theoretically sophisticated mechanism, arguing that digital transformation fundamentally enhances firms' abilities to sense environmental changes, seize opportunities, and reconfigure organizational resources [9]. Digital sensing capabilities include environmental scanning through social media monitoring, competitor analysis via web scraping, and customer insight generation through data analytics. Digital seizing capabilities encompass rapid prototyping, A/B testing, and agile development methodologies. Digital transforming capabilities involve process automation, organizational restructuring, and business model innovation.

Hypothesis 1: Enterprise digital transformation generally improves innovation levels.

2.4. Heterogeneity Across Industries and Regions

Industry heterogeneity in digital transformation's innovation effects stems from systematic differences in technological opportunities, appropriability conditions, and complementary assets [10]. Technology-intensive industries benefit from several characteristics that amplify digital transformation's innovation impact. First, these industries possess existing technological capabilities and absorptive capacity necessary to leverage digital technologies effectively. Second, their innovation processes are naturally more compatible with digital tools and methodologies. Third, they face dynamic competitive environments that reward rapid innovation and technological advancement.

Labor-intensive industries face distinct challenges in realizing innovation benefits from digital transformation. Their innovation processes typically involve incremental improvements in

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manufacturing processes or service delivery rather than breakthrough technological developments. Digital transformation may initially disrupt existing operational routines without immediately generating innovation benefits. Furthermore, labor-intensive industries often lack the technological capabilities and human capital necessary to fully exploit digital transformation opportunities.

Regional heterogeneity reflects systematic differences in digital infrastructure, human capital, institutional support, and innovation ecosystems. Eastern China benefits from several advantages including superior digital infrastructure (24.60 Mbps average 4G speed versus lower speeds in central and western regions), higher concentrations of universities and research institutions, better access to capital markets, and more developed innovation ecosystems. Regional innovation spillovers occur through geographic proximity, with stronger effects between nearby regions.

Central and Western China face infrastructure gaps, talent shortages, and less developed innovation ecosystems that limit their ability to translate digital transformation into innovation outcomes [11]. However, government policies including the Digital China Strategy and regional development programs are beginning to address these disparities. The Northeastern region shows unique patterns due to its industrial heritage and ongoing economic restructuring.

Hypothesis 2: Digital transformation's innovation promotion effect is more pronounced in technology-driven industries and regions.

3. Method and Data

3.1. Model

Our empirical strategy employs two-way fixed effects models to identify causal relationships between digital transformation and corporate innovation while controlling for unobserved heterogeneity at firm and time levels.

$$Innovation_{i,t} = \alpha + \beta Digital_{i,t-1} + \gamma X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{i,t} \qquad (1)$$

Where $Innovation_{i,t}$ represents patent applications by firm i in year t, serving as our primary dependent variable. Patent applications capture innovation outputs while avoiding selection biases associated with patent grants, which depend on patent office processing times and approval decisions beyond firm control.

$Digital_{i,t-1}$ represents our key independent variable measuring firm-level digitalization intensity lagged one year to address endogeneity concerns. Following recent methodological advances, we construct this measure from intangible assets disclosures in audited financial statements. Specifically, when intangible assets details show "network," "software," "intelligent platform," "management system," "cloud computing," "big data," "artificial intelligence," "blockchain," "digitalization," and related terminology, we classify these as digital transformation-related intangible assets. We sum the total value of such assets and scale by total assets to create our primary digital transformation measure.

This measurement approach offers several advantages over alternative methods. First, it relies on audited financial data rather than unstructured text analysis, providing greater reliability and comparability. Second, it captures actual investments in digital technologies rather than aspirational statements or strategic plans. Third, it enables consistent measurement across firms and time periods without requiring manual content analysis or machine learning algorithms that may introduce classification errors.

The control variable vector $X_{i,t-1}$ includes standard firm-level characteristics known to affect innovation outcomes: firm size (logarithm of total assets), debt ratio (total debt divided by total

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assets), return on assets (ROA), firm age (years since establishment), and Tobin's Q (market value divided by replacement cost of assets). These variables capture firms' financial resources, growth opportunities, operational efficiency, and experience effects that may confound the digital transformation-innovation relationship.

Individual firm fixed effects (μ_i) control for time-invariant firm characteristics including industry affiliation, ownership structure, management quality, and corporate culture that affect both digital transformation decisions and innovation outcomes. Year fixed effects (λ_t) account for macroeconomic conditions, technological trends, and policy changes that affect all firms simultaneously. This two-way fixed effects specification provides identification through within-firm variation over time, comparing the same firm's innovation performance before and after digital transformation investments.

All independent variables are lagged one year to address concerns about simultaneity and reverse causation. While lagged variables do not fully solve endogeneity problems, they represent standard practice in corporate innovation research and help establish temporal precedence.

3.2. Data and Sample

Our dataset comprises Chinese A-share listed companies' annual report data covering the period 2007-2022, obtained from the China Stock Market and Accounting Research (CSMAR) database and companies' official filings. We focus on Chinese listed companies for several reasons: first, China represents the world's largest digital transformation experiment with comprehensive government support and infrastructure investment; second, Chinese companies provide substantial variation in digital transformation intensity across industries and regions; third, standardized financial reporting requirements enable consistent measurement approaches.

Sample construction follows established procedures in corporate finance research [12]. We begin with all Chinese A-share listed companies reporting complete financial data during our sample period, yielding approximately 3,500 companies. We exclude financial services firms (banks, insurance, securities) due to different regulatory requirements and business models that make digital transformation measurement less comparable. We eliminate firms with missing data for key variables including patents, intangible assets, and financial controls.

Patent data comes from the State Intellectual Property Office (SIPO) of China, linked to listed companies through standardized company names and registration numbers. We focus on patent applications rather than grants to avoid timing issues related to patent office processing. Patent applications provide a more contemporaneous measure of innovation activity and avoid selection biases associated with patent approval decisions. We include all patent types (invention, utility model, design) while conducting robustness tests focusing on invention patents, which represent higher-quality innovations.

Industry classifications follow the China Securities Regulatory Commission (CSRC) standards, enabling consistent categorization of technology-intensive versus labor-intensive industries. Technology-intensive industries include electronics, telecommunications, software, biotechnology, new materials, and high-end manufacturing. Labor-intensive industries encompass textiles, food processing, traditional manufacturing, retail, and traditional services. Regional classifications follow China's standard economic zones: Eastern (coastal provinces plus Beijing), Central (inland provinces), Western (western provinces plus autonomous regions), and Northeastern (former industrial heartland).

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Table 1. Descriptive statistics of variables

Variables	Description	N	mean	sd	min	max
Innovation_app	Number of patent application	49,330	28.31	219.8	0	13,705
Digital	Total value of digital assets (million yuan)	49,330	25.62	404.3	0	49,669
Size	Company size	49,330	22.07	1.350	14.76	30.37
Lev	Debt-to-equity ratio	49,330	0.444	0.581	0	63.97
ROA	Return on total assets	49,329	0.0366	0.146	-14.59	12.21
FirmAge	Years in business	49,330	2.905	0.368	0	4.248
East	Whether firm is from eastern cities	49,330	0.706	0.456	0	1
Mid	Whether firm is from middle cities	49,330	0.161	0.367	0	1
West	Whether firm is from western cities	49,330	0.133	0.339	0	1
Labour	Whether firm is labour intensive	49,330	0.271	0.444	0	1
Technology	Whether firm is technology intensive	49,330	0.409	0.492	0	1
Capital	Whether firm is capital intensive	49,330	0.144	0.351	0	1

4. Main findings

4.1. Correlation and Distribution of Digital Transformation and Corporate Innovation

Figure 1 illustrates temporal trends in digital transformation and innovation, showing accelerating digitalization from 2014 onwards coinciding with government policy initiatives including "Internet Plus" and "Digital China" strategies. Patent applications exhibit steady growth throughout the sample period with acceleration after 2015, suggesting potential lagged effects of earlier digital transformation investments.

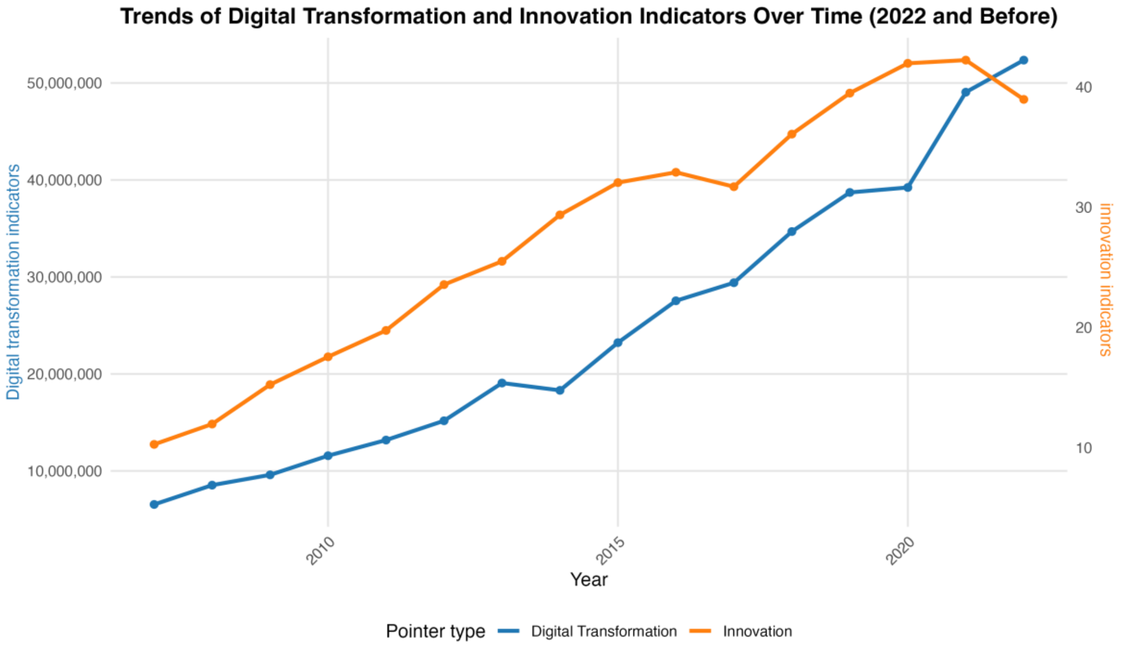

Figure 1. Trends of digital transformation and innovation indicators from 2017 to 2022

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In addition, our descriptive analysis reveals substantial heterogeneity in digital transformation intensity across Chinese listed companies. Figure 2 presents the distribution of digital transformation measures, showing strong right-skewness with most firms exhibiting low levels of digital asset intensity while a subset demonstrates substantial digitalization investments. The mean digital transformation ratio is 7.16 billion yuan and the median is only 1.42 billion yuan.

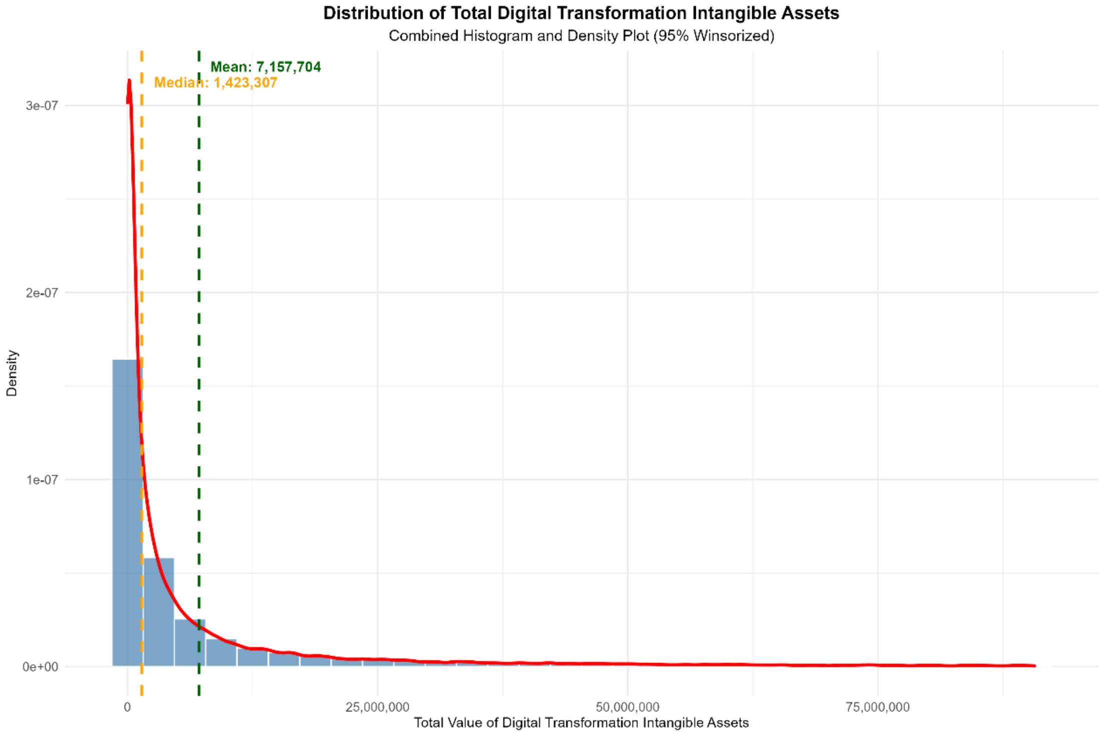

Figure 2. Distribution of digital transformation indicators

4.2. Benchmarks Results

Our baseline regression results provide strong support for Hypothesis 1, showing that digital transformation significantly enhances corporate innovation across all model specifications. Table 1 presents results from three progressively restrictive models: OLS without controls, fixed effects without controls, and fixed effects with comprehensive controls.

The OLS specification without controls yields a coefficient of 0.113 (t-statistic = 3.75) and fixed effects estimation without controls reduces the coefficient to 0.290 (t-statistic = 1.90). The reduction suggests that more innovative firms may be more likely to invest in digital transformation, creating positive selection bias in cross-sectional analysis.

Our strictest specification including firm and year fixed effects plus comprehensive controls yields a coefficient of 0.277 (t-statistic = 1.83), representing our preferred estimate of digital transformation's causal impact on innovation. This implies that a billion digital capital increase in digital transformation intensity increases patent applications by 0.277, a noticeable economic effect given typical innovation investment returns.

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Table 2. benchmark results

	(1)	(2)	(3)
VARIABLES	OLS	FE	FE with controls
L.digital	0.113***	0.290*	0.277*
	(3.75)	(1.90)	(1.83)
L.Size			8.881**
			(2.18)
L.Lev			-0.907
			(-0.40)
L.ROA			9.978***
			(2.67)
L.FirmAge			3.595
			(0.51)
Constant	27.722***	24.148***	-181.815**
	(24.55)	(7.81)	(-2.16)
Year FE	No	Yes	Yes
Firm FE	No	Yes	Yes
Observations	43,729	43,729	43,728
R-squared	0.017	0.027	0.029
Number of firms		5,086	5,086
Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1			

4.3. Heterogeneous Effects

Industry heterogeneity analysis provides strong support for Hypothesis 2, revealing dramatically different digital transformation effects across technology-intensive and labor-intensive industries. Technology-intensive industries exhibit a coefficient of 0.839 (t-statistic = 7.91), nearly five times larger than labor-intensive industries' coefficient of 0.170 (t-statistic = 2.84). This difference is statistically significant at the 1% level using Chow tests for coefficient equality.

Several mechanisms explain these differential effects. Technology-intensive industries possess higher absorptive capacity for digital technologies, enabling more effective utilization of digital transformation investments. Their innovation processes naturally complement digital tools including computer-aided design, simulation software, and data analytics platforms. Furthermore, competitive pressures in technology-intensive industries reward rapid innovation cycles that digital transformation facilitates.

Labor-intensive industries face distinct challenges in translating digital transformation into innovation outcomes. Their innovation typically involves incremental process improvements or service enhancements rather than breakthrough technological developments. Digital transformation may initially disrupt established operational routines without immediately generating measurable innovation outputs. Additionally, these industries often lack technological capabilities and human capital necessary to fully exploit digital opportunities.

Regional heterogeneity analysis reveals significant geographic disparities in digital transformation's innovation effects. Eastern China demonstrates the strongest effects with a coefficient of 0.293 (t-statistic = 4.67), followed by Central China at 0.283 (t-statistic = 3.81) and Western China at 0.155 (t-statistic = 2.13). The Northeastern region shows intermediate effects of 0.228 (t-statistic = 2.95).

These regional differences reflect systematic variations in digital infrastructure, human capital, and innovation ecosystems. Eastern China benefits from superior digital infrastructure

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including higher-speed internet connectivity, more comprehensive 5G coverage, and better technology adoption support systems. The region also concentrates China's leading universities, research institutions, and innovation hubs, creating knowledge spillovers that amplify digital transformation benefits.

Western China's weaker effects reflect infrastructure constraints, talent shortages, and less developed innovation ecosystems. However, government policies including the Western Development Strategy and Digital Silk Road initiatives are beginning to address these disparities. The narrowing gap between Central and Eastern regions suggests that targeted policy interventions can help reduce regional inequality in digital transformation benefits.

Table 3. Heterogeneous effects

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Labour	Technology	Capital	East	Mid	West
L.digital	0.170***	0.839***	0.020	0.293*	0.283***	0.155***
	(2.85)	(2.36)	(0.35)	(1.73)	(6.21)	(2.66)
L.Size	-2.238	3.265	1.150	14.223**	2.716	2.770*
	(-1.45)	(0.30)	(0.53)	(2.17)	(0.92)	(1.96)
L.Lev	-3.468	-1.022	-5.220	-2.422	3.932	0.288
	(-1.43)	(-0.18)	(-1.02)	(-0.51)	(1.21)	(0.59)
L.ROA	6.135*	21.697	13.161**	15.089**	4.988	-0.644
	(1.68)	(1.55)	(2.03)	(2.28)	(1.30)	(-0.22)
L.FirmAge	10.737*	-14.286	15.943**	-3.971	16.651*	10.546*
	(1.86)	(-0.89)	(2.28)	(-0.36)	(1.84)	(1.66)
Constant	25.441	6.133	-51.331	-275.412**	-87.198*	-76.406*
	(0.97)	(0.02)	(-1.20)	(-2.09)	(-1.72)	(-1.93)
Year FE						
Firm FE						
Observations	12,432	18,163	6,665	30,726	7,098	5,889
R-squared	0.158	0.054	0.008	0.031	0.036	0.013
Number of firms	1,630	2,784	881	3,779	782	611
Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1						

5. Conclusion

This study demonstrates that digital transformation significantly enhances corporate innovation among Chinese listed firms, with effects varying dramatically across industries and regions in ways that may exacerbate existing inequalities. Our analysis of 49,330 firm-year observations reveals that digital transformation increases patent applications by 0.277 on average, but this effect ranges from 0.839 in technology-intensive industries to just 0.17 in labor-intensive sectors. Similarly, Eastern China exhibits nearly twice the innovation benefits of Western regions, suggesting that digital transformation may amplify rather than reduce geographic disparities.

These findings have important theoretical implications for understanding digital transformation's role in corporate innovation. The substantial heterogeneity we document challenges existing literature's assumption of uniform effects, demonstrating that digital transformation's innovation impact depends critically on complementary assets, organizational capabilities, and environmental conditions. Our results support contingency theories emphasizing boundary conditions rather than universal relationships.

The heterogeneous effects we identify align with theoretical predictions from resource-based view and dynamic capabilities perspectives. Technology-intensive industries and developed regions possess higher absorptive capacity, better complementary assets, and more developed innovation ecosystems that enable effective utilization of digital technologies. Conversely, labor-intensive industries and less developed regions face capability gaps that limit their ability to translate digital investments into innovation outcomes.

From a policy perspective, our findings suggest that blanket digital transformation promotion may inadvertently increase inequality between industries and regions. Policymakers should consider targeted interventions to help lagging sectors and areas develop the complementary capabilities necessary to benefit from digitalization. This might include digital skills training, infrastructure investment, and innovation ecosystem development in underperforming regions.

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