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Research on the spillover effect of digital governance capability innovation among enterprises in the supply chain

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Abstract. The development of the digital economy has injected new momentum into enterprise innovation. The digital governance capabilities of supply chain partners—such as customers—play a significant role in influencing suppliers' innovation decisions and their resulting outcomes, warranting close attention. This study employs text mining techniques to construct an index system for measuring corporate digital governance capabilities, and further investigates how customer firms' digital governance capabilities affect the innovation activities of supplier firms. The findings confirm the existence of a spillover effect in the supply chain: customers' digital governance capabilities significantly enhance the innovation performance of upstream supplier firms. Heterogeneity tests reveal that the impact is more pronounced when suppliers are state-owned or innovation-driven enterprises. These conclusions remain robust after addressing endogeneity issues using propensity score matching. By examining the source of innovation performance improvement from the customer enterprise perspective, this study provides important insights for supply chain firms aiming to leverage customers' digital governance capabilities as a developmental opportunity.

Keywords: supply chain, digital governance capability, spillover effect, text analysis

1. Introduction

With the development of mobile internet, cloud computing, intelligent technologies, and a series of data technologies, digital technology has become one of the key drivers of economic growth and a core element in enhancing competitiveness and innovation across various fields and industries. In this context, exploring the role of enterprises' digital governance capabilities within supply chain relationships is of great practical significance for promoting a new wave of technological revolution, industrial transformation, and industry development. Based on this, this paper employs text analysis methods to construct a series of indicators to measure corporate digital governance capability and examines the impact of customer firms' digital governance capabilities on the innovation performance of upstream companies within the supply chain. Furthermore, it conducts heterogeneity tests based on different ownership types and industry classifications of supplier firms. The study finds that enterprises' digital governance capabilities exhibit a contagion effect within the supply chain. Specifically, customer firms' digital governance capabilities significantly and positively influence supplier firms' innovation activities, highlighting the real-world importance of understanding the transmission effects of digital governance within the supply chain.

In today's dynamic and uncertain business environment, companies seeking development and competitive advantage must possess a certain degree of digital governance capability. Digital governance capability refers to an enterprise's ability to integrate and effectively utilize various resources within a value creation network through a series of digital technologies, thereby generating digital value in response to ever-changing environments. Unlike the traditional resource-based view (RBV), which focuses on tangible and static resources, digital capabilities emphasize shareable digital assets and the application of digital technologies to organically integrate the power of all participants within the enterprise network for joint value creation. Previous research suggests that enhancing digital capabilities positively affects enterprise management, transformation, and innovation performance. For instance, Zhong [1] proposed that digital transformation improves information transparency, enhances customer insight, facilitates market segmentation, supports decision-making, and thereby helps promote business model transformation, product and service upgrades, and the enhancement of innovation capacity. Qi and Xiao explored how the digital economy drives enterprises to shift their objectives and thereby innovate their governance structures from a managerial perspective. However, other studies indicate that the digitalization process is not without challenges; enterprises often face high transformation costs and significant uncertainties [2].

From the perspective of supplier-customer interactions, existing literature mostly explores the effects on supply chain participants by focusing on the performance of core enterprises. In the field of corporate finance, interactions between suppliers and customers can influence a firm's risk of financial misreporting [2] and cash holding decisions [4]. In terms of product quality, whether through active assistance from customer firms or passive responses to their strict quality requirements, suppliers are prompted to optimize production processes to meet customer standards [5]. Moreover, the interest community formed by supplier-customer cooperation promotes high coordination of actions on both sides. For example, to avoid negative publicity, customer firms may actively urge suppliers to fulfill corporate social responsibilities, thereby enhancing corporate image and attracting investment [6]. In terms of factors influencing enterprise innovation behavior in the supply chain, current research mainly focuses on knowledge spillovers and information sharing within domestic production networks, such as knowledge diffusion [7] and network trust [8]. Chu et al. [9] found that the closer the geographical proximity between suppliers and customer firms, the greater the influence of downstream firms on suppliers' innovation. However, because the spillover of innovation can lead to private returns falling short of social returns, R&D investment is unlikely to reach socially optimal levels in the absence of policy intervention [10].

2. Sample selection and model specification

2.1. Sample selection

This study selects research samples from A-share listed companies on the Shanghai and Shenzhen stock exchanges in China from 2009 to 2022. The following samples were excluded: (1) ST (Special Treatment) stocks; (2) Companies in the financial industry; (3) Samples with missing relevant data; (4) The top and bottom 1% of data were winsorized to mitigate the influence of outliers. The exclusion of ST and financial firms is mainly due to the relatively poor financial quality of ST stocks and the unique accounting practices in the financial sector. The winsorization at 1% is intended to reduce the distortion caused by extreme values. The primary data source is the CSMAR database, and data processing is conducted using STATA software.

2.2. Variable definitions

2.2.1. Independent variable: digital capability of customer firms (ability)

Appendix table 1. Sub-indicators of digital capability

Technology Category	Keywords/Technologies
Artificial Intelligence	Business intelligence, image recognition, machine learning, decision support systems, biometric technology, deep learning, natural language processing, facial recognition, AI, speech recognition, identity authentication, intelligent data analytics, autonomous driving, intelligent robots, semantic search
Blockchain Technology	Smart contracts, distributed computing, Bitcoin, decentralization, differential privacy technology, digital currency, consensus mechanisms, consortium blockchain
Cloud Computing Technology	Mass concurrency, cloud computing, converged architecture, stream computing, brain-inspired computing, IoT, in-memory computing, cognitive computing, green computing, cyber-physical systems, graph computing, exabyte-level storage, secure multi-party computation
Big Data Technology	Augmented reality, data mining, mixed reality, heterogeneous data, big data, virtual reality, data visualization, credit investigation, text mining
Digital Technology Applications	Fintech, mobile payments, smart tourism, internet finance, mobile internet, intelligent marketing, connected vehicles, C2C, third-party payments, wearable technology, industrial internet, robo-advisors, unmanned retail, smart homes, B2B, digital finance, digital marketing, internet healthcare, O2O, B2C, smart healthcare, C2B, NFC payments, quantitative finance, e-commerce, smart agriculture, open banking, intelligent transportation, smart grid, smart environmental protection, smart energy, credit investigation

This study draws extensively on classic research in the field of corporate digitalization, including works by Chen et al. [11], Li et al. [12], and Ling et al [13]. Through systematic review and synthesis, we distilled a set of keywords closely related to digital capabilities.

In addition, this study refers to relevant policy documents and research reports—such as the Special Action Plan for Empowering SMEs through Digitalization, the Implementation Plan for Promoting the “Cloud Adoption, Data Utilization, and Intelligence Empowerment” Initiative, the 2020 Digital Transformation Trends Report, and recent Government Work Reports—to further enrich the digital transformation keyword library. The keywords are then structurally categorized into two dimensions: "underlying technology use" and "practical application of technology," ultimately forming a comprehensive list of keywords for "digital transformation" and corresponding word frequencies. These keywords span five major categories: artificial intelligence, blockchain, cloud computing, big data, and digital applications (see Appendix Table 1 for details).

To ensure data validity and relevance, expressions containing negations (such as "no," "none," or "not") preceding the keywords were excluded. Additionally, keywords not directly related to the focal company—such as those associated with shareholders, clients, suppliers, or senior executive bios—were filtered out. The remaining keyword frequencies were then extracted from annual reports. The digital capability variable for customer firms was calculated as the average frequency of these keywords, with the data subsequently log-transformed to facilitate further analysis.

2.2.2. Dependent Variable

Innovation Level of Upstream Firms (Innovation). This variable is measured by the number of invention patent applications and grants. Invention patents are considered a more accurate representation of a firm's true innovation capability.

2.2.3. Control Variables

Following related literature, this study includes a range of control variables that may influence innovation levels in listed firms, spanning executive, firm-level, and macro-level dimensions: Executive-level variables: Board size (Broad); Executive shareholding ratio (Manage); Proportion of independent directors (Indep); Dual role of chairman and CEO (Dual); Firm-level variables:; Firm size (Size); Leverage ratio (Lev); Analyst coverage (Report); Institutional ownership ratio (Insti); Macro-level variables: Legal environment (Law); Regional economic development level (Devep).

2.2.4. Mechanism Variables

(1) Information Disclosure Level of Customer Firms (Infor): This variable is measured using the KV metric method proposed by Kim and Verrecchia, which estimates the slope of a regression of stock returns on trading volume. The underlying principle is that when a listed firm has poor information disclosure, investors rely more heavily on information embedded in trading volume and less on the quality of disclosed information. In such cases, changes in trading volume can result in substantial price fluctuations. The specific calculation is as follows:

$$Ln\left|\frac{\Delta P_t}{P_{t-1}}\right| = \alpha + \beta(vol_t - vol_0) + \mu_i \tag{1}$$

Where ΔP_t represents the difference between P_t and P_{t-1}, with P_t denoting the closing price on day t, vol_t representing the trading volume on day t, and vol_0 denoting the average daily trading volume over the year. The indicator KV is calculated as KV=β*1000000. A lower KVKVKV value indicates a higher level of information disclosure.

(2) Innovation Level of Customer Firms (Patent): This is measured as the sum of the number of applications and grants of three types of patents—particularly invention patents, which best reflect true innovation capabilities. The natural logarithm of this total is then taken.

2.2.5. Heterogeneity Variables

(1) Ownership Type (Property): A dummy variable equal to 1 if the customer firm is a state-owned enterprise (SOE), and 0 otherwise.

(2) Industry Type (Type): Firms in the computer, communications and other electronic equipment manufacturing industry, pharmaceutical manufacturing, and electrical machinery and equipment manufacturing are classified as innovation-intensive industries. Other industries are classified as non-innovation-intensive. A dummy variable is set to 1 for innovation-intensive industries, and 0 otherwise.

Table 1. Variable definitions and measurements

Variable	Definition
Independent Variable	
Ability	Digital capability of customer (downstream) firms, as defined above.
Dependent Variable	
Innovation	Innovation level of upstream firms, as defined above.
Control Variables	
Broad	Board size, measured as the number of board members.

Table 1. (continued)

Manage	Executive shareholding ratio, measured as the total shareholding ratio of all executives.
Indep	Proportion of independent directors, measured as the ratio of independent directors to total directors.
Dual	CEO duality, indicating whether the chairman also serves as CEO.
Size	Firm size, measured as the natural logarithm of total assets at the end of the year.
Lev	Leverage, measured as the ratio of total liabilities to total assets at year-end.
Report	Analyst coverage, measured by the number of analyst reports.
Insti	Institutional ownership, measured as the total proportion of institutional shareholding.
Law	Legal environment, measured by the level of legal development in each province.
Devep	Economic development level, measured by the level of economic development in each province.
Pearson	Individual fixed effects.
Year	Year fixed effects.
Other Variables	
Infor	Information disclosure level of customer firms, measured as described above.
Patent	Innovation level of customer firms, measured as described above.
Property	Ownership type dummy variable, equal to 1 for SOEs, 0 otherwise.
Type	Industry type dummy variable, equal to 1 for innovation-intensive industries, 0 otherwise.

2.3. Model specification

To test the core hypotheses of this study, the following empirical model is constructed:

$$Innovation_{i,t+1} = \alpha_0 + \beta_1 Ability + \sum_{n=2}^{n} \beta_n Controls_{i,t} + Year_t + Firm_i + \varepsilon_{i,t} \quad (2)$$

Where $Innovation_{i,t+1}$ represents the dependent variable—namely, the innovation level of the upstream firm of company i in year t+1, $Ability_{i,t}$ denotes the core explanatory variable, i.e., the level of digital transformation of company i in year t, $Controls_{i,t}$ includes a set of control variables such as board size (Broad), executive shareholding ratio (Manage), proportion of independent directors (Indep), CEO duality (Dual), firm size (Size), leverage (Lev), analyst attention (Report), institutional ownership (Insti), legal environment (Law), and regional economic development level (Devep); α_i is constant term,$\varepsilon_{i,t}$ is the error term; $Year_t$和$Firm_i$ represent year fixed effects and firm fixed effects, respectively. $\beta_1$is the main regression coefficient of interest. This study expects $\beta_1$to be significantly positive, indicating that a customer's digital transformation can enhance the innovation performance of its upstream suppliers. To alleviate the issue of endogeneity arising from potential reverse causality, the dependent variable—innovation level—is lagged by one period in the model.

3. Empirical analysis

3.1. Descriptive statistics

Table 2. Descriptive statistics

Variable	N	Mean	Median	Std. Dev.	Min	Max
Patent1	4,355	3.026	3.136	1.572	0.000	6.765
Patent2	4,355	3.756	3.932	1.756	0.000	7.601
Ability	4,355	1.321	0.693	1.471	0.000	5.236
Broad	4,355	10.317	10.000	2.432	6.000	18.000
Manage	4,355	12.003	1.010	17.987	0.000	64.523
Indep	4,355	0.380	0.364	0.072	0.250	0.600
Dual	4,355	0.265	0.000	0.441	0.000	1.000
Size	4,355	22.364	22.228	1.212	20.123	25.823
Lev	4,355	0.435	0.439	0.186	0.060	0.856
Report	4,355	19.043	11.000	21.823	1.000	105.000
Insti	4,355	44.536	47.190	23.360	0.896	89.782

Table 2. (continued)

Law	4,355	9.047	9.880	1.862	3.610	10.960
Devep	4,355	0.129	0.122	0.027	0.080	0.267

Table 2 presents the results of the descriptive statistics. For the explanatory variable—digital capability of customer firms (Ability)—the mean is 1.321 and the median is 0.693, indicating a left-skewed distribution. The standard deviation is 1.471, with a minimum of 0 and a maximum of 5.236, suggesting a significant polarization in digital capability levels across different listed firms and years. For the dependent variable—innovation level (Patent1)—the mean is 3.026 and the median is 3.136, showing no significant skewness in the distribution. The standard deviation is 1.572, with values ranging from 0 to 6.765, indicating large variation and a polarized distribution in innovation levels across firms and years. The distribution of Patent2 (invention patent grants) is similar.

3.2. Pearson correlation analysis

Table 3. Pearson correlation analysis

	Patent1	Patent2	Number	Broad	Manage	Indep	Dual	Size	Lev	Report	Insti	Law	Devep
Patent1	1.000												
Patent2	0.992	1.000											
Ability	**0.132**	**0.129**	1.000										
Broad	0.055	0.050	-0.001	1.000									
Manage	-0.072	-0.067	0.114	-0.196	1.000								
Indep	0.023	0.024	0.068	-0.098	0.152	1.000							
Dual	0.017	0.014	0.107	-0.131	0.189	0.126	1.000						
Size	0.368	0.350	0.055	0.208	-0.364	-0.060	-0.117	1.000					
Lev	0.128	0.115	-0.100	0.154	-0.308	-0.074	-0.103	0.525	1.000				
Report	0.192	0.180	0.096	-0.013	0.029	0.036	0.040	0.298	-0.010	1.000			
Insti	0.066	0.057	-0.180	0.157	-0.693	-0.124	-0.171	0.382	0.198	0.172	1.000		
Law	0.080	0.083	0.232	-0.079	0.207	0.031	0.133	-0.119	-0.150	0.105	-0.118	1.000	
Devep	-0.036	-0.041	-0.078	0.064	-0.140	-0.089	-0.016	0.122	0.069	0.005	0.148	-0.166	1.000

Table 3 presents the results of the Pearson correlation analysis. It can be observed that the digital capability of customer (downstream) firms (Ability) is positively correlated with the innovation levels of upstream firms, with correlation coefficients of 0.132 and 0.129 for Patent1 and Patent2, respectively. This suggests that improvements in customer firms' digital capabilities are associated with enhanced innovation performance of upstream firms, providing preliminary support for Hypothesis H1. However, since this analysis does not control for other factors such as board size (Broad), executive shareholding ratio (Manage), proportion of independent directors (Indep), CEO duality (Dual), firm size (Size), leverage (Lev), analyst coverage (Report), institutional ownership (Insti), legal environment (Law), and regional economic development (Devep), more robust conclusions must be drawn from multivariate regression using two-way fixed effects.

3.3. Baseline regression

Table 4 presents the results of the two-way fixed effects multivariate regression based on Model (2), with the explanatory variable being the digital capability of customer (downstream) firms (Ability). Columns (1) and (2) use Patent1 (number of patent applications by upstream firms) as the dependent variable. The regression coefficients are 0.060 (t = 3.45) and 0.037 (t = 2.15), respectively, before and after controlling for other variables. Both coefficients are significantly positive. Columns (3) and (4) use Patent2 (number of invention patent grants by upstream firms) as the dependent variable. The regression coefficients are 0.066 (t = 4.33) and 0.044 (t = 2.91), respectively, again showing significantly positive effects. These findings consistently indicate that an increase in the digital capability of downstream firms significantly enhances the innovation performance of upstream firms (both in terms of patent applications and grants).

Table 4. Baseline regression results

	Innovation			
	Patent1		Patent2	
	(1)	(2)	(3)	(4)
Ability	**0.060***** **(3.45)**	**0.037**** **(2.15)**	**0.066***** **(4.33)**	**0.044***** **(2.91)**
Broad		-0.006 (-0.95)		0.008 (1.36)
Manage		0.002 (1.10)		0.003** (2.02)
Indep		0.069 (0.31)		-0.146 (-0.73)
Dual		0.002 (0.04)		-0.045 (-1.18)
Size		0.426*** (13.42)		0.404*** (14.77)
Lev		-0.098 (-0.73)		-0.252** (-2.13)
Report		0.000 (0.51)		0.001 (0.71)
Insti		0.001 (0.47)		-0.000 (-0.09)
Law		0.084*** (3.64)		0.057*** (3.03)
Devep		-2.334 (-1.63)		-3.705*** (-3.15)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	0.906*** (11.43)	-8.569*** (-11.88)	0.333*** (4.80)	-8.240*** (-13.38)
Adj. R^2	0.298	0.329	0.247	0.286
N	4,355	4,355	4,355	4,355

3.4. Robustness checks

The above findings preliminarily confirm that the digital capability of customer firms (Ability) positively influences the innovation performance of upstream firms (Patent1/Patent2). To ensure the robustness and reliability of these results, we conduct several robustness checks: Exclusion of Special Years: Considering the impact of the COVID-19 pandemic in 2020 on corporate operations, which may influence the empirical results, we exclude samples from 2020 and beyond. The results are shown in Table 5. Alternative Measurement of Innovation: In the baseline regressions, innovation was measured using the number of patent applications and grants. In the robustness tests, we replace these with two alternative measures: Patent3: R&D investment as a proportion of operating revenue; Patent4: R&D investment as a proportion of total assets. Results are reported in Table 6. Alternative Regression Approach: The fixed effects model assumes correlation between the error term and explanatory variables, whereas the random effects model assumes no such correlation. To verify model robustness, we re-estimate the regressions using a random effects model. Results are reported in Table 7.

Across all robustness tests, the core findings remain consistent with those from the baseline regression: the digital capability of downstream firms significantly promotes the innovation performance of upstream firms.

Table 5. Robustness check: excluding special years

	Innovation			
	Patent1		Patent2	
	(1)	(2)	(3)	(4)
Ability	**0.051***** **(2.78)**	**0.031*** **(1.69)**	**0.053***** **(3.33)**	**0.034**** **(2.14)**
Broad		-0.008 (-1.03)		0.009 (1.46)
Manage		0.002 (1.15)		0.002 (1.06)
Indep		0.056 (0.23)		-0.250 (-1.19)
Dual		-0.017 (-0.35)		-0.061 (-1.51)
Size		0.427*** (12.64)		0.367*** (12.79)
Lev		-0.077 (-0.54)		-0.255** (-2.04)
Report		-0.000 (-0.24)		0.000 (0.22)
Insti		0.001 (0.73)		-0.000 (-0.37)
Law		0.083*** (3.54)		0.055*** (2.91)
Devep		-2.935** (-2.01)		-3.417*** (-2.87)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	0.903*** (11.39)	-8.515*** (-11.19)	0.364*** (5.37)	-7.356*** (-11.48)
Adj. R^2	0.285	0.316	0.236	0.267
N	3,829	3,829	3,829	3,829

Table 6. Robustness check: alternative innovation measures

	Innovation			
	Patent3		Patent4	
	(1)	(2)	(3)	(4)
Ability	0.139*** (5.75)	0.146*** (6.05)	0.212*** (3.53)	0.204*** (3.36)
Broad		0.024*** (2.61)		0.037 (1.59)
Manage		0.001 (0.54)		-0.001 (-0.09)
Indep		-0.284 (-0.93)		-0.551 (-0.73)
Dual		0.007 (0.13)		0.270* (1.82)
Size		-0.511*** (-11.00)		-0.535*** (-4.57)
Lev		-0.226 (-1.21)		-2.326*** (-4.99)
Report		0.006*** (5.27)		0.002 (0.59)
Insti		0.000 (0.13)		-0.016*** (-3.29)

Table 6. (continued)

Law		0.147*** (3.72)		0.409*** (3.96)
Devep		-0.097 (-0.04)		-2.505 (-0.41)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	1.030*** (8.70)	10.388*** (9.55)	2.559*** (8.53)	12.041*** (4.36)
Adj. R^2	0.096	0.119	0.068	0.075
N	4,355	4,355	4,355	4,355

Table 7. Robustness check: random effects model

	Innovation			
	Patent1		Patent2	
	(1)	(2)	(3)	(4)
Ability	0.194*** (5.15)	0.126*** (5.14)	0.133*** (4.13)	0.075*** (3.46)
Broad		0.002 (0.18)		0.012 (1.58)
Manage		-0.005** (-2.47)		-0.003* (-1.69)
Indep		0.501* (1.83)		0.454* (1.73)
Dual		0.043 (1.30)		-0.000 (-0.01)
Size		0.482*** (14.78)		0.413*** (13.67)
Lev		-0.598*** (-5.05)		-0.653*** (-6.19)
Report		0.006*** (3.53)		0.005*** (3.53)
Insti		-0.004*** (-3.29)		-0.003** (-2.42)
Law		0.057*** (6.11)		0.048*** (6.66)
Devep		-3.316*** (-5.10)		-3.207*** (-6.33)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	1.944*** (16.32)	-8.650*** (-11.82)	1.254*** (14.11)	-7.864*** (-12.02)
Adj. R^2	0.037	0.186	0.024	0.174
N	4,355	4,355	4,355	4,355

3.5. Endogeneity test

The above results may still suffer from potential endogeneity problems, such as reverse causality, omitted variable bias, and sample selection bias. To address these concerns, this study adopts the Propensity Score Matching (PSM) method as a robustness check. Specifically, the following variables are used as covariates to construct the matched samples: board size (Broad), executive shareholding ratio (Manage), proportion of independent directors (Indep), dual role of CEO and chairman (Dual), firm size (Size), leverage (Lev), analyst attention (Report), institutional ownership (Insti), legal environment (Law), and regional economic development level (Devep). A 1:1 nearest-neighbor matching with replacement is employed, yielding 3,483 matched observations. The main hypothesis is then re-tested based on the matched sample, with the results presented in Tables 8 and 9.

Table 8. Propensity score matching: covariate balance test

	Before Matching			After Matching		
	Treated	Control	Diff. (%)	Treated	Control	Diff. (%)
Broad	10.356	10.261	3.9 (1.26)	10.355	10.343	0.5 (0.17)
Manage	13.000	10.545	13.7*** (4.43)	12.987	12.577	2.3 (0.81)
Indep	0.385	0.374	15.8*** (5.06)	0.385	0.386	-1.8 (-0.64)
Dual	0.299	0.216	19.2*** (6.17)	0.299	0.292	1.6 (0.54)
Size	22.471	22.208	21.8*** (7.05)	22.47	22.524	-4.5 (-1.54)
Lev	0.426	0.448	-12.4*** (-4.01)	0.426	0.424	0.9 (0.33)
Report	20.702	16.616	19.2*** (6.09)	20.691	20.996	-1.4 (-0.48)
Insti	42.927	46.889	-17.0*** (-5.52)	42.935	44.413	-6.3** (-2.20)
Law	9.335	8.626	38.4*** (12.57)	9.334	9.296	2.1 (0.80)
Devep	0.127	0.131	-11.4*** (-3.81)	0.127	0.128	-3.0 (-1.21)
Sample Size		4,355			3,483	

Table 8 presents the balance test results. Before matching, the differences in covariates between the treatment and control groups are relatively large, with several variables showing statistically significant imbalances. After matching, these differences are substantially reduced and no longer significant in most cases, indicating that the matching process is effective and reliable. Table 9 shows the regression results after applying the propensity score matching method: Columns (1) and (2) use Patent1 (number of patent applications by upstream firms) as the dependent variable. The estimated coefficients before and after controlling for covariates are 0.058 ($t = 3.03$) and 0.036 ($t = 1.94$), respectively—both of which are significantly positive. Columns (3) and (4) use Patent2 (number of invention patent grants by upstream firms) as the dependent variable. The corresponding coefficients are 0.050 ($t = 3.05$) and 0.028 ($t = 1.73$), also demonstrating significantly positive relationships. These results confirm the robustness of the findings: the digital capability of downstream firms (Ability) continues to significantly promote innovation in upstream firms, even after addressing potential endogeneity concerns through PSM.

Table 9. Propensity score matching: regression results

	Innovation			
	Patent1		Patent2	
	(1)	(2)	(3)	(4)
Ability	0.058*** (3.03)	0.036* (1.94)	0.050*** (3.05)	0.028* (1.73)
Broad		-0.009 (-1.21)		0.005 (0.79)
Manage		0.002 (1.02)		0.003** (2.06)
Indep		0.217 (0.85)		-0.074 (-0.33)
Dual		0.028 (0.57)		-0.026 (-0.62)
Size		0.389*** (11.27)		0.376*** (12.89)
Lev		-0.029 (-0.19)		-0.191 (-1.47)
Report		0.002 (1.53)		0.002** (2.29)
Insti		0.000 (0.08)		-0.001 (-0.63)

Table 9. (continued)

Law		0.074***		0.065***
		(3.10)		(3.45)
Devep		-2.528*		-2.641**
		(-1.71)		(-2.23)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	0.966***	-7.668***	0.410***	-7.793***
	(11.60)	(-9.86)	(5.71)	(-11.99)
Adj. R^2	0.288	0.314	0.222	0.261
N	3,483	3,483	3,483	3,483

3.6. Heterogeneity analysis

The preceding analysis has preliminarily verified that the digital capability of customer (downstream) firms (Ability) significantly enhances the innovation performance of upstream firms (Patent1/Patent2). To further explore the potential heterogeneity of this relationship, we conduct subgroup analyses based on ownership structure and industry type.

Table 10 presents the results of heterogeneity analysis by ownership structure. Columns (1) and (2) show the regression results for state-owned enterprises (SOEs), where the estimated coefficients of Ability on upstream firms' innovation outputs (Patent1 and Patent2) are 0.074 ($t = 2.31$) and 0.073 ($t = 2.51$), respectively—both significantly positive. This suggests a stronger positive spillover effect of downstream firms' digital capability on the innovation performance of upstream SOEs. A possible explanation is that SOEs generally exhibit lower operational efficiency, thus benefiting more from customers' digital transformation.

Table 10. Heterogeneity analysis: ownership structure

	Innovation			
	State-owned Enterprises		Non-state-owned Enterprises	
	Patent1	Patent2	Patent1	Patent2
	(1)	(2)	(3)	(4)
Ability	0.074**	0.073**	0.019	0.037**
	(2.31)	(2.51)	(0.95)	(2.11)
Broad	-0.008	0.013	-0.011	0.004
	(-0.75)	(1.37)	(-1.20)	(0.44)
Manage	-0.003	-0.005	0.001	0.001
	(-0.21)	(-0.40)	(0.55)	(0.48)
Indep	0.774**	0.266	-0.223	-0.355
	(1.99)	(0.74)	(-0.81)	(-1.46)
Dual	-0.088	-0.064	0.004	-0.042
	(-1.02)	(-0.81)	(0.09)	(-0.97)
Size	0.518***	0.494***	0.389***	0.380***
	(9.34)	(10.10)	(9.69)	(11.05)
Lev	-0.038	-0.270	-0.150	-0.260*
	(-0.16)	(-1.25)	(-0.92)	(-1.82)
Report	0.002	0.002	0.000	0.000
	(1.38)	(1.15)	(0.16)	(0.34)
Insti	-0.002	-0.003	0.001	-0.000
	(-0.61)	(-1.05)	(0.50)	(-0.19)
Law	0.068	0.028	0.109***	0.072***
	(1.61)	(0.81)	(3.98)	(3.24)
Devep	-2.736	-5.014***	-0.888	-3.287*
	(-1.36)	(-2.97)	(-0.43)	(-1.97)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	-10.742***	-9.994***	-7.833***	-7.620***
	(-8.84)	(-9.43)	(-8.52)	(-9.76)
Adj. R^2	0.391	0.361	0.298	0.247
N	1,544	1,544	2,811	2,811

Table 11 reports the results for different industry types. Compared to non-innovative industries (Columns 3 and 4), the estimated coefficients for innovative industries (Columns 1 and 2) are larger and more significant, indicating that the digital capabilities of downstream firms have a more pronounced positive effect on the innovation activities of upstream firms engaged in innovation-intensive sectors. This is consistent with the notion that innovative firms, due to their inherent innovation orientation, are more responsive to external knowledge and digital signals from their customers.

Table 11. Heterogeneity analysis: industry type

	Innovation			
	Innovation-Intensive Industries		Non-Innovation Industries	
	Patent1	Patent2	Patent1	Patent2
	(1)	(2)	(3)	(4)
Ability	0.102***	0.054*	0.060***	0.031
	(2.65)	(1.88)	(3.06)	(1.05)
Broad	0.001	0.005	-0.005	0.015***
	(0.03)	(0.47)	(-0.66)	(2.06)
Manage	0.002	-0.005*	0.002	0.006***
	(0.56)	(-1.81)	(1.00)	(3.41)
Indep	-0.068	-0.321	0.084	-0.112
	(-0.13)	(-0.84)	(0.35)	(-0.49)
Dual	-0.027	-0.159**	0.010	-0.023
	(-0.28)	(-2.24)	(0.21)	(-0.53)
Size	0.240***	0.212***	0.530***	0.496***
	(3.75)	(4.39)	(14.81)	(15.63)
Lev	-0.584*	-0.784***	-0.039	-0.200
	(-1.82)	(-3.31)	(-0.26)	(-1.49)
Report	-0.000	-0.001	0.001	0.002**
	(-0.11)	(-0.91)	(1.07)	(2.02)
Insti	-0.003	-0.006**	0.001	0.001
	(-0.79)	(-2.31)	(0.90)	(0.98)
Law	0.080*	0.082**	0.094***	0.063***
	(1.66)	(2.19)	(3.95)	(3.29)
Devep	-2.831	-3.150	-1.089	-2.263*
	(-0.91)	(-1.30)	(-0.73)	(-1.83)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	-4.788***	-3.871***	-10.952***	-10.566***
	(-3.33)	(-3.53)	(-13.63)	(-14.97)
Adj. R^2	0.243	0.277	0.368	0.307
N	1,024	1,024	3,331	3,331

4. Conclusion

This study constructs a novel measure of corporate digital governance capability through text analysis of the annual reports of listed companies. Based on this indicator, we investigate the spillover effects of downstream firms' digital capabilities on the innovation performance of upstream suppliers within the supply chain. The empirical results demonstrate that the digital governance capability of customer firms significantly enhances the innovation output of upstream enterprises. This finding supports the existence of a transmission effect of digital capability along the supply chain. Moreover, the heterogeneity analysis reveals that this spillover effect is more pronounced when the supplier is a state-owned enterprise or belongs to an innovation-intensive industry. Even after addressing potential endogeneity through propensity score matching (PSM), the core conclusions remain robust. By shifting the perspective to customer firms, this study sheds light on the source of innovation performance improvements among supply chain partners and provides important insights for suppliers to leverage the digital governance capabilities of their customers as a development opportunity.

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