

Research on the Impact of Downstream Firms' Digital Transformation on Upstream Firms' Green Innovation: A Supply-Chain Perspective

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Abstract

With the increasing popularity of digital technology in Chinese enterprises, how digital transformation affects the external green innovation of enterprises has become a question worth exploring. This study focuses on the upstream and downstream relationship to explore whether the digital transformation of downstream enterprises is related to the green innovation behavior of upstream suppliers under China's "dual carbon" policy. Based on the matching supply chain data of listed companies in China, the analysis shows that when the digital transformation of downstream partners is higher, the number of green patent applications of upstream enterprises is usually higher. The results of the study show that there is a direct causal relationship, but that this model is related to changes in the way of information exchange and coordination within the supply chain, which can reduce the uncertainty of green innovation activities. This relationship is more obvious in upstream enterprises in non-heavy pollution industries and enterprises with relatively strong technological foundations, which may be more flexible in innovative activities. In summary, the research results show that the digital transformation within the supply chain may affect the green innovation decision-making of the enterprise in a way that goes beyond the individual characteristics of the enterprise.

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1. Introduction

Against the background of China's carbon neutrality goal, enterprises are facing increasing pressure and need to adjust their production and innovation strategies. Among various countermeasures, green innovation has become important to maintain competitiveness while meeting environmental requirements. By improving resource use and reducing negative environmental impacts, green innovation can influence both firms' environmental performance and their longer-term development prospects. Therefore, researchers and policymakers are paying more and more attention to the driving factors behind enterprises' participation in green innovation. Over the past ten years, the integration between digital technologies and everyday industrial operations has become increasingly strong. Technologies are not only used to support production activities, but also to assist coordination and decision-making. However, such studies usually regard enterprises as relatively independent individuals.

In many industries, innovation activities do not take place within isolated enterprises, but in stable supply chain relationships. Upstream and downstream partners interact repeatedly through transactions, information exchange and technical cooperation. In this case, the digital transformation carried out by downstream enterprises may affect the innovative ways of upstream suppliers. For example, a more perfect digital system. It can improve the transparency of demand information and reduce the uncertainty of production plans. They may also alter coordination practices between firms, which can shape upstream firms' willingness and ability to invest in green innovation.

Empirical research has so far provided limited direct evidence on how digital transformation undertaken by downstream firms is related to green innovation activities among upstream suppliers, despite the practical relevance of this issue. Much of the existing work does not explicitly examine this relationship within a supply chain setting. In light of this, the present analysis focuses on upstream–downstream linkages and explores whether downstream digitalization is associated with changes in upstream firms' green innovation behavior, using matched data from Chinese listed firms. Early studies on supply chains concentrated on the role of stable trading relationships and examined how such stability affects coordination and collaborative outcomes (Fan and Goyal, 2006; Carvalho, 2014). Alongside this strand of research, work on digital technologies gradually began to document how digital tools alter value creation processes and coordination practices within firms and across organizational boundaries. From a broader level, digitalization is closely related to industrial upgrading and the transformation of global value chain organizations (Bloom et al., 2012; Brynjolfsson et al., 2021), while evidence at the enterprise level shows that reductions in information asymmetry and improvements in coordination and decision-making are associated with higher operational efficiency and innovation management (Bharadwaj et al., 2013; Vial, 2021; Bloom et al., 2013). In recent years, sustainability considerations have become more and more prominent in supply chain research. More and more studies emphasize

environmental regulations, ESG-related pressures and how collaborative practices in the green supply chain affect the innovative behavior of enterprises (Porter and van der Linde, 1995; Rennings, 2000; Horbach et al., 2012). Within this literature, green innovation across different stages of the supply chain is commonly viewed as an important element of sustainable production systems.

In the relevant literature, green innovation at all stages of the supply chain is generally considered an important component of a sustainable production system. The mechanisms discussed in the literature help explain why the results of green innovation are interrelated among supply chain partners. Downstream enterprises can influence upstream innovative decision-making through demand-related information and technical requirements, and digitalization can strengthen these connections by promoting the dissemination of information exchange and technical standards (Yue, 2025; Luo et al., 2024). Furthermore, regional regulations can encourage industries to adopt clean technologies, and their influence can also be extended throughout the entire supply chain (Aghion et al., 2016; Popp, 2002). In addition to these factors, the closer coordination brought by digital tools can reduce the uncertainty and adjustment costs related to green innovation, making collaborative innovation more feasible. Although these research directions provide relevant insights, they do not conduct a unified empirical assessment of how the digital transformation of downstream enterprises is associated with upstream green innovation in different industries and enterprise conditions. In order to solve this problem, this study examines the relationship between downstream digitalization and upstream green innovation, taking into account the pollution intensity of the industry and the differences in the technical capabilities of enterprises. Recent evidence shows that ESG-related practices and performance play a role in disseminating sustainability-related expectations among enterprises connected through supply chain relationships (Zheng and Zhang, 2023). In this context, this study focuses on the spillover effect of digital transformation in downstream industries on green innovations in upstream industries. This article takes the green innovation of upstream enterprises as the research object, and examines how downstream digitalization can reshape the information flow, resource allocation and innovation in the supply chain motivation.

This article first reviews the relevant literature, and then outlines the research design and empirical methods. Next, this article introduces the empirical evidence. Analysis and a series of robustness tests, and finally concluding comments and discussions on broader meanings.

2. Literature Review

Enterprise green innovation is widely regarded as an important micro-driving force to promote the green transformation of economic and social development. Early research mainly explains the green innovation of enterprises through external regulatory pressure (Porter and van der Linde, 1995) and internal resource endowment (Rennings, 2000). Recent studies have gradually turned the focus to the role of networking, cooperation and inter-enterprise links in the process of green innovation (Horbach et al., 2012; Cainelli et al., 2015). Such studies show that the environmental innovation activities of enterprises are often influenced by their position in the broader production and exchange networks, rather than being determined solely by internal decision-making. As digital technology is increasingly integrated into supply chain management practice, the way of information exchange and production coordination of enterprises is also changing. These changes may also affect the formation and transmission of innovation-related incentive mechanisms in different links of the supply chain. In this sense, digital transformation, green innovation and supply chain collaboration are closely intertwined, and studying their interactions helps to clarify how digitalization can reshape innovative behavior outside a single enterprise.

Numerous studies have investigated the relationship between the digital transformation of companies and green innovation outcomes. From the perspective of resource base, digital transformation is usually described as the process of enterprises adjusting their strategic resource utilization and organizational practices (Vial, 2021; Bharadwaj et al., 2013). Empirical research shows that digital technology can support innovation by improving research and development processes and promoting internal coordination (Brynjolfsson et al., 2021), as well as easing financial constraints (Fang et al., 2014). Other studies emphasize that digital transformation helps enterprises absorb knowledge and improve production processes, both of which are closely related to the development of green technology (Chen et al., 2014). At the operational level, digital tools can also influence green innovation by changing daily production and management practices. By reducing information asymmetry and transaction costs, digitalization can release the attention and resources of managers, otherwise these resources may be consumed by coordination problems, making it easier for enterprises to carry out long-term green research and development activities (Bloom et al., 2013; Wamba et al., 2017). These studies mainly focus on the internal operation mechanism of the enterprise. By contrast, downstream firms are often treated as sources of demand or regulatory pressure in studies of green innovation, with relatively little discussion of how changes in downstream firms themselves affect upstream suppliers. In particular, the implications of downstream firms' digital transformation for upstream innovation incentives remain underexplored.

Related evidence from the supply chain and digitalization literature offers some useful clues. Research on production networks and supply chain relationships shows that when leading firms improve information and coordination systems,

suppliers may benefit from better information access and financing conditions, thereby supporting innovation-related activities (Barrot and Sauvagnat, 2016; Yue, 2025). In addition, the industrial Internet platform can transmit production and environmental data upstream in a more timely manner. These data can provide clearer feedback on production status and environmental performance, thus improving predictability and reducing information-related risks in green innovation activities (Luo et al., 2024). Recent studies have also recorded some cases, showing that downstream digitalization affects changes in upstream innovation behavior through market interaction (Zheng and Zhang, 2023). In summary, the main focus of the current literature is on the relationship between digital transformation and green innovation within businesses, rather than on their effects beyond the supply chain. How downstream digitalization interacts with industry characteristics and enterprise capabilities, and thus affecting upstream green innovation, these questions still need to be answered.

In response to this problem, the study employs a vertical supply chain perspective to examine the relationship between the digital transformation of downstream enterprises and the green innovations of upstream enterprises. By using detailed upstream and downstream relationship data, this study focuses on analyzing how differences in pollution intensity and technical capabilities in the industry affect this relationship. The research results help to gain a deeper understanding of how digitalization affects green innovation through supply chain connections.

3. Model Specification, Variables, and Data

3.1 Model Specification

In order to verify the impact of digitalization of downstream enterprises on the green innovation of upstream enterprises, this paper establishes the following benchmark regression model:

$$\text{Patent/InvPatent/UPatent}_{i,t} = \alpha + \beta \text{Digital } S_{j,t} + \gamma CV + \text{year}_t + d_i + \varepsilon_{ijt} \quad (1)$$

Among these, the dependent variable $\text{Patent}_{i,t}$, $\text{InvPatent}_{i,t}$ and $\text{UPatent}_{i,t}$ represent the green innovation level of upstream firm i in year t , while the core explanatory variable $\text{Digital } S_{j,t}$ measures the digital transformation level of downstream client firm j in year t , CV denotes a set of control variables, d_i and year_t represent firm fixed effects and year fixed effects, respectively, and ε_{ijt} is the random disturbance term.

3.2 Variable Selection

3.2.1 Core Explanatory Variable

Regarding the conceptualization of enterprise digital transformation, the existing literature generally believes that it is not just a simple digitalization of information or tangible assets. On the contrary, prior studies suggest that digital transformation

involves the extensive application of digital technologies across firms' production, management, and operational activities, which may reshape organizational processes and value creation mechanisms (Bharadwaj et al., 2013; Vial, 2021). Previous studies further pointed out that digital transformation is closely related to the application of basic digital technologies such as artificial intelligence, cloud computing, big data analysis and blockchain and their application in specific business environments. Prior studies suggest that the adoption of digital technologies often requires complementary organizational and process changes, which can enhance operational efficiency and ultimately contribute to new forms of value creation (Brynjolfsson et al., 2021; Wamba et al., 2017). From a broader perspective, some studies regard digital transformation as a systematic process that connects digital technology with industrial activities. This process goes beyond a one-time technical upgrade and involves changes in organizational practices. Previous studies show that improvements in coordination, decision-making, and innovation-related activities are associated with higher firm productivity (Bloom et al., 2012; Brynjolfsson et al., 2021). At the measurement level, recent studies emphasize that corporate digital transformation should be treated as a multidimensional and ongoing process. Accordingly, text-based measures constructed from corporate disclosures have been increasingly used to capture firms' digital transformation at the micro level. These studies highlight that digitalization involves strategic orientation, business models, operational and production-related processes, and information infrastructure simultaneously (Vial, 2021; Zheng and Zhang, 2023).

Following this literature, this paper constructs a firm-level digital transformation indicator based on textual analysis of corporate disclosures. Using an updated database of annual reports, this study identifies keywords related to digital transformation in four dimensions: the use of digital technologies, Internet-based business models, intelligent manufacturing and modern information systems. Word segmentation and frequency statistics are then applied to calculate the disclosure frequency of these characteristic terms. Finally, the natural logarithm of one plus the total frequency of digital transformation-related keywords is used as the measure of corporate digital transformation, which helps reduce skewness and improve distributional properties (Zheng and Zhang, 2023; Yue, 2025).

3.2.2 Core Dependent Variable

The dependent variable in this study is the quantity of green innovations by upstream enterprises (*Patent*), measured by the logarithm of the total number of green innovation patent applications filed by upstream enterprises plus one. WIPO categorizes its international green patent classification into seven groups, distinguishing between invention patents and utility model patents. Invention patents are generally considered to represent higher-quality innovation. Therefore, the logarithm of the total number of green invention patent applications filed by upstream enterprises plus one (*InvPatent*) is used as the measure of green

innovation invention quality. Subsequently, the logarithm of the total number of green utility model patent applications filed by upstream enterprises plus one (*UPatent*) is employed as the measure of green innovation utility quality.

3.2.3 Control Variables

This research studies the factors as influencing corporate green innovation, specifically including: age of upstream firms, return on assets (ROA) of upstream firms, Tobin's Q ratio of upstream firms, book-to-market ratio (BM) of upstream firms, cash ratio of upstream firms, and total asset growth rate. Among these, the age of upstream firms (*Age*) is measured using the logarithm of the current year minus the year of the firm's IPO plus one.

Table 1: Variable Definitions for Econometric Model

Variable Symbol	Description
InvPatent	Upstream Enterprise Green Innovation Invention Quality
UPatent	Upstream Enterprise Green Innovation Utility Quality
Patent	Upstream Enterprise Green Innovation
DigitalS	Downstream Enterprise Digital Transformation
Age	Upstream Enterprise Age
ROA	Upstream Enterprise Return on Assets
Tobin	Upstream Enterprise Tobin's Q Ratio
BM	Upstream Enterprise Book-to-Market Ratio
Cashratio	Upstream Firm Cash Ratio
Growth	Upstream Firm Total Assets Growth Rate

3.3 Data Description

This study uses supply chain relationship data for the top five suppliers of Shanghai and Shenzhen A-share listed firms from 2008 to 2022 as the research sample. Financial data, supply chain information, green innovation patent data, and measures of digital transformation are obtained from the CSMAR database and the CNRDS database. The raw data are processed as follows. First, firm-year observations labeled as ST, *ST, or PT during the sample period are excluded. Second, observations with missing financial data or green innovation patent data are removed. It should be noted that the CNRDS database reports only the top five suppliers of each firm. To reduce potential measurement bias caused by unobserved long-term supply relationships, this study adopts the following assumption based on existing research: once a firm appears in the top five supplier list, it is assumed

to maintain a supply relationship with the focal firm for five years before its first appearance and five years after its last appearance. After applying these screening and adjustment procedures, the final sample consists of 5,014 supply chain-year observations.

Table 2: Descriptive Statistics of Key Variables

VarName	Obs	Mean	SD	Min	Max
Patent	5014	0.319	0.723	0.000	5.464
InvPatent	5014	0.275	0.693	0.000	5.759
UPatent	5014	0.250	0.607	0.000	5.587
Age	5014	2.062	0.889	0.000	3.434
ROA	5014	0.036	0.455	-4.741	22.005
Tobin	5014	1.970	2.015	0.692	69.244
BM	5014	0.652	0.250	0.014	1.444
Cashratio	5014	0.166	0.140	0.001	0.884
Growth	5014	0.388	5.905	-0.740	287.966

4. Main Results

4.1 Benchmark Results Analysis

Table 3 reports the benchmark regression results. Columns (1) and (4) use upstream firms' green innovation output as the dependent variable (*Patent*). Columns (2) and (5) use the invention quality of upstream firms' green innovation as the dependent variable (*InvPatent*). Columns (3) and (6) use the *Patent* utility model quality of upstream firms' green innovation as the dependent variable (*UPatent*).

Columns (1), (2), and (3) report the regression results without control variables. The estimated coefficients of *DigitalS* on *Patent*, *InvPatent* and *UPatent* are 0.033, 0.030, and 0.022, respectively. All coefficients are statistically significant at the 1% level. Columns (4), (5), and (6) further include control variables. After adding these controls, the estimated coefficients of *DigitalS* increase to 0.038, 0.036, and 0.029, respectively. These coefficients remain statistically significant at the 1% level. Overall, the results indicate that downstream firms digital transformation significantly promotes upstream firms' green innovation. This finding provides strong support for the research hypothesis of this paper.

Table 3: Benchmark Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent	InvPatent	UPatent	Patent	InvPatent	UPatent
DigitalS	0.033***	0.030***	0.022***	0.038***	0.036***	0.029***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)
Age				-0.003	-0.004	-0.023**
				(0.013)	(0.013)	(0.011)
ROA				0.002	0.009	0.002
				(0.022)	(0.021)	(0.018)
Tobin				-0.010*	-0.004	-0.001
				(0.006)	(0.006)	(0.005)
BM				0.243***	0.281***	0.353***
				(0.056)	(0.055)	(0.048)
Cashratio				-0.022	-0.050	-0.136**
				(0.081)	(0.079)	(0.069)
Growth				0.003*	0.001	0.002
				(0.002)	(0.002)	(0.001)
Fixed Effects	yes	yes	yes	yes	yes	yes
N	5014	5014	5014	5014	5014	5014
Adj. R²	0.069	0.047	0.054	0.076	0.055	0.070

*** p<0.01. ** p<0.05. * p<0.1.

4.2 Robustness Checks

To enhance the credibility of the benchmark regression results, this study conducts a series of robustness tests from the following two aspects.

(1) Alternative measurement of the dependent variable. The benchmark regression focuses on the quantity of green innovation. To further examine innovation quality, this study replaces the dependent variable with a measure of green innovation efficiency. Specifically, green innovation efficiency is measured as the ratio of a firm's total green patent applications to its total patent applications in a given year. In addition, a dummy variable is constructed to capture whether a firm engages in green innovation. If the organization submits at least one green patent application in a given year, then the dummy variable equals one; otherwise, it equals zero. Table 4 reports the results of these robustness tests. Columns (1) and (2) use green innovation efficiency (*EffPatent*) and the green innovation dummy variable (*Patent_dummy*) as dependent variables, respectively. Both regressions include control variables. The estimated coefficients of *DigitalS* on *EffPatent* and *Patent_dummy* are 0.010 and 0.027, respectively, and are statistically significant at the 1% level. These results support the main hypothesis of this paper.

(2) Alternative measurement of the explanatory variable. The baseline regression measures downstream firms' digital transformation using the logarithm of the total frequency of digital transformation-related terms in the current year plus one.

According to this definition, a company's digital transformation is defined as the integration of core digital technologies, such as artificial intelligence, blockchain, cloud computing, and big data, and their effective application to business operations. Based on this definition, a feature-word dictionary for enterprise digital transformation is constructed. As an alternative measure, this study uses the logarithm of downstream firms' digital transformation plus one as a proxy for digital transformation intensity. Compared to the indicator based on the initial text, this indicator presents companies' digital transformation from a broader and more systematic perspective. Table 4 reports the corresponding regression results. Columns (3), (4), and (5) use upstream firms' green innovation output (*Patent*), green invention patent quality (*InvPatent*), and green utility model patent quality (*UPatent*) as dependent variables, respectively. All regressions include control variables. The regression coefficients for DigitalS on *Patent*, *InvPatent*, and *UPatent* are 0.050, 0.055, and 0.024, respectively, and are all statistically significant at the 1% level. These findings further confirm the initial observations.

Table 4: Robustness Checks Results: Alternative Measurement of the Dependent Variable and Alternative Measurement of the Explanatory Variable

	(1)	(2)	(3)	(4)	(5)
	EffPatent	Patent_dummy	Patent	InvPatent	UPatent
DigitalS	0.010***	0.027***			
	(0.002)	(0.005)			
DigitalS1			0.050***	0.055***	0.024***
			(0.009)	(0.009)	(0.008)
Age	-0.009***	0.000	-0.006	-0.008	-0.025**
	(0.003)	(0.007)	(0.013)	(0.013)	(0.011)
ROA	-0.001	0.001	0.003	0.011	0.002
	(0.005)	(0.012)	(0.022)	(0.021)	(0.018)
Tobin	-0.003**	-0.007**	-0.010	-0.003	-0.001
	(0.001)	(0.003)	(0.006)	(0.006)	(0.005)
BM	0.018	0.162***	0.245***	0.286***	0.350***
	(0.013)	(0.032)	(0.056)	(0.055)	(0.048)
Cashratio	-0.009	-0.015	-0.042	-0.076	-0.139**
	(0.018)	(0.046)	(0.081)	(0.079)	(0.069)
Growth	0.000	0.002**	0.003*	0.001	0.002*
	(0.000)	(0.001)	(0.002)	(0.002)	(0.001)
Fixed Effects	yes	yes	yes	yes	yes
N	5014	5014	5014	5014	5014
Adj. R²	0.071	0.074	0.078	0.059	0.070

(3) Add control variables. Based on the control variables used in the benchmark regression, which mainly capture upstream firm characteristics, this study further includes downstream firm-level controls. These variables include downstream firm age (*AgeS*), return on assets (*ROAS*), Tobin's Q (*TobinS*), book-to-market ratio (*BMS*), cash ratio (*CashratioS*), and total asset growth rate (*GrowthS*). Among them, downstream firm age (*AgeS*) is measured as the logarithm of the current year minus the firm's IPO year plus one. Table 5 reports the estimation results. Columns (1), (2), and (3) use upstream firms' green innovation quantity (*Patent*), green invention quality (*InvPatent*), and green utility model quality (*UPatent*) as dependent variables, respectively. The regression results show that the coefficients of *DigitalS* on *Patent*, *InvPatent*, and *UPatent* are 0.034, 0.031, and 0.028, respectively. All coefficients are significant at the 1% level, which further supports the main hypothesis of this study.

(4) Lagged explanatory variable. The explanatory variable is re-measured using one-year lagged downstream digital transformation data. Considering the potential time lag in the spillover effects of downstream firms' digital transformation, this study uses the logarithm of one plus the total frequency of digital transformation-related keywords, lagged by one year, as the explanatory variable in the robustness test. Table 5 reports the corresponding results. Columns (4), (5), and (6) use upstream firms' green innovation quantity (*Patent*), green invention quality (*InvPatent*), and green utility model quality (*UPatent*) as dependent variables, respectively. Control variables are included in all specifications. The regression coefficients for *DigitalS* on *Patent*, *InvPatent*, and *UPatent* are 0.030, 0.026, and 0.023, respectively, and remain significant at the 1% level. This indicates that the baseline conclusions remain robust after accounting for lagged effects.

Table 5: Robustness Checks Results: Add Control Variables and Lagged Explanatory Variable

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent	InvPatent	UPatent	Patent	InvPatent	UPatent
DigitalS	0.034***	0.031***	0.028***			
	(0.009)	(0.009)	(0.008)			
DigitalS_lag				0.030***	0.026***	0.023***
				(0.009)	(0.009)	(0.008)
AgeS	-0.018	-0.018	-0.042***			
	(0.013)	(0.013)	(0.011)			
ROAS	-0.012	0.001	0.024			
	(0.031)	(0.030)	(0.026)			
TobinS	-0.009	-0.002	0.001			
	(0.009)	(0.008)	(0.007)			
BMS	-0.034	0.007	0.155***			
	(0.056)	(0.055)	(0.047)			
CashratioS	0.187*	0.247***	0.024			
	(0.098)	(0.095)	(0.083)			
GrowthS	-0.001	-0.001	-0.000			
	(0.002)	(0.002)	(0.002)			
Age	-0.004	-0.005	-0.024**	-0.003	-0.003	0.000
	(0.013)	(0.013)	(0.011)	(0.013)	(0.013)	(0.013)
ROA	0.003	0.010	0.002	0.001	0.001	0.008
	(0.022)	(0.021)	(0.018)	(0.022)	(0.022)	(0.021)
Tobin	-0.010	-0.003	-0.001	-0.010*	-0.010*	-0.004
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
BM	0.268***	0.303***	0.345***	0.244***	0.244***	0.271***
	(0.058)	(0.056)	(0.049)	(0.058)	(0.058)	(0.056)
Cashratio	-0.043	-0.070	-0.144**	-0.033	-0.033	-0.040
	(0.082)	(0.079)	(0.069)	(0.085)	(0.085)	(0.082)
Growth	0.003*	0.001	0.002*	0.003*	0.003*	0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Fixed Effects	yes	yes	yes	yes	yes	yes
N	5014	5014	5014	4775	4775	4775
Adj. R²	0.077	0.056	0.074	0.076	0.054	0.071

The results of the regression analysis consistently show that the digital transformation of downstream companies has a significant positive impact on the green innovations of upstream companies. The results suggest that upstream firms become more involved in green innovation activities in the presence of downstream digital transformation, potentially supporting greener supply chain development. The overall pattern remains consistent with the benchmark results.

4.3 Heterogeneity Analysis

(1) Heavy pollution industries. Listed companies are classified as high-polluting or low-polluting industries based on standard industry criteria. Companies operating in high-polluting industries must comply with strict environmental requirements, bear higher compliance costs, and face greater public scrutiny. Therefore, their green innovation activities are mainly driven by compliance motivation. Their digital investment mainly focuses on terminal management and pollution monitoring. These investments have a limited short-term impact on green patent output. In contrast, the external constraints faced by enterprises in non-heavy pollution industries are relatively weak. Their digital transformation is more likely to improve the entire production process, including cleaner production methods and circular economy practices. These changes directly support the emergence of source-based green patents.

Table 6 reports the heterogeneity analysis results. Columns (1) and (4) present the regression results for upstream firms' green innovation output (*Patent*). Columns (2) and (5) report the results for green invention patent quality (*InvPatent*). Columns (3) and (6) report the results for green utility model patent quality (*UPatent*). Columns (1), (2), and (3) show the results for heavily polluting industries. The estimated coefficients of DigitalS on *Patent*, *InvPatent*, and *UPatent* are -0.013, -0.002, and 0.019, respectively. Columns (4), (5), and (6) present the results for non-heavily polluting industries. The corresponding coefficients are 0.056, 0.048, and 0.028, respectively, and are statistically significant at the 1% level. As a result, it is evident that digital transformation strongly encourages green innovation in industrial companies with low pollution levels. On the other hand, its impact is weak or non-existent in the most polluting sectors.

Table 6: Heterogeneity Analysis Results: Heavy Pollution Industries

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent	InvPatent	UPatent	Patent	InvPatent	UPatent
	Heavily polluting industries			Non-heavily polluting industries		
DigitalS	-0.013	-0.002	0.019	0.056***	0.048***	0.028***
	(0.015)	(0.017)	(0.015)	(0.012)	(0.011)	(0.009)
Age	-0.062***	-0.188***	-0.136***	0.020	0.067***	0.023*
	(0.022)	(0.025)	(0.021)	(0.016)	(0.014)	(0.013)
ROA	-0.292	-0.142	-0.489***	0.005	0.010	0.005
	(0.186)	(0.210)	(0.178)	(0.023)	(0.021)	(0.018)
Tobin	-0.032	0.022	0.035	-0.009	-0.006	-0.004
	(0.024)	(0.027)	(0.023)	(0.007)	(0.006)	(0.005)
BM	0.039	0.297**	0.417***	0.324***	0.330***	0.384***
	(0.120)	(0.136)	(0.115)	(0.072)	(0.065)	(0.057)
Cashratio	-0.105	-0.571***	-0.365**	-0.004	0.082	-0.084
	(0.156)	(0.176)	(0.149)	(0.098)	(0.088)	(0.078)
Growth	-0.004	-0.016	-0.008	0.003	0.001	0.002
	(0.015)	(0.017)	(0.014)	(0.002)	(0.002)	(0.001)
Fixed Effects	yes	yes	yes	yes	yes	yes
N	1634	1634	1634	3380	3380	3380
Adj. R²	0.021	0.051	0.056	0.089	0.081	0.094

(2) High-tech enterprises. Following existing classification standards, firms are divided into high-tech and non-high-tech enterprises. High-tech firms possess stronger R&D human capital and more advanced digital infrastructure. These advantages support the integration of digital technologies into supply chain collaboration platforms. Through such platforms, coordination with upstream suppliers is improved. Digital collaboration platforms provide upstream firms with real-time information on production processes, material inputs, and energy use. This reduces learning costs related to green technologies and lowers innovation uncertainty. As a result, high-tech downstream firms are more effective in stimulating upstream green patent output. By contrast, non-high-tech firms have weaker digital capabilities and lower incentives to invest in digital collaboration. Their downstream partners also show lower sensitivity to environmental requirements. As a result, the digital spillover effect on upstream green innovation is limited.

Table 7 reports the heterogeneity analysis results. Columns (1) and (4) present the regression results for upstream firms' green innovation output (*Patent*). Columns (2) and (5) report the results for green invention patent quality (*InvPatent*). Columns (3) and (6) report the results for green utility model patent quality (*UPatent*). Columns (1), (2), and (3) show the results for supply chains led by high-tech firms. The estimated coefficients of *DigitalS* on *Patent*, *InvPatent*, and *UPatent* are 0.039, 0.038, and 0.027, respectively, and are statistically significant

at the 1% level. Columns (4), (5), and (6) show the results for supply chains led by non-high-tech firms. The corresponding coefficients are 0.007, -0.002, and 0.031, respectively. Overall, the results indicate that downstream digital transformation significantly promotes upstream green innovation when downstream firms are high-tech enterprises, while the effect is weak or insignificant for non-high-tech enterprises.

Table 7: Heterogeneity Analysis Results: High-tech Enterprises

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent	InvPatent	UPatent	Patent	InvPatent	UPatent
	High-tech enterprises			Non-high-tech enterprise		
DigitalS	0.039***	0.038***	0.027***	0.007	-0.002	0.031
	(0.010)	(0.010)	(0.009)	(0.019)	(0.018)	(0.019)
Age	0.004	0.001	-0.030**	-0.006	0.013	0.029
	(0.015)	(0.014)	(0.012)	(0.023)	(0.022)	(0.024)
ROA	0.004	0.010	0.005	-0.360**	-0.068	-0.467***
	(0.023)	(0.022)	(0.019)	(0.174)	(0.164)	(0.178)
Tobin	-0.008	-0.001	0.001	-0.031	-0.027	-0.033
	(0.006)	(0.006)	(0.005)	(0.028)	(0.026)	(0.028)
BM	0.308***	0.327***	0.394***	-0.076	0.129	0.101
	(0.064)	(0.062)	(0.053)	(0.135)	(0.128)	(0.138)
Cashratio	-0.027	-0.055	-0.136*	0.089	0.063	-0.000
	(0.091)	(0.089)	(0.076)	(0.156)	(0.147)	(0.159)
Growth	0.003	0.001	0.002	0.003	-0.026	-0.006
	(0.002)	(0.002)	(0.001)	(0.032)	(0.030)	(0.033)
Fixed Effects	yes	yes	yes	yes	yes	yes
N	4232	4232	4232	780	780	780
Adj. R²	0.081	0.059	0.082	0.055	0.076	0.044

5. Conclusions and Recommendations

Against the joint background of carbon neutrality targets and the expansion of the digital economy, this study examines how digital transformation undertaken by downstream firms is connected to green innovation outcomes among upstream firms within Chinese supply chains. The analysis uses the supply chain relationship data of Chinese A-share listed companies from 2008 to 2022 to record the systematic connection between downstream digitalization and upstream green innovation activities.

Specifically, when downstream partners show a higher level of digital transformation, upstream enterprises are more likely to participate in green patent applications. This model is reflected in both green invention patents and green utility model patents, and persists in different model settings and measurement methods. Evidence shows that digital transformation is not limited to enterprises that directly invest in digital technology, but can have a spillover effect and extend upstream through supply chain relationships.

Further research shows that this relationship is inconsistent among different enterprises. Among the upstream enterprises of non-heavy pollution industries, downstream digital transformation is more closely related to green innovation activities. In contrast, this relationship seems to be much weaker for enterprises in heavily polluted industries, which may be related to stricter regulatory constraints and higher adjustment costs. In addition, upstream enterprises with stronger technical capabilities have shown a clearer response to downstream digital transformation, which is consistent with the view that the absorption capacity determines the ability of enterprises to transform external digital signals into innovative results.

In addition to these empirical models, the research results are also of great significance to policy design. They show that promoting digital collaboration in the supply chain can complement enterprise-level policies aimed at promoting green innovation. For example, a shared digital platform that promotes the exchange of information on energy use, carbon accounting and environmental standards can help reduce the uncertainty faced by upstream enterprises. At the same time, the research results show that it is crucial to adjust the policy method according to the characteristics of the industry. Digital supply chain initiatives may be more effective in industries with higher technological flexibility, while industries with severe pollution may require a combination of regulatory supervision and targeted support for digital infrastructure upgrading.

Finally, the analysis emphasizes the role of institutional arrangements for managing data sharing between enterprises. Strengthening the data governance framework and encouraging the mutual recognition of environmental certification can reduce transaction costs and improve digital signal transmission along the supply chain. Such arrangements help to strengthen demand-oriented green innovation incentives while avoiding the adoption of unified policies in heterogeneous industries.

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