sustainability

Article

The Impact of Digital Trade Development on Regional Green Innovation

Jingyi Liang and Cuixia Qiao *

School of Economics, Shandong Normal University, Jinan 250300, China; 202227230111@stu.sdnu.edu.cn
* Correspondence: cuixiaqiao@163.com

Abstract: Using provincial panel data from China spanning 2011 to 2022, this paper analyzes the impact, mechanisms, and regional differences in digital trade's effects on regional green innovation. It also explores the threshold effect between digital trade and green innovation, with environmental regulation serving as the threshold variable. The results indicate the following: first, after accounting for government intervention, foreign direct investment, human capital, industrialization, information technology infrastructure, and economic development, digital trade significantly promotes regional green innovation. This conclusion remains valid after a series of robustness tests. Second, digital trade promotes regional green innovation through three mechanisms: accelerating industrial structure upgrading, promoting industrial agglomeration, and enhancing technology transfer. Third, environmental regulation leads to a non-linear relationship between digital trade and green innovation. Higher levels of environmental regulation make digital trade's contribution to green innovation more significant. Finally, the effects of digital trade on green innovation vary by region in China. This impact is more pronounced in eastern provinces, regions with advanced digital economies, areas with well-developed transport infrastructure, and provinces with a higher degree of trade openness. These findings hold substantial implications for advancing green innovation and promoting sustainable social development in China.

Keywords: digital trade; green innovation; industrial structure upgrade

check for updates

Citation: Liang, J.; Qiao, C. The Impact of Digital Trade Development on Regional Green Innovation. *Sustainability* **2024**, *16*, 10090. https://doi.org/10.3390/su162210090

Academic Editor: Bruno Barbosa Sousa

Received: 4 October 2024
Revised: 7 November 2024
Accepted: 18 November 2024
Published: 19 November 2024

1. Introduction

As a new form of trade, digital trade has unique advantages and potential. In the era of continuous global economic integration, digital trade is significantly changing the global economic landscape [1,2]. The report of the Twentieth Party Congress emphasizes the need to "promote the optimization and upgrading of trade in goods, innovate the mechanism for the development of trade in services, promote digital trade, and accelerate the construction of a strong trading nation". With the rapid development of information technology, digital trade has become a key driver of high-quality economic growth [3,4]. Its advancement facilitates the sharing of information and technology, accelerated the flow of goods and services, and deepened the optimization of industrial structure [5]. It also provides robust technical support for regional green innovation and brings new vitality to the high-quality development of regional economies. As a key engine of economic growth [6], regional green innovation is closely tied to the competitiveness and sustainable development potential of the regional economy. On the one hand, regional innovation promotes industrial transformation, strengthening the core competitiveness of a regional economy. On the other hand, it enhances the region's position in the global industrial and value chains, pushing regional economic development to a higher level [7].

The swift advancement of digital trade expands opportunities and provides greater potential for environmentally conscious innovation [8]. First, digital trade overcomes time and space limitations, enabling the optimal allocation and efficient use of innovation resources. It also promotes cross-border integration and innovation, fostering new drivers of economic growth [9]. Second, digital trade introduces new business models and industrial forms, facilitating the digital and low-carbon transformation of traditional industries [3]. This promotes deep integration within the industrial and value chains, laying a stronger foundation for regional green innovation. Furthermore, the openness and inclusiveness of digital trade encourage cultural exchanges and the exchange of ideas across regions, providing broader perspectives and inspiring new approaches to innovation. Based on this premise, this study constructs a theoretical framework and establishes empirical models to explore how digital trade growth influences green innovation and its specific mechanisms.

The marginal contributions of this paper have the following aspects. Firstly, by using the super-efficiency SBM method to measure green innovation, the limitation of entropy weight method used in most existing studies is broken. At the same time, by examining the influence of digital trade on regional green innovation, the paper expands the scope of research regarding the factors driving green innovation. It also provides practical insights for fostering corporate innovation, R&D, and promoting green development. Second, by analyzing the influence of digital trade on regional green innovation ability, this paper enriches the internal mechanism of driving regional green innovation. This analysis provides a scientific basis for formulating more precise and effective policy interventions. Thirdly, the threshold effect of digital trade and green innovation when environmental regulation is a threshold variable is discussed. It reveals the specific changes in the degree of impact of digital trade on green innovation under different levels of environmental regulation. It provides a practical basis for policy makers to design environmental regulations. Finally, by studying the heterogeneous impact of digital trade on regional green innovation, this paper not only improves our understanding of regional differences in this impact but also supports the development of differentiated regional policies. These findings are significant for promoting sustainable regional development, strengthening inter-regional economic ties and interactions, and facilitating resource sharing and complementarity.

2. Literature Review

The impact effects of digital trade have been extensively studied in the existing literature. In terms of economic benefits, the growth of digital trade has played an important role in promoting economic prosperity [10,11], and the application of big data and the Internet has enabled innovation across a range of industries. First, digital trade significantly enhances access to and processing of information, allowing firms to understand international market dynamics quickly and accurately. This, in turn, enhances the technological sophistication of manufacturing exports [12]. Second, digital trade facilitates the integration and innovation of logistics transit hubs, which improves transit efficiency, reduces costs, and offers new possibilities for optimizing transportation [13]. Third, smart grids are a product of the convergence of digital trade and emerging technologies. They utilize ICT and automation technologies to enable intelligent monitoring, scheduling, and management of power grids. This enhances the reliability and economics of the grid while creating a framework for the broader application of developing technologies in the energy supply [14]. In terms of eco-efficiency, as digital trade advances, infrastructure is improved and resource efficiency is further enhanced. This not only promotes green technological advances [15] and enhances green productivity [16], but also accelerates technological innovation while ensuring ecological sustainability [17]. In addition, the widespread adoption of renewable energy and low-carbon technologies across all sectors can help optimize business inventory management, reduce unnecessary transportation and warehousing costs, and encourage the spread of online consumption. This will increase the efficiency of production, transportation, and distribution and significantly reduce carbon emissions [18] and ecological footprint [19]. In addition, Wang et al. (2023) argued that the adverse effects of uncertain economic policies on increasing resource footprints can be mitigated by digital trade [20].

Scholars have also extensively discussed the influencing factors of regional green innovation. First, in terms of government intervention, Chen et al. (2020) argue that while abundant natural resources may hinder innovation, government intervention can positively impact innovation [21]. Specifically, digital government transformation promotes the development of green finance, the gathering of green talent [22], and the establishment of a digital society [23], all of which contribute positively to regional green innovation. Moreover, government subsidies play a role in filling the R&D funding gap of enterprises, effectively alleviating the risk–return asymmetry, reducing the risks faced by enterprises, and encouraging them to engage in green innovation [24]. Based on the above studies, it can be found that government intervention positively affects regional green innovation [25]. However, Lu et al. (2022) also emphasized that in some cases, such as in resource-depleted cities, excessive government intervention may hinder innovation by fostering zombie firms and distorting land markets [26]. Second, in terms of industrial agglomeration and cluster development, industrial structure upgrading and fostering industrial clusters have a significant impact on regional green innovation. Factors such as improved quality of invention patents [27], peer competition [28], development of digital finance [29], advancement of fintech [30], and investment in public education [31] contribute to enhancing regional green innovation. In particular, industrial clusters, recognized as key drivers of innovation [32], greatly increase the innovation efficiency of nearby cities. The strength of this enhancement effect is positively related to the level of cluster specialization [33]. Finally, from the perspective of infrastructure, the new infrastructure promoted by the government plays a significant role in fostering green innovation [34]. Yang and Ma (2023) confirmed that high-speed rail (HSR) has the ability to overcome multiple regional boundaries, shorten inter-regional distances, and promote cross-regional innovation. This is primarily realized through three mechanisms: market regulation, innovation activation, and human capital matching [35]. Moreover, after the opening of HSR, factors such as production distribution, production cost, spillover elasticity, and carbon emission will affect the choice of regional green innovation diffusion paths, which will significantly enhance the spillover effects of green innovation [36].

There is limited research on the relationship between digital trade and regional green innovation, with existing literature focusing on the relationship between the digital economy and regional green innovation. Most scholars agree that the digital transformation of enterprises has significantly promoted green technology innovation [37–39]. First, the development of the digital economy provides new financing channels and models, facilitating SMEs in obtaining innovative financial support [39]. Secondly, the digital economy improves the standardization and transparency of government funds and the market, making both the allocation of funds and the allocation of market resources more accurate and efficient. This further enhances the degree of marketization and promotes a more reasonable allocation of green innovation resources [40]. Third, the increased advancement of the digital economy enhances the ability to reduce market segmentation constraints and improve regional innovation efficiency [41].

In summary, the existing literature has explored the impact of external factors, such as government intervention and natural resources, and internal factors, such as the quality of inventions and patents, on the formation of regional green innovation. It also studies the economic benefits such as promoting economic development and ecological effects such as reducing carbon emissions brought by the development of digital trade. However, existing research can be further expanded in two main areas: first, more comprehensive studies are needed to determine how regional green innovation is impacted by the rise of digital trade. Second, elucidating the channels through which digital trade affects regional green innovation can provide valuable insights for governments to promote sustainable development. Therefore, the purpose of this study is to develop a theoretical framework to investigate the mechanisms through which digital trade affects regional green innovation and to establish an empirical model to comprehensively examine the intrinsic linkages between the two.

3. Mechanism Analysis and Research Hypothesis

Regional green innovation is closely related to the local industrial structure and industrial agglomeration. With the continuous development of digital trade, the industrial structure evolves toward high technology and high added value, resulting in the formation of industrial clusters. At this stage, rapid dissemination and sharing of knowledge among enterprises can be realized, thus promoting knowledge spillover, facilitating technology diffusion, and enhancing the ability of regions to transform knowledge into tangible results. In addition, digital trade significantly facilitates the global flow and transfer of technology through open data flows, intellectual property transactions, and cross-border cooperation projects. This technology transfer, in turn, nurtures and develops strategic emerging industries, enhancing regional green innovation by combining advanced external knowledge with local industrial practices. Based on this, this paper will conduct a theoretical analysis and propose corresponding research hypotheses.

3.1. Industrial Structure Upgrading Effect

Against the backdrop of the development of digital trade, the role of industrial structural upgrading has become increasingly prominent. By promoting the continuous integration of traditional sectors with ICT, digital trade guides industries towards higher technological content and added value, and traditional industries gradually realize digital transformation [42]. This transformation not only optimizes the production process and reduces resource consumption and pollution emissions but also improves product quality and market responsiveness and significantly enhances innovation performance [43]. At the same time, digital trade has spawned new industries such as e-commerce, digital content, and intelligent manufacturing. Relying on the core competitive advantages and broad market prospects of digital technology, these industries continue to promote the industrialization of cutting-edge green technologies and greatly enhance the regional green innovation capability [44]. Further, digital trade also reduces agency costs [37] and encourages companies to spontaneously upgrade their green strategies [45]. With the deepening of industrial structure upgrading, enterprises are increasingly required to adopt new technologies, processes, and equipment in their efforts to adapt to market changes and meet consumer demand, which directly drives the increase in R&D investment, thus enhancing green innovation capacity [46]. In addition, the upgrading of the industrial structure promotes cooperation and resource sharing among enterprises, thereby strengthening the links between the industrial chain and the supply chain. Such cooperation not only helps to reduce innovation risks but also facilitates the diffusion of knowledge and technology, which ultimately becomes a vital driver of regional green innovation and sustainable development.

3.2. Industrial Agglomeration Effect

The development of digital trade has significantly strengthened the industrial agglomeration effect. Industrial agglomeration is defined as the geographic concentration of a specific industry along with its related supporting industries or the clustering of different industries in a specific region, which creates a sustainable competitive advantage [47]. Industrial agglomeration not only greatly improves innovation efficiency [48] but also generates innovation spillover effects [49,50]. These effects are achieved by promoting information sharing, reducing transaction costs, optimizing resource allocation, and enhancing firm interaction. In terms of information sharing, advanced digital technologies and network platforms greatly enhance the convenience and efficiency of information exchange among enterprises. This significantly reduces communication costs among enterprises and is conducive to the agglomeration and development of enterprises [51]. Once a cluster is formed, enterprises can more easily share information, exchange experiences, and negotiate cooperation. These exchanges not only promote close cooperation between enterprises but also accelerate knowledge spillover and technology diffusion, allowing green innovation to be more widely applied. In addition, enterprises concentrated in the same region can use digital platforms to achieve seamless upstream and downstream connections, which makes the operation of the entire industrial chain smoother and more efficient [52]. This leads to a reduction in waste emissions and energy consumption, promoting the formation of a green industrial chain. In terms of transaction costs, digital trade promotes structural reforms in important production and development sectors, reduces economic friction and barriers, and significantly lowers transaction costs among enterprises [53]. At the same time, the digital platform also simplifies the transaction process, reduces the intermediate links, and mitigates the transaction costs caused by information asymmetry. Low-cost transactions make more enterprises willing to concentrate in one area and further reduce additional costs such as transportation and coordination through proximity [54]. A series of cost reductions enable enterprises to allocate more resources to green technology innovation and product development, thus further improving the overall level of innovation. In terms of resource allocation, digital trade, through its information technology, breaks information barriers and enables enterprises to obtain market, technology, and resource information more conveniently. This allows enterprises to enter the same agglomeration area to reduce the time and cost of searching for resources and partners [55]. The scale effect brought by such agglomeration attracts capital, talent, technology, and other innovation elements to flow accurately to this region [56], providing an adequate resource base for green innovation.

3.3. Technology Transfer Effects

With the advancement of digital trade, the technology transfer effect has produced significant results. First, digital trade accelerates the flow and sharing of technological knowledge through digital platforms. Through digital trade, advanced technology and management experience are no longer just concentrated in a specific sector or enterprise; rather, they can be spread more effectively across industrial sectors [57]. Based on this, enterprises can more easily acquire advanced green technology and knowledge and quickly apply it to the production process, promoting the rapid transfer and diffusion of technology [58]. This flow and exchange of green technological knowledge not only overcomes geographical barriers but also narrows the technology gaps, thus enhancing regional green innovation [59]. Second, digital trade enables the deep integration of technology transfer and industrial innovation. The optimization of industrial structure influenced by the digital economy serves as a channel for effective technology transfer [60]. Due to the development characteristics of digital trade, with digital technology and platforms at its core, labor-intensive industries must transform into knowledge-intensive industries [61]. This transformation increases the demand of these industries for advanced technologies from other enterprises, thus promoting technology transfer [62]. By absorbing and adjusting these technologies and experiences, the green innovation ability and market competitiveness of enterprises are continuously enhanced [19]. Finally, digital trade facilitates technology transfer by reducing associated costs and risks. Traditional technology transfer methods often involve high costs and complex procedures, while digital trade simplifies the process through digitalization, thereby reducing the risks and information asymmetry involved in the process of technology transfer [63,64] and enabling more innovations to be successfully transformed and applied. This process significantly improves the efficiency and effectiveness of regional green innovation and injects new impetus into the sustainable development of the regional economy. Based on the above analysis, the following research hypotheses are proposed.

Hypothesis 1. *Digital trade development can enhance regional green innovation.*

Hypothesis 2. *Digital trade development enhances regional green innovation through the effects of industrial structure upgrading, industrial agglomeration, and technology transfer.*

3.4. Impact of Environmental Regulation

Digital trade accelerates the flow of resources, technology, and information through information technology, Internet platforms, and big data, making innovation more efficient and globalized. Environmental regulation, as a policy tool, can influence the choice of paths and effects of green innovation in this context. On the one hand, environmental regulation amplifies the role of technology flow and information sharing in digital trade at a higher intensity, enhancing the efficiency and effectiveness of green innovation. When environmental regulations are stricter, enterprises are forced to adopt digital means to accelerate the innovation process in order to achieve environmental compliance as they face greater compliance pressure. For example, companies optimize energy consumption and production processes with IoT and big data technologies or access international advanced environmental technologies and management experience through digital platforms. In regions with looser environmental regulations, companies lack sufficient incentive to innovate. In this case, even if digital trade provides easy access to technology, it cannot be effectively transformed into green innovation. It can be seen that controlling environmental pollution is an important prerequisite for the sustainable development of China's resource-based industries, and strengthening environmental regulation is an inevitable choice to effectively promote the development of resource-based industries [65]. On the other hand, environmental regulation promotes the diffusion of green technology. Digital trade provides an efficient technology diffusion platform, which enables enterprises in different regions to acquire green technologies and innovative experiences faster. However, only with a higher level of environmental regulation will companies have an incentive to actively pursue technology transfer and cooperation. Specifically, under strict carbon or pollutant emission restrictions, enterprises may introduce low-carbon technologies from other countries or regions through digital platforms and carry out secondary development and innovation tailored to their actual needs. In less regulated contexts, enterprises lack incentives to innovate, and even if digital trade can facilitate technology transfer, the process of absorbing and transforming green technologies will still be constrained.

Hypothesis 3. *The influence of digital trade development on regional green innovation has a threshold effect.*

4. Model Specification and Variable Description

4.1. Empirical Model Construction

This paper uses a panel data model to explore the impact of digital trade expansion on regional green innovation capacity. Before constructing the model, the Hausman test method is used to determine whether fixed effects or random effects should be applied. After testing, the Hausman test statistic is 40.99 and the p-value is 0.0000, indicating that the fixed effect model is appropriate. Therefore, with reference to the study by Wang et al. (2024) [66], the following econometric model is proposed:

$$Inn_{pt} = \alpha + \beta Dig_{pt} + \gamma Control_{pt} + \mu_p + \sigma_t + \varepsilon_{pt} \tag{1}$$

where: Inn_{pt} denotes the regional innovation capacity in year t of province p. Dig_{pt} represents the level of digital trade development. $Control_{pt}$ refers to the set of control variables. μ_{pt} and σ_{pt} are added to the model to capture the fixed effects of province and year, respectively, ε_{pt} is a random error term of the equation. The coefficient β is the key parameter to be estimated, measuring the impact of digital trade on regional innovation capacity. If β is noticeably higher than 0, it certificates that the growth of digital trade benefits regional innovation.

4.2. Definition of Variables

4.2.1. Explained Variable: Regional Innovation Capacity (Inn)

Considering that green innovation is a complex concept, this paper draws on the analysis of [67] and examines it as an input–output process. Inputs include labor, capital, and energy inputs, which are the basis of green innovation. Intended output indicators include the number of patent applications, revenue from new product sales, and green coverage, all of which reflect a region's green innovation capacity. Undesirable output is represented by environmental pollution [68]. This definition comprehensively reflects that, while pursuing economic efficiency, green innovation also considers social and environmental sustainability. The specific evaluation index system is shown in Table 1. Based on this, this paper applies the super-efficiency SBM model with undesirable outputs to achieve a comprehensive evaluation of green innovation efficiency. The mathematical expressions are as follows:

$$\min\rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{p_i^-}{x_{i0}}}{1 - \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{p_r^+}{y_{r0}} + \sum_{t=1}^{q_2}\frac{p_t^{b-}}{b_{t0}}\right)}$$

$$s.t.\begin{cases} \sum\limits_{j=1,j\neq j_0}^{n} x_j\lambda_j - p^- \leq x_0(i = 1,\cdots,m) \\ \sum\limits_{j=1,j\neq j_0}^{n} x_j\lambda_j - p^- \leq x_0(i = 1,\cdots,m) \\ \sum\limits_{j=1,j\neq j_0}^{n} x_j\lambda_j - p^- \leq x_0(i = 1,\cdots,m) \\ 1 - \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{p_r^+}{y_{r0}} + \sum_{t=1}^{q_2}\frac{p_t^-}{b_{t0}}\right) > 0 \\ \lambda_j, p_i^-, p_r^+, p_t^{b-} \geq 0(j = 1,\cdots,n, j \neq j_0) \end{cases} \tag{2}$$

where: j is the individual decision-making unit (DMU); m, q_1, q_2 are the number of indicators for inputs, desired outputs, and undesired outputs, respectively; n is the number of DMUs; ρ is the efficiency value; p_i^-, p_r^+, p_t^{b-} are the slack variables for inputs, desired outputs, and undesired outputs, respectively; q_1 is the dimensionally desired output variable; q_2 is the dimensional non-desired output variable; λ_j is the intensity variable; x_j, y_j, b_j are the multi-dimensional input variables of the jth DMU, respectively; and x_0, y_0, b_0 are the input, output, and non-desired output variables of the evaluated decision unit DMU_0, respectively.

Table 1. Green innovation efficiency evaluation system.

Type of Indicator	Primary Index	Secondary Index	Unit
Input indicators	Human capital inputs	Full-time equivalent of R&D personnel	Person
	Capital investment	R&D expenditure	Ten thousand yuan
	Energy inputs	Electricity consumption	Hundreds of millions of kilowatt hours
		Completed investment in industrial pollution control	Ten thousand yuan
Expected output indicators	Technical outputs	Number of patent applications	Pieces
	Economic Benefit	Revenue from sales of new products	Ten thousand yuan
	Ecological Benefit	Greening coverage in built-up areas	%
Non-expected outputs	Negative environmental benefits	Total industrial sulfur dioxide emissions	Tons
		Total industrial wastewater discharge	Ten thousand tons
		Generation of general industrial solid waste	Ten thousand tons

4.2.2. Core Explanatory Variables: Digital Trade Development Level (Dig)

Referring to the evaluation system of digital trade development constructed by Yao (2021) [69] and Jia et al. (2021) [70], this study develops an evaluation framework consisting of four primary indicators: digital trade capacity, digital network infrastructure, logistics and transportation, and trade potential. Among these, digital trade capacity measures the performance of regions in digital trade activities such as e-commerce and cross-border e-commerce, which constitutes the core element of digital trade. Good digital network infrastructure provides the foundation and support for the efficient operation of digital trade. An efficient logistics system ensures the rapid and safe cross-border flow of goods, serving as essential support for digital trade. Trade potential determines the future growth space of digital trade. Fifteen secondary indicators are derived from these primary indicators. The specific indicator system is shown in Table 2. This paper uses the entropy value method to evaluate the digital trade development level of the sample provinces.

Table 2. Evaluation system of digital trade development level.

Target Level	System Level	Indicator Layer	Unit	Weight	Variation
Digital Trade Development Level	Digital network infrastructure	Number of domain names	10 thousand	0.0690	Positive
		Number of websites	10 thousand	0.1484	Positive
		Internet broadband access port	10 thousand	0.0394	Positive
		Length of long-distance fiber optic cable lines	Kilometers	0.0416	Positive
		Broadband access user	10 thousand people	0.0430	Positive
	Logistics	Logistics- and transportation-related workers	Person	0.0130	Positive
		Ownership of road-operating goods vehicles	10 thousand	0.1020	Positive
		Civilian transportation ship ownership	Vessel	0.0007	Positive
	Digital trade capacity	Digital trade sales	Billion yuan	0.0971	Positive
		Revenue from express delivery operations	Billion yuan	0.1341	Positive
		Total telecommunication services	Billion yuan	0.0024	Positive
		Revenue from software operations	10 thousand yuan	0.1131	Positive
	Trade potential	Total exports and imports	Billion yuan	0.1143	Positive
		Market openness	%	0.0542	Positive
		GDP per capita	Yuan	0.0277	Positive

The steps of comprehensive measurement using the entropy value method are as follows: in the first step, positive and negative indicators are processed, where $\max\{\chi_{ij}\}$ is the maximum value of the indicator in all years, and $\min\{\chi_{ij}\}$ is the minimum value of the indicator in all years.

The positive indicator is calculated:

$$\chi_{ij} = \frac{\chi_{ij} - \min\{\chi_{ij}\}}{\max\{\chi_{ij}\} - \min\{\chi_{ij}\}} \tag{3}$$

Negative indicator calculation methodology:

$$\chi_{ij} = \frac{\max\{\chi_{ij}\} - \chi_{ij}}{\max\{\chi_{ij}\} - \min\{\chi_{ij}\}} \tag{4}$$

In the second step, the share of indicator j in year i is calculated.

$$\omega_{ij} = \frac{\chi'_{ij}}{\sum_{i=1}^{m} \chi'_{ij}} \tag{5}$$

In the third step, calculate the information entropy and redundancy of the indicator. Define the information entropy of the indicator as e_j, the information entropy redundancy as d_i, and m as the number of years to be evaluated.

$$\mathrm{e}_j = -\frac{1}{\ln m} \sum_{i=1}^{m} (\omega_{ij} \times \ln \omega_{ij}), 0 \le e \le 1 \tag{6}$$

$$d_j = 1 - e_j \tag{7}$$

In the fourth step, the weights of the metrics v_j are calculated based on the information entropy redundancy.

$$v_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{8}$$

In the fifth step, the core explanatory variable digital trade (*Dig*) is calculated by the weighting method.

$$Dig_i = \sum_{j=1}^{m} v_j \times \omega_{ij} \tag{9}$$

4.2.3. Control Variable

With reference to the existing literature, the selected control variables are as follows: (1) degree of government intervention (*Gov*). Policy support can create an enabling environment for digital trade. Policy incentives can also directly promote the development of green innovation [71]. (2) Foreign direct investment (*Fdi*). On the one hand, foreign investment can introduce advanced business models and technologies for digital trade and promote regional green innovation. However, it may also reduce the cost of technology acquisition and hinder green innovation [72]. (3) Level of human capital (*Edu*). A high level of human capital generally means a greater store of knowledge, which helps to make more effective use of digital technologies, providing talent support for innovation [73]. (4) Level of industrialization (*Ind*). Highly industrialized regions often have better supply chains and production systems, which are better able to support the role of digital trade in promoting green innovation [74]. (5) Level of information technology infrastructure (*lnCyb*). Information technology infrastructure is the basic support for the development of digital trade. It provides efficient information-sharing channels for innovation, accelerates the flow of innovation resources, and provides necessary technical support for green innovation [75]. (6) Level of economic development (*lnGdp*). This value determines innovation input. The more economically developed regions generally have higher funding flexibility for technology research and development, as well as higher levels of digital technology. This is clearly conducive to green innovation [76]. Through the selection of these control variables, this paper tries to reduce the influence of these factors on the relationship between digital trade and regional green innovation, so as to evaluate this relationship more accurately and ensure the scientific accuracy and reliability of the research results. The variables are defined in Table 3.

Table 3. Definition of variables.

Variable Types	Abbreviations	Definition	Measurement
Explained variable	*Inn*	Regional innovation capacity	Super-efficiency SBM Model
Core explanatory variable	*Dig*	Digital trade development level	The entropy method
Control variables	*Gov*	Degree of government intervention	Ratio of fiscal expenditure to GDP
	Fdi	Foreign direct investment	The proportion of foreign enterprise investment in the country
	Edu	Level of human capital	The proportion of students enrolled in postsecondary education to the overall population of the area
	Ind	Industrialization	The industrial added value to GDP ratio
	lnCyb	Level of information technology infrastructure	The cable length measured logarithmically
	lnGdp	Level of economic development	GDP per capita based on 2010

4.3. Data Sources

The data for this study come from China Statistical Yearbook, China Information Yearbook, China Communications Industry Statistical Yearbook, China Education Statistical Yearbook, China Population and Employment Statistical Yearbook, China Provincial Statistical Yearbook, and the National Bureau of Statistics of China. Taking into account the availability of data, the analysis used data from 30 provinces in China, excluding the Tibet Autonomous Region. The year 2011 marks the starting point of China's 12th Five-Year Plan, which proposes "innovation-driven" and "green development" strategies. Since this year, China has introduced a series of policies to promote industrial digitization and accelerate the development of e-commerce and cross-border e-commerce platforms. Therefore, this paper chooses 2011–2022 as the analysis period. The missing data were supplemented by the linear interpolation method. Table 4 displays the descriptive statistics of the obtained indicators.

Table 4. Descriptive statistics.

Variables	N	Mean	Sd	Min	Max
Inn	360	0.502	0.426	0.003	1.824
Dig	360	0.116	0.113	0.005	0.631
Gov	360	0.244	0.101	0.094	0.643
Fdi	360	0.018	0.015	0	0.080
Edu	360	0.016	0.007	0.004	0.036
Ind	360	0.321	0.082	0.101	0.556
lnCyb	360	13.59	0.918	10.83	15.28
lnGdp	360	9.333	0.464	8.542	10.81

5. Results

5.1. Baseline Regression

In this paper, baseline regression analysis is conducted by controlling fixed effects. Table 5 presents the results. Specifically, columns (1) and (3) use OLS to represent the case without province and year fixed effects. The results indicate that digital trade has a positive impact on regional green innovation, and government intervention and foreign direct investment are conducive to regional innovation. In columns (2) and (4), the fixed effects of year and province are controlled. The results also confirm that the development of digital trade promotes regional green innovation. In this paper, column (5) with both control variables and double fixed effects is analyzed. Statistically speaking, for every 1 unit increase in the development level of digital trade, the regional green innovation efficiency increases by 1.7710 units on average. From the perspective of economic significance, for every 1 unit standard deviation increase in the development level of digital trade, the average increase in regional green innovation efficiency is equivalent to 46.98% ($\approx 1.7710 \times 0.113/0.426$) of the sample standard deviation. This validates research Hypothesis 1.

Table 5. Baseline Regression.

Variables	**Baseline Estimate**		**Adding Control Variables**	
	OLS (1)	**FE (2)**	**OLS (3)**	**FE (4)**
Dig	1.6150 *** (0.1804)	1.7141 *** (0.2108)	1.7278 *** (0.2939)	1.7710 *** (0.2857)
Gov			0.9563 *** (0.2562)	0.9832 *** (0.3386)
Fdi			6.4564 *** (1.4556)	5.7012 *** (1.7524)
Edu			4.1917 (3.5962)	8.4750 * (4.4639)
Ind			−0.7740 *** (0.2509)	−0.7987 *** (0.2396)
lnCyb			−0.0710 ** (0.0335)	−0.0690 (0.0428)
lnGdp			0.1819 ** (0.0762)	0.1310 (0.0916)
Constant	0.3140 *** (0.0292)	0.3024 *** (0.0292)	−0.5997 (1.0376)	−0.2282 (1.2767)
Province FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
N	360	360	360	360
R^2	0.1807	0.1759	0.4327	0.4241

Values in parentheses are standard errors, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.2. Mechanism Analysis

The growth of digital trade provides significant support for promoting green innovation through three main channels. First, digital trade promotes the transformation and upgrading of traditional industries, infusing them with new vitality and enhancing their competitiveness. Second, it facilitates the regional agglomeration of related industries, boosting synergistic effects and enabling the sharing of innovation resources. Finally, digital trade promotes technology transfer, accelerating the popularization and application of green technology and further enhancing regional green innovation capacity. Therefore, this paper examines how these three mechanisms operate to influence green innovation.

5.2.1. Upgrading of Industrial Structure

To gauge the level of industrial structure upgrading in each province, this article considers two factors—industrial structure advancement and rationalization. To address potential heteroskedasticity, both factors are log-transformed.

(1) Industrial structure upgrading (*IS*). Because this is a dynamic process, it can be quantitatively evaluated by calculating the proportion of the output value of the tertiary industry in GDP. The higher the value of this indicator, the higher the level of industrial structure upgrading.

(2) Rationalization of industrial structure (TL). Drawing on the method of Gan et al. (2011) [77], this paper uses the Theil index, a negative indicator, to measure the industrial structure rationalization. Specifically, the more the TL value tends to 0, the more rational the industrial structure is. Conversely, the higher the TL value is, the more the industrial structure deviates from rationalization. The specific measurement methods are as follows:

$$TL = \sum_{i=1}^{3} [\frac{\Delta Y_i}{Y} \times \ln \frac{\frac{Y_i}{L_i}}{\frac{Y}{L}}] \tag{10}$$

where Y represents the total output value, and L denotes the total number of people employed. ΔY_i represents the value added of industry i and L_i denotes the number of people employed in industry i.

5.2.2. Industrial Agglomeration

As an essential component of manufacturing development, industrial agglomeration is crucial for fostering innovation in green technology [78]. In this paper, we use the number of employed people divided by the area of the administrative region and take its corresponding value to measure the degree of industrial agglomeration.

5.2.3. Technology Transfer

The technology market turnover rate reflects the efficiency of technological products and technological achievements from the research and development stage to actual application. A high turnover rate indicates that more technological achievements are successfully transformed into actual products or services, thus promoting industrial upgrading. Therefore, this paper measures the degree of technology transfer by dividing the value of technology market turnover by GDP.

The results are shown in Table 6. Regarding the industrial structure upgrading effect, the results in columns (1) and (2) show that digital trade has a positive impact on the industrial structure advancement and rationalization. At the same time, this conclusion has strong economic significance. When the development level of digital trade increases by 1 unit of the standard deviation, the level of industrial structure upgrading increases by 4.91% (≈0.0387 × 0.113/0.089) on average, and the rationalization degree of industrial structure increases by 35.76% (≈0.2975 × 0.113/0.094) on average. This shows that the development of digital trade promotes the optimization and upgrading of industries in the direction of high added value, low energy consumption, and sustainable development. The essence of industrial structure optimization and upgrading is the transfer of production factors from low-efficiency sectors to high-efficiency sectors, and the allocation of innovation resources in this process will inevitably promote the output of technological innovation. Regarding the industrial agglomeration effect, column (3) shows that the development of digital trade promotes the industrial agglomeration effect. As for its economic significance, when the development level of digital trade increases by 1 unit of the standard deviation, the industrial agglomeration degree increases by 7.29% (≈0.0129 × 0.113/0.020) on average. This may be due to digital trade's reliance on information and communication technology, which has significantly accelerated Internet technology advancements. On one hand, these advancements improve enterprise communication efficiency, reduce communication costs, and facilitate enterprise clustering [51]. On the other hand, they incentivize enterprises to relocate closer to others, lowering coordination and transportation costs [54]. Under this agglomeration effect, key production factors such as capital, talent, and technology naturally gather in a specific region, providing enterprises with unprecedented innovation resources. This centralized allocation of resources not only significantly reduces enterprises' green innovation costs but also greatly accelerates the process of green innovation activities, thereby improving overall green innovation efficiency. Meanwhile, the close interaction and cooperation among firms within an industrial cluster address challenges in the innovation process and promote the in-depth development of green technological innovation through knowledge sharing and resource integration. Regarding the technology transfer effect, column (4) indicates that digital trade positively influences technology transfer. This conclusion also has economic significance. When the development level of digital trade increases by 1 unit of the standard deviation, the degree of technology transfer increases by 49.62% ($\approx 6.1613 \times 0.113/1.403$) on average. This suggests that the technology transfer effect is particularly prominent in the context of booming digital trade [62]. Technology transfer not only drives resource flow across geographical areas but also serves as a core mechanism that stimulates innovation and fosters coordinated regional development, injecting substantial momentum into the enhancement of regional green innovation. In summary, the empirical results confirm that the industrial structure upgrading effect, industrial agglomeration effect, and technology transfer effect are key channels through which digital trade development influences regional green innovation, thereby validating research Hypothesis 2.

Table 6. Mechanism tests.

Variables	Industrial Structure Upgrading Effect		Industrial Clustering Effect	Technology Transfer Effect
	IS	*TL*		
	(1)	**(2)**	**(3)**	**(4)**
Dig	0.0387 ***	0.2975 ***	0.0129 ***	6.1613 ***
	(0.0113)	(0.0572)	(0.0027)	(0.8438)
Gov	0.1035 ***	0.0979	0.0036	4.1444 ***
	(0.0312)	(0.0849)	(0.0045)	(0.7353)
Fdi	−0.5764 ***	−0.4618 ***	0.0190	6.3962
	(0.1029)	(0.0953)	(0.0322)	(4.1785)
Edu	0.8214 *	0.2000	0.0562	167.7090 ***
	(0.4354)	(0.9985)	(0.0587)	(10.3236)
Ind	−0.6253 ***	0.5390 ***	−0.0022	1.7445 **
	(0.0095)	(0.0421)	(0.0049)	(0.7203)
lnCyb	0.0341 ***	−0.0171 **	0.0006	−0.0858
	(0.0028)	(0.0058)	(0.0010)	(0.0962)
lnGdp	−0.1221 ***	0.0623 ***	0.0042 **	−0.8356 ***
	(0.0090)	(0.0174)	(0.0016)	(0.2186)
Constant	1.3420 ***	−0.3800	−0.0280 **	−1.0072
	(0.1066)	(0.2422)	(0.0125)	(2.9787)
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	360	360	360	360
R^2	0.9389	0.7456	0.1733	0.5691

Values in parentheses are standard errors, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3. Threshold Effect Test

The costs and benefits of green technology innovation, as well as the supply and demand in the market, are significantly affected by environmental regulations. Consequently, enterprises must reconfigure the resources for investing in green technology innovation. This adjustment ultimately determines the timing of the launch of green technology innovation projects, the scale of implementation, and the extent of their in-depth development [79]. Therefore, environmental regulation as a government or policy-level constraint and incentive on the environmental behavior of enterprises directly affects the innovation motivation and behavior of enterprises. Only when the government sets higher environmental requirements are firms usually forced or incentivized to adopt more environmentally friendly production technologies and business models in order to avoid penalties, improve compliance, or gain policy support. Similar threshold effects may exist regarding the impact of digital trade development on regional green innovation. In this paper, we use the ratio of the completed investment in industrial pollution control to the added value of industry to measure environmental regulation (*Env*), considering it as a threshold variable, and use a threshold regression model to analyze the threshold effect of the level of digital trade development on regional green innovation. First, the threshold number needs to be determined. Table 7 lists the test results obtained using the bootstrap self-sampling method for different threshold numbers of regional green innovation capacity. The results show that in the test for a single threshold effect, the F-statistic is 9.63 with a p-value of 0.0025, while the double threshold fails the significance test. Therefore, only one threshold exists, and a single threshold model is adopted to analyze the regional green innovation capacity. The threshold regression model is set as follows:

$$\begin{gathered} lnInn_{pt} = \alpha + \beta_1 lnDig_{pt} I(lnEnv_{pt} \le \lambda) + \beta_2 lnDig_{pt} I(lnEnv_{pt} > \lambda) + \\ \gamma Control_{pt} + \mu_p + \sigma_t + \varepsilon_{pt} \end{gathered} \tag{11}$$

where β is the coefficient, $I(.)$ is the indicative function, *lnEnv* is the threshold variable, and λ is the threshold value. Other variables are consistent with the baseline model.

Table 7. Threshold effect test.

Threshold Variable	Threshold Number	F-Value	p-Value	BS Degree	Self-Sampling Critical Value		
					10%	5%	1%
Env	Single	9.63 ***	0.0025	300	14.2984	17.4959	31.1039
	Double	5.65	0.3867	300	10.3317	12.6319	17.5490

*** $p < 0.01$.

Table 8 shows the results of the threshold effect regression, which indicate that the promotion of regional innovation by digital trade is more pronounced in the case of higher environmental regulation than in the case of lower environmental regulation. This phenomenon occurs because higher environmental regulations create pressure on enterprises, rendering traditional high-pollution and high-energy-consumption production methods unsustainable. Consequently, enterprises are compelled to enhance their competitiveness through green innovation. During this process, enterprises have greater incentives to obtain advanced green technologies, products, and services via digital trade platforms, thereby promoting green innovation. In this case, the stricter the environmental regulations, the more significant the demand from enterprises for green technologies and innovations. The technologies, information, and resources provided by digital trade can be more readily transformed into green innovations, resulting in a more pronounced effect.

Table 8. Threshold effect regression results.

Variables	*Inn*
lnDig(*lnEnv* ≤ −5.2008)	0.0680 ***
	(0.0287)
lnDig(*lnEnv* > −5.2008)	0.3620 ***
	(0.1385)
lnGov	1.4668 ***
	(0.3584)
lnFdi	−0.1188 **
	(0.0565)
lnEdu	0.0404
	(0.2154)
lnIndustry	0.3307
	(0.2705)
lnCyber	−0.0987
	(0.1282)
lnGdp	0.5049
	(0.5657)
_cons	−1.2787
	(5.5540)
Province fixed effects	Yes
Year fixed effects	Yes
N	360
R^2	0.2797

Values in parentheses are standard errors, ** $p < 0.05$, *** $p < 0.01$.

5.4. Endogeneity Test

When analyzing the impact of digital trade on regional innovation, potential endogeneity issues may have an impact on the accuracy of the estimated results. First of all, an omitted variable is one of the important factors leading to endogeneity. Although this paper controls for many relevant variables, some of them are inevitably ignored. This can lead to bias in the estimates. Second, reverse causality. The improvement of green innovation ability can promote the wide application of new technologies and enhance the strength of regional development, while reducing costs and improving transaction efficiency. These positive results can also promote the vigorous rise and development of cross-border e-commerce, digital service trade, and other border trade modes and expand the market space of digital trade. At the same time, it can also promote trade facilitation and liberalization and build a more sound digital trade ecosystem. This bidirectional relationship may lead to deviations in the identification of causality. Third, the problem of sample selection bias. In this study, sample selection bias may be caused by differences in regional economic development level, industrial structure, and policy factors. Specifically, the eastern coastal provinces are more prominent in digital trade and innovation due to their developed economy and perfect digital infrastructure, while the central and western regions are relatively lagging behind. Such regional differences may lead to an upward bias in the estimation results towards the provinces with faster development, thus affecting the universality of the conclusions. Therefore, this paper deals with the endogenous problem.

5.4.1. Instrumental Variable

Referring to the practice of Huang et al. (2019) [80], who used the number of landline telephones per 100 inhabitants in each city in 1984 as the first instrumental variable to determine the degree of development of digital trade in a city. The growth of Internet technology is closely related to the development of digital trade. This choice has a profound historical background and logical connection: The development of Internet technology and the flourishing of digital trade are strongly intertwined. Higher telephone penetration during the early years established a more solid foundation for the subsequent advancement of Internet technology, thereby promoting the overall development of digital trade. It is worth noting that most of the early Internet access services in China relied on telephone dialing, which precisely verifies the significant correlation between instrumental variables and endogenous explanatory variables and satisfies the strict requirements of the correlation assumption of instrumental variables. In addition, since these are historical data and they have no direct causal relationship with current regional green innovation, they are not affected by current economic activity and do not directly affect the explanatory variables. This satisfies the exogenous hypothesis of instrumental variables. In addition, referring to the study of Ivus et al. (2015) [81], the second instrumental variable for the degree of digital trade development is each province's topographic relief. First, the degree of terrain undulation reflects the complexity of the local terrain. A higher degree of undulation means that the more complex the terrain, the more difficult it is to install digital infrastructure. Given that the relief of the terrain is a natural feature independent of other economic factors like the growth of digital trade, it satisfies the exogeneity criterion necessary for an instrumental variable. In addition, the degree of terrain undulation does not vary over time and remains essentially constant throughout the year. However, since the above two instrumental variables are fixed values, they cannot be used directly for estimation. Therefore, this paper takes them and the cross-multiplier of the national income of the IT service industry in the previous year as instrumental variables and uses the two-stage least square method for regression. The variables were log-transformed to minimize the effect of heteroskedasticity in the data. The results of the regression are presented in Table 9. The results show that all estimated coefficients for digital trade are significantly positive, proving the robustness of the estimates.

Table 9. Endogeneity Test (1).

Variables	IV_1		IV_2	
	First Stage (1)	Second Stage (2)	First Stage (3)	Second Stage (4)
lnIV	0.1458 ***		−0.0558 ***	
	(0.041)		(0.014)	
lnDig		0.5847 ***		0.7048 ***
		(0.060)		(0.085)
lnGov	−0.5725 ***	0.9712 **	−0.4690 ***	1.0327 ***
	(0.086)	(0.393)	(0.085)	(0.360)
lnFdi	0.0840 ***	0.0471	0.0726 ***	0.0359
	(0.019)	(0.076)	(0.020)	(0.071)
lnEdu	−0.1933 ***	0.1961	−0.2034 ***	0.2174
	(0.062)	(0.187)	(0.061)	(0.178)
Ind	−0.9748 ***	−0.4515	−0.9579 ***	−0.3392
	(0.256)	(0.866)	(0.255)	(0.815)
lnCyb	0.6338 ***	−0.2672	0.6607 ***	−0.3455
	(0.036)	(0.439)	(0.036)	(0.390)
lnGdp	1.0316 ***	0.3799	0.9625 ***	0.2576
	(0.049)	(0.682)	(0.050)	(0.606)
Constant	−23.8208 ***	3.2862	−21.1464 ***	5.9133
	(0.908)	(14.545)	(0.744)	(12.901)
Kleibergen–Paap rk LM	12.976 ***		20.459 ***	
	[0.000]		[0.000]	
Kleibergen–Paap rk Wald F	11.458		19.006	
	{8.96}		{8.96}	
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	360	360	360	360
R^2	0.903	0.376	0.904	0.380

** $p < 0.05$, *** $p < 0.01$. Standard errors in small brackets; *p*-values in middle brackets; Stock–Yogo test critical values in large brackets.

5.4.2. Lagged Core Explanatory Variables

When studying causality, it is common for events from the previous year to influence outcomes in the following year. Therefore, the main explanatory variables are lagged by one period to mitigate potential endogeneity issues in the model. According to the data in column (1) of Table 10, the *L. Dig* coefficient is significant. This shows that the contribution of digital trade development to regional green innovation remains strong.

Table 10. Endogeneity Test (2).

Variables	Lagged Core Explanatory Variables (1)	SYS-GMM (2)
L. Dig	1.9267 ***	
	(0.3126)	
L. Inn		0.6453 ***
		(0.0179)
Dig		0.7194 ***
		(0.1958)
Gov	1.1177 ***	1.7453 ***
	(0.3509)	(0.1641)
Fdi	6.0512 ***	4.8000 ***
	(1.8224)	(0.9665)
Edu	6.3631	0.5864
	(4.3312)	(2.7833)

Table 10. *Cont.*

Variables	Lagged Core Explanatory Variables (1)	SYS-GMM (2)
Ind	−0.7946 ***	0.7488 ***
	(0.2486)	(0.2824)
lnCyb	−0.0654	0.0081
	(0.0429)	(0.0193)
lnGdp	0.1709 *	0.1867 ***
	(0.0892)	(0.0689)
Constant	−0.6469	−2.5217 ***
	(1.2775)	(0.7676)
Province FE	Yes	Yes
Year FE	Yes	Yes
AR(1)		−2.58
		0.010
AR(2)		0.08
		0.939
Hansen test		24.74
		0.642
N	330	330

Values in parentheses are standard errors, * $p < 0.1$, *** $p < 0.01$.

5.4.3. Replacement of Estimation Methodology

SYS-GMM estimation can effectively address the endogeneity of dynamic panel data models. Therefore, this paper utilizes the higher-order lag terms as an instrumental variable and uses the SYS-GMM model to remove endogeneity. The estimation results are shown in Table 10. The results in column (2) indicate that the lag of regional green innovation has a substantial positive impact on current regional green innovation, suggesting that regional green innovation exhibits a significant growth effect. Meanwhile, the degree of digital trade development also demonstrates a positive effect on regional green innovation. This finding indicates that the estimation of the impact of digital trade development on local innovation capacity is valid.

It is important to emphasize that the SYS-GMM model includes the lag term of the explained variable as an instrumental variable, which may raise the potential issue of over-identification. For this reason, results of the Hansen statistic test, which is particularly relevant in the two-step SYS-GMM framework, are shown in Table 10, column (2). Test findings indicate that the model passes with a high *p*-value, thus failing to reject the null hypothesis of over-identification constraints. Additionally, the table displays *p*-values for AR(1) and AR(2), which show that the model contains only first-order autocorrelation and not second-order autocorrelation. This discovery is consistent with the presumptions needed to apply SYS-GMM, guaranteeing the accuracy of the outcomes.

5.5. Robustness Tests

5.5.1. Replacement of Core Variables

Numerous studies have employed the quantity of domestic invention patent applications as a surrogate measure of innovation. Therefore, this paper re-runs the regression by replacing the core explanatory variables with the logarithm of the number of domestic green patent applications. The results in Table 11, column (1) show that the promotion of regional green innovation through digital trade development remains robust, even after this substitution. In addition, for further validation, this paper constructs a comprehensive evaluation system for digital trade that includes four indicators: the ratio of exports of digital service forms to total service exports, the trade restriction index of digital services, the ratio of exports of ICT services to total service exports, and the ratio of exports of ICT products to total product exports. These indicators are measured using the entropy value method. The regression results in column (2) confirm that the development of digital trade has a positive impact on regional green innovation.

Table 11. Robustness Tests.

Variables	Replacement of Explained Variable (1)	Replacement of Core Explanatory Variables (2)	Excluding 2020 (3)	Control *Fin* (4)	Control *Agg* (5)
Dig	6.1021 ***	0.3903 ***	1.8739 ***	1.7197 ***	1.4994 ***
	(0.5231)	(0.0898)	(0.3210)	(0.3035)	(0.2955)
Gov	−1.9622 ***	1.3430 ***	0.8033 ***	0.8931 *	0.4191
	(0.4892)	(0.3302)	(0.2743)	(0.4725)	(0.4905)
Fdi	5.8664 **	5.8965 ***	6.0622 ***	6.0529 ***	6.4738 ***
	(2.5495)	(1.9659)	(1.5242)	(1.7897)	(1.6812)
Edu	80.3825 ***	−0.4253	5.4467	5.1767	−2.5340
	(6.2985)	(4.0646)	(3.8416)	(5.3130)	(5.7200)
Ind	−0.1707	−0.5581 **	−0.7206 ***	−0.7796 ***	−0.7401 ***
	(0.4785)	(0.2513)	(0.2635)	(0.2641)	(0.2607)
lnCyb	0.6469 ***	0.0236	−0.0870 **	−0.0579	−0.1063 **
	(0.0629)	(0.0342)	(0.0358)	(0.0412)	(0.0469)
lnGdp	−0.1975	0.4006 ***	0.1398 *	0.1534	−0.0388
	(0.1199)	(0.0693)	(0.0816)	(0.0944)	(0.1216)
Fin				0.0185	0.0087
				(0.0374)	(0.0371)
Agg					0.0722 ***
					(0.0236)
Constant	1.1581	−4.0049 ***	0.0008	−0.5651	1.9677
	(1.7453)	(0.9297)	(1.1067)	(1.3020)	(1.6815)
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	360	360	330	360	360
R^2	0.8744	0.3924	0.4210	0.4229	0.4424

Values in parentheses are standard errors, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.5.2. Removal of Anomalous Data

According to Zhao et al. (2023) [82], the COVID-19 pandemic in 2020 caused a significant shock to China's economy. Therefore, the 2020 sample data were excluded. In column (3) of Table 11, the coefficient of *Dig* remains positive. This implies that the positive effects of digital trade development on local green innovation are unaffected by removing the anomalous data.

5.5.3. Control for Level of Financial Development (Fin) and Degree of Synergistic Industrial Agglomeration (Agg)

Since financial development enhances regional green innovation by boosting capital investment in innovation activities, fostering risk management, facilitating knowledge spillovers, and optimizing industrial structure, this study uses GDP divided by the balance of deposits and loans of financial institutions to measure the degree of financial development. In addition, synergistic industrial agglomeration affects regional innovation primarily through mechanisms such as knowledge and technology sharing, scale effects, competition, and cooperation. When companies in the same industry gather together, knowledge and technology sharing can be realized and the overall development of regional innovation can be promoted. Accordingly, this study follows the methodology of Yang et al. (2006) [83] and uses the synergistic agglomeration index between productive service industries and high-tech industries across different provinces to indicate the degree of spatial synergy between the two sectors. After the gradual addition of these two variables, the *Dig* coefficients in columns (4) and (5) of Table 11 remain positive and significant, indicating that the conclusion of the baseline regression is robust.

6. Further Analysis

6.1. Provincial Location Heterogeneity

Due to geographical differences, there are significant differences between China's eastern and western regions in terms of resource endowment, transportation infrastructure, and biological environment. The eastern regions benefit from more developed logistics, transportation, and information technology infrastructure, along with higher levels of economic development, creating favorable conditions for an accelerated growth in digital trade. As a result, digital trade in these regions grows faster and has more resources available for local innovation. The central and western areas have lower levels of digital trade development and weaker regional green innovation due to slower economic development and relatively poor transportation and IT infrastructure. Therefore, it is crucial to test the differential impact of digital trade growth on the innovation potential of eastern and central and western China. The results of these tests can provide effective policy recommendations for promoting a coordinated regional development strategy. The study divides the area into eastern, central, and western provinces. The regression results are presented in Table 12. The *Dig* coefficient in column (1) is 2.0997, which is significant at the 1% level, suggesting that digital trade promotes regional green innovation in eastern China. However, the *Dig* coefficients in columns (2) and (3) do not pass the significance test, indicating that the ability to innovate in central and western China is not significantly affected by the expansion of digital trade. This suggests that digital trade has a stronger role in promoting regional green innovation in the eastern provinces compared to the central and western provinces. The potential reasons for this phenomenon are: first, the economy and infrastructure in the eastern region are more developed, which provides favorable conditions for the development of digital trade. Second, the eastern region's competitive market environment and large number of enterprises drive firms to adopt strategies such as digital trade to expand their markets and enhance their competitiveness. Third, governments in the eastern region offer greater policy and financial support for the integrated development of digital trade and regional green innovation, further enhancing the green innovation capacity of these provinces. In summary, the main factors behind the stronger influence of digital trade on regional green innovation in the eastern provinces include developed infrastructure, intense market competition, and increased policy support.

Table 12. Heterogeneity Analysis (1).

Variables	Eastern (1)	Central (2)	Western (3)
Dig	2.0997 ***	2.7197	0.5058
	(0.3485)	(2.2363)	(1.0432)
Gov	3.5086 ***	−0.2324	0.4638
	(0.6579)	(1.8815)	(0.3922)
Fdi	−1.1510	5.3822	5.4156
	(2.3854)	(4.1305)	(6.4423)
Edu	4.1326	19.5608 *	−17.6350 ***
	(8.5018)	(10.8240)	(6.2678)
Ind	−0.5522	−0.7890	1.0408 **
	(0.4171)	(0.6275)	(0.4713)
lnCyb	−0.0592	−0.3367 *	0.0146
	(0.0659)	(0.1912)	(0.0638)
lnGdp	0.4181 ***	−0.8537 *	0.3508 ***
	(0.1527)	(0.5086)	(0.1280)
Constant	−3.5199 **	12.5241 **	−3.3472 *
	(1.6754)	(5.6458)	(1.8849)
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	132	96	132
R^2	0.5981	0.1355	0.0439

Values in parentheses are standard errors, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.2. Digital Economy Heterogeneity

Digital technology serves as the primary engine of the digital economy, with digital information and knowledge as critical production inputs. The goal of this approach is to continuously raise the level of networked, intelligent, and digitalized society and the economy by merging digital technology with the real economy. As a result of the continuous progress and widespread use of digital technologies, more and more enterprises and industries have implemented digital production and transaction methods, which contributes to the digital transformation of the global economy and the growth of digital trade. This study hypothesizes that the influence of digital trade on local innovation capacity will intensify as the digital economy expands. To test this hypothesis, the digital economy is quantified using the Digital Financial Inclusion Index, following the methodology of Zhu and Liang (2022) [84]. Then, the regression test is re-run by dividing the provincial samples into two groups: according to the annual median, there are two regions: one region has a higher degree of digital economy, and the other region has a lower level of digital economy. The results are shown in Table 13. Column (1) displays the regression findings for the group with a more advanced digital economy, where the *Dig* coefficient is larger. This suggests that the role of digital trade is greater in provinces with mature digital economies. In contrast, the regression results for the group with a less developed digital economy are shown in column (2), where the *Dig* coefficient does not pass the significance test, indicating that the impact of digital trade on regional green innovation is not significant in the provinces with underdeveloped digital economy. This confirms the previous hypothesis. Possible reasons for this difference include: first, differences in market environment and degree of openness. Market environments in regions with mature digital economies are generally more open and vibrant. Firms in these regions are more likely to be exposed to internationally advanced technologies and management practices and to enhance their innovation capabilities through introduction, absorption, and re-innovation. In contrast, regions with underdeveloped digital economy tend to have less market openness, making it more difficult for enterprises to access internationally advanced technologies and management practices, thus limiting their ability to enhance their innovation capabilities. In addition, the relatively closed market environment in less developed regions also restricts the growth of digital trade and limits development opportunities. Second, there are differences in policy support and guidance. In more developed regions, government support for digital economy development is generally stronger. These regions tend to implement a series of policy measures to encourage innovation and support digital trade, such as tax incentives, financial assistance, and talent recruitment. These measures provide a favorable innovation environment for enterprises and enhance regional green innovation. In contrast, regions with lagging digital economies tend to have weaker policy support and guidance. These regions may lack targeted policy measures or insufficient support for the development of the digital economy, making it difficult to effectively stimulate the innovation potential and vitality of enterprises.

Table 13. Heterogeneity Analysis (2).

Variables	Development Level of Digital Economy		Construction Level of Transportation Infrastructure		Degree of Opening Up	
	Higher (1)	**Lower (2)**	**Higher (3)**	**Lower (4)**	**Higher (5)**	**Lower (6)**
Dig	1.8001 ***	3.3472 ***	1.6307 ***	1.1204	2.2729 ***	−0.8277
	(0.2695)	(0.7238)	(0.3521)	(0.8132)	(0.3273)	(1.1942)
Gov	1.8960 ***	0.0836	2.7200 ***	0.4426	2.6086 ***	0.8769 *
	(0.3885)	(0.3626)	(0.7604)	(0.3805)	(0.6359)	(0.4829)
Fdi	5.3596 **	4.0932 *	4.1844 **	6.9274 ***	0.8297	14.4472 ***
	(2.5020)	(2.2243)	(2.0725)	(1.8495)	(2.1295)	(3.9933)

Table 13. *Cont.*

Variables	Development Level of Digital Economy		Construction Level of Transportation Infrastructure		Degree of Opening Up	
	Higher (1)	**Lower (2)**	**Higher (3)**	**Lower (4)**	**Higher (5)**	**Lower (6)**
Edu	0.2648	19.7574 ***	−12.8247 *	3.7426	4.9392	7.2499
	(5.8438)	(5.8136)	(7.3116)	(4.4656)	(6.2447)	(6.2951)
Ind	−1.2250 ***	−0.5124	0.9328 **	−1.5490 ***	−0.4908	−0.6354
	(0.3006)	(0.3234)	(0.3800)	(0.3115)	(0.3842)	(0.4352)
lnCyb	−0.0695	−0.1685 ***	0.1859 **	−0.0131	−0.1207 **	−0.0167
	(0.0568)	(0.0642)	(0.0920)	(0.0465)	(0.0588)	(0.0617)
lnGdp	0.2133 *	−0.1661	0.1725	0.2204 **	0.1803	0.0840
	(0.1132)	(0.1410)	(0.1383)	(0.1010)	(0.1177)	(0.1495)
	−0.9148	3.7497 *	−4.8019 **	−1.2520	−0.2785	−0.4677
Constant	(1.6746)	(1.9763)	(2.2045)	(1.3668)	(1.5721)	(2.0642)
	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	180	180	180	180	180	180
N	0.5612	0.3662	0.4162	0.5677	0.4929	0.1335
R^2	0.5087	0.0258	0.4202	0.5246	0.4643	0.1172

Values in parentheses are standard errors, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.3. Transport Infrastructure Heterogeneity

Infrastructure development significantly impacts innovation by facilitating the diffusion of knowledge and technology spillovers between cities along transportation routes [85]. Therefore, this paper adopts the logarithm of total freight traffic to measure transportation infrastructure development and re-tests the regression based on the median by dividing the provincial sample into two groups with higher and lower levels of transportation infrastructure development. The regression results are shown in Table 13. As can be seen from column (3), the *Dig* coefficient is 1.6307, which is significant at the 1% level, indicating that digital trade promotes regional innovation in provinces with better transportation infrastructure. The coefficient in column (4) does not pass the significance test, indicating that in provinces with poor transportation infrastructure, the growth of digital trade does not significantly affect regional innovation potential. This discrepancy may arise because well-developed transportation infrastructure integrates multiple modes of transportation into an extensive network, creating an efficient logistics system. This reduces trade costs, increases the speed of goods movement, and allows provinces with better infrastructure to integrate more effectively into national and global digital trade networks. Strengthening economic and trade cooperation with other regions encourages the expansion of regional green innovation and accelerates the cross-regional flow and sharing of innovative resources. In contrast, in provinces with underdeveloped transportation infrastructure, inefficient logistics systems and poor information exchange hinder the development of digital trade. Problems such as poor transportation and difficulties in attracting and retaining high-quality talent, coupled with limited external investment, have led to a loss of innovation resources, making it difficult for these provinces to establish sustainable innovation ecosystems.

6.4. Opening to the Outside World Heterogeneity

Qayyum et al. (2022) found that increased international openness can improve regional innovation activities in China, which suggests that trade openness can promote innovation [86]. Based on this finding, this study re-runs the regression test using the median ratio of total import and export value to GDP and divides the sample of provinces into two groups: provinces with a higher degree of openness and provinces with a lower degree of openness. The results are shown in Table 13, columns (5) and (6). As seen in column (5), digital trade growth has a favorable impact on regional green innovation in more open regions. The coefficient of *Dig* is significant. Conversely, the statistic of *Dig* in column (6) does not pass the significance test, which indicates that the growth of digital trade does not have a significant impact on regional innovation potential in less open provinces. In provinces with a high degree of openness to the outside world, they are more connected to the international market and have a higher level of digital trade development, which in turn provides these provinces with wider access to international advanced technologies, innovative ideas, and market information, thus promoting local innovation capacity. In addition, a high degree of openness typically reflects a more open and inclusive policy environment, which helps to stimulate market dynamics and foster innovation. In contrast, enterprises in provinces with a low degree of openness have less exposure to international markets and digital trade is relatively underdeveloped. This limits their access to advanced technologies and innovation resources from abroad. Therefore, it is essential to increase the level of openness and optimize the policy environment in less open provinces to promote digital trade and support regional green innovation.

7. Discussion

With the vigorous development of the global digital economy, the role of digital trade in promoting green innovation has gradually become a focal point of academic attention. Current research on green innovation primarily concentrates on measurement methods and multi-dimensional influencing factors. However, studies examining digital trade within this context remain relatively limited. In comparison to traditional trade, digital trade can more effectively facilitate technology diffusion, optimize resource allocation, and innovate environmental governance, thus demonstrating significant potential for advancing green innovation. This paper thoroughly analyzes the influence and specific mechanisms through which digital trade development impacts regional green innovation. It reveals the threshold effect and regional heterogeneity of environmental regulation, while also exploring new growth channels for regional green innovation. This section mainly addresses the significance of the findings, potential limitations of the study, and future research directions.

7.1. Study Implication

The conclusion of this study shows that the development of digital trade promotes regional green innovation, which is consistent with previous studies. Specifically, Xiong and Luo (2023) believe that when the development level of digital trade is high, it can promote the improvement of green productivity [16]. Wang et al. (2024) found that enterprise digital transformation promotes green technology innovation by easing financing constraints, and this effect is more obvious when economic policy uncertainty is stronger [37]. Chen and Xu (2024) and Chen et al. (2024) have the same conclusion and argue that this effect is particularly significant in state-owned enterprises and highly polluting industries [39,76]. Fan et al. (2024) found that regional digitalization can enhance enterprises' dynamic capabilities in perception, grasp, and reconstruction, thus promoting the double improvement of green innovation in terms of quantity and quality [87]. This paper examines how digital trade influences green innovation by promoting the mechanism of industrial upgrading, industrial agglomeration, and technology transfer, enriching the research perspective of the influence of green innovation factors.

At the same time, through the threshold effect test, this paper finds that digital trade has a single threshold effect on promoting regional green innovation under different environmental regulation intensities. When environmental regulation is strict, the positive effect is significantly enhanced. When environmental regulations are relaxed, this effect is relatively weak. This finding is consistent with the findings of [88,89] that high-intensity environmental regulation creates an external pressure for companies to invest more in green innovation to meet compliance needs. In regions with lax regulation, enterprises have less incentive to innovate, and even if digital trade provides easy access to technology, the effect of green innovation is still limited. This finding has important guiding significance for future environmental policy making.

In addition, this paper also discusses the heterogeneity under different geographical locations, different levels of digital economy development, different levels of transportation infrastructure construction, and different degrees of opening up in China. Among them, in the eastern region, the region with developed digital economy, the region with superior infrastructure, and a higher degree of opening up, the positive impact of digital trade is more significant. This indicates that, under these conditions, the advantages of economic level and infrastructure [87], the drive of market competition [90,91], and the effect of policy support [92] are more obvious. This makes it easier for these regions to access international advanced technologies, management practices, and innovation resources, which contributes to the improvement of innovation capacity. On the contrary, poor geographical location and low economic level, infrastructure level, and market openness make it difficult for this region to obtain favorable green innovation resources, thus limiting the improvement of innovation ability in this region. The conclusion reveals the difference in the impact of digital trade on green innovation under different external macro-conditions, which is helpful for local governments to carry out targeted policy design according to local conditions.

7.2. Limitations and Future Research Directions

First, the data in this paper are based on provincial panel data, and although they can capture the overall relationship between digital trade and green innovation at the regional level, they cannot deeply reflect the specific context of individual cities or companies, which may lead to bias in the applicability of the results at different levels. Future research may consider using micro-data to explore the green innovation performance of different types of enterprises in the digital trade environment, so as to better understand the innovation differences of enterprises in the digital background.

Secondly, this paper mainly discusses the specific mechanism of digital trade affecting green innovation through the industrial upgrading effect, industrial agglomeration effect, and technology transfer effect. However, green innovation can be influenced by a variety of factors within the enterprise, such as management's emphasis on environmental protection [93] and corporate culture [94], which are difficult to quantify and control directly through macro-data. Therefore, the detailed mechanism at the enterprise level still needs to be further studied.

Finally, this study focuses on the impact of digital trade at the provincial level in China. However, international trade, with its higher technological mobility, information sharing, and cross-border capital flows, may have a different contribution to green innovation [95]. Future studies can incorporate international trade into the analytical framework of the relationship between digital trade and green innovation and provide a more general policy basis for the development of global green economy.

In addition, future research needs to focus on how to enhance the green innovation capacity of regions with less developed digital economy. For example, the promotion effect of digital infrastructure construction and digital transformation on green innovation in less developed regions with digital economy is discussed, and the applicability of local innovation experiment policies to less developed regions with digital economy is evaluated, so as to build a green innovation path more suitable for less developed regions with a digital economy.

8. Conclusions and Policy Recommendations

Based on data of 30 provinces (cities) in China from 2011–2022, this paper empirically studies the impact of digital trade development on regional green innovation and its mechanism. The findings show that: first, the development of digital trade enhances regional green innovation even when controlling for government intervention, foreign direct investment, human capital level, industrialization, information technology infrastructure, and economic development. This result remains robust after robustness tests such as solving endogenous problems, replacing core variables, excluding abnormal data in 2020, controlling financial development, and synergistic industrial agglomeration. Second, the impact of digital trade on regional green innovation is realized through three key mechanisms: industrial structure upgrading effect, industrial agglomeration effect, and technology transfer effect. Third, the impact of digital trade development on regional green innovation has a threshold effect. When the environmental regulations are lenient, this impact effect is small; when environmental regulations are strict, this impact effect is obvious. Fourth, the examination of heterogeneity reveals that the influence of the digital trade growth on local green innovation varies in different regions of China. The favorable impact of digital trade on regional green innovation is more pronounced in eastern regions, regions with a higher degree of digital economic growth, regions with superior transportation infrastructure, and regions with a greater degree of openness to the outside world.

Therefore, the following policy recommendations are proposed to accelerate the deep integration of digital technologies with the real economy and to support regions in realizing innovative and sustainable development.

(1) Develop a digital trade development strategy to promote regional green innovation. Research results show that digital trade growth is a major factor affecting regional green innovation. Therefore, on the one hand, investment in Internet infrastructure, logistics facilities, and information platforms should be increased to strengthen the integration of Internet platforms with the real economy and automation and intelligence in the production process. On the other hand, a more proactive digital trade development strategy should be formulated and implemented to promote resource sharing and complementarity between the Internet and the real economy. This can be achieved through policy guidance and market mechanisms to encourage the rapid growth of digital trade. It is necessary to strengthen intellectual property protection, create a good business environment, promote seamless integration of the real economy and the Internet, and foster regional innovation.

(2) Optimize the design of environmental regulation to improve green innovation motivation. Research has found that a high level of environmental regulation can stimulate enterprises' incentives for green innovation. In this regard, the government should further strengthen the scientific and flexible nature of environmental regulations to ensure that they are sufficiently robust to promote green innovation. At the same time, avoid being too strict and inhibit the innovation ability of enterprises. Differentiated environmental regulation policies should be formulated based on factors such as industry characteristics and regional development levels. For example, in industries with high pollution and high energy consumption, more stringent emission standards and environmental protection requirements should be implemented to encourage enterprises to increase the research and development and application of green technologies. Additionally, for innovative enterprises, incentives such as tax breaks for research and development of environmentally friendly technologies and preferential market access for green products should be provided. This approach aims to enhance the motivation for enterprises to adopt green technologies and support their progress toward sustainable development.

(3) Implement differentiated policies to promote coordinated regional development. Governments must take into account the differences in the development of digital trade in each region and formulate rules that suit each region's unique needs and attributes. The eastern provinces of China have made progress in digitalization compared to the western and central provinces. Therefore, for eastern provinces with developed digital economies and well-equipped supporting facilities, digital trade policies should focus on building innovation ecosystems and deepening innovation cooperation. This includes especially promoting partnerships among research institutions, enterprises, and government agencies to accelerate the research and development and commercialization of green technologies. In regions with less developed digital economies, investments in digital infrastructure and funding for green innovation research are critical. The government can create better conditions for green innovation in these regions by improving infrastructure such as

networks, communications, and data centers. Additionally, setting up special funds or providing tax incentives can encourage traditional industries in less developed areas to achieve digital upgrading and transformation. Furthermore, in regions with more stringent environmental regulations, governments can establish special R&D subsidies or tax breaks to encourage enterprises to innovate in green technologies with the support of digital technologies. In areas with looser environmental regulations, the government can foster a green digital economy ecosystem through training support, demonstration projects, and policy guidance. This approach will drive more enterprises to participate in green transformation and enhance local awareness of green innovation. In addition, attention should be paid to policy coordination among regions. Through policy coordination, cross-regional synergies can be created to promote regional green innovation and upgrading.

Author Contributions: Conceptualization, J.L.; methodology, J.L.; software, J.L.; validation, J.L. and C.Q.; formal analysis, J.L.; data curation, J.L.; writing—review and editing, J.L.; supervision, C.Q.; project administration, C.Q.; funding acquisition, J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Shandong Normal University Undergraduate Research Fund Project (BKJJ2024013).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data sets used in this study are available from the Yearbook, the Chinese Bureau of Statistics, http://www.stats.gov.cn/sj/ (accessed on 16 January 2024).

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Peng, Q.; Gao, F.; Li, J. Invisible Digital Barriers: Barriers to trade in digital services and global cross-border mergers and acquisitions. *Chin. Ind. Econ.* **2024**, 43–61. [CrossRef]
2. Li, Z.M.; Zhou, W.Y.; Tian, Z.T. Digital trade: Development trend, impact and countermeasures. *Int. Econ. Rev.* **2014**, *6*, 131–144+138.
3. Yu, H.; Yao, L. The impact of digital trade regulation on the manufacturing position in the GVC. *Econ. Model.* **2024**, *135*, 106712. [CrossRef]
4. Ma, S.Z.; Famg, C.; Liang, Y.F. Digital trade and its times value and research prospects. *Int. Trade Issues* **2018**, *5*, 16–30. [CrossRef]
5. Pei, G.F.; Liu, Y. The impact of digital trade development on industrial structure upgrading in China: An empirical study based on spatial Durbin model. *Stat. Decis.* **2024**, *40*, 162–166. [CrossRef]
6. Ou, Z.H.; Jiang, N.; Ma, Y.W. Research on the impact mechanism of intellectual property protection on digital service trade from the perspective of country differences. *Sci. Res. Manag.* **2024**, *45*, 161–170. [CrossRef]
7. Gai, W.Q. On regional economic development and regional innovation environment. *Acad. Res.* **2002**, *16*, 60–63.
8. Peters, M.A. Digital trade, digital economy and the digital economy partnership agreement (DEPA). *Educ. Philos. Theory* **2023**, *55*, 747–755. [CrossRef]
9. Huang, K.; Madnick, S.; Choucri, N.; Zhang, F. A Systematic Framework to Understand Transnational Governance for Cybersecurity Risks from Digital Trade. *Glob. Policy* **2021**, *12*, 625–638. [CrossRef]
10. Shaobin, G.; Ahmad, K.; Khan, N.U. Natural resources, geopolitical conflicts, and digital trade: Evidence from China. *Resour. Policy* **2024**, *90*, 104708. [CrossRef]
11. Danish; Khan, S.; Haneklaus, N. Sustainable economic development across globe: The dynamics between technology, digital trade and economic performance. *Technol. Soc.* **2023**, *72*, 102207. [CrossRef]
12. Liu, Y.; Hu, W.; Luo, K.; Guo, Y.; Wang, Z. How does digital trade promote and reallocate the export technology complexity of the manufacturing industry? Evidence from 30 Chinese provinces, 2011–2020. *PLoS ONE* **2023**, *18*, e0291464. [CrossRef] [PubMed]
13. Popkova, E.G.; Sergi, B.S. A Digital Economy to Develop Policy Related to Transport and Logistics. Predictive Lessons from Russia. *Land Use Policy* **2020**, *99*, 105083. [CrossRef]
14. Kloppenburg, S.; Boekelo, M. Digital platforms and the future of energy provisioning: Promises and perils for the next phase of the energy transition. *Energy Res. Soc. Sci.* **2019**, *49*, 68–73. [CrossRef]
15. Sun, L.; Li, X.; Wang, Y. Digital trade growth and mineral resources In developing countries: Implications for green recovery. *Resour. Policy* **2024**, *88*, 104338. [CrossRef]
16. Xiong, S.; Luo, R. Investigating the relationship between digital trade, natural resources, energy transition, and green productivity: Moderating role of R&D investment. *Resour. Policy* **2023**, *86*, 104069. [CrossRef]

17. Zhang, X.; Song, X.; Lu, J.; Liu, F. How financial development and digital trade affect ecological sustainability: The role of renewable energy using an advanced panel in G-7 Countries. *Renew. Energy* **2022**, *199*, 1005–1015. [CrossRef]
18. Wang, Y.; Liu, J.; Zhao, Z.; Ren, J.; Chen, X. Research on carbon emission reduction effect of China's regional digital trade under the "double carbon" target—Combination of the regulatory role of industrial agglomeration and carbon emissions trading mechanism. *J. Clean. Prod.* **2023**, *405*, 137049. [CrossRef]
19. Ashraf, M.Z.; Wei, W.; Usman, M.; Mushtaq, S. How can natural resource dependence, environmental-related technologies and digital trade protect the environment: Redesigning SDGs policies for sustainable environment? *Resour. Policy* **2024**, *88*, 104456. [CrossRef]
20. Wang, C.; Zheng, C.; Hu, C.; Luo, Y.; Liang, M. Resources sustainability and energy transition in China: Asymmetric role of digital trade and policy uncertainty using QARDL. *Resour. Policy* **2023**, *85*, 103845. [CrossRef]
21. Chen, J.; Wang, L.; Li, Y. Natural resources, urbanization and regional innovation capabilities. *Resour. Policy* **2020**, *66*, 101643. [CrossRef]
22. Yang, X.; Ran, R.; Chen, Y.; Zhang, J. Does digital government transformation drive regional green innovation? Evidence from cities in China. *Energy Policy* **2024**, *187*, 114017. [CrossRef]
23. Zhao, S.; Teng, L.; Arkorful, V.E.; Hu, H. Impacts of digital government on regional eco-innovation: Moderating role of dual environmental regulations. *Technol. Forecast. Soc. Chang.* **2023**, *196*, 122842. [CrossRef]
24. Sun, G.; Wang, J.; Ai, Y. The impact of government green subsidies on stock price crash risk. *Energy Econ.* **2024**, *134*, 107573. [CrossRef]
25. An, J.; He, G.; Ge, S.; Wu, S. The Impact of Government Green Subsidies on Corporate Green Innovation. *Financ. Res. Lett.* **2024**, *71*, 106378. [CrossRef]
26. Lu, H.; Liu, M.; Song, W. Place-based policies, government intervention, and regional innovation: Evidence from China's Resource-Exhausted City program. *Resour. Policy* **2022**, *75*, 102438. [CrossRef]
27. Block, J.; Lambrecht, D.; Willeke, T.; Cucculelli, M.; Meloni, D. Green patents and green trademarks as indicators of green innovation. *Res. Policy* **2025**, *54*, 105138. [CrossRef]
28. Ghisetti, C.; Montresor, S.; Vezzani, A. Design and environmental technologies: Does 'green-matching' actually help? *Res. Policy* **2021**, *50*, 104208. [CrossRef]
29. Hui, P.; Zhao, H.; Liu, D.; Li, Y. How does digital finance affect regional innovation capacity? A spatial econometric analysis. *Econ. Model.* **2023**, *122*, 106250. [CrossRef]
30. Yang, L.; Wang, S. Do fintech applications promote regional innovation efficiency? Empirical evidence from China. *Socio-Econ. Plan. Sci.* **2022**, *83*, 101258. [CrossRef]
31. Liu, Z.; Chen, S.; Tang, T.; Luo, H.; Guan, Q. How public education investment and advanced human capital structure affect regional innovation: A spatial econometric analysis from the perspective of innovation value chain. *Socio-Econ. Plan. Sci.* **2024**, *91*, 101800. [CrossRef]
32. Krieger, B. Heterogeneous university funding programs and regional firm innovation: An empirical analysis of the German Excellence Initiative. *Res. Policy* **2024**, *53*, 104995. [CrossRef]
33. Mo, C.; He, C.; Yang, L. Structural characteristics of industrial clusters and regional innovation. *Econ. Lett.* **2020**, *188*, 109003. [CrossRef]
34. Zhang, F.; Wang, F.; Yao, S. Does government-driven infrastructure boost green innovation? Evidence of new infrastructure plan in China. *J. Asian Econ.* **2024**, *95*, 101828. [CrossRef]
35. Yang, Y.; Ma, G. How can HSR promote inter-city collaborative innovation across regional borders? *Cities* **2023**, *138*, 104367. [CrossRef]
36. Zhou, Y.; Xu, X.; Tao, L. The impact mechanism of high-speed railway on regional green innovation spillover under multi-dimensional paths. *Environ. Impact Assess. Rev.* **2022**, *95*, 106795. [CrossRef]
37. Wang, B.; Khan, I.; Ge, C.; Naz, H. Digital transformation of enterprises promotes green technology innovation—The regulated mediation model. *Technol. Forecast. Soc. Chang.* **2024**, *209*, 123812. [CrossRef]
38. Fang, X.; Liu, M. How does the digital transformation drive digital technology innovation of enterprises? Evidence from enterprise's digital patents. *Technol. Forecast. Soc. Chang.* **2024**, *204*, 123428. [CrossRef]
39. Chen, Z.; Xu, W. The role of the digital economy in enhancing green innovation: Evidence from Chinese A-share listed enterprises. *Financ. Res. Lett.* **2024**, *71*, 106381. [CrossRef]
40. Feng, H.; Wang, F.; Song, G.; Liu, L. Digital Transformation on Enterprise Green Innovation: Effect and Transmission Mechanism. *Int. J. Environ. Res. Public Health* **2022**, *19*, 10614. [CrossRef]
41. Deng, F.; Feng, F.B.; Yang, X.D. Market segmentation, digital economy and regional innovation efficiency. *Stat. Decis.* **2022**, *38*, 17–20. [CrossRef]
42. Song, L.; Yuan, J.; Li, T. Harmonizing digital trade for sustainable stride: Unveiling the industrial pollution reduction effect of China's cross-border E-commerce comprehensive pilot zones. *J. Environ. Manag.* **2024**, *370*, 122834. [CrossRef] [PubMed]
43. Li, R.; Rao, J.; Wan, L. The digital economy, enterprise digital transformation, and enterprise innovation. *Manag. Decis. Econ.* **2022**, *43*, 2875–2886. [CrossRef]
44. Azadegan, A.; Wagner, S.M. Industrial upgrading, exploitative innovations and explorative innovations. *Int. J. Prod. Econ.* **2011**, *130*, 54–65. [CrossRef]

45. Yu, Y.; Zhang, J.Z.; Cao, Y.; Kazancoglu, Y. Intelligent transformation of the manufacturing industry for Industry 4.0: Seizing financial benefits from supply chain relationship capital through enterprise green management. *Technol. Forecast. Soc. Chang.* **2021**, *172*, 120999. [CrossRef]
46. Wang, D.; Liang, Y.F.; Dou, W. How does urban industrial structure upgrading affect green productivity? The moderating role of smart city development. In *Structural Change and Economic Dynamics*; Elsevier: Amsterdam, The Netherlands, 2024. [CrossRef]
47. Wang, Z.L.; Tan, Q.M.; XU, X.D. *An Empirical Study on the Measurement of Industrial Agglomeration Level*; China Soft Science: Beijing, China, 2006; pp. 109–116.
48. Li, T.; Shi, Z.; Han, D.; Zeng, J. Agglomeration of the new energy industry and green innovation efficiency: Does the spatial mismatch of R&D resources matter? *J. Clean. Prod.* **2023**, *383*, 135453. [CrossRef]
49. Li, X.; Lai, X.; Zhang, F. Research on green innovation effect of industrial agglomeration from perspective of environmental regulation: Evidence in China. *J. Clean. Prod.* **2021**, *288*, 125583. [CrossRef]
50. Xiangxiang, S.; Zhangwang, C.; Lawrence, L. Exploring the Effect of Digital Economy on PM2.5 Pollution: The Role of Technological Innovation in China. *Front. Environ. Sci.* **2022**, *10*, 904254.
51. Zeng, G.; Wu, M.; Yuan, X. Digital economy and industrial agglomeration. *Econ. Anal. Policy* **2024**, *84*, 475–498. [CrossRef]
52. Gao, L.; Huang, R. Digital transformation and green total factor productivity in the semiconductor industry: The role of supply chain integration and economic policy uncertainty. *Int. J. Prod. Econ.* **2024**, *274*, 109313. [CrossRef]
53. Wei, Y.; Tao, X.; Zhu, J.; Ma, Y.; Yang, S.; Ayub, A. Examining the relationship between international digital trade, green technology innovation and environmental sustainability in top emerging economics. *Heliyon* **2024**, *10*, e28210. [CrossRef] [PubMed]
54. Wu, L.; Wan, X.; Jahanger, A.; Li, M.; Murshed, M.; Balsalobre-Lorente, D. Does the digital economy reduce air pollution in China? A perspective from industrial agglomeration. *Energy Rep.* **2023**, *9*, 3625–3641. [CrossRef]
55. Wang, X.; Tian, N.; Wang, S. The Impact of Information and Communication Technology Industrial Co-Agglomeration on Carbon Productivity with the Background of the Digital Economy: Empirical Evidence from China. *Int. J. Environ. Res. Public Health* **2022**, *20*, 316. [CrossRef]
56. Waqas, M.; Honggang, X.; Ahmad, N.; Khan, S.A.R.; Iqbal, M. Big data analytics as a roadmap towards green innovation, competitive advantage and environmental performance. *J. Clean. Prod.* **2021**, *323*, 128998. [CrossRef]
57. Dinca, V.M.; Dima, A.; Rozsa, Z. Determinants of cloud computing adoption by Romanian SMEs in the digital economy. *J. Bus. Econ. Manag.* **2019**, *20*, 798–820. [CrossRef]
58. Wang, M.; Ren, S.; Xie, G. Going "green trade": Assessing the impact of digital technology application on green product export. *Technol. Soc.* **2024**, *77*, 102487. [CrossRef]
59. Adams, K.; Attah-Boakye, R.; Yu, H.; Chu, I.; Mali, D. African Continental Free Trade Area and Regional Trade in ICT and Digital Technologies. *J. Int. Manag.* **2024**, *30*, 101156. [CrossRef]
60. Tang, L.; Zhang, Y.; Gao, J.; Wang, F. Technological Upgrading in Chinese Cities: The Role of FDI and Industrial Structure. *Emerg. Mark. Financ. Trade* **2020**, *56*, 1547–1563. [CrossRef]
61. Loonam, J.; O'Regan, N. Global value chains and digital platforms: Implications for strategy. *Strateg. Chang.* **2022**, *31*, 161–177. [CrossRef]
62. Cai, H.; Wang, Z.; Ji, Y.; Xu, L. Digitalization and innovation: How does the digital economy drive technology transfer in China? *Econ. Model.* **2024**, *136*, 106758. [CrossRef]
63. Wang, J.; Cao, Y.; Fang, X.; Li, G.; Cao, Y. Identification of the trade-offs/synergies between rural landscape services in a spatially explicit way for sustainable rural development. *J. Environ. Manag.* **2021**, *300*, 113706. [CrossRef] [PubMed]
64. Nicolau, J.L.; Sellers, R. The quality of quality awards: Diminishing information asymmetries in a hotel chain. *J. Bus. Res.* **2010**, *63*, 832–839. [CrossRef]
65. Li, W.; Sun, H.; Tran, D.K.; Taghizadeh-Hesary, F. The Impact of Environmental Regulation on Technological Innovation of Resource-Based Industries. *Sustainability* **2020**, *12*, 6837. [CrossRef]
66. Wang, W.; Wang, J.; Wu, H. The impact of energy-consuming rights trading on green total factor productivity in the context of digital economy: Evidence from listed firms in China. *Energy Econ.* **2024**, *131*, 107342. [CrossRef]
67. Han, J. Research on efficiency of regional green innovation in China. *Res. Financ. Econ. Issues* **2012**, *34*, 130–137.
68. Shen, N.; Zhou, J.J. Study on the efficiency of green innovation and its key factors in China from the perspective of technological heterogeneity: Based on Hybrid DEA and structured equation model. *J. Manag. Eng.* **2018**, *32*, 46–53. [CrossRef]
69. Yao, Z.Q. Digital trade, industrial structure upgrading and export technology complexity: Multiple mediating effects based on structural equation model. *Reformation* **2021**, *1*, 50–64.
70. Jia, H.Q.; Gao, X.Y.; Xu, X.J.; Fang, Y.X. The conceptual framework, index system and measurement method of digital trade measurement. *Stat. Res.* **2021**, *38*, 30–41. [CrossRef]
71. Hou, G.; Shi, G. Green finance and innovative cities: Dual-pilot policies and collaborative green innovation. *Int. Rev. Financ. Anal.* **2024**, *96*, 103673. [CrossRef]
72. Zhou, H.; Zheng, M. Foreign direct investment and green innovation in China: An examination of quantile regression. *Innov. Green Dev.* **2024**, *3*, 100150. [CrossRef]
73. Wang, M.; Xu, M.; Ma, S. The effect of the spatial heterogeneity of human capital structure on regional green total factor productivity. *Struct. Chang. Econ. Dyn.* **2021**, *59*, 427–441. [CrossRef]

74. Yang, Y.; Su, X.; Yao, S. Can green finance promote green innovation? The moderating effect of environmental regulation. *Environ. Sci. Pollut. Res. Int.* **2022**, *29*, 74540–74553. [CrossRef]
75. Liu, J.; Meng, X.; Xia, Q. Information infrastructure and corporate green innovation quality incentive. *Heliyon* **2024**, *10*, e30784. [CrossRef] [PubMed]
76. Chen, M.; Liu, S.; Gao, L. Digital finance, financial flexibility and corporate green innovation. *Financ. Res. Lett.* **2024**, *70*, 106313. [CrossRef]
77. Gan, C.H.; Zheng, R.G.; Yu, D.F. The impact of industrial structure change on economic growth and fluctuation in China. *Econ. Res.* **2011**, *46*, 4–16+31.
78. Xu, S.; Zhang, Y. Impact of Manufacturing Agglomeration on the Green Innovation Efficiency-Spatial Effect Based on China's Provincial Panel Data. *Int. J. Environ. Res. Public Health* **2023**, *20*, 4238. [CrossRef]
79. Liu, J.; Zhao, M.; Zhang, C.; Ren, F. Analysis of the Influence of Heterogeneous Environmental Regulation on Green Technology Innovation. *Sustainability* **2023**, *15*, 3649. [CrossRef]
80. Huang, Q.H.; Yu, Y.Z.; Zhang, G.L. Internet development and productivity improvement in manufacturing: Internal mechanisms and China's experience. *Chin. Ind. Econ.* **2019**, 5–23. [CrossRef]
81. Boland, M.; Ivus, O. The Employment and Wage Impact of Broadband Deployment in Canada. *Can. J. Econ. Rev. Can. D'Econ.* **2015**, *48*, 1803–1830. [CrossRef]
82. Zhao, J.M.; Li, Y.Q.; Zhong, H. Digital economy, inter-provincial trade cost and national unified big market. *Economist* **2023**, 89–99. [CrossRef]
83. Yang, S.W.; Yi, M.; Wang, W.C.; Feng, B. Research on industrial cluster development based on transaction cost. *Manag. World* **2006**, 154–155. [CrossRef]
84. Zhu, J.G.; Liang, X.Q. Research on standardization construction and cost elasticity of enterprises: Evidence from China's A-share manufacturing listed companies. *Econ. Res.* **2022**, *57*, 31–50.
85. Lu, Y.; Yang, S.; Li, J. The influence of high-speed rails on urban innovation and the underlying mechanism. *PLoS ONE* **2022**, *17*, e0264779. [CrossRef] [PubMed]
86. Qayyum, M.; Yu, Y.; Tu, T.; Nizamani, M.M.; Ahmad, A.; Ali, M. Relationship between economic liberalization and intellectual property protection with regional innovation in China. A case study of Chinese provinces. *PLoS ONE* **2022**, *17*, e0259170. [CrossRef]
87. Fan, Z.; Long, R.; Shen, Z. Regional digitalization, dynamic capabilities and green innovation: Evidence from e-commerce demonstration cities in China. *Econ. Model.* **2024**, *139*, 106846. [CrossRef]
88. Peng, D.; Kong, Q. Corporate green innovation under environmental regulation: The role of ESG ratings and greenwashing. *Energy Econ.* **2024**, *140*, 107971. [CrossRef]
89. Huang, L.; Zhou, X.; Chi, L.; Meng, H.; Chen, G.; Shen, C.; Wu, J. Stimulating innovation or enhancing productivity? The impact of environmental regulations on agricultural green growth. *J. Environ. Manag.* **2024**, *370*, 122706. [CrossRef]
90. Liu, B.; Wang, Y.; Jiang, N.; Zhang, X. The impact of digital industrialization and industrial digitalization on regional green innovation efficiency in China -From the perspective of the innovation value chain. *J. Clean. Prod.* **2024**, *478*, 144015. [CrossRef]
91. Dong, X.; Guo, K.; Zhao, X. Does digital economy promote regional green innovation? An empirical study based on the transmission effect and threshold effect of marketization. *J. Digit. Econ.* **2024**, *3*, 47–61. [CrossRef]
92. Zhang, G.; Wang, Y.; Zhang, Z.; Su, B. Can green finance policy promote green innovation in cities? Evidence from pilot zones for green finance reform and innovation in China. *J. Environ. Manag.* **2024**, *370*, 122816. [CrossRef]
93. Su, X.; Xu, A.; Lin, W.; Chen, Y.; Liu, S.; Xu, W. Environmental Leadership, Green Innovation Practices, Environmental Knowledge Learning, and Firm Performance. *SAGE Open* **2020**, *10*, 2158244020922909. [CrossRef]
94. Yang, Z.; Sun, J.; Zhang, Y.; Wang, Y. Green, Green, It's Green: A Triad Model of Technology, Culture, and Innovation for Corporate Sustainability. *Sustainability* **2017**, *9*, 1369. [CrossRef]
95. Meng, Y.; Wu, H.; Wang, Y.; Duan, Y. International trade diversification, green innovation, and consumption-based carbon emissions: The role of renewable energy for sustainable development in BRICST countries. *Renew. Energy* **2022**, *198*, 1243–1253. [CrossRef]