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*Original Research*

# The Impact of Digital Trade on Regional Carbon Emissions: Evidence from China

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**Abstract**

With the rise of China's economy and the expansion of China's foreign trade scale, the carbon emissions generated by China's trade are attracting extensive attention from political and academic circles. In the context of global 'decarbonization', this paper focuses on the new trade model of digital trade and uses China's provincial panel data from 2013 to 2021 to deeply explore the effect of digital trade development on carbon emissions and its transmission mechanism. We find that digital trade development can reduce regional carbon emissions through structural and technological effects; specifically, industrial structure upgrading, consumption upgrading, and green technology innovation play a crucial intermediary role in this process. Subsequent investigation reveals a non-linear, diminishing trend in the marginal impact of digital trade on emission reduction. Furthermore, once digital trade surpasses the threshold of environmental regulation its marginal effect on emission reduction becomes more pronounced. Additionally, employing a spatial econometric model has revealed that the advancement of digital trade can also contribute to reducing carbon emissions in neighboring regions. Heterogeneity analysis results demonstrate that the eastern region exhibits the most significant emission reduction effect in relation to digital trade, followed by the western and central regions.

**Keywords:** digital trade, carbon emissions, upgrading of industrial structure, consumption upgrading, manufacturing agglomeration

## Introduction

The global climate issue is a matter of great concern for all nations. The Intergovernmental Panel on Climate Change (IPCC) of the United Nations has highlighted that, based on 2019 global carbon emissions, a reduction of 43% in global greenhouse gas emissions by 2030, it is imperative to achieve the objective set by the Paris Agreement of limiting warming to 1.5 degrees Celsius by the end [1]. Consequently, urgent measures are required to regulate worldwide carbon emissions. With the growth of China's economy, its carbon emissions resulting from industrialization and their share in global emissions have continued to increase. As such, China bears a significant responsibility for reducing these emissions. In 2020, China's carbon emissions accounted for 32.6 percent of global carbon emissions [2]. As the world's factory and a major trading country,

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China's carbon emissions generated in the process of trade should also not be underestimated. In response to this pressing challenge, China has proactively assumed responsibility for emission reduction by committing to peaking its carbon emissions by 2030 and achieving carbon neutrality by 2060 [3]. Confronted with the dual challenge of economic recovery and emission reduction, countries are increasingly concerned about how to minimize the impact on economic growth while effectively reducing emissions without compromising it.

Previous studies have indicated that international trade not only leads to the unsustainable utilization of environmental resources but also facilitates the transboundary diffusion of pollution. The processes of trade and transportation can inflict considerable harm on the environment. As a prominent trading nation, China must transition from its conventional extensive development and trade patterns to accomplish its dual carbon objectives. In pursuit of this objective, the Ministry of Industry and Information Technology of China has sequentially released policy documents such as the Three-Year Action Plan for the Development of New Data Centers (2021-2023) and the 14th Five-Year Plan for Green Industrial Development [4, 5], with a focus on leveraging digital technology to facilitate carbon emission reduction and achieve carbon neutrality. The extensive and in-depth application of digital technology across various industries has made significant contributions to China's efforts towards reducing emissions. Furthermore, the development of the digital economy has given rise to a new form of trade - digital trade - which has fundamentally transformed traditional modes of trade and provided a novel pathway for China's emission reduction measures. According to the Digital Trade Development and Cooperation Report 2022, jointly released by the Department of Foreign Economic Research at the Development Research Center of the State Council and the China Academy of Information and Communications Technology, China's total import and export value of digital services reached $359.7 billion in 2021, indicating a significant year-on-year increase of 22.3% [6]. This growth aligns with the observed gradual decline in China's carbon emission intensity. The development of digital trade has revolutionized the way and pattern of trade, effectively streamlined intermediary transactional processes, and enhanced overall efficiency. Moreover, it has significantly transformed residents' consumption patterns while driving optimization and upgrading within industrial frameworks. Consequently, this transformative phenomenon is anticipated to offer novel policy alternatives for China's emission reduction objectives.

In this context, this paper aims to investigate whether digital trade has contributed to reducing carbon emissions and examines the specific mechanisms through which digital trade affects carbon emissions. Furthermore, we analyze the non-linear and spatial effects of digital trade on emission reduction, which will not only supplement current research on the environmental impact of digital trade, but also provide insights for future studies. In terms of the practical research value of this paper, the findings can assist China in achieving its emission reduction targets while offering theoretical support and empirical evidence for other countries seeking to reduce their carbon footprint and mitigate global warming.

The remaining sections of this paper are structured as follows: In the literature review section, we systematically examine existing research and emphasize the unique contribution of this study while identifying limitations in previous studies. The section on theoretical analysis and research hypotheses provides a comprehensive mechanism analysis of the emission reduction effect of digital trade and presents the fundamental hypothesis for this study. The research design section describes the construction of the empirical model and provides an overview of the variables used. In the empirical analysis section, we present regression results from our econometric model to validate the aforementioned hypotheses. Finally, in the conclusions and policy recommendations section, we summarize our findings and provide policy recommendations.

## Literature Review

With the acceleration of the new wave of information and communication technology revolution and industrial transformation, digital trade is reshaping the global trade pattern and industrial competition, constituting a vital component of international trade, and gradually garnering attention from various sectors of society. The literature closely related to this paper mainly includes the following two categories:

The first is research on the impact of international trade on the environment. While it has long been widely acknowledged that free trade can enhance the economic welfare of participating nations, an increasing number of scholars have also raised concerns and questioned the environmental pollution resulting from trade [7-9]. The research and discourse surrounding the nexus between trade and environment have a rich historical backdrop, with prevailing scholarly perspectives encompassing the theories of trade benefits, trade detriments, and uncertainty. Based on the environmental Kuznets curve theory, supporters of the trade benefit theory argue that foreign trade growth can mitigate environmental pollution at a certain level of economic growth [10, 11]. In addition, trade liberalization can facilitate the diffusion of technology, thereby facilitating the adoption and utilization of clean technologies in developing countries, so that international trade tends to mitigate environmental pollution [12]. The empirical results of numerous scholars also lend support to this view. For instance, Jayanthakumaran and Liu [13] demonstrated that the increase in income resulting from international trade contributed to a reduction in carbon dioxide emissions. Al-Mulali [14] and Ahmed [15], based on data from European countries and newly industrialized nations, respectively, corroborated the presence of the environmental Kuznets curve hypothesis, which posits that trade openness leads to long-term decreases in carbon dioxide emissions.

The pollution paradise hypothesis underpins the theory of trade harm, positing that developing countries tend to assume industries with high environmental pollution from developed countries during foreign trade, thereby exerting significant pressure on their own environmental governance. For instance, Kim et al. [16] observed a relationship between foreign trade and carbon across different country types and found that both North-North cooperation and South-South cooperation contributed to reducing carbon emissions in developing countries, while north-south trade resulted in an increase in carbon emissions for these countries. Based on the "pollution refuge hypothesis", Lin and Xu [17] investigated the association between bilateral trade and carbon emissions in the context of China-Russia relations. The findings revealed that China's export trade to Russia emerged as a primary driver for increased carbon emissions within China, while imports of oil, coke, and other commodities from Russia contributed to alleviating China's carbon emission burden. Grossman and Krueger [18] and Antweiler [19] have posited that the environmental impact of trade is primarily contingent upon the direction, magnitude, and interplay of the scale effect, structure effect, and technology effect. The structure effect and technology effect tend to mitigate carbon emissions, whereas the scale effect tends to exacerbate them. Consequently, this gives rise to the theory of trade uncertainty.

The second is research on digital trade and its economic effects. At present, scholars have not reached a consensus on the definition and connotation of digital trade, but the digitalization of trade modes and trade objects is the essential core of digital trade. According to the definition provided in the China Digital Trade Development Report 2021, issued by the Department of Trade in Services and Commercial Services of the Ministry of Commerce, digital trade refers to a series of foreign trade activities that take data resources as the key factors of production, modern information networks as the important carriers, and the effective use of information and communication technology to promote efficiency improvement and structural optimization. While existing studies have primarily focused on the economic implications of digital trade development, such as the technological complexity of exports, industrial structure upgrading, and consumption patterns [20-22], the potential impact of digital trade on carbon emissions has received limited attention. In the existing literature, Wang et al. [23] investigated the impact of digital trade on emission reduction, considering both production and consumption perspectives, while also examining the moderating effects of industrial agglomeration and carbon emission trading pilot policies. In contrast, Ji et al. [24] primarily focused on exploring heterogeneity in the emission reduction effects of digital trade. The findings revealed that regional disparities, levels of trade openness, and carbon emission intensity contribute to variations in the carbon emission reduction effect of digital trade.

Through the review of the aforementioned literature, it becomes evident that current research on the emission reduction impact of digital trade is still in its nascent stage. Further supplementation is required to demonstrate the emission reduction mechanism and spatial spillover effect of digital trade, thereby offering potential for marginal contribution to this study. This paper attempts to take China, the largest developing country, as an example to construct the digital trade development index of each province in China and to evaluate the emission reduction effect of digital trade development through its impact on industrial structure, household consumption structure, and green technology innovation. Compared with the existing research, this paper offers potential innovations in the following aspects: First, it is worth noting that existing studies primarily focus on the impact of the digital economy and trade liberalization on carbon emissions, with limited attention given to the environmental implications of digital trade. In light of this research gap, our study specifically examines the influence of digital trade on carbon emissions, thereby making an innovative contribution from a research perspective. Secondly, in terms of research content, this paper builds upon the traditional trade-environment theory by introducing the mechanism of consumption structure and examining the intermediary role of industrial structure, consumption structure, and green technology innovation in the emission reduction effect of digital trade. Furthermore,it delves into the moderating role of manufacturing agglomeration, the threshold effect of digital trade itself and environmental regulation, and the spatial effect of digital trade in reducing carbon dioxide emissions. This not only enriches and expands existing research on the environmental impact of digital trade but also provides valuable insights for future studies. Thirdly, from the perspective of research value, in recent years, the challenge of reconciling economic development with environmental protection has posed a significant dilemma for China and other developing nations. Hence, this study may offer a novel perspective and practical approach to assist countries in attaining their carbon emission reduction targets.

## Theoretical Analysis and Research Hypotheses

### Analysis of the Direct Effect of Digital Trade on Reducing Carbon Emissions

Firstly, compared with traditional trade in goods, the digitization of digital trade objects exhibits a characteristic of environmental friendliness. As the scale of the digital service trade expands, an increasing number of conventional service trades are being substituted by digital service trades, leading to the emergence of novel digital products and services such as online education, film and television animation, and digital healthcare. Notably, these sectors demonstrate lower carbon emissions during production when compared to their traditional counterparts. Furthermore, the digitalization of digital trade delivery modes can eliminate reliance on traditional logistics and transportation methods, thereby mitigating potential carbon emissions associated with goods transportation [25]. Moreover, as digital infrastructure construction continues to advance, foreign trade enterprises can leverage big data, blockchain technology, artificial intelligence, and other digital technologies alongside information and communication technologies more conveniently. This significantly reduces transaction costs and information search expenses across various trade links while enhancing trade efficiency. Consequently, energy consumption in commodity production and circulation processes is reduced. Based on the aforementioned, this paper proposes the research hypothesis:

Hypothesis 1: Digital trade can help reduce regional carbon emissions.

## Analysis of the Indirect Effect of Digital Trade on Reducing Carbon Emissions

### *Structure Effect*

The development of digital trade has had a profound impact on the industrial structure. From the perspective of digital industrialization, scientific and technological advancements, along with the continuous expansion of trade's scope and application scenarios driven by digital technology, are fostering substantial growth in digital products and services. Simultaneously, data, as a novel input factor, is constantly giving rise to new products and innovative business models [26]. From the perspective of industrial digitalization, the integration of digital and traditional industries is realized through the provision of technology, products, and service solutions for other industries by the digital industry. This promotes the transformation and upgrading of traditional industries towards intelligence. The introduction of advanced digital technology not only accelerates enterprise-level digital transformation but also facilitates the efficient flow of various production factors within an enterprise while improving resource utilization efficiency. Furthermore, it drives other enterprises in the industrial chain to undergo their own digital transformations, which ultimately improves overall digitization levels across all aspects of the industrial chain and leads to integrated and coordinated development that accelerates industrial structure upgrades [27]. In addition, the widespread adoption of digital technologies, such as big data, cloud computing, blockchain, and artificial intelligence, has effectively transcended geographical and industrial boundaries.

It has facilitated the seamless flow of production factors like data, talent, and capital, enabling efficient and accurate resource allocation while reducing market distortions and mismatches within and across regions and industries [28]. Consequently, it creates a favorable market environment for optimizing and upgrading industrial structures. Industrial activities are significant contributors to carbon emissions; numerous studies have demonstrated the role of industrial structure upgrading in emission reduction [29-31], which will not be reiterated here.

From the perspective of consumption upgrading, digital trade has expanded market boundaries and facilitated the global exchange of previously non-tradable or challenging-to-trade goods, thereby augmenting the variety and quantity of tradable products. Additionally, digital trade has engendered novel consumption models like online education, telemedicine, and digital tourism, thus broadening consumer choices and enhancing consumer welfare. With the widespread implementation of big data, artificial intelligence, and other digital technologies in the field of commodity circulation, the previously existing information and circulation barriers in residents' consumption links have been eliminated. As a result, there is now a more precise match between supply and demand for commodities. The rapid advancement of the platform economy further empowers consumers to access diverse goods from different countries at any time and place, thereby catering to their personalized and diversified consumer needs. These requirements are then fed back into the research and development (R&D), design, and production processes of manufacturing enterprises. To address these demands effectively, companies will drive flexible transformations within their production processes while achieving digitalization and intelligent upgrading. Consequently, this facilitates a reduction in carbon emissions during the production process. Moreover, digital trade facilitates the active involvement of small, medium, and micro enterprises in international trade. This not only integrates them into the global value chain system but also enhances market dynamism and fosters competition in product markets. Consequently, it promotes both product innovation and quality improvement while offering consumers access to novel products and services that meet their demand for high-quality consumption. Thus, it contributes significantly to the realization of consumption upgrading [32]. As household consumption structure improves, there is a shift from survival-oriented expenditure to enjoyment-oriented spending. This transition entails an increase in non-material consumption such as services while reducing material consumption substantially at the consumer end, thereby leading to a significant reduction in carbon emissions [33]. Based on the aforementioned analysis, this paper presents the following hypothesis:

Hypothesis 2: Digital trade can reduce carbon emissions through industrial structure upgrading and consumption upgrading.

*Technology Effect*

Existing studies primarily examine the technological effect of digital trade from the perspective of traditional technological progress. However, faced with the pressure of green political achievements, local governments are increasingly concerned about enterprises' adoption of green clean technologies. Diverging from previous research, this paper places greater emphasis on exploring the potential progress in green technology resulting from the development of digital trade and its subsequent reduction in carbon emissions. The green technology innovation effect resulting from digital trade can be elucidated from two perspectives. On one hand, the integration of digital technology and traditional trade enhances the comprehensiveness of trade information on both supply and demand sides, leading to a significant reduction in costs associated with information acquisition, decision-making, and adjustment [34]. Moreover, digital production can further drive down labor expenses. Consequently, this cost reduction directly empowers foreign trade enterprises to allocate more resources towards the development of environmentally friendly technologies. On the other hand, digital trade not only fosters regional trade expansion but also facilitates technology spillover effects, thereby creating favorable conditions for technology exchange and promoting innovation in green technologies between trading partners. Consequently, it aids enterprises in developing clean and advanced technologies. In this way, the development and application of low-carbon and clean technologies can help enterprises eliminate production equipment with high energy consumption and pollution, improve energy efficiency, and achieve emission reduction [35]. Based on this, this paper posits the hypothesis:

Hypothesis 3: Digital trade can reduce carbon emissions by promoting green technology innovation.

## Moderating Effects of Manufacturing Agglomeration

Manufacturing agglomeration refers to the spatial concentration of manufacturing industries, and excessive agglomeration can result in a crowding effect, leading to negative environmental externalities [36]. While manufacturing agglomeration can generate economies of scale and accelerate the industrialization process, it also leads to increased energy consumption and carbon dioxide emissions. Furthermore, the agglomeration of manufacturing enterprises enables them to obtain higher bargaining power over the government when implementing environmental regulations, allowing these enterprises to evade strict environmental regulations and engage in unrestricted production activities with high pollution and emissions [37]. In the process of digital trade development, in order to give full play to the advantages of economies of scale and promote the professional division of labor among industries, it is inevitable to confront the trend of manufacturing agglomeration, so manufacturing agglomeration may potentially undermine the emission reduction impact of digital trade. Based on the aforementioned analysis, this paper posits the subsequent research hypothesis:

Hypothesis 4: The presence of manufacturing agglomerations moderates the emission reduction effect of digital trade while simultaneously weakening its impact.

# Research Design

## Econometric Model

*Benchmark Regression Model*

Based on the above analysis, in order to investigate the emission reduction effect of digital trade, this paper establishes the following two-way fixed effect model:

$$ce_{it} = \alpha_0 + \alpha_1 dt_{it} + \alpha_c controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

In Equation (1), $i$ and $t$ denote province and year, respectively; $\alpha_0$ is a constant term; $ce$ represents carbon emissions; $dt$ is the digital trade development index; $controls$ is a series of control variables; $\mu_i$ and $\delta_t$ represent the fixed effects of control individual and time, respectively. $\varepsilon_{it}$ represents the random error term.

*Mediating Effect Model*

To examine the channel through which digital trade affects emission reduction, this study incorporates industrial structure, consumption structure, and green technology innovation as mediating variables between regional digital trade development and carbon emissions. Following Baron and Kenny's [38] research framework, we establish the following mediating effect model based on Equation (1):

$$mv_{it} = \beta_0 + \beta_1 dt_{it} + \beta_c controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (2)$$

$$ce_{it} = \gamma_0 + \gamma_1 dt_{it} + \gamma_2 mv_{it} + \gamma_c controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (3)$$

Where $mv_{it}$ represents the mediating variables mentioned above, and the interpretations of other parameters remain unchanged.

*Moderating Effect Model*

In order to test the moderating effect of manufacturing agglomeration, this paper constructs the following moderating effect model:

$$ce_{it} = \varphi_0 + \varphi_1 dt_{it} + \varphi_2 agg_{it} + \varphi_3 (dt_{it} \times agg_{it}) + \varphi_c controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{4}$$

Where $agg_{it}$ represents the level of manufacturing agglomeration, and other parameters are the same as above.

## Definition of Variables

### *Dependent Variable*

Carbon emissions (*ce*). As carbon dioxide emissions primarily stem from the combustion of fossil fuels and the cement industry's production process, this study adopts the calculation method proposed by Chen et al. [39] to estimate $CO_2$ emissions resulting from fossil fuel combustion across seven energy sources, namely raw coal, coke, gasoline, kerosene, diesel, fuel oil, and natural gas. The calculation formula employed is as follows:

$$EC = \sum_{i=1}^{7} \frac{44}{12} \times E_i \times CF_i \times CC_i \times COF_i \tag{5}$$

In Equation (5), *EC* represents the total $CO_2$ emissions resulting from the consumption of seven different energy sources, where *i* denotes the specific type of energy and $E_i$ signifies the total consumption of that particular energy type in each province. $CC_i$ signifies the carbon content per unit calorific value, while $COF_i$ denotes the oxidation factor. Additionally, $CF_i \times CC_i \times COF_i$ refers to the carbon emission coefficient, with 44/12 representing the molecular weight ratio of carbon dioxide to carbon, and $44/12 \times E_i \times CF_i \times CC_i \times COF$ is called the carbon dioxide emission coefficient.

The formula for calculating carbon emissions in the cement production process is as follows:

$$CC = Q \times EF_{cement} \tag{6}$$

Where *CC* represents the total $CO_2$ emissions in the cement production process, *Q* represents the cement production volume, and $EF_{cement}$ is the $CO_2$ emission coefficient of cement production. The carbon emissions (*ce*) utilized in this study are derived by aggregating the $CO_2$ emissions from fossil fuel combustion and cement production processes, dividing them by the GDP of each province, and subsequently applying a logarithmic transformation.

### *Core Explanatory Variable*

Digital trade development level (*dt*). The measurement of digital trade development has not yet reached a consensus in the academic community. This study adopts the research ideas proposed by Wang et al. [23] and constructs an evaluation system for the digital trade development index based on five dimensions: digital infrastructure, digital technology environment, digital and industrial integration, potential for digital trade, and logistics environment (refer to Table 1). The entropy weight method is employed to calculate the digital trade development index (*dt*) for each region.

### *Control Variables*

In order to comprehensively evaluate the overall impact of digital trade development on regional carbon emissions and mitigate estimation errors resulting from omitted variables, this study incorporates the following variables that have been identified in existing research as potential determinants of carbon emissions: The economic development level (*lnpgdp*) is represented by the logarithm of per capita GDP. Financial development (*fin*) is indicated by the ratio of the balance of deposits and loans of financial institutions to GDP at the end of each year in each region. Fiscal decentralization (*fisca*) is expressed as the ratio of regional fiscal budget revenue to expenditure. Tax burden level (*tax*) is measured by the ratio of tax revenue to GDP in each region. Science and education investment (*te*) is denoted by the proportion of fiscal expenditure on science and technology education in relation to GDP. Thr human capital level (*lnhc*) is represented as the logarithm of average years of education in each province. Fixed asset investment (*lnfi*) is indicated by the logarithmic value representing investment in fixed assets. Urbanization level (*urban*) represents the proportion of non-agricultural population in each province.

### *Mediating Variables*

Industrial structure (*is*). Referring to the idea of Ren et al. [40], the hierarchical coefficient of industrial structure is introduced to measure the optimization level of industrial structure:

$$is_{it} = \sum\nolimits_{j=1}^{3} \frac{Y_{it,j}}{Y_{it}} \times j \tag{7}$$

Where $is_{it}$ denotes the optimization level of industrial structure, $Y_{it}$ is GDP, and $Y_{it,j}$ is the added value of the industry *j*. The higher the value of "*is*", the greater the level of optimization of industrial structure.

Consumption upgrade (*cu*). Referring to the study conducted by Wei et al. [41], an income elasticity of 0.8 is considered the threshold for categorizing the various consumption demands of urban residents in China. Items with an elasticity below 0.8 are classified as essential subsistence consumption, including food, education, culture and entertainment services, medical care, and other goods and services consumption. On the other hand, items with an elasticity above 0.8 are categorized as indulgent enjoyment consumption, encompassing clothing, housing, daily necessities and services,

Table 1. Evaluation system of the digital trade development index.

| First-level indicators | Second-level indicators | Indicator attributes |
|---|---|---|
| Digital infrastructure | Mobile phone penetration rate (units/100 people) | + |
| | Number of domain names (10,000) | + |
| | Internet broadband access ports (ten thousand) | + |
| | Length of optical cable line (km) | + |
| Digital technology environment | Number of domestic patent applications accepted (items) | + |
| | Information transmission, computer services and software Employment in urban units (ten thousand) | + |
| | R&D expenditure of industrial enterprises above the designated size (ten thousand yuan) | + |
| | Fiscal expenditure on science and technology (100 million yuan) | + |
| Digital and industrial integration | E-commerce sales (100 million yuan) | + |
| | Proportion of enterprises with e-commerce transactions (%) | + |
| | Number of Internet broadband users (ten thousand) | + |
| | Revenue from the software business (ten thousand yuan) | + |
| | Total telecommunications business volume (100 million yuan) | + |
| Digital trade potential | Total imports and exports (ten thousand dollars) | + |
| | Total retail sales of consumer goods (100 million yuan) | + |
| | Trade openness (%) | + |
| Logistics environment | Total length of postal routes (km) | + |
| | Express volume (ten thousand pieces) | + |
| | Revenue from the express delivery business (ten thousand yuan) | + |

transportation, and communication expenditures. The proportion of expenditure allocated to developing hedonic consumption within the total expenditure serves as a measure for assessing consumption upgrading.

Green technology innovation (*gi*) is quantified by the per capita green patent application rate in each region.

### *Moderating Variable*

Manufacturing agglomeration (*agg*). According to previous research, the location entropy method is employed for quantifying the level of industrial agglomeration in each province, with its calculation method presented in Equation (8).

$$agg_{it} = \frac{m_{it} / M_{it}}{m_t / M_t} \tag{8}$$

Where $m_{it}$ denotes the number of manufacturing employees in each respective region, while $M_{it}$ represents the aggregate number of individuals employed across all industries within each respective region, $m_t$ represents the total number of manufacturing employees across the entire country, and finally, $M_t$ represents the aggregate number of employees across all industries nationwide.

### Sample Selection and Data Description

Considering the availability of data, the research samples selected in this paper are the panel data of 30 provinces, autonomous regions, and municipalities in China (except Tibet, Hong Kong, Macao, and Taiwan) from 2013 to 2021. The data sources used in this study are provincial statistical yearbooks, China Energy Statistical Yearbooks, and the CNRDS database. The descriptive statistical results of each variable are shown in Table 2.

## Empirical Analysis

### Benchmark Regression Analysis

To examine the aforementioned hypothesis, we conducted the Hausman test to determine whether a fixed effect or random effect model is more appropriate for our analysis. The results of this test indicate support for the fixed effect model. Based on these findings, we employed the stepwise regression method for further analysis in this study. The regression results in Table 3 demonstrate that even after controlling for the fixed effect of province and time, as well as incorporating

Table 2. Descriptive statistics of each variable.

| Variable | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| ce | 270 | 9.595 | 0.72 | 7.581 | 11.567 |
| dt | 270 | 0.129 | 0.133 | 0.006 | 0.838 |
| fisca | 270 | 0.489 | 0.186 | 0.151 | 0.931 |
| tax | 270 | 0.082 | 0.029 | 0.044 | 0.2 |
| fin | 270 | 3.394 | 1.129 | 1.674 | 8.131 |
| lnfi | 270 | 9.665 | 0.8 | 7.767 | 11.046 |
| te | 270 | 0.044 | 0.014 | 0.024 | 0.081 |
| city | 270 | 0.602 | 0.117 | 0.365 | 0.942 |
| lnhc | 270 | 2.232 | 0.091 | 2.017 | 2.54 |
| lnpgdp | 270 | 10.94 | 0.42 | 10.05 | 12.123 |
| is | 270 | 2.412 | 0.118 | 2.132 | 2.834 |
| cu | 270 | 0.482 | 0.038 | 0.356 | 0.607 |
| gi | 270 | 0.964 | 1.186 | 0.054 | 8.332 |
| agg | 270 | 0.879 | 0.577 | 0.24 | 2.454 |

control variables sequentially, the coefficient estimate of the core explanatory variable (*dt*) consistently maintains its significantly negative direction at a statistical level of 1%. This finding provides robust evidence supporting hypothesis 1, indicating that digital trade plays a crucial role in effectively reducing regional carbon emissions.

## Endogeneity Issue

The potential endogeneity problem in this study cannot be overlooked, and two empirical testing methods are employed. Firstly, the instrumental variable method is utilized. Following the approach of Nunn and Qian [42] and Huang et al. [43], this paper constructs an interaction term by multiplying the number of Internet broadband access ports in each province from the previous year with the number of fixed telephones in 1984. This interaction term serves as an instrumental variable for examining the development of digital trade. On one hand, the establishment of communication infrastructure serves as a crucial prerequisite for the advancement of digital trade, exerting a profound influence on its development and aligning with the requirements of instrumental variable correlation. On the other hand, in tandem with scientific and technological progress, there has been a gradual decline in the utilization frequency of conventional communication tools, such as the fixed-line telephone, which exhibits negligible impact on carbon emissions and satisfies exogeneity criteria. The regression results in Column (1) of Table 4 indicate that the Kleibergen-Paaprk LM statistic rejects the null hypothesis of "unidentifiability of instrumental variables" at a significance level of 1%. Additionally, the Cragg-Donald Wald F statistic exceeds the critical value of 10%, according to the Stock-Yogo weak identification test. These findings provide evidence against the presence of a weak instrumental variable problem [44]. After passing the aforementioned tests, the estimated coefficient of digital trade development (*dt*) remains significantly negative at a 1% significance level. This indicates that even after employing instrumental variable methods to address endogeneity concerns, the inhibitory impact of digital trade on carbon emissions continues to be statistically significant. Secondly, to establish a dynamic panel model, we incorporate the lagged term of the key dependent variable and employ the system generalized method of moments (SYS-GMM) approach to address potential endogeneity concerns. The findings presented in Column (2) of Table 6 reveal that the AR (2) coefficient stands at 0.437. Furthermore, the Sargan test results confirm the effectiveness of our model. Notably, the regression coefficient for the key explanatory variable (*dt*) remains statistically significant at the 10% level. These outcomes affirm that the conclusions derived from our benchmark regression analysis remain robust.

## Robustness Test

In order to further validate the robustness of the benchmark regression results, this paper also conducts additional robustness tests to enhance the credibility of our findings. (1) Changing the core explanatory variable. The level of digital trade development in the benchmark regression is assessed using the entropy weight method. To mitigate potential biases arising from different measurement approaches, principal component analysis (PCA) is employed to reevaluate

Table 3. Benchmark regression results.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | ce | ce | ce | ce | ce | ce | ce | ce |
| dt | -1.421*** | -1.421*** | -1.312*** | -1.275*** | -0.839*** | -0.837*** | -0.843*** | -0.750*** |
| | (0.322) | (0.321) | (0.261) | (0.253) | (0.218) | (0.221) | (0.225) | (0.212) |
| fisca | | -0.354 | -0.444 | -0.197 | -0.065 | -0.069 | -0.073 | 0.281 |
| | | (0.425) | (0.354) | (0.323) | (0.289) | (0.297) | (0.296) | (0.291) |
| tax | | | 9.595*** | 8.494*** | 7.204*** | 7.189*** | 7.256*** | 5.176*** |
| | | | (0.822) | (1.074) | (0.859) | (0.903) | (0.914) | (1.543) |
| fin | | | | 0.066** | 0.032 | 0.033 | 0.030 | -0.011 |
| | | | | (0.028) | (0.027) | (0.028) | (0.028) | (0.025) |
| lnfi | | | | | -0.263*** | -0.263*** | -0.261*** | -0.193*** |
| | | | | | (0.041) | (0.041) | (0.042) | (0.057) |
| urban | | | | | | 0.046 | 0.071 | -0.263 |
| | | | | | | (0.415) | (0.415) | (0.365) |
| lnhc | | | | | | | -0.304 | -0.191 |
| | | | | | | | (0.415) | (0.389) |
| lnpgdp | | | | | | | | -0.432*** |
| | | | | | | | | (0.164) |
| _cons | 9.779*** | 9.953*** | 9.194*** | 8.934*** | 11.571*** | 11.552*** | 12.203*** | 16.343*** |
| | (0.042) | (0.209) | (0.203) | (0.190) | (0.423) | (0.456) | (0.965) | (1.590) |
| Province FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Obs | 270 | 270 | 270 | 270 | 270 | 270 | 270 | 270 |
| $R^2$ | 0.968 | 0.968 | 0.980 | 0.980 | 0.984 | 0.984 | 0.984 | 0.985 |

Standard errors are in parenthesis; ***, **, and * indicate statistical significance at the levels of 1%, 5%, and 10% respectively.

the digital trade development index for each region. Based on the regression results presented in Column (1) of Table 5, the coefficient estimates of the digital trade development index (*dt_pca*), obtained through principal component analysis, remain significantly negative. This suggests that the variable measurement method does not affect the outcomes derived from the benchmark regression model, thereby confirming the robustness of our research conclusion. (2) Changing the dependent variable. The dependent variable, carbon emissions (*ce*), in the benchmark regression is originally calculated based on carbon emission intensity, which is obtained by dividing carbon emissions by GDP. For robustness testing purposes, this paper substitutes it with the logarithm of per capita carbon emissions (*ce_substitute*). The estimated coefficient of digital trade (*dt*) in Column (2) of Table 5 remains negative and statistically significant even after replacing the dependent variable, indicating that our conclusion is robust. (3) Lagging explanatory variables. Due to the potential time lag between the development of digital trade and its impact on carbon emissions, all explanatory variables in this study were processed one-order lagged. The regression results obtained, shown in column (3) of Table 5, indicate that even after considering the hysteresis effect of emission reduction from digital trade, the coefficient of the digital trade lag term (*L.dt*) remains significantly negative, thus confirming the robustness of our baseline regression results.

## Mechanism Analysis

The mediating effect model is employed to investigate the mechanism through which industrial structure, consumption upgrading, and green technology innovation impact the emission reduction effect of digital trade. The regression results are presented in Table 6. Columns (1), (3), and (5) represent the regression outcomes with industrial structure, consumption upgrading, and green technology innovation as

Table 4. Endogeneity test results.

| | (1) | (2) |
|---|---|---|
| | ce | ce |
| L.ce | | 0.752*** |
| | | (0.192) |
| dt | -0.882*** | -1.178* |
| | (0.224) | (0.672) |
| _cons | 15.938*** | 0.315 |
| | (1.794) | (4.266) |
| Kleibergen-Paap rk LM statistic | 24.895*** | |
| Cragg-Donald Wald F statistic | 256.929 | |
| AR(1) | | 0.064 |
| AR(2) | | 0.437 |
| Sargan | | 0.584 |
| Controls | YES | YES |
| Province FE | YES | YES |
| Time FE | YES | YES |
| Obs | 240 | 240 |

Standard errors are in parenthesis; ***, **, and * indicate statistical significance at the levels of 1%, 5%, and 10% respectively.

Table 5. Results of the robustness test.

| | (1) | (2) | (3) |
|---|---|---|---|
| | ce | ce_ substitute | ce |
| dt_pca | -0.174*** | | |
| | (0.046) | | |
| dt | | -0.553*** | |
| | | (0.206) | |
| L.dt | | | -0.692*** |
| | | | (0.249) |
| _cons | 16.288*** | -0.836 | 14.889*** |
| | (1.655) | (1.617) | (1.689) |
| Controls | YES | YES | YES |
| Province FE | YES | YES | YES |
| Time FE | YES | YES | YES |
| Obs | 270 | 270 | 240 |
| $R^2$ | 0.986 | 0.983 | 0.985 |

Standard errors are in parenthesis; ***, **, and * indicate statistical significance at the levels of 1%, 5%, and 10% respectively.

dependent variables, respectively. The findings reveal that the estimated coefficient of digital trade exhibits significant positive effects at a significance level of at least 10%, indicating that the advancement of digital trade can effectively facilitate upgrades in industrial structure, consumption patterns, and green technology innovation. On this basis, columns (2), (4), and (6) include digital trade and intermediary variables as explanatory variables in the regression model. The findings demonstrate that the coefficients of digital trade development and each intermediary variable exhibit a significant negative relationship. This implies that digital trade development can facilitate industrial upgrading through the optimization effect on industrial structure, enhance residents' consumption structure via the consumption upgrading effect, foster green technology innovation ability through the technology effect, and ultimately unleash carbon dioxide emission reduction effects as a result of the dividends generated by digital trade development. As such, both hypothesis 2 and hypothesis 3 are confirmed.

## Moderating Effect Test

The moderating effect test results in Table 7 reveal a significantly positive estimated coefficient (*dt*agg*) for the interaction term between digital trade and manufacturing agglomeration at the 1% significance level. This finding suggests that the emission reduction effect of digital trade is influenced by the level of manufacturing agglomeration, with manufacturing agglomeration attenuating the impact of digital trade on emissions reduction. Thus, Hypothesis 4 of this paper is verified. The possible reason for this result is that the manufacturing industry fails to realize reasonable agglomeration, which leads to the low level of manufacturing agglomeration fails to give full play to the technology spillover effect and sharing effect of the agglomeration area, and thus fails to achieve the diffusion of energy saving and emission reduction technology and reduce energy consumption, resulting in the weakening of the emission reduction effect of digital trade.

## Further Analysis

### *Threshold Effect Analysis*

In the benchmark regression model, we examine whether digital trade has significantly reduced regional carbon emissions. However, in the case of unbalanced economic development in China's provinces and significant differences in the level of digital trade development, digital trade may have a non-linear impact on carbon emissions; that is, digital trade has a threshold effect on carbon emissions. In addition, environmental regulation is an important means to achieve the goal of carbon reduction. Due to the different development environments and development stages, there are also

Table 6. Mediating effect test results.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | is | ce | gi | ce | cu | ce |
| dt | 0.070* | -0.641*** | 6.019*** | -0.450** | 0.093*** | -0.583*** |
| | (0.038) | (0.186) | (1.016) | (0.221) | (0.027) | (0.200) |
| is | | -1.456*** | | | | |
| | | (0.451) | | | | |
| gi | | | | -0.048*** | | |
| | | | | (0.016) | | |
| cu | | | | | | -1.699*** |
| | | | | | | (0.578) |
| _cons | 2.183*** | 19.699*** | 21.540*** | 17.565*** | 0.413** | 17.222*** |
| | (0.298) | (1.723) | (7.887) | (1.697) | (0.206) | (1.580) |
| Controls | YES | YES | YES | YES | YES | YES |
| Province FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Obs | 270 | 270 | 270 | 270 | 270 | 270 |
| $R^2$ | 0.982 | 0.987 | 0.939 | 0.986 | 0.914 | 0.986 |

Standard errors are in parenthesis; ***, **, and * indicate statistical significance at the levels of 1%, 5%, and 10% respectively.

Table 7. Test results of the moderating effect.

| | (1) |
|---|---|
| | ce |
| dt | -2.075*** |
| | (0.386) |
| dt*agg | 0.824*** |
| | (0.200) |
| agg | 0.313*** |
| | (0.088) |
| _cons | 17.198*** |
| | (1.593) |
| Controls | YES |
| Province FE | YES |
| Time FE | YES |
| Obs | 270 |
| $R^2$ | 0.987 |

Note: Standard errors are in parenthesis; ***, **, and * indicate statistical significance at the levels of 1%, 5%, and 10% respectively.

great differences in the environmental governance means adopted by the government and the intensity of local environmental regulation, which leads to the difference in the emission reduction effect of digital trade. In regions characterized by low environmental regulation intensity, digital trade enterprises face reduced pressure to mitigate emissions and exhibit insufficient motivation to adopt clean technology, thereby hindering the realization of emission reduction advantages in digital trade. As regional environmental regulation intensity improves, relevant enterprises will be compelled to standardize production practices and pollution discharge behavior, leading to further enhancement of the emission reduction potential in digital trade.

In order to further investigate the nonlinear impact of digital trade on carbon emissions, this study adopts the research methodology proposed by Hansen [45], considers digital trade and environmental regulation as threshold variables, and constructs the subsequent panel threshold model:

$$ce_{it} = \phi_0 + \phi_1 dt_{it} \times I(Th_{it} \leq \theta) + \varphi_2 dt_{it} \times I(Th_{it} > \theta) + \varphi_c controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (9)$$

Among them, $Th_{it}$ serves as the threshold encompassing digital trade (*dt*) and environmental regulation (*er*). To measure environmental regulation, this study adopts the research concept proposed by

Table 8. Threshold model test results.

| Threshold variable | Model | RSS | MSE | F-value | P-value | 10% | 5% | 1% |
|---|---|---|---|---|---|---|---|---|
| dt | Single threshold | 1.8149 | 0.0070 | 30.72 | 0.0900 | 28.9391 | 35.9790 | 42.8752 |
| | Double threshold | 1.7096 | 0.0066 | 16.08 | 0.3567 | 24.4022 | 28.8338 | 40.0084 |
| er | Single threshold | 1.8188 | 0.0070 | 30.10 | 0.0400 | 16.1245 | 23.9667 | 94.5984 |
| | Double threshold | 1.7524 | 0.0067 | 9.88 | 0.3600 | 35.5693 | 45.0612 | 62.0137 |

Guan et al. [46], which utilizes the ratio of completed investment in industrial pollution control to the added value of the secondary industry. $\theta$ represents an unknown threshold value, while the remaining parameters retain their previously defined meanings.

After conducting 300 iterations of the Bootstrap method, we observe that both digital trade and environmental regulation successfully pass the single threshold test but fail to meet the criteria for the double threshold test (refer to Table 8). The outcomes presented in Table 9 demonstrate a significant diminishing marginal effect on carbon emissions as digital trade development progresses. Furthermore, Column (2) of Table 9 reveals that an increase in regional environmental regulation leads to a further enhancement in the emission reduction impact of digital trade. These findings highlight that the influence of digital trade development on carbon emissions is not solely determined by its own level but also influenced by non-linear effects resulting from variations in environmental regulation intensity. Notably, when environmental regulation intensity reaches a certain threshold, the emission reduction effect of digital trade becomes more pronounced.

Table 9. Regression results of the threshold model.

| | (1) | (2) |
|---|---|---|
| Threshold variable | dt | er |
| Threshold value $\theta$ | 0.053 | 0.008 |
| $\mathrm{dt} \times I(Th \leq \theta)$ | -3.234*** | -0.681*** |
| | (0.515) | (0.172) |
| $\mathrm{dt} \times I(Th > \theta)$ | -0.623*** | -4.486*** |
| | (0.169) | (1.497) |
| Constant | 8.007 | 7.356 |
| | (1.466) | (1.497) |
| Controls | YES | YES |
| Province FE | YES | YES |
| Time FE | YES | YES |
| $R^2$ | 0.823 | 0.814 |

Note: Standard errors are in parenthesis; ***, **, and * indicate statistical significance at the levels of 1%, 5%, and 10% respectively

*Spatial Effect Analysis*

Existing research has indicated that digital trade, during its developmental process, will generate a significant amount of data and information flow. This will break down the barriers to circulation caused by inadequate technology or information thereby accelerating cross-regional flows of both technology and information. As a result, spatial spillover effects are likely to occur. To investigate the potential impact of digital trade on reducing carbon emissions through such spillover effects, this paper constructs a spatial panel model for analysis. Traditional models in spatial econometrics include the Spatial Durbin Model (SDM), Spatial Lag Model (SAR), and Spatial Error Model (SEM). The specific formulas for these models are as follows:

SDM:

$$e_{it} = K_1 Wce_{it} + \theta_1 dt_{it} + K_2 Wce_{it} + \theta_c controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (10)$$

SAR: $$e_{it} = \rho Wce_{it} + \tau_1 dt_{it} + \tau_c controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (11)$$

SEM: $$e_{it} = \eta_1 dt_{it} + \eta_c controls_{it} + \mu_i + \delta_t + \upsilon_{it}, \upsilon_{it} = \pi W \upsilon_{it} + \varepsilon_{it} \quad (12)$$

Where $W$ is the n×n dimensional spatial weight matrix. $K$, $\rho$, and $\pi$ represent the spatial autoregressive terms.

Based on the spatial distance matrix, the global *Moran's I* index was computed from 2013 to 2021 to assess spatial correlation. The results of the spatial correlation test presented in Table 10 indicate a significant spatial association between China's digital trade and carbon emissions distribution. Considering both the spatial effect of the explained variable and error term, the spatial Durbin model is selected for regression analysis as it provides a better estimation of individual-generated spatial spillover effects. Following a Hausman test, we confirm that our chosen model is a two-way fixed effects spatial Durbin model.

It can be seen from the results of the spatial Durbin model in Column (1) of Table 11 that the coefficient of the spatial term (W×dt) is -0.560, which

Table 10. Results of the spatial correlation test.

| Year | dt | | ce | |
|---|---|---|---|---|
| | Moran's I | z-Score | Moran's I | z-Score |
| 2013 | 0.022* | 1.656 | 0.096*** | 3.637 |
| 2014 | 0.028* | 1.836 | 0.093*** | 3.563 |
| 2015 | 0.034** | 2.013 | 0.095*** | 3.687 |
| 2016 | 0.036** | 2.090 | 0.095*** | 3.589 |
| 2017 | 0.033** | 2..015 | 0.093*** | 3.556 |
| 2018 | 0.030** | 1.958 | 0.094*** | 3.570 |
| 2019 | 0.029* | 1.947 | 0.092*** | 3.528 |
| 2020 | 0.028* | 1.921 | 0.089*** | 3.466 |
| 2021 | 0.030* | 1.985 | 0.089*** | 3.459 |

Table 11. Decomposition results of spatial effects.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ce | Direct effect | Indirect effect | Total effect |
| dt | -0.604*** | -0.644*** | -0.868*** | -1.512*** |
| | (0.161) | (0.168) | (0.291) | (0.398) |
| Wx×dt | -0.560*** | | | |
| | (0.191) | | | |
| Spatial:rho | 0.226** | | | |
| | (0.091) | | | |
| Controls | YES | YES | YES | YES |
| Province FE | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES |
| Obs | 270 | 270 | 270 | 270 |
| $^{R}2$ | 0.067 | 0.067 | 0.067 | 0.067 |

Note: Standard errors are in parenthesis; ***, ** and * indicate statistical significance at the levels of 1%, 5%, and 10% respectively.

is significant at the statistical level of 1%, indicating that the development of digital trade in all regions of China will have a negative spatial spillover effect on carbon emissions in surrounding areas. The results of columns (2) - (4) show that the impact of digital trade on carbon emissions, whether direct effect, indirect effect, or total effect, is significantly negative, which indicates that the development of digital trade can not only reduce the carbon emissions of the region, but also play a radiation role in digital trade. This indicates that the development of digital trade can not only reduce the carbon emissions of the local region, but also reduce the carbon dioxide emissions of neighboring regions.

Based on the results of the spatial Durbin model presented in column (1) of Table 11, it is evident that the coefficient of the spatial term (W × dt) is -0.560, which exhibits statistical significance at a 1% level. This finding suggests that the development of digital trade across different regions of China exerts a negative spatial spillover effect on carbon emissions in neighboring areas. Furthermore, employing the partial differential method to decompose these spillover effects, columns (2) to (4) reveal significant negative impacts of digital trade on carbon emissions, whether through direct, indirect, or total effects. These outcomes indicate that digital trade not only reduces carbon emissions locally but also leverages its radiation effect to mitigate carbon dioxide emissions in adjacent regions.

*Heterogeneity Analysis*

Given the substantial disparities in resource endowments and levels of economic development across

Table 12. Results of heterogeneity analysis.

| | (1) | (2) | (3) |
|---|---|---|---|
| | ce | ce | ce |
| dt | -3.079*** | -0.571*** | -2.441*** |
| | (0.830) | (0.171) | (0.748) |
| _cons | 19.140*** | 18.588*** | 25.939*** |
| | (2.593) | (1.589) | (3.143) |
| Controls | YES | YES | YES |
| Province FE | YES | YES | YES |
| Time FE | YES | YES | YES |
| Obs | 171 | 198 | 99 |
| $R^2$ | 0.983 | 0.991 | 0.989 |

Note: Standard errors are in parenthesis; ***, **. and * indicate statistical significance at the levels of 1%, 5%, and 10% respectively.

various regions in China, this study further stratifies the sample of 30 provinces into the eastern, central, and western regions for conducting regional heterogeneity analysis[1]. The results of the regional heterogeneity test on the impact of digital trade on carbon emissions are presented in Table 12. Grouping regression analysis reveals that, even after controlling for two-way fixed effects, the emission reduction effect of digital trade development remains statistically significant at a 1% level across all three regions. From a regional perspective, the eastern region exhibits the strongest emission reduction effect of digital trade development, followed by the western region, while the central region shows relatively weaker effects. This discrepancy may be attributed to the relatively mature state of digital trade development in the eastern region, resulting in a more intense impact on carbon emissions. In contrast, the western region is experiencing an ongoing improvement in its digital infrastructure and thus demonstrates a gradually increasing marginal effect on reducing carbon emissions through digital trade activities. However, it appears that there might be some lagging inhibiting effect of digital trade on carbon emissions within the central region; therefore, further efforts are needed to enhance its emission reduction potential.

[1] The eastern region includes 11 provinces: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; The central region includes Shanxi, Jilin, Heilongjiang, Henan, Hubei, Hunan, Anhui, and Jiangxi provinces. The western region includes 11 provinces, including Inner Mongolia Autonomous Region, Chongqing Municipality, Sichuan Province, Guangxi Zhuang Autonomous Region, Guizhou Province, Yunnan Province, Shaanxi Province, Gansu Province, Qinghai Province, Ningxia Hui Autonomous Region, and Xinjiang Uygur Autonomous Region.

## Conclusions and Policy Recommendations

Digital trade, which integrates digital technology with traditional trade, plays an increasingly pivotal role in enhancing factor allocation efficiency, promoting industrial structure upgrading, and optimizing residents' consumption patterns. By driving production and consumption mode transformation as well as technological iteration, digital trade contributes to the gradual reduction of carbon dioxide emissions. The profound impact of digital technology on international trade not only injects new impetus into global commerce but also offers a viable pathway for achieving national emission reduction targets. In this context, this study examines the detailed and comprehensive influence of digital trade development on regional carbon emissions by analyzing a sample of 30 provinces in China while exploring potential channels and influencing mechanisms. The principal findings of this study are as follows: (1) The development of digital trade significantly mitigates regional carbon dioxide emissions, with industrial transformation, consumption upgrading, and green technology innovation playing a pivotal role in this process. (2) The impact of digital trade on carbon emissions reduction will be regulated by the degree of manufacturing agglomeration, whereby manufacturing agglomeration attenuates the efficacy of emission reduction through digital trade. (3) The impact of digital trade development on carbon emissions exhibits a non-linear relationship. Once the development of digital trade surpasses its own threshold, its capacity to reduce emissions will diminish. Conversely, as regional environmental regulations intensify and exceed their respective thresholds, the emission reduction potential of digital trade will be enhanced. (4) Through spatial effect analysis, we have identified that the advancement of digital trade not only contributes to local carbon emissions reduction but also facilitates a spillover effect on neighboring regions, resulting in reduced carbon emissions. (5) Furthermore, heterogeneity analysis reveals that the emission reduction impact of digital trade is most pronounced in the eastern region, followed by the western and central regions.

Based on the aforementioned research findings, this paper puts forward the subsequent policy recommendations: (1) Relying on digital technology innovation to bolster the momentum of digital trade development, China should strive to enhance its autonomous capacity for digital and information communication technology innovation, expedite the establishment of a robust digital industry framework, and propel high-quality digitized trade through comprehensive measures. Additionally, drawing from the experience gained in constructing free trade zones, it is advisable to explore pilot initiatives for establishing demonstration zones dedicated to digital trade. This endeavor would facilitate harmonization between international standards and both digital and trade norms while fostering an enabling institutional environment conducive to flourishing digital commerce. This will enable comprehensive exploration of China's potential in digital commerce as well as its capacity for emission reduction through digital trade. (2) The promotion of digital trade to reduce carbon emissions relies on crucial measures such as industrial transformation, consumption upgrading, and green technology innovation. In this regard, the government should support foreign trade enterprises in their transition towards digitalization and intelligence while promoting rationalization and optimization of industrial structures. Additionally, creating a relaxed and inclusive policy environment for platform economy development and reducing trade barriers for foreign trade enterprises is crucial. By deepening international trade relations, not only can diverse goods and services be provided to consumers, but also consumer consumption patterns and structures can be transformed, fostering low-carbon consumption habits that contribute to reduced carbon emissions at the consumer level. Furthermore, it is imperative to incentivize enterprises to proactively embrace technologies and production processes that foster clean production. Simultaneously, providing financial and policy support for green technology innovation will facilitate the transition of conventional manufacturing enterprises into low-carbon entities, thereby effectively mitigating their carbon emissions during the production phase. (3) Given the threshold effect of digital trade itself and environmental regulation on carbon emissions, it is necessary to guide the systematic and standardized development of regional digital trade while curbing the disorderly expansion of industries associated with digital trade. In addition, governmental collaboration with appropriate environmental regulations is essential to maximizing the emission reduction potential of digital trade. (4) The research findings demonstrate that digital trade not only exhibits spatial spillover effects but also displays significant regional heterogeneity in terms of emission reduction. Therefore, it is crucial to enhance inter-regional and inter-industrial exchanges and cooperation, fostering the coordinated development of regional digital trade. On the other hand, it is also imperative to leverage the pivotal role of the eastern region in promoting digital trade development while progressively bridging the digital infrastructure gap between the central and western regions vis-à-vis the eastern region. Tailored strategies should be devised to empower provinces with deficient digital infrastructure to overcome the digital divide, alongside formulating context-specific strategies for advancing emission reduction efficacy within digital trade.

Although this study has conducted an effective analysis of the emission reduction effect of digital trade, there are still several deficiencies. Firstly, regarding the selection of research samples, it should be noted that the samples in this paper are limited to 30 provinces in China and may not fully represent the characteristics of developing countries universally. Secondly, concerning the construction of the index for measuring the level of digital trade development, given that a clear and universally accepted definition is lacking in academia, there might be potential bias in the index measurement employed in this paper. Lastly, due to data acquisition challenges, only $CO_2$ emissions were considered when examining the impact of digital trade, while potential effects on other pollutants, such as water pollutants, were not explored extensively. We believe that future studies can supplement these limitations with advancements in national statistical standards unification, increased accessibility to statistical data, and enhanced utilization of digital technology within trade.

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## Conflict of Interest

The authors declare no conflict of interest.

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