agriculture

Article

Rural E-Commerce and Agricultural Carbon Emission Reduction: A Quasi-Natural Experiment from China's Rural E-Commerce Demonstration County Program Based on 355 Cities in Ten Years

Kaiwen Ji [1], Qiaoyun Hou [2], Yi Yu [2] and Dan Pan [2,*]

1 College of Political Science and Law, Jiangxi Normal University, Nanchang 330022, China; 202140101034@jxnu.edu.cn
2 School of Economics, Jiangxi University of Finance and Economics, Nanchang 330013, China; 2202003157@stu.jxufe.edu.cn (Q.H.); 2202110042@stu.jxufe.edu.cn (Y.Y.)
* Correspondence: pandan@jxufe.edu.cn; Tel.: +86-791-8381-6042

Abstract: Reducing carbon emissions is of paramount importance to the accomplishment of the 2030 Sustainable Development Goals. The effect of rural e-commerce on agricultural carbon emissions (ACEs) is controversial, and particularly the mechanism behind the effect is unknown. To identify the impact of rural e-commerce on agricultural carbon emissions and its mechanisms, we take advantage of China's Rural E-Commerce Demonstration County Program (REDCP) as a quasi-natural experiment and use the multi-period difference-in-difference (DID) model to investigate the relationship between rural e-commerce and agricultural carbon emissions. Our data are based on panel data of 355 prefecture-level cities from 2010 to 2019 in China. We identify that rural e-commerce can reduce agricultural carbon emissions by an average of 14.4%, but this effect is not long-lasting. Mechanism analyses suggest that the reduction effect of rural e-commerce on agricultural carbon emissions is mainly due to fostering agricultural economic growth, increasing the share of low-carbon industry, and improving agricultural total factor productivity (TFP). Further heterogeneity analyses demonstrate that rural e-commerce has better carbon emissions reduction performance in eastern cities as well as in non-major grain-producing cities in China.

Keywords: carbon emission reduction; agricultural carbon emission; rural e-commerce; quasi-natural experiment; China's rural e-commerce demonstration county program

check for updates

Citation: Ji, K.; Hou, Q.; Yu, Y.; Pan, D. Rural E-Commerce and Agricultural Carbon Emission Reduction: A Quasi-Natural Experiment from China's Rural E-Commerce Demonstration County Program Based on 355 Cities in Ten Years. *Agriculture* **2024**, *14*, 75. https://doi.org/10.3390/agriculture14010075

Academic Editor: Mariusz J. Stolarski

Received: 13 November 2023
Revised: 19 December 2023
Accepted: 27 December 2023
Published: 30 December 2023

1. Introduction

Reducing carbon emissions is of paramount importance to the accomplishment of the 2030 Sustainable Development Goals. Agricultural carbon emissions (ACEs) are a significant contributor to global carbon emissions. According to statistical data from FAO, agriculture accounts for approximately 20% of global carbon emissions [1]. ACEs in China, the world's most populous country and a major agricultural producer with a rapid agricultural economic growth rate, are alarmingly high. It is estimated that China's ACEs reached 1.33 billion metric tons in 2018, accounting for over 17% of the ACEs worldwide and about 34% of total national carbon emissions [2]. The Chinese government declared in 2020 that stronger policy measures will be taken to achieve peak carbon by 2030 and reach carbon neutrality by 2060 [3]. Taking decisive actions to curb ACEs is imperative to achieve this "double carbon" target and improve people's welfare in China.

Numerous studies have investigated how to decrease ACEs. The existing related literature has confirmed that ACEs are affected by agricultural economic development [4–6], agricultural technology [7], urbanization [8], agricultural subsidies [9], energy consumption [10–12], etc. However, relatively few studies have examined how ACEs are influenced by rural e-commerce. Rural e-commerce is a type of e-commerce corresponding to urban e-commerce, which takes agriculture, rural areas, and farmers as its service targets and uses the internet, computers, and other modern information technologies to enable the main production and operation entities in agriculture-related fields to conduct business transactions such as sales, purchases, and electronic payments of products or services over the internet [13]. Recent years have seen rapid growth in rural e-commerce, which is considered a remarkable characteristic in rural China. In 2019, there were 4310 Taobao villages with e-commerce, up from 3 in 2009 [14,15], and China's share of total rural e-tailing transactions increased from 2.5% in 2010 to 17.3% in 2018 [16]. This significant expansion of rural e-commerce has far-reaching implications for the rural economy and the well-being of the rural population [17]. Existing research has demonstrated that rural e-commerce is essential for increasing rural income [18], reducing regional poverty [19], improving agricultural product prices [20], reducing income inequality [21], and promoting rural industry development [22]. These studies primarily concentrate on rural e-commerce's implication for farmers' behavior and economic growth. However, the effect of e-commerce on ACEs in rural China, and the underlying mechanisms, remain unclear.

In reality, rural e-commerce could make a significant contribution to regulating carbon emissions. On one hand, rural e-commerce may lower carbon emissions by fostering agricultural economic development, increasing the proportion of low-carbon industry, and enhancing agricultural total factor productivity. Ji et al. [23] discovered that rural e-commerce can bring about environmental improvements by reducing fertilizer and non-point source pollution. Li et al. [24] pointed out that rural e-commerce will increase consumers' willingness to buy high-quality products at high prices, leading farmers to use more green technologies for agricultural production and to produce better products, and it will exert positive impacts on ACE reduction. On the other hand, rural e-commerce may also contribute to increased carbon emissions, as it can lead to larger production scales and rising demand for resource-intensive products, as noted by Tang and Zhu [22]. Consequently, the impact of rural e-commerce on carbon emissions remains uncertain, and further investigation is needed to understand the underlying mechanisms that link these two contradictory effects.

Accordingly, this research intends to address the following research questions: what role does rural e-commerce play in influencing carbon emissions? What are the mechanisms through which carbon emissions are affected by rural e-commerce? Are rural e-commerce's impacts on carbon emissions heterogeneous across different contexts? This study answers the above questions and addresses the knowledge gap by utilizing China's Rural E-Commerce Demonstration Counties Program (REDCP), which entails various policies supporting rural e-commerce construction and which was implemented in 2014, as a quasi-natural experiment. The main focuses of our research are examining the average and dynamic effects of REDCP on ACEs; analyzing the heterogeneous effects of REDCP on ACEs in various regions; and identifying the impact mechanisms of REDCP on ACEs. We discover that REDCP lowers ACEs by an average of 14.4%. Mechanism analysis indicates that REDCP might, primarily through fostering agricultural economic growth, increasing the share of low-carbon industry, and improving agricultural green total factor productivity, help decrease ACEs. Heterogeneity analyses reveal that REDCP performs better in reducing ACEs in eastern and non-major grain production cities in China.

The authors fill the academic gap in research on ACEs by concentrating on rural e-commerce's effects in three ways.

First, we provide the first thorough empirical evidence on the environmental performance of rural e-commerce. Most current studies have focused on the economic and social performance of rural e-commerce. For instance, Li et al. [25] claimed that rural e-commerce is designed to increase farmers' income. Benyam et al. [26] held that rural e-commerce exerts an impact on facilitating industry conformity and improving green agricultural productivity. Peng et al. [19] declared that the "digital dividend" from rural e-commerce greatly boosts rural income. What is more, rural e-commerce empowers rural women by giving them more control over their working hours and increasing their participation in production activities [27]. Little research, particularly in developing countries, has focused on the environmental impacts of rural e-commerce, which prevents us from gaining an in-depth understanding of the effects of rural e-commerce. We demonstrate that rural e-commerce will result in a reduction in ACEs. We also dive deeper into the heterogeneity effect of rural e-commerce. Our findings can provide insightful advice for implementing future rural e-commerce policy decisions in China as well as in other developing countries.

Second, we contribute to the growing discussion on the relationship between the digital economy and environmental sustainability. An increasing body of research attempts to explain how digital economy development and environmental sustainability are related, yet opposing viewpoints exist. Most studies claim that digital technology development helps to realize energy conservation, emission reduction, and the improvement of environmental quality. This type of study mainly posits that the digital economy can optimize the monitoring of environmental quality by government departments [28], improve the production technology of enterprises [29], and promote the formation of the concept of green consumption among the public [30]. However, some other studies argue that rapid advances in digital technologies will increase energy consumption, such as electricity use, thus driving growth in carbon emissions [31,32]. Using a relatively rigorous empirical approach, we discover that rural e-commerce contributes to the decline of ACEs. This finding adds to the debate over the link between environmental sustainability and digital economy development, especially in underdeveloped countries.

Third, we examine how rural e-commerce works in China, the world's largest developing country, in contrast to the previous literature, which primarily focuses on the effects of rural e-commerce in developed countries [33]. There are huge differences in e-commerce performance between developing and developed countries. This is due to the fact that in developed countries the market is the most natural driver of e-commerce development, whereas in developing countries the government has a strong influence on e-commerce development [34]. We examine the effects of the Chinese government's extensive rural e-commerce investments on ACEs, which helps in understanding the role of government in promoting environmental sustainability in underdeveloped areas.

The remaining sections of the paper are structured as follows. Section 2 describes the policy context and builds the theory framework. Section 3 explains the data sources and model settings. Section 4 demonstrates the results of a series of empirical analyses. Section 5 concludes the empirical results and makes targeted policy recommendations.

2. Policy Background and Theory Framework

2.1. Policy Background: REDCP

REDCP is one of the primary efforts that the Chinese government has put in place to support the growth of the rural digital economy. In July 2014, the Ministry of Finance and Ministry of Commerce of the People's Republic of China issued the "Notice on Comprehensive Demonstration of Rural E-Commerce", a comprehensive deployment of REDCP, to develop rural e-commerce. Since then, the REDCP project has become an extremely important policy in digital rural construction. By the end of 2021, a total of 1466 counties had implemented REDCP [23].

Rural e-commerce development has received substantial financial backing from REDCP. By the end of 2020, a cumulative investment of more than RMB 10 billion from the central government had been invested in REDCP. These funds are mainly directed to the following five areas: infrastructure construction of service sites, the establishment of rural logistics and distribution systems, cultivation of branded products, transformation and upgradation of rural trade and circulation enterprises, and rural e-commerce training. Due to these massive investments, e-commerce infrastructure construction in rural areas has benefited greatly from REDCP. At the end of 2020, courier outlets' coverage in townships and couriers' proportion in the countryside had increased to over 50%. Based on the REDCP list of China from 2014 to 2019, the geographical distribution of REDCP cities in China is illustrated in Figure 1.

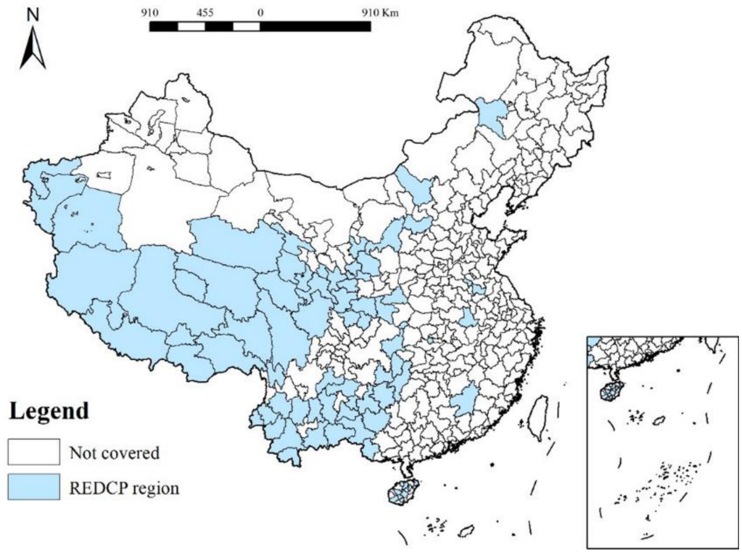

Figure 1. The geographical distribution of REDCP cities (Data source: The website of China's State Council. http://www.mofcom.gov.cn/article/jiguanzx/201908/20190802893332.shtml (accessed on 19 December 2023)).

REDCP offers a range of financial, poverty alleviation, and industrial policies in rural e-commerce demonstration county areas, which may have an impact on ACEs. For example, the actions taken by REDCP will affect the expansion of the agricultural economy by helping to develop rural areas' logistical infrastructure and e-commerce business environment. REDCP can boost the e-commerce of farm products, rural industrial products, village tours, and service products, which facilitates the growth of low-carbon industries. A precision poverty alleviation e-commerce platform has emerged with the ongoing promotion of REDCP, which helps consumers trace the origin of their products through internet technology and monitors farmers to encourage them to produce products according to sustainable standards, which helps reduce ACEs.

2.2. Theory Framework

In accordance with studies by Grossman and Krueger [35], we propose that the scale effect, structural effect, and technological effect are the main factors contributing to REDCP's effects on ACEs (as Figure 2 shows). The following subsections provide thorough justifications.

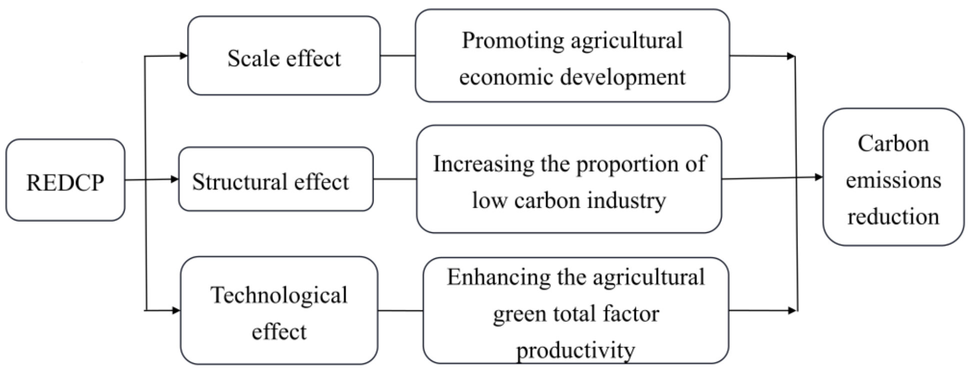

Figure 2. The mechanisms of REDCP on ACEs (Source: Drawings by the authors of this article).

2.2.1. Scale Effect: Promoting Agricultural Economic Development

REDCP will increase the agricultural economic development of REDCP areas, which will lead to a reduction in ACEs [20].

First, REDCP can bring economic development opportunities for people living in rural areas [16]. Zhang et al. [36] indicated that by bringing information on technical development to enable the sustainable flow and interchange of urban–rural elements, REDCP facilitates industry upgrading and employment de-agriculturalization, thus stimulating rural economic development. Second, REDCP can train farmers on internet use knowledge and e-commerce skills, which is also beneficial for income improvement [19]. Third, rural e-commerce platforms in REDCP enable farmers and rural entrepreneurs to connect directly with consumers, bypassing intermediaries and reducing transportation-related emissions. This direct-to-consumer model promotes agricultural economic development by providing farmers with fair prices for their products and reducing food waste through more efficient supply chains. Higher agricultural economic development further contributes to the reduction of ACEs. Similarly, Hailemariam et al. [37] asserted that as countries become richer, those countries tend to invest in the study and development of cleaner production technologies to decrease carbon emissions and enhance eco-efficiency. Deng et al. [38] claimed that economic development will promote technological progress in agriculture, which contributes to the reduction of ACEs.

2.2.2. Structural Effect: Increasing the Proportion of Low-Carbon Industry

REDCP can increase the proportion of low-carbon industries and thus reduce ACEs. First, the government will promote the integration of e-commerce with some low-carbon industries, such as rural tourism and folk culture, through financial support in the process of implementing REDCP [36,39], which will contribute to the growth of low-carbon industries. Second, e-commerce operations will increase the employment demand of service industries such as customer service and operation management, thus helping to increase the proportion of low-carbon industries [40].

2.2.3. Technological Effect: Enhancing the Agricultural Total Factor Productivity

REDCP can enhance agricultural total factor productivity (TFP), thus decreasing ACEs. First, through access to e-commerce platforms, farmers can gain access to information, knowledge, and tools that can help them optimize their farming practices, including efficient irrigation systems, pest-management techniques, and sustainable fertilization methods. This increased knowledge and access to resources can boost agricultural TFP, leading to more efficient use of inputs such as water, fertilizer, and energy, and ultimately reducing carbon emissions associated with resource-intensive agricultural practices. Second, REDCP promotes green agriculture growth by increasing the expected price and marginal returns of non-polluted farming products, which helps reduce carbon emissions [3]. Third, REDCP can let consumers control product quality by tracking product information [41]. Consumers are more likely to purchase high-value-added green agricultural products, and farmers are prone to produce green products with low carbon emissions [42].

3. Materials and Methods

3.1. Materials

3.1.1. Measurement of Dependent Variable: ACEs

Referring to Liu et al. [2], ACEs are the aggregate greenhouse gases (GHG) emitted from the entire agricultural sector, which are directly or indirectly caused by fertilizers, pesticides, agricultural films, irrigation, and tillage during agricultural production. Based on the carbon emission equations established by Tian et al. [43], the evaluation model for ACEs is formulated as follows.

$$ACE = \sum E_i = T_i \cdot \delta_i \tag{1}$$

where ACE represents the total ACEs; E_i indicates the ACEs of each carbon source, including fertilizers, pesticides, agricultural films, irrigation, and tillage; T_i denotes the carbon emissions of each source; and δ_i are the carbon emission coefficients of each carbon source, which are listed in Table 1. In addition, because ACEs are linked to agricultural economic development, we employ the logarithm of agricultural carbon intensity, which represents the proportion of ACE to agricultural output, to denote ACEs.

Table 1. Carbon emission factors for main sources in agriculture.

Carbon Sources	Carbon Emission Coefficient	Reference Source
Fertilizers	0.896 kg·kg^{-1}	Oak Ridge National Laboratory, ORNL
Pesticides	4.934 kg·kg^{-1}	Oak Ridge National Laboratory, ORNL
Plastic sheeting	5.180 kg·kg^{-1}	Institute of Resources, Ecosystem, and Environment of Agriculture, IREEA
Irrigation	20.476 kg·hm^{-2}	Dubey and Lal [44]
Tillage	312.600 kg·hm^{-2}	College of Biotechnology, China Agricultural University

3.1.2. Measurement of the Independent Variable: REDCP

REDCP, a dummy variable showing whether or not a prefecture-level city has applied REDCP in a particular year, is the core independent variable. According to Zeng [45], REDCP is defined as 1 when 80% or more of the counties in a municipality i implemented REDCP in a certain year; otherwise, it is regarded as 0.

3.1.3. Control Variables

To avoid endogenous problems arising from omitted variables, we select four indicators as control variables that may influence ACEs: rural population, agricultural structure, agricultural fertilizer structure, and agricultural mechanization. The specifics are listed in Table 2.

Table 2. The major variables' statistical analysis.

Variable	Definition	Mean	SD	N
REDCP	=1, if city i at year t implemented REDCP; =0, otherwise	0.078	0.269	2167
ACEs	The logarithm of total agricultural carbon emissions intensity	14.837	0.678	2167
Rural population	The logarithm of the total rural population	4.789	1.048	2116
Agricultural structure	The ratio of agriculture to the total primary sector output	0.566	0.842	2167
Agricultural fertilizer structure	The ratio of nitrogen fertilizer to the total fertilizer use	0.598	2.139	2167
Agricultural mechanization	The logarithm of the total power of agricultural machinery	5.278	1.128	2105

(1) Rural population. This variable is measured as the logarithm of the entire rural population to avoid the effects of extreme values and the problem of covariance. ACEs will rise with a larger rural population, as there are more individuals working in agriculture [46,47].

(2) Agricultural structure. This indicator is measured using the proportion of agriculture to aggregate output of the primary industry. Agricultural internal structure may impact ACEs [48]. At a given level of primary industry, ACEs are higher when a larger share of agricultural production is arable [49].

(3) Agricultural fertilizer structure. This variable is measured by the ratio between nitrogen fertilizer and total fertilizer applied (in pure form). Use of nitrogen fertilizers in agricultural production increases crop yields, but nitrogen fertilizer application is also positively correlated with ACEs. Thus, the decreasing share of nitrogen fertilizers in agricultural fertilizers helps to reduce ACEs [50].

(4) Agricultural mechanization. To avoid the effects of extreme values and the problem of covariance, we use the logarithm of the gross agricultural machinery power for this variable. Inefficient application of machinery for farming and the energy it consumes can both cause a rise in ACEs [51].

3.1.4. Sample Selection and Data Source

REDCP was first implemented in 2014. By the end of 2019, the data from China's State Council show that a total of 1231 counties had implemented REDCP. Given abundant missing data at the city level after 2019, based on a reasonable selection of the study sample and the available data, 355 cities' data from 2010 to 2019 are selected as our study sample. Among them, 76 prefecture-level cities where 80% or more of counties have implemented REDCP—1 in 2014, 3 in 2015, 5 in 2016, 12 in 2017, 33 in 2018, and 22 in 2019—are taken as experimental groups, and the controlling groups are the remaining 279 prefecture-level municipalities.

The *China Statistical Yearbook for Regional Economy*, *China Rural Statistical Yearbook*, and *China Statistical Yearbook* for 2010–2019 provide the data for this study [52–54]. To fill in some of the missing values, local statistical yearbooks and statistical bulletins are manually collected. Samples with a large amount of missing data are eliminated, and the rest of the missing values are plugged in by a linear interpolating method.

3.2. Method: Multi-Period DID Method

To accurately depict how REDCP affects ACEs, we employ the multi-period DID approach. Unlike multiple regression, multi-period DID solves the omitted variable endogeneity problem, allowing for precise identification of causation. In this paper, data is analyzed using the statistical software Stata 17. Based on Beck et al. [55], the model below is employed.

$$ACEs_{i,t} = \alpha_0 + \alpha_1 REDCP_{i,t} + \alpha_2 X_{i,t} + \mu_i + \theta_t + \varepsilon_{i,t} \quad (2)$$

where $ACEs_{i,t}$ denotes the ACEs for city i in year t; $REDCP_{i,t}$ is a treatment variable which is 1 if city i has implemented REDCP in year t and 0 otherwise; and $X_{i,t}$ denotes control variables affecting ACEs. μ_i refers to city fixed effects controlling for time-varying effects, and θ_t represents time-fixed effects that do not vary with cities. $\varepsilon_{i,t}$ indicates stochastic errors.

Equation (2) only estimates the statical average effect of how REDCP affects ACEs; we further use an event study approach to obtain the dynamic effects. The following is the model.

$$ACEs_{i,t} = \varphi_0 + \sum_{k=0}^{k=3} \sigma_k REDCP_{i,t}^k + \rho X_{i,t} + \mu_i + \theta_t + \varepsilon_{i,t} \quad (3)$$

where $REDCP_{i,t}^k = 1$ signifies the post-REDCP city; otherwise, $REDCP_{i,t}^k = 0$. σ_k indicates the impact of REDCP on ACEs in year k after REDCP implementation. The remaining components are identical to those in Equation (2).

4. Results

4.1. The Average Effect of REDCP on ACEs

The estimates based on Formula (2) are given in Table 3. Results in column (1) do not incorporate control variables, while column (2) results do. It is clear that REDCP's coefficient is significantly negative in both columns. According to column (2)'s findings, REDCP notably reduces ACEs by 14.4% at the 1% level of significance, implying that REDCP can contribute to the reduction of ACEs.

Table 3. The average effect of REDCP on ACEs.

Variables	(1)	(2)
REDCP	−0.183 *** (0.051)	−0.144 *** (0.049)
Rural population		0.005 (0.051)
Industrial structure		−0.035 (0.048)
Agricultural fertilizer structure		−0.006 (0.005)
Agricultural mechanization		0.024 (0.022)
City fix-effect	Yes	Yes
Year fix-effect	Yes	Yes
R^2	0.837	0.846
Observations	2166	2052

Note: "***" means estimates at the 1% significance level, and standard deviations are in parentheses.

4.2. The Dynamic Effect of REDCP on ACEs

Table 3's findings solely display REDCP's average effect on ACEs. However, reducing carbon emissions is crucial for long-term economic sustainability, so we should concentrate on how REDCP affects ACEs dynamically.

Table 4 demonstrates the dynamic impact of REDCP on ACEs based on Formula (3). We can see that although there is an upward trend, the effect of REDCP on reducing ACEs is not long-lasting. Notably, the coefficients of REDCP in column (2) when including control variables increase from 0.198 in the first year of REDCP implementation to 0.337 in the second year of REDCP implementation. This result indicates that the impact of REDCP on ACEs lasts for two years after REDCP implementation. Nevertheless, there is no significant coefficient in the third year of REDCP implementation. Therefore, we can conclude that REDCP's impact on ACEs is not sustainable over the long term.

Table 4. The dynamic effects of REDCP on ACEs.

Variables	(1)	(2)
$REDCP^{-4}$	0.077 (0.092)	0.082 (0.099)
$REDCP^{-3}$	−0.004 (0.080)	0.006 (0.089)
$REDCP^{-2}$	−0.047 (0.089)	−0.026 (0.099)
$REDCP^{-1}$	0.009 (0.086)	0.043 (0.095)
$REDCP^{0}$	−0.111 (0.091)	−0.073 (0.102)
$REDCP^{1}$	−0.294 *** (0.111)	−0.198 * (0.102)
$REDCP^{2}$	−0.363 ** (0.165)	−0.337 ** (0.161)
$REDCP^{3}$	−0.240 * (0.138)	−0.183 (0.141)
Controls	No	Yes
City fix-effect	Yes	Yes
Year fix-effect	Yes	Yes
R^2	0.839	0.848
Observations	2166	2052

Notes: "***", "**", and "*" mean estimates at the 1%, 5%, and 10% significance levels, respectively; and standard deviations are in parentheses.

4.3. Robustness Testing

4.3.1. Parallel Trend Test

The pivotal premise in deriving the DID regression results is that the ACE trend before REDCP implementation is consistent between REDCP and non-REDCP cities. Following Beck et al. [55], we use the fifth year prior to REDCP implementation as the reference period and omit this period to avoid the multicollinearity bias. The common trend test findings are displayed in Figure 3. We find that the REDCP coefficients are insignificant within the 95% confidence interval from zero for all years prior to the implementation of REDCP, suggesting a common trend and passing the pre-existing trend test for this study design. Therefore, we can use the DID model to explore how REDCP affects ACEs.

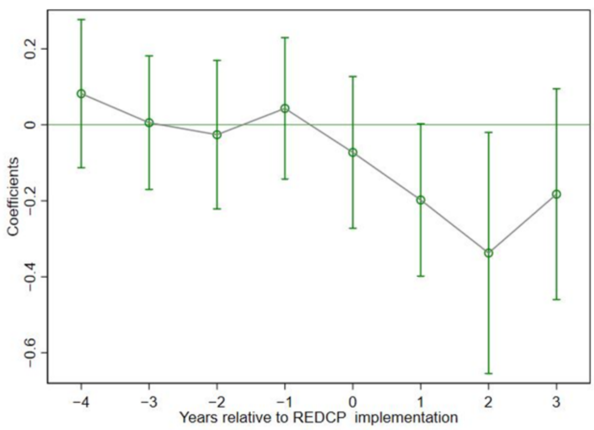

Figure 3. Common trend test.

4.3.2. Placebo Test

To rule out the presence of any further unobservable influences, we run a placebo experiment based on Cai et al. [56]. By choosing the year and city where the REDCP is applied at random, we specifically create a "false REDCP" variable. The regression based on Model (1) is then repeated with the "false REDCP" variable. The process is replicated 500 times. If the "false REDCP" significantly affects ACEs, it is possible that other unobservable factors are influencing the benchmark results. Conversely, if the "false REDCP" has no significant effect on ACEs, it can be inferred that the estimation results are robust and that it is the REDCP that causes the effect, not other unobservable differences.

The results presented in Figure 4 show that the estimation coefficients (represented by the red vertical dashed line for the value of −0.144) for randomly generated "false REDCP" cities are mostly close to 0. Therefore, the random sampling does not affect carbon emissions, and the empirical results are robust.

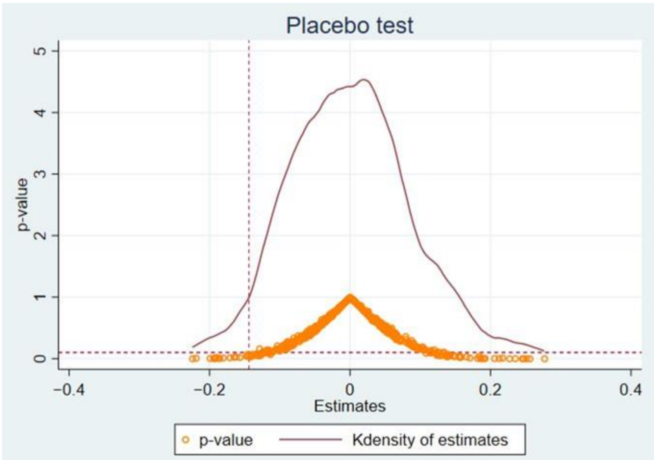

Figure 4. Placebo test.

4.3.3. Excluding Other Policies' Interference

In addition to REDCP, other policies implemented during this study period, like the Low Carbon City Pilot (LCCP) Policy and China's Old Revolutionary Development Program (ORDP), could also affect ACEs and influence the results of our assessment. Therefore, to guarantee the dependability and robustness of the empirical findings, these interfering policies should be excluded.

Firstly, the LCCP policy may affect ACEs. In 2010, 2012, and 2017, the Chinese National Development and Reform Commission (NDRC) conducted the LCCP policy. The LCCP policy aims to enhance carbon efficiency and reduce ACEs by developing low-carbon-intensive industries while striving to incentivize low-carbon-emitting lifestyles, developing low-carbon-emission techniques, and mitigating the impacts of climate change [57].

Secondly, ORDP has a positive effect on ACEs. ORDP was implemented in 2012. ORDP provides multiple avenues of support for the development of targeted regions that may affect ACEs. For example, as the national priority support policy for ecological management in old revolutionary areas increases, ORDP provides cleaner production technologies to improve ecological management capacity and thus increase green TFP [58], which to some extent contributes to the mitigation of ACEs.

In accordance with Zheng et al. [59], we add these policies into the baseline regression model as dummy variables and re-estimate the impact of REDCP on ACEs. If the coefficients of REDCP align with the benchmark results, this suggests that the two policies do not affect the findings of this paper.

Table 5 gives the estimation results, which are almost identical to the baseline results. The results reveal that at the 1% level, REDCP estimates remain significantly negative after eliminating the effects of the two policies mentioned above, demonstrating the reliability of the empirical findings.

Table 5. Several robustness tests results.

Variables	Baseline Result	Eliminate the Interference of LCCP	Eliminate the Interference of ORDP	Lagging Control Variables for One Phase	Adjusting the Sample Time Bandwidth	Winsorizing Extreme Value (1%)
	(1)	(2)	(3)	(4)	(5)	(6)
REDCP	−0.144 *** (0.049)	−0.143 *** (0.049)	−0.143 *** (0.049)	−0.162 *** (0.050)	−0.119 ** (0.052)	−0.121 *** (0.045)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City fix-effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fix-effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.846	0.846	0.846	0.854	0.870	0.878
Observations	2052	2052	2052	1725	1725	1926

Notes: "***" and "**" mean estimates at the 1% and 5% significance levels, respectively; and standard deviations are in parentheses.

4.3.4. Control Variables for One Period Delay

To alleviate potential endogenous issues, we delay the regression of all controlling variables for one period considering a potential inverse effect of the control variables with respect to the establishment of REDCP. As illustrated in column (4) of Table 5, the estimate is still significant at −0.162, further substantiating the findings' robustness.

4.3.5. Adjusting the Sample Time Bandwidth

Considering that the period setting may affect the baseline results, referring to Yang et al. [60], we adjust the sample time width. Because the COVID-19 pandemic may affect ACEs, we apply the panel data from 2010–2018 to adjust the sample period and re-estimate Model (1). The findings in Table 5's column (5) demonstrate that the REDCP coefficient remains significantly negative over the new time horizon, proving the robustness of the baseline regression results.

4.3.6. Winsorizing Extreme Values

An additional concern regarding the baseline regression is the potential impact of extreme outliers on the policy effect of REDCP. Hence, we conducted regression analyses to remove the effects of outliers based on 1–99% of the data for the explanatory variables. Column (6) of Table 5 displays the results after removing the extreme values. Clearly, after tailoring the data, REDCP still significantly reduces ACEs. Thus, the baseline findings remain robust.

4.4. Mechanism Analysis

According to previous empirical findings, REDCP can significantly reduce ACEs, but the exact mechanism of this effect is unclear. Therefore, in reference to Baron and Kenny [61], we employ the following three-step approach to validate the mechanism of REDCP on ACEs.

$$ACEs_{i,t} = \alpha_0 + \alpha_1 REDCP_{i,t} + \alpha_2 X_{i,t} + \mu_i + \theta_t + \varepsilon_{i,t} \tag{4}$$

$$M_{i,t} = \omega_0 + \omega_1 REDCP_{i,t} + \omega_2 X_{i,t} + \mu_i + \theta_t + \varepsilon_{i,t} \tag{5}$$

$$ACEs_{i,t} = \varphi_0 + \varphi_1 REDCP_{i,t} + \varphi_2 M_{i,t} + \varphi_3 X_{i,t} + \mu_i + \theta_t + \varepsilon_{i,t} \tag{6}$$

where $M_{i,t}$ denotes three mechanisms, which are discussed in the "Theory framework" section. The scale effect signifies the agricultural economic development level, represented as the logarithm of the value added of the primary sector. Structural effects indicate industrial restructuring, represented as the logarithm of the value added by the secondary sector and tertiary sector to the GDP. The technological effect represents technological progress, expressed as the agricultural TFP index calculated by the DEA Malmquist model. α_1 represents the overall effect of REDCP on ACEs. φ_1 indicates the direct impact of REDCP on ACEs; $\omega_1 \times \varphi_2$ is the indirect effect of REDCP on ACEs.

Table 6 displays the results. Column (1) presents the overall impact of REDCP on ACEs. In columns (2)–(7), we proceed to examine the impacts through each of the three mechanisms. Firstly, the results for the scale effect are shown in columns (2)–(3). It is clear that φ_2 (−0.624) is significant at the 1% level, indicating that economic development has a reducing effect on ACEs. $\omega_1 \times \varphi_2$ has the same sign as φ_1 (−0.098). The above results suggest that agricultural economic development plays a mediating role. Secondly, the results for structural effects are shown in columns (4)–(5). As we can see, the effect of REDCP on ACEs φ_1 (−0.148) is significant. However, the coefficient of industrial structure ω_1 (0.004) is not significant. Therefore, to further investigate whether a mediating effect exists, we carry out the bootstrap test. The result (0.039) in Table 7 is significant at 1% level, verifying the existence of an industrial structure mediating mechanism. Thirdly, the effect of technology is depicted in columns (6)–(7). The coefficient of REDCP φ_1 (−0.082) is significant at 10%, while the coefficient of technological progress ω_1 (0.002) is not significant. As a result, we further examine the potential for a mediating effect using the bootstrap test. Table 7 shows that the indirect effect is −0.011, significant at 10% level, confirming technological effects are also a mechanism.

Table 6. Mechanism analysis.

Variables		Scale Effect		Structural Effect		Technological Effect	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ACEs	Economic Development	ACEs	Industrial Structure	ACEs	Technological Progress	ACEs
REDCP	−0.150 *** (0.049)	0.092 *** (0.015)	−0.098 ** (0.048)	0.004 (0.004)	−0.148 *** (0.049)	0.002 (0.018)	−0.082 * (0.046)
Economic development			−0.624 *** (0.127)				
Industrial structure					−0.490 (0.385)		
Technological progress							−0.120 (0.076)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fix-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fix-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.845	0.991	0.851	0.961	0.845	0.234	0.850
Observations	2052	2044	2044	2052	2052	1280	1280

Notes: "***", "**", and "*" mean estimates at the 1%, 5%, and 10% significance levels, respectively; and standard deviations are in parentheses.

Table 7. The bootstrap test for industrial structure and technological progress on ACEs.

Mechanism	Bootstrap Test	Coefficient	Std. Err.	P	Conf. Interval
Industrial structure	Indirect effect	0.039	0.011	0.001	[0.017, 0.062]
Technological progress	Indirect effect	−0.011	0.007	0.092	[−0.027, −0.002]

4.5. Heterogeneity Analysis

Previous empirical findings have shown that REDCP can alleviate ACEs, but it is important to note that REDCP does not equally affect all cities. Therefore, the following section analyzes the heterogeneous influence of REDCP on ACEs across different regions and grain functional areas.

4.5.1. Heterogeneity Effects across Different Regions

The implementation of REDCP is nationwide, and China is a sizable nation with variations in resource endowments, economy status, and population size. Therefore, with reference to Du and Li [62], we examine the heterogeneity effect of REDCP by categorizing the sample into eastern, central, and western parts according to the geographical location of the province where they are located.

Table 8 provides the findings in columns (1) to (3). It is evident that only the eastern region's ACEs are significantly affected by REDCP. However, REDCP had no significant effect on ACEs in central and western China. This implies that REDCP can reduce ACEs only in the eastern zone, but not in the central and western parts.

Table 8. Heterogeneity effects.

Variables	Different Regions			Different Grain Functional Areas	
	East	Central	West	Major Grain-Producing Areas	Non-Major Grain-Producing Areas
	(1)	(2)	(3)	(4)	(5)
REDCP	−0.220 * (0.121)	−0.042 (0.088)	−0.074 (0.061)	−0.089 (0.101)	−0.106 * (0.056)
Controls	Yes	Yes	Yes	Yes	Yes
City fix-effect	Yes	Yes	Yes	Yes	Yes
Year fix-effect	Yes	Yes	Yes	Yes	Yes
R^2	0.915	0.859	0.817	0.868	0.849
Observations	698	608	746	1059	993

Notes: "*" means estimates at the 10% significance level; and standard deviations are in parentheses.

This conclusion could be explained by the fact that the agricultural development level and use of clean production technologies in the central and western cities are relatively low compared to the East. The government's main goal is to improve agricultural development through e-commerce, rather than reducing ACEs [63]. As a result, ACEs in the Midwest will become higher with the rapid development of agricultural production brought by e-commerce, but with low use of clean production technology.

4.5.2. Heterogeneity Effects across Different Grain Functional Areas

The influence of REDCP on ACEs generated in the agricultural production process may differ significantly depending on grain functional areas. Therefore, based on China's grain circulation reform in 2001, the sample in this paper is divided into two sections: major grain production areas and non-major grain production areas. We then examine the heterogeneity effects of these two categories of grain functional area separately.

The regression findings are given in columns (4)–(5) of Table 8. Consistent with the results of the primary study, REDCP significantly reduces ACEs at the 10% level in non-major grain production areas. However, REDCP has no apparent effect on reducing ACEs in major grain production areas. This finding may be due to the following reasons. On the one hand, REDCP will increase ACEs in a major grain production region. This is because rural e-commerce has the potential to expand the distribution channels for agricultural products, which encourages farmers in major grain production regions to raise agriculture production factor inputs (such as fertilizers, etc.), thereby increasing ACEs [64]. On the other hand, REDCP will also decrease ACEs in major grain production region. This is because rural e-commerce development actually contributes to information technology advancement, which improves agricultural production technology and increases the agricultural TFP in a major grain production region. Therefore, the two impacts may cancel each other out, leading to an insignificant impact of REDCP on ACEs in major grain production regions.

5. Discussion

It is important for every country to actively participate in the global governance of carbon emission reduction and fulfill the international aim of the 2030 Agenda for Sustainable Development. Given ACEs' substantial role in global carbon emissions, taking decisive action to curb them is crucial for attaining China's "dual carbon" goal and enhancing the welfare of the Chinese population. There is a wealth of research on ACEs. However, there is relatively limited research on how rural e-commerce affects ACEs. Moreover, the impact of e-commerce on ACEs in rural China and its underlying mechanisms remain unclear.

This study analyzes the effect of REDCP on ACEs in depth. We find that REDCP can significantly decrease ACEs. This finding extends our knowledge on the effectiveness of rural e-commerce on environmental management and also adds to the debate over the link between environmental sustainability and digital economy development, particularly in underdeveloped nations. However, we also find that the positive impact of REDCP on ACEs' reduction only exists in the short term. There is no long-term relationship between REDCP and ACEs, implying that the environmental performance of REDCP should be more focused on in future policy optimization, which has also been put forward in the studies of Ji et al. [23] and Li et al. [24]. We also provide evidence that the agricultural economic growth, the share of low-carbon industry, and agricultural TFP are three mechanisms by which REDCP affects ACEs, deepening our understanding of the intrinsic mechanism by which REDCP influences ACEs.

Although a thorough empirical analysis of the effect of REDCP on ACEs has been conducted, this paper still has some limitations. First, due to data accessibility and the complexity of e-commerce development, we only examine REDCP's impacts on ACEs and fail to analyze the impact on overall carbon emissions. Second, this paper only examines the effects of REDCP on ACEs over a relatively short time frame, and although it can provide relevant recommendations for policymakers, data availability prevents this paper from analyzing the effects of REDCP on ACEs over a longer time frame. Future research could explore REDCP's long-term effect on ACEs more thoroughly.

6. Conclusions and Suggestions

In this paper, we employ the multi-period DID method to investigate how REDCP affects ACEs, drawing on panel data for 355 prefectures from 2010–2019. The results show that, first, REDCP can significantly decrease ACEs, but this effect is not long-lasting. The results' reliability has been demonstrated by six robustness tests. Second, according to mechanism analyses, the impact of REDCP on ACEs is mostly achieved by fostering agricultural economic growth, increasing the share of low-carbon industry, and improving agricultural TFP. Further, heterogeneity analyses show that the effect of REDCP on ACEs is only evident in eastern cities and non-major grain production cities.

In light of the above results, several policy implications are proposed below. First, REDCP implementation should continue in order to reduce ACEs. The empirical results show that REDCP helps to reduce ACEs, but the dynamic effect results indicate that the policy effect will weaken or even disappear in the long term. Therefore, to sustain the favorable results of REDCP, governments should support REDCP implementation and enforce accountable implementation by relevant agencies, thus improving carbon mitigation. Second, it is important to constantly boost the agricultural economy and continuously increase the proportion of low-carbon industries. According to the results of mechanism analysis, the scale effect and structural effect are the two main paths for rural e-commerce to reduce ACEs. Hence, to raise the share of low-carbon industries and lower ACEs, governments ought to strongly support the coupling of e-commerce and low-carbon industries, while also strengthening the training of agricultural employees in internet use and e-commerce skills to improve the income of relevant employees. Third, the agricultural TFP in the Midwest and the major grain production areas should be enhanced. The heterogeneity analysis findings show that REDCP fails to significantly lower ACEs in Midwest China as well as the major grain production areas. Thus, the government should push forward clean agricultural production technology development in central and western cities, thereby developing green agriculture. Meanwhile, the major grain production areas should fully utilize the increase in information technology progress brought about by REDCP to optimize farming methods and enhance agricultural TFP, while promoting organic fertilizers and reducing reliance on chemical fertilizers and pesticides for sustainable agricultural development.

Author Contributions: Conceptualization, K.J. and D.P.; data curation, Q.H. and Y.Y.; formal analysis, K.J. and Q.H.; funding acquisition, D.P.; methodology, Q.H., Y.Y. and K.J.; project administration, D.P.; software Q.H., Y.Y. and D.P.; writing—original draft, K.J., Q.H., Y.Y. and D.P.; writing—review and editing, K.J., D.P. and Q.H. All authors have read and agreed to the published version of the manuscript.

Funding: We would like to express thanks for the financial support from the National Natural Science Foundation of China (No. 72363012; No. 71863016), National Social Science Foundation of China (No. 23FGLB006), Jiangxi Social Science Foundation Program (No. 23ZXRC14; No. 22SKJD08).

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare that they have no competing interest.

Abbreviations

REDCP	Rural E-Commerce Demonstration County Program
ACEs	Agricultural carbon emissions
DID	Difference-in-difference
TFP	Total factor productivity
GHG	Greenhouse gases
LCCP	Low Carbon City Pilot
ORDP	Old Revolutionary Development Program
NDRC	National Development and Reform Commission

References

1. Wang, R.; Zhang, Y.; Zou, C. How does agricultural specialization affect carbon emissions in China? *J. Clean. Prod.* **2022**, *370*, 133463. [CrossRef]
2. Liu, D.; Zhu, X.; Wang, Y. China's agricultural green total factor productivity based on carbon emission: An analysis of evolution trend and influencing factors. *J. Clean. Prod.* **2021**, *278*, 123692. [CrossRef]
3. Chen, Z.; Shu, W.; Guo, H.; Pan, C. The Spatial Characteristics of Sustainable Development for Agricultural Products E-Commerce at County-Level: Based on the Empirical Analysis of China. *Sustainability* **2021**, *13*, 6557. [CrossRef]
4. Bulatovic, I.; Papatheodorou, A. Civil aviation and tourism demand in Montenegro: A panel data approach. *J. Tour. Herit. Res.* **2023**, *9*, 25–36. [CrossRef]
5. Wang, H.; Fang, L.; Mao, H.; Chen, S. Can e-commerce alleviate agricultural non-point source pollution?—A quasi-natural experiment based on a China's E-Commerce Demonstration City. *Sci. Total Environ.* **2022**, *846*, 157423. [CrossRef] [PubMed]
6. Raihan, A.; Muhtasim, D.A.; Farhana, S.; Hasan, M.A.U.; Pavel, M.I.; Faruk, O.; Rahman, M.; Mahmood, A. Nexus between economic growth, energy use, urbanization, agricultural productivity, and carbon dioxide emissions: New insights from Bangladesh. *Energy Nexus* **2022**, *8*, 100144. [CrossRef]
7. Xiong, C.; Wang, G.; Su, W.; Gao, Q. Selecting low-carbon technologies and measures for high agricultural carbon productivity in Taihu Lake Basin, China. *Environ. Sci. Pollut. Res.* **2021**, *28*, 49913–49920. [CrossRef]
8. Xiong, C.; Chen, S.; Xu, L. Driving factors analysis of agricultural carbon emissions based on extended STIRPAT model of Jiangsu Province, China. *Growth Change* **2020**, *51*, 1401–1416. [CrossRef]
9. Du, J.; Liu, H.; Yuan, Y. On the impacts of agricultural subsidies on agricultural carbon emissions in China: Empirical evidence from microdata of rice production. *Environ. Sci. Pollut. Res.* **2023**, *30*, 101151–101167. [CrossRef]
10. Monchuk, D.C.; Chen, Z.; Bonaparte, Y. Explaining production inefficiency in China's agriculture using data envelopment analysis and semi-parametric bootstrapping. *China Econ. Rev.* **2010**, *21*, 346–354. [CrossRef]
11. Shen, Z.; Wang, S.; Boussemart, J.; Hao, Y. Digital transition and green growth in Chinese agriculture. *Technol. Forecast. Soc. Change* **2022**, *181*, 121742. [CrossRef]
12. Zheng, J.; Mi, Z.; Coffman, D.; Milcheva, S.; Shan, Y.; Guan, D.; Wang, S. Regional development and carbon emissions in China. *Energy Econ.* **2019**, *81*, 25–36. [CrossRef]

13. China, M.M.O.C. The Ministry of Commerce Held a National Commerce Circulation Area to Promote Online and Offline Interaction and Innovative Development and Rural E-Commerce Site Meeting. Available online: http://dzsws.mofcom.gov.cn/article/d/201511/20151101161808.shtml (accessed on 12 November 2015). (In Chinese)
14. Aliresearch. Ten years of Taobao Village: Digital Economy Promotes Rural Revitalization, System Report on China Taobao Villages: 2009–2019. Available online: http://www.199it.com/archives/935385.html (accessed on 19 December 2023). (In Chinese).
15. Chu, H.; Hassink, R.; Xie, D.; Hu, X. Placing the platform economy: The emerging, developing and upgrading of Taobao villages as a platform-based place making phenomenon in China. *Camb. J. Reg. Econ. Soc.* **2023**, *16*, 319–334. [CrossRef]
16. Mei, Y.; Mao, D.; Lu, Y.; Chu, W. Effects and mechanisms of rural E-commerce clusters on households' entrepreneurship behavior in China. *Growth Chang.* **2020**, *51*, 1588–1610. [CrossRef]
17. Singh, R.; Sibi, P.S. E-loyalty formation of Generation Z: Personal characteristics and social influences. *J. Tour. Herit. Res.* **2023**, *9*, 3–14. [CrossRef]
18. Leng, X. Digital revolution and rural family income: Evidence from China. *J. Rural Stud.* **2022**, *94*, 336–343. [CrossRef]
19. Peng, C.; Ma, B.; Zhang, C. Poverty alleviation through e-commerce: Village involvement and demonstration policies in rural China. *J. Integr. Agric.* **2021**, *20*, 998–1011. [CrossRef]
20. Liu, M.; Min, S.; Ma, W.; Liu, T. The adoption and impact of E-commerce in rural China: Application of an endogenous switching regression model. *J. Rural Stud.* **2021**, *83*, 106–116. [CrossRef]
21. Qiu, L.; Zhong, S.; Sun, B. Blessing or curse? The effect of broadband Internet on China's inter-city income inequality. *Econ. Anal. Policy* **2021**, *72*, 626–650. [CrossRef]
22. Tang, W.; Zhu, J. Informality and rural industry: Rethinking the impacts of E-Commerce on rural development in China. *J. Rural. Stud.* **2020**, *75*, 20–29. [CrossRef]
23. Ji, X.; Xu, J.; Zhang, H. Environmental effects of rural e-commerce: A case study of chemical fertilizer reduction in China. *J. Environ. Manag.* **2023**, *326*, 116713. [CrossRef] [PubMed]
24. Li, B.; Xu, C.; Zhu, Z.; Kong, F. Does e-commerce drive rural households engaged in non-timber forest product operations to adopt green production behaviors? *J. Clean. Prod.* **2021**, *320*, 128855. [CrossRef]
25. Li, X.; Guo, H.; Jin, S.; Ma, W.; Zeng, Y. Do farmers gain internet dividends from E-commerce adoption? Evidence from China. *Food Policy* **2021**, *101*, 102024. [CrossRef]
26. Benyam, A.A.; Soma, T.; Fraser, E. Digital agricultural technologies for food loss and waste prevention and reduction: Global trends, adoption opportunities and barriers. *J. Clean. Prod.* **2021**, *323*, 129099. [CrossRef]
27. Yu, H.; Cui, L. China's E-Commerce: Empowering Rural Women? *China Q.* **2019**, *238*, 418–437. [CrossRef]
28. Zhao, S.; Hafeez, M.; Faisal, C.M.N. Does ICT diffusion lead to energy efficiency and environmental sustainability in emerging Asian economies? *Environ. Sci. Pollut. Res.* **2022**, *29*, 12198–12207. [CrossRef] [PubMed]
29. Li, M.; Du, W. Can Internet development improve the energy efficiency of firms: Empirical evidence from China. *Energy* **2021**, *237*, 121590. [CrossRef]
30. Zhang, X.; Wei, C. The economic and environmental impacts of information and communication technology: A state-of-the-art review and prospects. *Resour. Conserv. Recycl.* **2022**, *185*, 106477. [CrossRef]
31. Cheng, Z.; Li, L.; Liu, J. The effect of information technology on environmental pollution in China. *Environ. Sci. Pollut. Res.* **2019**, *26*, 33109–33124. [CrossRef]
32. Ruiz, D.; San Miguel, G.; Rojo, J.; Teriús-Padrón, J.G.; Gaeta, E.; Arredondo, M.T.; Hernández, J.F.; Pérez, J. Life cycle inventory and carbon footprint assessment of wireless ICT networks for six demographic areas. *Resour. Conserv. Recycl.* **2022**, *176*, 105951. [CrossRef]
33. Borenstein, S.; Saloner, G. Economics and Electronic Commerce. *J. Econ. Perspect.* **2001**, *15*, 3–12. [CrossRef]
34. Li, L.; Du, K.; Zhang, W.; Mao, J. Poverty alleviation through government-led e-commerce development in rural China: An activity theory perspective. *Inf. Syst. J.* **2019**, *29*, 914–952. [CrossRef]
35. Grossman, G.M.; Krueger, A.B. Environmental Impacts of a North American Free Trade Agreement. *Natl. Bur. Econ. Res.* **1991**, *3914*, 1–57. [CrossRef]
36. Zhang, Y.; Long, H.; Ma, L.; Tu, S.; Li, Y.; Ge, D. Analysis of rural economic restructuring driven by e-commerce based on the space of flows: The case of Xiaying village in central China. *J. Rural Stud.* **2022**, *93*, 196–209. [CrossRef]
37. Hailemariam, A.; Dzhumashev, R.; Shahbaz, M. Carbon emissions, income inequality and economic development. *Empir. Econ.* **2020**, *59*, 1139–1159. [CrossRef]
38. Deng, Y.; Cui, Y.; Khan, S.U.; Zhao, M.; Lu, Q. The spatiotemporal dynamic and spatial spillover effect of agricultural green technological progress in China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 27909–27923. [CrossRef] [PubMed]
39. Asthana, S. Twenty-five years of SMEs in tourism and hospitality research: A bibliometric analysis. *J. Tour. Herit. Res.* **2022**, *8*, 35–47. [CrossRef]
40. Cao, X.; Deng, M.; Li, H. How does e-commerce city pilot improve green total factor productivity? Evidence from 230 cities in China. *J. Environ. Manag.* **2021**, *289*, 112520. [CrossRef]
41. Zhu, Z.; Bai, Y.; Dai, W.; Liu, D.; Hu, Y. Quality of e-commerce agricultural products and the safety of the ecological environment of the origin based on 5G Internet of Things technology. *Environ. Technol. Innov.* **2021**, *22*, 101462. [CrossRef]
42. Li, M.; Wang, J.; Zhao, P.; Chen, K.; Wu, L. Factors affecting the willingness of agricultural green production from the perspective of farmers' perceptions. *Sci. Total Environ.* **2020**, *738*, 140289. [CrossRef]

43. Tian, Y.; Zhang, J.; He, Y. Research on Spatial-Temporal Characteristics and Driving Factor of Agricultural Carbon Emissions in China. *J. Integr. Agr.* **2014**, *13*, 1393–1403. [CrossRef]
44. Dubey, A.; Lal, R. Carbon footprint and sustainability of agricultural production systems in Punjab, India, and Ohio, USA. *J. Crop. Improv.* **2009**, *23*, 332–350. [CrossRef]
45. Zeng, L. Research on the Effect of the Revitalization and Development Policy of the Old Revolutionary Areas–Evidence from Quasi-Natural Experiment. Master's Thesis, Jiangxi Normal University, Nanchang, China, 2020.
46. Cui, Y.; Khan, S.U.; Deng, Y.; Zhao, M. Spatiotemporal heterogeneity, convergence and its impact factors: Perspective of carbon emission intensity and carbon emission per capita considering carbon sink effect. *Environ. Impact Assess. Rev.* **2022**, *92*, 106699. [CrossRef]
47. Ma, L.; Zhang, W.; Wu, S.; Shi, Z. Research on the Impact of Rural Population Structure Changes on the Net Carbon Sink of Agricultural Production-Take Huan County in the Loess Hilly Region of China as an Example. *Front. Environ. Sci.* **2022**, *10*, 911403. [CrossRef]
48. Wen, S.; Hu, Y.; Liu, H. Measurement and Spatial-Temporal Characteristics of Agricultural Carbon Emission in China: An Internal Structural Perspective. *Agriculture* **2022**, *12*, 1749. [CrossRef]
49. Raza, M.Y.; Wu, R.; Lin, B. A decoupling process of Pakistan's agriculture sector: Insights from energy and economic perspectives. *Energy* **2023**, *263*, 125658. [CrossRef]
50. Jiang, Z.; Zhong, Y.; Yang, J.; Wu, Y.; Li, H.; Zheng, L. Effect of nitrogen fertilizer rates on carbon footprint and ecosystem service of carbon sequestration in rice production. *Sci. Total Environ.* **2019**, *670*, 210–217. [CrossRef]
51. Jiang, M.; Hu, X.; Chunga, J.; Lin, Z.; Fei, R. Does the popularization of agricultural mechanization improve energy-environment performance in China's agricultural sector? *J. Clean. Prod.* **2020**, *276*, 124210. [CrossRef]
52. NBS of PRC (National Bureau of Statistics of People's Republic of China). *China Statistical Yearbook for Regional Economy*; China Statistics Press: Beijing, China, 2010–2019. (In Chinese)
53. NBS of PRC (National Bureau of Statistics of People's Republic of China). *China Rural Statistical Yearbook*; China Statistics Press: Beijing, China, 2010–2019. (In Chinese)
54. NBS of PRC (National Bureau of Statistics of People's Republic of China). *China Statistical Yearbook*; China Statistics Press: Beijing, China, 2010–2019. (In Chinese)
55. Beck, T.; Levine, R.; Levkov, A. Big Bad Banks? The Winners and Losers from Bank Deregulation in the United States. *J. Financ.* **2010**, *65*, 1637–1667. [CrossRef]
56. Cai, X.; Lu, Y.; Wu, M.; Yu, L. Does environmental regulation drive away inbound foreign direct investment? Evidence from a quasi-natural experiment in China. *J. Dev. Econ.* **2016**, *123*, 73–85. [CrossRef]
57. Yu, Y.; Zhang, N. Low-carbon city pilot and carbon emission efficiency: Quasi-experimental evidence from China. *Energy Econ.* **2021**, *96*, 105125. [CrossRef]
58. Pan, D.; Chen, Y.; Kong, F. The role of place-based policies on carbon emission: A quasi-natural experiment from China's old revolutionary development program. *Heliyon* **2023**, *9*, e15964. [CrossRef] [PubMed]
59. Zheng, Q.; Wan, L.; Wang, S.; Wang, C.; Fang, W. Does ecological compensation have a spillover effect on industrial structure upgrading? Evidence from China based on a multi-stage dynamic DID approach. *J. Environ. Manag.* **2021**, *294*, 112934. [CrossRef]
60. Yang, X.; Lin, S.; Li, Y.; He, M. Can high-speed rail reduce environmental pollution? Evidence from China. *J. Clean. Prod.* **2019**, *239*, 118135. [CrossRef]
61. Baron, R.M.; Kenny, D.A. The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J. Pers. Soc. Psychol.* **1986**, *51*, 1173–1182. [CrossRef]
62. Du, G.; Li, W. Does innovative city building promote green logistics efficiency? Evidence from a quasi-natural experiment with 285 cities. *Energy Econ.* **2022**, *114*, 106320. [CrossRef]
63. Xu, G.; Li, J.; Schwarz, P.M.; Yang, H.; Chang, H. Rural financial development and achieving an agricultural carbon emissions peak: An empirical analysis of Henan Province, China. *Environ. Dev. Sustain.* **2022**, *24*, 12936–12962. [CrossRef]
64. Su, L.; Peng, Y.; Kong, R.; Chen, Q. Impact of E-Commerce Adoption on Farmers' Participation in the Digital Financial Market: Evidence from Rural China. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 1434–1457. [CrossRef]