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Original Research

Commodity Market Segmentation Hinders Carbon Productivity Gains in Chinese Agriculture: Moderating Effects of Economic and Informational Development

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Abstract

The negative externalities of China's commodity market segmentation have aroused public concern. At the same time, agricultural carbon emission reduction is an important part of China's "two-carbon" target. Therefore, exploring the impact of China's commodity market segmentation on agricultural carbon productivity can provide a useful reference for market-oriented economic development and low-carbon development of developing countries. To this end, based on the panel data of 31 provinces in China from 2004 to 2021, we analyzed the impact of Chinese commodity market segmentation on agricultural carbon productivity. The research conclusion shows that, in China, the commodity market segmentation will significantly inhibit the improvement of agricultural carbon productivity. However, in the process of this negative influence, economic development and information technology development play a positive regulatory role, which can alleviate this inhibitory influence. To this end, China should speed up the construction of a unified domestic market, constantly improve the level of economic development and information technology, reduce the segmentation of commodity markets, and improve agricultural carbon productivity.

Keywords: Commodity market segmentation, agriculture carbon productivity, low-carbon economy

Introduction

In March 2023, the United Nations Intergovernmental Panel on Climate Change (IPCC) issued the Comprehensive Report on the AR6 Synthesis Report: Climate Change 2023, which integrates the conclusions of three working group reports and three special reports issued by the IPCC since 2018. The report further clarified that greenhouse gas emissions from human activities are the main cause of global warming. Compared with 1850-1900, the global average surface temperature increased by 1.1℃ from 2011 to 2020. In this context, the low-carbon economy has been regarded as an inevitable choice to deal with climate change and environmental change. Low-carbon economy contains two meanings: "development" and

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"emission reduction". While reducing carbon emissions, it can obtain more economic output, that is, taking into account the dual goals of "maintaining growth" and "promoting emission reduction". The essential feature of a low-carbon economy is to improve carbon productivity, that is, each unit of carbon emissions can produce more GDP. Carbon productivity is an important indicator to measure the level of low-carbon economic development. Productivity usually refers to the ratio of output to input in the production process. Carbon productivity, first proposed by Kaya and Yokobori, refers to the level of GDP generated by unit carbon emission space, reflecting the economic benefits of unit carbon emission [1].

In human activities, agricultural activities are the main source of greenhouse gas emissions. According to the report "The Road to Agricultural Carbon Neutral", jointly released by The Boston Consulting Group and XAG in July 2022, greenhouse gases from agricultural activities and land use changes account for approximately 17 percent of the total global greenhouse gas emissions, being the second largest source of emissions. As a developing agricultural country, China is facing huge pressure and challenges of carbon emission reduction. According to the second two-year Update Report on Climate Change released in 2019, agricultural activities account for 7.4 percent of China's total greenhouse gases, while agricultural activities account for 48 percent of non-carbon dioxide greenhouse gas emissions. How to balance the development requirements of increasing agricultural production and income and achieve the ecological goal of emission reduction and carbon sequestration, that is, during the rapid growth of the agricultural economy, to promote the "dual carbon" goal of agriculture will be a major problem for China. Agricultural carbon productivity takes into account the dual goals of agricultural economic growth and carbon emission reduction, and improving agricultural carbon productivity is an inevitable requirement for promoting green and low-carbon agricultural development [2]. Agricultural carbon productivity refers to the agricultural economic output generated per unit of agricultural carbon emission.

However, as the largest developing country in the world, China's balanced development of the regional economy is still its top priority. Over the past 40 years of reform and opening up, although China has gradually transformed into an open economy, it has a vast territory and obvious regional differences. The invisible obstacles formed by the competition between local governments have hindered the inflow or outflow of factor resources, and the phenomenon of market segmentation is still widespread [3]. In the economic consequences caused by market segmentation, the impact on the ecological environment cannot be ignored. Market segmentation could prompt local governments to increase their protection of high-tax companies. Most of these enterprises are traditional manufacturing industries, with the typical characteristics of high energy consumption and high emissions. At the same time, market segmentation limits the free flow of labor, capital, and other resources, which may lead to resource mismatch, which is not conducive to the adjustment of industrial structure and energy structure, as well as green technology innovation [4-5]. The mismatch of labor and capital resources is caused by market segmentation, which is an important factor leading to environmental pollution [6]. In terms of carbon pollution, market segmentation or market integration has a significant impact on carbon emissions. From the perspective of market segmentation, it has a significant negative effect on carbon emission reduction, which is manifested as increasing carbon emissions and carbon emission intensity, while reducing carbon emission efficiency [7-11]. From the perspective of market integration, it has a significant positive effect on carbon emission reduction, that is, market integration can significantly reduce carbon emissions [12]. However, there is no literature research on the impact of market segmentation on carbon productivity, especially on agricultural carbon productivity.

Therefore, in view of the current practical background and insufficient research, we will take 31 provinces in China (excluding Hong Kong, Macao, and Taiwan) as the research sample and take the period 2004-2021 as the research period to analyze the impact of commodity market segmentation on China's agricultural carbon productivity. Taking China as an example, exploring the impact of commodity market segmentation on agricultural carbon productivity can provide a useful reference for market-oriented economic development and low-carbon development of developing countries. Through this study, we will mainly address the following two questions. The first question is, how will commodity market segmentation affect China's agricultural carbon productivity? Will it be restrained? Or improved? The second question is, are there any other factors regulating the impact of commodity market segmentation on agricultural carbon productivity? Accordingly, the innovation of our research is reflected in the following two aspects. First, the innovative research theme and research content. Because there is no literature integrating commodity market segmentation and agricultural carbon productivity in the same analytical framework, the causal relationship between the two is poorly studied. Therefore, our study will compensate for the lack of the existing literature. Second, it expands the research boundary. The influence effect of commodity market segmentation and the influence factors of agricultural carbon productivity have been well expanded. And the role of other economic factors in this impact process will also be explored.

Literature Review

Commodity market segmentation has a profound impact on many aspects of economic and social development, mainly reflected in the following aspects. First, commodity market segmentation has an impact on resource allocation and production efficiency. On the one hand, the segmentation of commodity markets will hinder the free flow of factors and make resources unable to be effectively allocated to the required regions and sectors, thus resulting in the problem of resource mismatch [13]. For example, increased market segmentation of goods will reduce the flow of labor across provinces [14]. At the same time, the segmentation of the commodity market is not conducive to regional economic coordination and industrial division, intensifies homogeneous competition, causes overcapacity and other problems, and reduces the efficiency of resource allocation [15, 16]. On the other hand, the segmentation of the commodity market will increase transaction costs, hinder technological innovation and industrial transformation and upgrading, and reduce the total factor productivity of the whole city and enterprises. Moreover, its "mutually exclusive effect" has a weakening effect on the spatial spillover of the total factor productivity, which damages the total factor productivity of the surrounding areas [17, 18]. Second, commodity market segmentation has an impact on economic growth. On the economic growth effect of commodity market segmentation, academia has not reached a consistent conclusion. On the one hand, some scholars believe that market segmentation is negatively correlated with economic growth, which has an obvious hindering effect on economic growth and is not conducive to high-quality economic development [19-22]. In particular, labor market segmentation will aggravate wage distortions, hinder full employment, and affect the smooth operation of the economy [23]. On the other hand, some scholars concluded that the relationship between commodity market segmentation and economic growth is non-linear, that is, there is an "inverted U"-shaped curve relationship between the two. When the level of commodity market segmentation is low, it helps to promote economic growth, but with the improvement of the segmentation degree, it is detrimental to economic growth [24, 25]. Third, the segmentation of the commodity market has an impact on scientific and technological innovation. Market expansion is an important internal driving force for enterprise innovation, and therefore, the segmentation of the commodity market will hinder technological innovation [26-27]. However, the segmentation of the commodity market has a significant inhibitory effect on enterprises' participation in innovation and will weaken the incentive effect of foreign and domestic "dual market" on enterprise innovation [28]. Commodity market segmentation mainly suppresses the improvement of innovation ability by reducing the efficiency of resource allocation, inhibiting the accumulation of human capital, and locking the scale of market demand [29]. Fourth, commodity market segmentation has an impact on industrial upgrading. At present, there are two main types of research conclusions regarding this effect. The first kind of conclusion, commodity market segmentation hinders industrial upgrading. The segmentation of the commodity market will not only hinder the rationalization of industrial structure, but it will also hinder the progress of advanced industrial structure by inhibiting technological progress [30, 31]. At the same time, the segmentation of the commodity market will hinder the improvement of regional industrial specialization, which is not conducive to the innovation and entrepreneurial development of high-tech industries [32, 33]. The second type of conclusion, the impact of commodity market segmentation on industrial upgrading is uncertain. Commodity market segmentation has an "inverted U" -shaped impact on the performance of industrial transformation, that is, for most regions, commodity market segmentation can significantly improve the performance of industrial transformation [34].

Agricultural carbon productivity is a key indicator to measure the sustainable development of low-carbon agriculture. In general, the more developed the agricultural economy, the higher the agricultural carbon productivity [35]. The existing literature has analyzed the direct influencing factors of agricultural productivity from several aspects of agricultural economic development. First, the impact of national fiscal expenditure on agricultural carbon productivity. Fiscal agricultural expenditure has a significant effect on the promotion of agricultural carbon productivity. Fiscal agricultural expenditure can be achieved through the agricultural planting structure and agricultural mechanization level, agricultural technology innovation and scale of operation efficiency, and other channels to improve agricultural carbon productivity, so as to promote increased agricultural output and curb carbon emissions [36, 37]. Second, the impact of urbanization on agricultural carbon productivity. The influence of urbanization on agricultural carbon productivity varies greatly. On the one hand, in the process of urbanization, the agricultural population decreases, large-scale agriculture is developed, the level of agricultural mechanization is improved, per unit agricultural output is increased, and agricultural carbon productivity increases [38, 39]. On the other hand, based on China's urbanization, multi-dimensional urbanization is one of the main forces restraining agricultural carbon productivity, among which, population urbanization and social urbanization are not conducive to the improvement of agricultural carbon productivity, while land urbanization has a positive role in promoting [40, 41]. Third, the impact of agricultural industry aggregation on agricultural carbon productivity. Agricultural specialization agglomeration can significantly improve agricultural carbon productivity by affecting the level of agricultural technology [42]. In addition, the improvement of the agricultural industrial agglomeration degree can significantly strengthen the infrastructure construction, and the infrastructure construction can have a positive impact on the improvement of agricultural carbon productivity [43]. Fourth, the influence of other factors. For example, agricultural digital transformation promotes the improvement of agricultural carbon productivity through the upgrading of agricultural industrial structure and agricultural scale operation [44]. Agricultural insurance realizes the improvement of agricultural carbon productivity by promoting agricultural industry agglomeration and agricultural technology progress [45], and land transfer has a positive impact on agricultural carbon productivity [46].

Theoretical Analysis

The Direct Influence Effect

China is still a developing country, and regional economic development has always been the top priority of local governments. Driven by the "GDP Championship", local governments will adopt market segmentation behavior to protect local enterprises with weak competitiveness but can quickly create economic benefits. In addition, resources are often invested in "short, flat, and fast" construction projects, thus forming a "fragmented" regional economic development model [47]. However, for the overall market, the segmentation of the commodity market will limit the free flow of factor resources between regions, resulting in improper allocation of resources, which adversely affects the long-term carbon generation rate [48]. Brock and Taylo believe that the impact of economic activities mainly affects environmental pollution through economic scale, industrial upgrading, and technological innovation [49]. Commodity market segmentation also affects agricultural carbon productivity in these three ways.

First of all, due to the existence of commodity market segmentation, the market is not fully competitive with the market, so there are differences in carbon emission costs between different regions, and the inconsistency of carbon emission costs creates conditions for excess carbon emissions [50]. At the same time, in order to avoid environmental regulations or reduce environmental costs, enterprises with high energy consumption and pollution levels will gather in areas with loose environmental regulatory policies. Therefore, the segmentation of the commodity market essentially weakens the regional "environmental barriers", and local governments become the providers of pollution shelters for high energy consumption and high-emission enterprises [51]. Although the commodity market segmentation has achieved short-term growth of the local economy, it also increases the risk of regional carbon emissions, which is not conducive to carbon emission reduction, and is not conducive to the improvement of carbon productivity [52]. Second, the price distortion caused by the segmentation of commodity markets hinders the free flow of factor resources between regions. This improper allocation of resources does not eliminate the energy-intensive industries in the region, which are the largest source of carbon emissions in China [53]. Therefore, commodity market segmentation intensifies environmental pollution by affecting the allocation of resources [54] and leads to the loss of the motivation and ability of green and low-carbon technology innovation in traditional industries. Third, technological innovation can help to reduce carbon emissions. Carbon emissions will be offset by technological innovation [55]. However, the segmentation of the commodity market hinders the free flow of factor resources, which makes efficient enterprises unable to obtain sufficient resources, leading to resource mismatch and inefficiency, and thus hindering technological innovation [56]. At the same time, the higher the degree of commodity market segmentation, the more difficult it is for advanced technology and experience to spread between regions or industries, thus having a negative impact on regional or inter-industry technological innovation [57]. Commodity market segmentation affects the improvement of agricultural technology, increases agricultural carbon emissions, and has a negative impact on agricultural carbon productivity.

Moderating Effect of Economic Development

Economic development plays an important role that cannot be ignored in the process of commodity market segmentation affecting carbon productivity in agriculture. On the one hand, economic development can restrain the commodity market segmentation. While promoting regional economic development, it inevitably makes the market competition become increasingly fierce. If local governments take local protectionist measures, it may lead to the deepening of domestic commodity market segmentation. In the long run, it will not be conducive to regional economic growth. From the perspective of development, reducing the segmentation degree of the commodity market is a necessary condition to improve China's socialist market economic system. The construction of the modern market system will be conducive to the continuous improvement of the price mechanism, ensure the full free flow of factors and resources in the market, and realize the decisive role of the market in the allocation of resources. Economic growth can play a positive role in market integration, and the higher the level of economic development, the more it can stimulate the level of market integration. Therefore, the continuous improvement of the level of economic development will inevitably reduce the degree of commodity market segmentation and accelerate the establishment of a modern market economic system.

On the other hand, economic development can boost agricultural carbon productivity. Economic growth has a positive impact on improving carbon productivity and can promote the low-carbon development of the whole society [58]. For example, GDP per capita is positively correlated with carbon productivity [59]. As for agricultural carbon productivity, with the improvement of the overall level of national economic development, the Chinese government has timely adjusted the goal of fiscal support for agriculture policies. The fiscal support for agriculture policy takes into account both ecological and economic functions, mainly reflected in the increase of subsidies for green ecological agriculture. There are two ways to influence agricultural carbon productivity through economic development. The first way is the agricultural planting structure effect. Financial support for agriculture will lead to the adjustment of the agricultural planting structure, which has an impact on agricultural carbon productivity from the two aspects of desired agricultural economic output and non-desired carbon emissions [60]. The second way is the agricultural machinery input effect. Financial input in support of agriculture, especially subsidies for the purchase of agricultural machinery, will increase agricultural machinery input, which will affect agricultural production efficiency and carbon emissions, and then affect agricultural carbon productivity [61].

Moderating Effect of Information Development

For a long time, due to the geographical restriction of distance and local protection, there has been a lack of exchanges and cooperation between various regions in China, and the degree of domestic market integration was low. However, this situation has changed fundamentally with the application and popularization of information technology. In the digital information age, the boundary of economic activity between traditional sectors and regions has been significantly weakened [62]. The popularization of information technology will integrate the discrete and fragmented regional and regional markets in an unprecedented way, and promote the integration of regional markets [63]. With the help of an information network, commodity services and information transmission are no longer limited to a specific region. The elements of different spaces can be efficiently connected and reorganized according to their own needs, and cross-platform technology can "break" commodity market segmentation barriers to accelerate market integration [64]. The increasing substitution of Internet trade for traditional trade leads to increasing competition pressure on manufacturers, and it is more and more difficult to maintain the segmentation of the commodity market by relying on administrative intervention and regional monopoly. The strengthening of factor liquidity also makes local protection useless, thus significantly weakening the power of local protection [65].

The development of information technology provides new ways and new drivers for carbon emission reduction and carbon productivity. Internet development can not only significantly reduce the carbon dioxide intensity of enterprises [66], and has significantly improved total factor carbon emission performance [67]. In terms of carbon emissions, information technology helps to optimize the agricultural production process and improve the efficiency of resource allocation. The optimization and improvement of agricultural production, transportation, and sales can improve the efficiency of information transmission in the agricultural production process by information technology, reduce the cost of information collection and transaction cost, improve the efficiency of resource allocation and production, make the agricultural industrial structure more reasonable, and realize the improvement of agricultural carbon emission efficiency [68]. In terms of carbon productivity, the continuous integration of information technology and agriculture has changed the structure of agricultural production factors, improved the level of agricultural digitalization and the efficiency of agricultural resources use, reduced agricultural carbon emissions, and improved agricultural carbon productivity. These major changes are mainly manifested in three aspects. First, information technology helps to improve the level of informatization and intelligence of agriculture, optimize the management links, promote the efficient use of energy, compress the total amount of carbon emissions, and promote the improvement of agricultural carbon productivity. Second, information technology relies on the internet, the internet of things, artificial intelligence, etc., to promote agricultural energy transformation, realize the efficient allocation of energy elements, promote the green development of agriculture, and then improve agricultural carbon productivity. Third, with the penetration of information technology into the agricultural field, the development of the agricultural industry has turned to digital and green. At the same time, it has also improved the agricultural planting structure, optimized the agricultural production mode and supply chain, reshaped the allocation structure of agricultural factors, and promoted the low-carbon development of agriculture.

Material and Methods

Model Setting

Our study aimed to examine the impact of commodity market segmentation on agricultural carbon productivity in China. In order to accurately test whether commodity market segmentation has a significant impact on agricultural carbon productivity, and whether it is a positive or negative impact. According to the sample data type, we use the panel data regression model commonly used in the existing literature for estimation. In addition, existing studies have shown that agricultural carbon productivity is affected by many factors, although it is difficult to cover everything in econometric models. However, if some of the important influencing factors are not controlled, the reliability of the estimation results and the accuracy of the research conclusions will be directly affected. In view of this, according to the existing research, the level of opening up, urbanization level, industrialization level, agricultural mechanization level, and financial development level are selected as the control variables. The selection of related variables indicators, data processing, and data sources will be described in detail below. Therefore, the benchmark regression model is set as follows:

$$ACP_{it} = \lambda_0 + \lambda_1 CMS_{it} + \lambda_2 X_{it} + \omega_i + \delta_t + \varepsilon_{it} \quad (1)$$

In the above equation, the ACP_{it} represents the province i (i = 1, ..., 31) agricultural carbon productivity in t (t = 2004,..., 2021) years. λ_1 represents the influence coefficient of commodity market segmentation on agricultural carbon productivity. X_{it} represents the groups of control variables, including: FDI_{it} represents the level of openness, UL_{it} represents the level of urbanization, IL_{it} represents the level of industrialization, AML_{it} represents the level of agricultural mechanization, FD_{it} represents the level of financial development. λ_2 is the influence coefficient of each control variable on agricultural carbon productivity. i represents the province, t represents the year. ω_i is a fixed effect on individuals (cross-section) in each province, used to handle individual heterogeneity in each province. δ_t is a fixed effect for the year (time), used to control for unobservable factors that change over time. ε_{it} is the random error term. To eliminate potential heteroscedasticity in the data, all relevant variables were logarithmized. At the same time, in order to alleviate the interference of heteroscedasticity to the regression results as much as possible, the robust standard error is adopted by default in the regression estimation process, and the Cluster robust standard error (provincial individual cluster) is used for empirical regression estimation.

In the process of the impact of commodity market segmentation on agricultural carbon productivity, in order to further identify the regulatory effects of other factors, we will discuss the regulating role of economic development level ($pgdp$) and informationization development (ID) respectively. According to the practice of Shi and Li (2020), use the intersection of core explanatory variables and regulatory variables, and construct the regulatory effect models respectively, as shown in Equations (2) and (3):

$$ACP_{it} = \beta_0 + \beta_1 CMS_{it} + \beta_2 pgdp_{it} + \beta_3 CMS_{it} \times pgdp_{it} + \beta_4 X_{it} + \omega_i + \delta_t + \varepsilon_{it} \quad (2)$$

$$ACP_{it} = \alpha_0 + \alpha_1 CMS_{it} + \alpha_2 ID_{it} + \alpha_3 CMS_{it} \times ID_{it} + \alpha_4 X_{it} + \omega_i + \delta_t + \varepsilon_{it} \quad (3)$$

Above, β_1 and α_1 represent the influence coefficient of commodity market segmentation on agricultural carbon productivity under different regulating variables. $CMS_{it} \times pgdp_{it}$ denotes the multiplication term between the segmentation of commodity markets and the level of economic development. $CMS_{it} \times ID_{it}$ denotes the multiplication term between the segmentation of the commodity market and the informationization development. β_3 and α_3 represent the regulatory effect coefficients for the different regulatory variables. Other parameter meaning and estimation methods are the same as those used in Equation (1).

Variable Selection and Data Source

Agricultural Carbon Productivity (*ACP*). At present, the most common method for measuring agricultural carbon productivity in the literature is the single-factor productivity measurement method. According to the definition of carbon productivity by Kaya and Yokobori [1], agricultural carbon productivity is defined as the ratio of total agricultural output value to total agricultural carbon emissions. Agricultural carbon productivity represents the output value per unit of carbon emission in agriculture, which is in line with the development requirements of green, low-carbon, and sustainable agriculture. The calculation formula is:

$$ACP = AGDP / ACE \quad (4)$$

The Gross Agricultural Product (*AGDP*) in Equation (4) is based on the annual agricultural output value published by the National Bureau of Statistics. *ACE* represents the total amount of agricultural carbon emissions. Meanwhile, following the approach of Liao et al. [69], the specific calculation formula for total agricultural carbon emissions is:

Table 1. Carbon emission coefficient of agricultural land utilization.

Agricultural carbon emission sources	Agricultural carbon emission coefficient	Reference source
Chemical fertilizer	0.89 kg/kg	Oak Ridge National Laboratory [70]
Pesticide	4.93 kg/kg	Oak Ridge National Laboratory [70]
Diesel oil	0.59 kg/kg	IPCC2013（IPCC, 2013)
Agricultural film	5.18 kg/kg	The Institute of Agricultural Resources and Eco-Environment, Nanjing Agricultural University [71]
Irrigate	266.48 kg/hm^2	Duan et al. [72]
Turn over	312.60 kg/km^2	Li and Zhang [73]

$$ACE = \sum_{i=1}^{k} T_i \times \theta_i \tag{5}$$

In equation (5), T_i represents the agricultural carbon emission source, θ_i represents the agricultural carbon emission coefficient, and *i* represents the province. We use fertilizers, pesticides, agricultural films, diesel, agricultural planting, and agricultural irrigation as sources of agricultural carbon emissions. The emission coefficients of these agricultural emission sources are shown in Table 1.

Commodity market segmentation (*CMS*). According to the existing construction method of the commodity market segmentation index, refer to Gui et al., the price method is used to calculate the degree of commodity market segmentation in each province from 2004 to 2021 [74]. The price method measures the market segmentation status based on the relative difference in commodity prices between different regions. According to the meaning of this method, if the boundary effect and coefficient of variation of commodity prices between different regions shrink, or commodity prices converge statistically, it means that the degree of market integration between regions is increasing, while the degree of market division of commodities is decreasing. At the same time, the commodity market segmentation index calculated by the price method contains more information, and the data is relatively easy to obtain, and the calculation is relatively simple, so this method has become a common method to measure the regional commodity market segmentation in China. We will measure and measure the segmentation degree of China's commodity market based on the price method.

The measurement of commodity market segmentation includes three specific methods: co-integration analysis method, correlation analysis method, and relative price method. However, the theoretical basis of the co-integration analysis method and related analysis method is weak, and there is a lack of sufficient economic principles explanation for practical problems. Therefore, the relative price method is currently the most common method in the research literature. The relative price method includes two specific methods: unit root test and variance test. The unit root test is the unit root test of the time series of relative prices. If the null hypothesis that the relative price follows the unit root change cannot be rejected, it means that the sequence is a random process with unstable relative price, and its variance will continuously expand over time, and there will be a market segmentation between the two regions. On the contrary, if the null hypothesis is rejected, indicating that the variance of the relative price is fixed and the external shock is only temporary, then the relative price will return to the no-arbitrage range in the long term. The variance test takes the variance of the relative price as a dynamic index to measure the market segmentation. If time goes by, the variance of the relative price is narrowing, which means that the fluctuation range of the relative price is narrowing, the "melting" ratio is decreasing, and the no-arbitrage range is also narrowing, that is, the degree of market segmentation is in a downward trend. Parsley and Wei's research found that the variance of relative price can more objectively measure the degree of commodity market segmentation between regions, and without losing generality [75]. We will use this method to measure the segmentation of the commodity market.

The theoretical basis of the relative price method comes from the "law of one price" and the "glacier cost" model. The "glacier" cost model believes that due to the existence of transaction costs such as transportation, even if goods are completely arbitraged in different regions, the price of commodities will "melt" part of the trade process like a "glacier". If the size of "melting" is a fixed proportion of each unit price, there will be arbitrage opportunities only if the price of one place is still higher than that of the other place, and trade between the two regions can occur [76]. In order to calculate the relative price variance of the segmentation degree of the Chinese commodity market, three-dimensional ($m \times k \times t$) panel data should be selected. Where *m* is the region, *k* is the commodity, and *t* is the time. Drawing the ideas and methods of Kong [77], the specific calculation steps are as follows.

In the first step, the absolute value $\left|\Delta Q_{ijt}^{k}\right|$ of the relative prices of regions *i* and *j* are calculated. Here, the first-order difference form of the relative price is used to measure the commodity market segmentation. This is mainly based on two aspects, one is the state of commodity market segmentation, the relative price Q_{ijt}^{k} will achieve convergence, and the corresponding ΔQ_{ijt}^{k} convergence, so there is no obvious difference between the two in statistical significance. Second, China's commodity price index uses the month-on-month index, rather than the absolute index, and the month-on-month commodity price index can be directly expressed by ΔQ_{ijt}^{k}. In addition, the absolute value is calculated because after taking the logarithm, the position of the molecular denominator in *i* and *j* will cause the ΔQ_{ijt}^{k} reverse change of the sign, so the absolute value is adopted.

$$\begin{aligned} \Delta Q_{ijt}^{k} &= ln\,(p_{it}^{k} \quad p_{jt}^{k}) - ln\,(p_{it-1}^{k} / p_{jt-1}^{k}) \\ &= ln\,(p_{it}^{k} - p_{it-1}^{k}) - ln\,(p_{jt}^{k} / p_{jt-1}^{k}) \end{aligned} \tag{6}$$

In equation 6, p_{it}^{k} represents the price of the *i* province and *k* commodity in period *t*. Based on the idea of Parsley and Wei, according to the situation of neighboring provinces of China, the relative price variance of 69 pairs of neighboring provinces in the past 18 years is calculated [78]. In the pairing combination of the adjacent two places, the order of the two places does not affect the value of the variable, so only one group is retained. For example, the value of the variables under the two combinations of "Beijing-Tianjin" and "Tianjin-Beijing" is unchanged, so only the combination of “Beijing-Tianjin” is retained. The final calculation of variance data is 1242 (18×69). In the process of calculating the commodity market segmentation index, we choose the neighboring province as the analysis object, because whether the market of the neighboring province is divided is the main information to judge whether the national market is divided. The reason is that if a local government adopts the policy of market segmentation for other places, and this policy will first have an impact on neighboring provinces, then the evidence of the market segmentation of neighboring provinces can be applied in other provinces, and only in this way can a more general conclusion of the national market segmentation be obtained. China has a vast territory, which is a natural barrier for the division of commodity markets in the two regions with very long geographical distances (such as between Tibet and Shanghai, and between Heilongjiang and Hainan).

In the second step, the non-additivity in $\left|\Delta Q_{ijt}^{k}\right|$ due to commodity differentials is eliminated. We assume a fixed effect related to the commodity variety a^k, for the corresponding year t. *We* calculate the mean value $\left|\Delta \overline{Q_t^{k}}\right|$ of $\left|\Delta Q_{ijt}^{k}\right|$ for the corresponding product type k in $k×(k\text{-}1)/2$ adjacent provinces. Then, we subtract $\left|\Delta \overline{Q_t^{k}}\right|$ from $k×(k\text{-}1)/2$ $\left|\Delta Q_{ijt}^{k}\right|$'s separately to obtain:

$$\left|\Delta Q_{ijt}^{k}\right| - \left|\Delta \overline{Q_t^{k}}\right| = a^k - a^{\bar{k}} + (\mu_{ijt}^{k} - \mu_{ijt}^{\bar{k}}) \tag{7}$$

In Equation 7, $\mu_{ijt}{}^{k}$ represents the changes related to the two provinces of *i, j*, special markets, or other random factors. Further order:

$$q_{ijt}^{k} = (\mu_{ijt}^{k} - \mu_{ijt}^{\bar{k}}) = \left|\Delta Q_{ijt}^{k}\right| - \left|\Delta Q_t^{\bar{k}}\right| \tag{8}$$

In the third step, the calculated $q_{ijt}{}^{k}$ variance, and denoted by $var(q_{ijt}{}^{k})$, reflects the arbitrage range due to the segmentation of the domestic market for the commodity. That is, the range of price fluctuations for the k commodity, the larger the value of $var(q_{ijt}{}^{k})$, the larger the arbitrage band and the greater the degree of segmentation in the domestic commodity market. On the basis of the above, averaging $k×(k\text{-}1)/2$ domestic commodity markets by year can calculate the overall domestic commodity market segmentation index. According to this method, the merger by provinces can calculate the domestic commodity market segmentation index of each province.

Referring to existing studies and combined with our subjects, the following control variables were selected. The level of opening up (*FDI*) is measured by the proportion of foreign direct investment in GDP in each province. The level of urbanization (*UL*) is measured by the proportion of the urban population in the total population of each province at the end of each year. The level of agricultural mechanization (*AML*) is measured by the total power of agricultural machinery (10,000 kilowatts) used in the total sown area of crops (1,000 hectares) in each province. Industrialization level (*IL*), is the proportion of total industrial output value to GDP in each province. The level of financial development (*FD*) is measured by the ratio of the sum of deposits and loans to GDP at the end of each year.

The Regulating variables mainly include two. The first is the level of economic development (*pgdp*), which is expressed by GDP per capita. In order to overcome the possible heteroscedasticity phenomenon, the per capita GDP is taken as the log. The second is Informationization development (*ID*), which uses the proportion of the number of Internet users in the total population.

Table 2 lists the main variables and the specific measures.

Table 2. Main variables and measurement methods.

Type of variable	Variable name	Variable abbreviation	Measurement method
Explained variable	Agricultural carbon productivity	*ACP*	Agricultural carbon emissions / total output value of agriculture, forestry, animal husbandry and fishery
Core explanatory variables	Commodity market segmentation	*CMS*	From equation (4.5-4.7)
Controlled variable	Level of openness to the outside world	*FDI*	The proportion of foreign direct investment in GDP
	Level of urbanization	*U L*	The proportion of the urban population in the total population
	Level of agricultural mechanization	*AML*	The total power of agricultural machinery used in the total sown area of crops
	Industrialization level	*I L*	The proportion of the total industrial output value in GDP
	Level of financial development	*FD*	The ratio of the combined deposits and loans to GDP
Regulating variables	Economic Development level	*pgdp*	Per capita GDP
	Informatization Development level	*ID*	The proportion of Internet users in the total population

Table 3. Descriptive statistics.

Variable	Average value	Standard deviation	Minimum value	Maximum values	Sample size	Median
ACP	0.4741	0.2535	0.1506	2.3502	558	0.4119
CMS	0.0267	0.0192	0.0035	0.1332	558	0.0211
FDI	0.0215	0.0203	0.0001	0.1210	558	0.0171
UL	0.5425	0.1496	0.2029	0.8958	558	0.5332
AML	0.6446	0.3542	0.1698	2.6979	558	0.5565
IL	0.3468	0.0979	0.0705	0.5738	558	0.3569
FD	3.0484	1.2063	1.3920	8.7220	558	2.8004
pgdp	10.2245	0.6958	8.3533	12.0749	558	10.2207
ID	0.3173	0.2665	0.0098	1.0745	558	0.2358

Data Source

Given the availability and completeness of the data, panel data from 31 Chinese provinces (autonomous regions, municipalities, excluding Hong Kong, Macao, and Taiwan) from 2004 to 2021. The statistical caliber of the agricultural industry in each province is “big agriculture”, that is, agriculture, forestry, animal husbandry, and fishery. Relevant data are from the China Statistical Yearbook, China Rural Statistical Yearbook, and the statistical yearbooks of the provinces, and some of the missing values are supplemented by the average method. The economic data in the paper are adjusted according to the 2004 constant price to eliminate the influence of price factors. The descriptive statistics of each variable are shown in Table 3.

The Empirical Analysis

The Benchmark Regression Results

We used the gradual regression method to examine the impact of commodity market segmentation on agricultural carbon productivity in China. Before regression estimation, conduct a Hausmanm-test of the model to determine whether to use the fixed effect model or the random effect model. Based on the Hausmanm-test results, we estimated them with a fixed-effects panel model. In Table 4, column (1) did not include the control variable, and column (2) included the control variable, both columns with a fixed time. Column (3) without control variables, column (4), and the bidirectional fixed effects of province and time were used in both columns. The results show that the regression coefficients of commodity market segmentation estimated by all four methods are significantly negative, which confirmed that the commodity market segmentation would inhibit the increase of agricultural carbon productivity. Under the two-way fixed effect model, the influence coefficient of commodity market segmentation on agricultural carbon productivity was -0.9662, which was significant at the 1% level, indicating that for every 1% increase in commodity market segmentation, agricultural carbon productivity decreased by about 1 percentage point. This result shows that, in China, commodity market segmentation will curb the increase in agricultural carbon productivity. At the same time, the column (3) and (4) can be found that the control of other factors may affect agricultural carbon productivity, the two-way fixed effect model of commodity market segmentation of agricultural carbon productivity, the influence coefficient of larger, agricultural carbon productivity is not only affected by commodity market segmentation, will be affected by other factors.

For the control variables, under a two-way fixed-effects model. The parameter value of the level of opening up is -2.3344, which is significantly negative, indicating that a larger proportion of foreign direct investment in GDP is not conducive to the improvement of agricultural carbon productivity. This may be due to the fact that foreign capital imported into China is mainly invested in the manufacturing and service sectors, resulting in a large flow of domestic capital and talent to the manufacturing and service sectors, which is not conducive to the enhancement of the efficiency of agricultural carbon production. The parameter value of urbanization is 2.0056, and it is significant at the 1% level, indicating that the urbanization process is conducive to the improvement of agricultural carbon productivity. The higher the level of urbanization, the decrease in agricultural employees, and the scale of agricultural agriculture and mechanization level will be greatly improved, which will contribute to the improvement of agricultural carbon production efficiency. The parameter value for agricultural mechanization was 0.1083, which was significant at the 1% level. The higher the level of agricultural machinery replacement labor force, the higher the agricultural production efficiency will be effectively improved. In the same case of carbon emissions, if the output value increases, the carbon productivity will inevitably

Table 4. Benchmark regression results.

Variable	(1)	(2)	(3)	(4)
CMS	-5.0222*** (0.5868)	-0.7930*** (0.2603)	-0.8119** (0.3997)	-0.9662*** (0.3608)
FDI		-2.6850*** (0.4134)		-2.3344*** (0.3487)
UL		2.5252*** (0.1576)		2.0056*** (0.3379)
AML		0.0694* (0.0359)		0.1083*** (0.0384)
IL		-0.6717*** (0.1079)		-0.4790*** (0.1483)
FD		-0.0586*** (0.0134)		-0.0792*** (0.0120)
Constant	0.7692*** (0.0388)	-1.0077*** (0.1082)	0.3723*** (0.0289)	-0.5073** (0.2363)
Time effect	No	No	Yes	Yes
Province effect	Yes	Yes	Yes	Yes
Sample size	558	558	558	558
R^2	0.3436	0.8188	0.8081	0.8506

Note: (1) *, * *, * * * indicate the 10%, 5%, and 1% significance levels, respectively. (2) “Yes” and “No” indicate whether the model controls for the relevant variables.

increase. The parameter value for industrialization was -0.4790, significant at the 1% level. The improvement of industrialization level leads to agricultural over-dependence on chemical fertilizers and pesticides, which maximizes the carbon emissions of fossil energy inputs in agricultural carbon emissions, and thus restricts the improvement of agricultural carbon productivity. The parameter value for financial development was -0.0792, also significant at the 1% level. It shows that financial development is not conducive to the improvement of agricultural carbon productivity. Financial development provides a large amount of funds for the industry and promotes the development of chemical fertilizer and pesticide industries, so it also restricts the improvement of agricultural carbon productivity.

Endogeneity Discussion and Robustness Test

In benchmark regression, although we controlled for other factors that may affect agricultural carbon productivity, as well as fixed effects on provinces and time, there may still be endogeneity issues such as omitted variables and reverse causality. Therefore, first, we lag the core explanatory variables by one period, and then perform regression estimation to overcome the endogeneity problem caused by reverse causality. From the regression results in column (1) of Table 5, it can be seen that the commodity market segmentation after one period of lag has a significant negative effect on agricultural carbon productivity, which is basically consistent with the basic regression results. Secondly, in order to better address endogeneity issues, we chose transportation infrastructure as the instrumental variable and used two-stage least squares (2SLS) to perform regression estimation on the model. The transportation infrastructure is represented by the sum of railway and highway mileage in each province. Regarding the exogeneity and correlation conditions of instrumental variables. Transportation infrastructure can provide convenience for commodity trading and accelerate the circulation of goods. Generally speaking, the more complete the transportation infrastructure, the lower the degree of segmentation in the commodity market. Meanwhile, this instrumental variable has exogeneity, meaning that it will not affect regional commodity market segmentation through some omitted variables, satisfying exclusivity constraints. Table 5, column (2) reports the regression results of the first stage. It is evident that this instrumental variable has a significant correlation with commodity market segmentation, with a correlation coefficient of -0.0058, and has passed the 1% significance level test. Column (3) reports the regression results of the second stage, where the statistical test result of Kleibergen Paap rk LM is 15.238, greater than 10, and significant at the 1% level. The Cragg Donald Wald F-statistic test result is 16.644. From this, it can be seen that the instrumental variables meet the identifiability test and weak instrumental variable test, indicating that the selected instrumental variables are reasonable and effective. From the regression estimation coefficient, the estimated coefficient value of commodity market segmentation on agricultural carbon

Table 5. Endogeneity discussion and robustness test.

Variable	(1)	(2)	(3)	(4)	(5)
CMS	-0.9924*** (0.3633)		-11.6140*** (3.5080)		-0.8803* (0.4898)
MI				0.0203* (0.0116)	
TI		-0.0058*** (0.0011)			
Control variable	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes
Province effect	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM			15.238 [0.0001]		
Cragg-Donald Wald F			16.644 [16.38]		
Sample size	527	558	558	558	486
R^2	0.8494	0.4144	0.1444	0.8495	0.8508

Note: (1) *, * * * indicate the 10%, 1% significance levels, respectively.(2) "Yes" and "No" indicate whether the model controls for the relevant variables.

productivity is -11.6140, which is significant at the 1% level. This indicates that endogeneity issues did not have a significant impact on the research findings.

To verify the reliability of the benchmark regression results, we used the following method for robustness testing. First, replace the core explanatory variable indicators. We use the market index (*MI*) as a negative alternative indicator for commodity market segmentation. The calculation method of the market index in China refers to Fan et al. approach [79]. The market index was used as the core explanatory variable, and the results are shown in Table 5 (2). The parameter value of the market index is 0.0203, which is significant at the 10% level, indicating that improving the market index can promote agricultural carbon productivity. This result is just the opposite of the regression result of the commodity market segmentation. Second, reduce the study sample. Because the municipality level of economic development is high, and the scale of agricultural production is small. Therefore, the agricultural carbon productivity level of the municipality will be higher than that of other provinces, so as to reduce the impact of commodity market segmentation on agricultural carbon productivity. Therefore, we excluded the sample data from Beijing, Tianjin, Shanghai, and Chongqing municipalities, and the results are shown in Table 5 (3). The influence coefficient of commodity market segmentation on agricultural carbon productivity is significantly negative at the 10% level. The results show that commodity market segmentation has a significant negative impact on agricultural carbon productivity production after excluding 4 municipalities. The results of the above test methods can test the negative influence of commodity market segmentation on agricultural carbon productivity, indicating that the benchmark regression results have good robustness.

Analysis of the Regulating Effects

In the process of regulating effect testing, due to the need to add the product term to the econometric model, it may lead to the production of multicollinearity between the core explanatory variable and the regulatory effect variable and the product term of both. To eliminate the problem of multicollinearity, we refer to the approach of Robinson and Schumacher and perform zero mean processing on the data [80]. Data perform zero mean processing refers to subtracting the data from its mean or mathematical expectation. Data zero-mean processing is a data preprocessing method that aims to eliminate variability between variable characteristics, which allows different characteristic variables to have the same scale, and thus a consistent degree of influence of the variables on the parameters. Data zero-mean processing does not affect the correlation between variables. Data zero-mean processing mainly includes two steps. In the first step, data zero-mean processing is carried out on the core explanatory variables and moderating effect variables, respectively, in order to weaken the covariance between univariate variables and the product terms of the variables. In the second step, the core explanatory variables and the moderating effect variables after the zero-mean processing are multiplied together, and the product terms are brought into regression equations.

Based on the theoretical analysis, we will empirically test the moderating effects of the level of economic development and the level of informationization development. After zero-mean processing, the core

Table 6. Test of regulatory effects.

Variable	(1)	(2)
CMS	-0.5952* (0.3210)	-0.6109 (0.3769)
CMS × pgdp	0.8585** (0.4257)	
CMS × ID		3.4652** (1.3923)
Control variable	Yes	Yes
Time effect	Yes	Yes
Province effect	Yes	Yes
Sample size	558	558
R^2	0.8633	0.8531

Note: (1) *, * * indicate the 10%, 5%, significance levels, respectively.(2) "Yes" and "No" indicate whether the model controls for the relevant variables.

explanatory variables and the regulatory effect variables, *CMS × pgdp* and *CMS × ID,* were applied to two product terms separately into Equations (2) and (3), and regression was estimated. The regression estimates are shown in Table 6, where the coefficients of the two product terms were 0.8585 and 3.4652, and all passed the 5% significance level test. The results show that both regulatory effect variables have significant positive regulatory effects on the results of commodity market segmentation, affecting agricultural carbon productivity. That is, the level of economic development and information development is conducive to alleviating the inhibitory influence of commodity market segmentation on agricultural carbon productivity. With the improvement of economic development level, economic cooperation between regions will be more frequent, and the level of opening to the outside world will be further improved, thus reducing the degree of commodity market segmentation [81]. The development of information technology represented by the Internet has had a profound impact on business activities, among which the most important role is to reduce the information asymmetry in transactions and significantly reduce the degree of market segmentation [82]. The improvement of the economic development level and informationization development level is conducive to the promotion of agricultural production efficiency and agricultural technology level, as well as the realization of agricultural carbon emission reduction and the increase of agricultural output value.

Conclusions

In China, commodity market segmentation is an economic phenomenon with a specific negative externality of customers. Low-carbon development of agriculture is an important area for China to achieve the overall "dual-carbon" goal, which has a significant and far-reaching impact on China's sustainable development. To this end, we took China's commodity market segmentation and agricultural carbon productivity as the research theme and took 31 provinces in China (excluding Hong Kong, Macao, and Taiwan due to data acquisition reasons) as the sample, and took the study period of 2004-2021. We used interprovincial panel data to build a panel data regression model and a regulatory effect model and explored the impact of commodity market segmentation on agricultural carbon productivity at both theoretical and empirical levels. The following conclusions are drawn.

First, commodity market segmentation has significantly inhibited the increase of agricultural carbon productivity. The empirical results show that the influence coefficient of commodity market segmentation on agricultural carbon productivity is -0.9662, and it is significant at the 1% level. The results show that for every 1% increase in commodity market segmentation, agricultural carbon productivity decreases by nearly 1 percentage point. After the endogenous problem treatment and the robustness test, the results did not change, indicating the good robustness of this negative effect.

Secondly, improving the level of economic development and accelerating the development of information technology can play a very good role in regulating this negative impact. In the process of the negative impact of commodity market segmentation on agricultural carbon productivity, economic development, and information development can well alleviate this negative impact. The empirical results show that the coefficient value of the interaction term of commodity market segmentation and economic development level is 08585, which is significant at the 5% level. The coefficient value of the interaction item of commodity market segmentation and information development level is 3.4652, which is also significant at the 5% level. This result indicates that the two regulatory variables have a significant positive regulatory role in the negative effect of commodity market segmentation on agricultural carbon productivity.

Based on the main conclusions of the above empirical analysis, we propose relevant suggestions to the Chinese government to reduce the segmentation of the commodity market and improve agricultural carbon productivity. First, we will accelerate the development of a unified national market. The national unified market can weaken the segmentation of commodity markets and is an important measure to boost the efficient operation of the market. In terms of direct influence, on the one hand, the national unified large market is used to break the monopoly of local governments from the macro level, and further standardize and unify the regulatory policies of various regions, so that the agricultural environmental governance and agricultural project investment in various regions meet the requirements of low-carbon development. On the other hand, the national unified large market is used to help agricultural enterprises reduce carbon emissions from the micro level. Make agricultural enterprises in the market of synchronous development of factor resources and goods and services, and make the cross-regional allocation of agricultural low-carbon factor resources smoother. At the same time, the effective market discovery function should be used to help agricultural enterprises find the profit space for green transformation faster and attract the low-carbon development of agricultural enterprises. In terms of indirect influence, on the one hand, we should give full play to the energy-intensive effect of the national unified large market, improve the efficiency of agricultural energy use, and achieve agricultural carbon emission reduction. Through the construction of an agricultural energy market with unified systems and rules, we should not only establish a standardized trading channel for the agricultural energy market, but also improve the integration degree of the agricultural energy market. On the other hand, we should accelerate the agglomeration of agricultural innovation elements through a unified national market, promote high-quality green innovation in agriculture, and then achieve agricultural carbon emission reduction. We should take the construction of a unified factor resource market as the core of building a unified national market, eliminate the barriers to the flow of agricultural factors, optimize the efficiency of agricultural resources allocation, and promote the agglomeration of green innovation elements to high-quality agricultural innovation fields or projects.

Second, accelerate the level of information technology, promote the high-quality development of the agricultural economy, and improve agricultural carbon productivity. We should take the development of information technology as an opportunity to accelerate the construction of a unified national market. We will promote the combination of information technology and agricultural production, improve the informatization level of socialized agricultural services, and promote carbon emission reduction in agriculture. We will encourage the integration of emerging agricultural technologies with traditional technologies to achieve high-quality agricultural development. Make full use of the time dividend of information technology and data elements, form the scale effect of technology "reservoir", encourage and guide agricultural business entities to actively use the new green and low-carbon agricultural intelligent technology, and improve the intelligent level of agricultural machinery. We will strengthen the coordinated development of information technology, in particular, narrow the regional differences in the construction of smart agricultural infrastructure, realize high-quality spatial information interconnection, and ensure that the diffusion and scale effects of information technology play a greater role in agricultural carbon emission reduction.

Our study provides a good complement to the existing studies on commodity market segmentation and agricultural carbon productivity in China, but there are some limitations. First, in terms of sample selection, due to the availability of data, only provinces are currently used as samples. However, the number of provincial samples in China is small and lacks sufficient universality. Secondly, in the path of influence, we did not conduct an in-depth exploration of the path of commodity market segmentation to restrain agricultural carbon productivity. Therefore, in future research, we will expand the study sample to the prefecture-level cities in China, the study sample will reach about 300, and the sample size will be greatly expanded. At the same time, we will focus on the internal path of commodity market segmentation affecting agricultural carbon productivity.

Conflict of Interest

The authors declare no conflict of interest.

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