Article

Research on the Relationship between Prices of Agricultural Production Factors, Food Consumption Prices, and Agricultural Carbon Emissions: Evidence from China's Provincial Panel Data

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Abstract: China is a large agricultural country with a high level of agricultural carbon emissions. Whether market prices can be used in agricultural production as a means of agricultural carbon emissions reduction is of great significance to improve the allocation of agricultural production factors and expand large-scale production. This paper applies an autoregressive distributed lag-pooled mean group(ARDL-PMG) model to evaluate the relationship between agricultural production factor prices, food consumption prices, and agricultural carbon emissions, using Chinese provincial panel data from 1994 to 2018. The results show that agricultural carbon emissions and agricultural production factor prices show environmental Kuznets curve (EKC) characteristics; agricultural carbon emissions and food prices show a U-shaped curve; and agricultural production factors are positively correlated with food price in both directions in the long-term. The results of Granger causality tests show that price is the cause of agricultural carbon emissions; the price of agricultural production factors and the price of food consumption are mutually causal. Such results have implications for price, agriculture, and environmental policies. The analysis implies that the market price can be applied to agricultural carbon reduction, which will help policymakers to implement effective price policies in order to reduce agricultural carbon emissions. One implication is that promoting the marketization of agricultural production factors and reducing price distortions will be conducive to carbon emissions reduction in agriculture, which in turn will increase food consumption prices. Therefore, subsidies are needed at the consumption end, which will eventually achieve further carbon emissions reduction at the production and consumption ends.

Keywords: prices of agricultural production factors; food consumption prices; agricultural carbon emissions; China

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1. Introduction

The increase in greenhouse gas emissions is one of the most significant causes leading to global warming. Climate warming is related to sustainable development. Carbon reduction is an important part of achieving the UN's Sustainable Development Goals globally [1]. In order to deal with global warming, the UN has formulated a series of emissions reduction rules—for example, the UNFCCC, or The Kyoto Protocol. To achieve the goals of the Paris Agreement will require significant reductions in greenhouse gas emissions. Many studies have shown that economic expansion is closely related to carbon dioxide emissions; thus, carbon dioxide emissions reduction is an important indicator of improved environmental quality [2,3]. Therefore, research on carbon emissions reduction has been paid continuous attention by governments and academia.

At present, most research is looking at how to reduce carbon emissions from industrial production, but focusing on industry alone will not meet the goals of the Paris Agreement [4]. Industry is recognized as the main source of greenhouse gas emissions, but agriculture also releases a significant amount of greenhouse gas emissions into the atmosphere. Although most greenhouse gas emissions come from industrial production and services, greenhouse gases from agricultural activities should not be ignored [5]. The development of agriculture is directly related to the stability of society and the sustainable development of the economy [6], but greenhouse gas emissions from agricultural production are an important component of global greenhouse gas emissions [7,8]. The global agricultural system is a major source of greenhouse gas emissions, accounting for about 30% of the global total emissions [9]; more than 44% of emissions from the agricultural sector come from the Asian continent [10]. As the population increases, the demand for food increases, which causes the rapid development of agricultural activities [11–13]. The agricultural system has become the second largest greenhouse gas emitter in the world, and is growing at a rapid rate of about 1% per annum [14,15]. There are many sources of greenhouse gases in the agricultural system. The main sources of agricultural carbon emissions are land cultivation, input of production factors, animal husbandry, and agricultural energy use [16,17]. About 16 billion tons of carbon dioxide per year are produced by from agricultural systems [4,18]. Agricultural systems are humanity's biggest source of non-CO₂ greenhouse gases; agricultural CH₄ and N₂O emissions represent around 10–12% of total anthropogenic greenhouse gas emissions—40% of the total CH₄ and 60% of the total N₂O, respectively [19–21]. Research has shown that current trends in carbon emissions from the global agricultural system would hinder the achievement of the 1.5 °C target and threaten the achievement of the 2 °C target by the end of the century [4].

Because of the long-term high level of economic growth, resulting in a large quantity of greenhouse gas emissions, China has become the world's largest carbon dioxide emitter. As the largest emitter of greenhouse gases, the Chinese government has pledged to reduce greenhouse gas emissions per unit of GDP by 60–65% by 2030, compared with 2005 levels [22]. Therefore, each industry sector should set a clear carbon reduction target. China is a great agricultural country, and its agricultural economy is developing rapidly. Since the reform and opening up, China's agriculture has made remarkable achievements, having not only successfully solved the problem of feeding more than 1.3 billion Chinese people, but also having made significant contributions to the world's agriculture. China's agricultural added value increased from CNY 101.85 billion in 1978 to CNY 6474.52 billion in 2018; arable land area increased from 99,389.5 million hectares in 1978 to 134,881.2 million hectares in 2018; grain output rose from 304.765 million tons in 1978 to 657.892 million tons in 2018. People's living standards have been improving. The per capita disposable income of Chinese residents increased from CNY 171.2 in 1978 to CNY 28,228 in 2018—of which the per capita disposable income of urban residents increased from CNY 343.4 to CNY 39,250.8, and the per capita net income of rural residents increased from CNY 134 to CNY 14,617. People's demand for living standards is gradually improving, and the demand for food is also changing in the direction of diversification. This leads to the rapid expansion of the scale of agricultural production, and especially the increase in the input of agricultural production factors, causing China's agriculture to face many problems, such as the rapid rise in carbon emissions. China has 20% of the world's population, but only 10% of the world's arable land [6]. By the end of 2020, China had solved absolute poverty, and agricultural development played a key role in this, but greenhouse gases from agricultural activities should not be ignored [23]. The quality of carbon emissions reduction directly affects the implementation of China's dual-control emissions reduction targets (total volume and intensity). China's agricultural production produces more carbon than any other country [24]. Agriculture accounts for 16–17% of China's greenhouse gas emissions [25], while in the United States it accounts for 6–7% [26]. If China does not take effective measures to reduce carbon emissions, agricultural greenhouse gases could reach

30% of the total by 2050 [27]. China's agricultural sector accounts for 50% of CH₄ and 92% of N₂O emissions [28,29]. Hence, this is a problem worthy of attention and research.

As a major agricultural country, China's agricultural carbon emissions are growing rapidly. In the agriculture sector, reducing CO₂ emissions is not only a technical issue but also a socio-economic issue [30]. Farmers tend to pay more attention to the price of factors of production and the market price of products when they engaging in agricultural production [31,32]. To increase agricultural output, the use of production factors has been increasing year by year. By consulting the data, we found that the amount of chemical fertilizer converted increased from 8.84 million tons in 1978 to 56.5342 million tons in 2018, the amount of agricultural diesel oil increased from 9.38 million tons in 1993 to 2.0339 million tons in 2018, the amount of pesticides used increased from 845,000 tons in 1993 to 1,503,600 tons in 2018, and the amount of plastic film used in agriculture increased from 707,321 tons in 1993 to 2,466,795 tons in 2018. China implements price subsidy policy for the agricultural means of production, which will promote the over-input of the agricultural means of production to some extent. The heavy use of factors of production increases carbon dioxide emissions from agriculture. In the process of production, the producer should consider the price of factors of production and the market price of products, and consider the input of factors of production and the change in production scale according to changes in market prices. Therefore, changes in market prices will affect agricultural carbon emissions.

The literature review shows that previous research has been extensively carried out on agricultural carbon emissions. However, the impact of market prices on agricultural carbon emissions is still small. Therefore, this study studies the long-term and short-term effects of market price changes on agricultural carbon emissions from the perspective of product market price changes at the production and consumption ends. As one of the largest carbon dioxide emission sectors, the agriculture sector has a responsibility to find ways to reduce carbon emissions and achieve sustainable development [33]. From the perspective of price, this study used Chinese provincial panel data from 1994 to 2018 to explore the relationship between the price of factors of production, the price of food, and agricultural carbon emissions. Due to the unavailability of specific price data, the price index of the agricultural means of production is used to represent the price of agricultural production factors, and the consumer price index of food is used to represent the consumer price of food in this paper. This study is expected to contribute to the study of agricultural carbon emissions from a new perspective; it is expected that the findings of this study will provide appropriate policy references for China's agricultural carbon emissions and pricing system, and may provide reference for the formulation of China's agricultural subsidy policy, and thus promote the sustainable development of China's ecological agriculture.

2. Methodology and Data

2.1. Calculating Carbon Emissions

The calculation of agricultural carbon emissions is the basis of this research. According to the different types of agricultural carbon emissions [5,13,16], we calculate the agricultural carbon emissions by referring to the calculation method of the IPCC. Due to emissions of CH₄ and N₂O, we need to convert CH₄ and N₂O into carbon emissions. The formula for the calculation of the agricultural carbon emissions is as follows:

$$C = \sum_{i=1}^n T_i \times \delta_i \quad (1)$$

where C denotes agricultural carbon emissions, the main source of carbon emissions is the input of agricultural production: CH₄ from rice growth, N₂O released by soil tillage, and CH₄ and N₂O released from animal husbandry, T_i represents the agricultural carbon emissions from other sources; and δ_i is the coefficient of different agricultural carbon sources.

2.2. Economic Specifications

The main purpose of this paper is to estimate the relationship between prices of factors of agricultural production, food price, and carbon emissions from the agricultural system. Therefore, in accordance with the available research, multivariate analysis was used in this paper. The equation relationship between variables can be described as:

$$C = f(PP, FP) \quad (2)$$

In order to reduce issues of heteroscedasticity, we take the natural logarithm of the formula, which can be written in the following form:

$$\ln C_{i,t} = \theta_0 + \alpha \ln PP_{i,t} + \beta \ln FP_{i,t} + ECM_{i,t} \quad (3)$$

where C denotes agricultural carbon emissions; and PP denotes the prices of factors of agricultural production. Since the price data of factors of agricultural production are not available, we used the changes in the price index of the agricultural means of production to represent the change in the prices of agricultural factors of production. FP denotes food price—we used changes in the food consumer price index to represent the change in food price. α and β indicate the coefficients of $\ln PP$ and $\ln FP$, respectively; θ_0 denotes the intercept term, and $ECM_{i,t}$ denotes the error correction term.

2.3. ARDL–PMG Approach

Autoregressive distributed lag (ARDL) models can eliminate the endogeneity problem by including the lag length in the variables. Mean group (MG) models can not only study the short-term influence of the corresponding variables of independent variables, but also study the long-term influence of the corresponding variables of independent variables [34]; while the short-term influence of the variables tends to differ, their long-term influence is often the same. Therefore, a pooled mean group (PMG) model was selected; a PMG estimator is an intermediate estimator that guarantees that short-term unit parameters vary while allowing for the same long-term elasticities. The basic usefulness of PMG implementation is to allow for the distinction of short-term dynamic parameters while restricting the equality of long-term coefficients. Regarding the estimation of the panel's ARDL model, Pesaran introduced the PMG estimation [35], and the ARDL model was written in the form of error correction in order to include the long-term influence as a single parameter in the regression equation. If the error term is a normal distribution with independent and identical distribution, the likelihood function of the observed value can be constructed by using the error correction model, and the estimated value of all variables is the parameter value of the maximized likelihood function. Therefore, a PMG estimation method was used in this study. According to Pesaran's method, with regards to examining the relationship between the variables, the PMG estimation method represented via a panel ARDL model can be expressed as:

$$\begin{aligned} \Delta C_{i,t} = & \theta_0 + \alpha_1 \ln PP_{i,t} + \alpha_2 \ln FP_{i,t} + \alpha_3 \ln C_{i,t-1} + \\ & \sum_{i=1}^n \beta_1 \Delta \ln \ln C_{i,t-1} + \sum_{i=1}^n \beta_2 \Delta \ln \ln PP_{i,t-1} + \sum_{i=1}^n \beta_3 \Delta \ln \ln FP_{i,t-1} + ECM_{i,t} \end{aligned} \quad (4)$$

$$\begin{aligned} \Delta PP_{i,t} = & \theta_0 + \alpha_1 \ln C_{i,t} + \alpha_2 \ln FP_{i,t} + \alpha_3 \ln PP_{i,t-1} + \\ & \sum_{i=1}^n \beta_1 \Delta \ln \ln C_{i,t-1} + \sum_{i=1}^n \beta_2 \Delta \ln \ln PP_{i,t-1} + \sum_{i=1}^n \beta_3 \Delta \ln \ln FP_{i,t-1} + ECM_{i,t} \end{aligned} \quad (5)$$

$$\begin{aligned} \Delta FP_{i,t} = & \theta_0 + \alpha_1 \ln C_{i,t} + \alpha_2 \ln PP_{i,t} + \alpha_3 \ln FP_{i,t-1} + \\ & \sum_{i=1}^n \beta_1 \Delta \ln \ln C_{i,t-1} + \sum_{i=1}^n \beta_2 \Delta \ln \ln PP_{i,t-1} + \sum_{i=1}^n \beta_3 \Delta \ln \ln FP_{i,t-1} + ECM_{i,t} \end{aligned} \quad (6)$$

where i and t denote provinces and time, respectively; β_1 , β_2 and β_3 denote the short-term coefficients; α_1 , α_2 and α_3 denote the long-term coefficients; θ_0 denotes the intercept term; $ECM_{i,t}$ denotes the error correction term; and Δ is the difference operator.

2.4. Data Sources

Due to the availability of data, the study area does not include Beijing, Tianjin, Shanghai, Chongqing, Tibet, Hong Kong, Macao, or Taiwan. The time span of this study is 1994–2018. Research data are from the China Rural Statistical Yearbook (1995–2019) and the China Price Statistical Yearbook (1995–2019). The study variables include the price index of the agricultural means of production (PP), the consumer price index for food (FP), and agricultural carbon emissions (C). Before detailed analysis, all variables were converted to their natural logarithms to ensure the stability of the data. The price index can be converted using 1991 as the base year to reflect real price changes.

Table 1 shows the measures of central tendency, mean, and median that form the center of the distribution estimates. It is evident that, on average, agricultural carbon emissions, the price index of the agricultural means of production, and the consumer price index for food were 10.11, 176.80, and 176.63, respectively. Agricultural carbon emissions, the price index of the agricultural means of production, and the consumer price index for food are positively skewed. From the descriptive statistics of the variables, it can be found that the standard deviation of the consumer price index for food was the largest among the three variables. Table 2 shows the correlation analysis between the variables; we found that agricultural carbon emissions were negatively correlated with the price index of the agricultural means of production, that agricultural carbon emissions were positively correlated with the consumer price index for food, and that the price index of the agricultural means of production was positively correlated with the consumer price index for food.

Table 1. Descriptive statistics of the variables.

	Mean	Max	Min	SD	Skewness	Kurtosis	Observations
C	10.11	22.50	0.87	5.41	0.25	1.95	650.00
PP	176.80	306.42	100.00	52.51	0.39	1.81	650.00
FP	176.63	329.90	100.00	61.17	0.63	2.02	650.00

Table 2. Correlation analysis.

Variables	C	PP	FP
C	1.00		
PP	−0.03	1.00	
FP	0.07	0.94	1.00

3. Results and Discussion

3.1. Cross-Sectional Dependence Tests and Unit Root Tests

Before the unit root tests, cross-sectional dependence tests were performed. We used Pesaran's test and the Breusch–Pagan LM test to check the cross-sectional dependence of the variables. We found that the cross-sectional dependence was rejected at the significance level of 1%; the results are shown in Table 3. These results imply the presence of cross-sectional dependence in the underlying data. This indicates that the variation of variables in one province could affect the other provinces. Thus, in the case of cross-sectional dependence, panel unit root tests are used to test the data stability.

Table 3. Results of the cross-sectional dependence tests.

Variables	Pesaran CD		Pesaran Scaled LM		Breusch-Pagan LM	
	Statistic	<i>p</i>	Statistic	<i>p</i>	Statistic	<i>p</i>
LnC	14.760	0.000	92.669	0.000	2687.606	0.000
LnPP	88.891	0.000	297.229	0.000	7902.894	0.000
LnFP	89.834	0.000	303.795	0.000	8070.293	0.000

The stability of the data should be verified prior to model analysis. Therefore, the stationarity of these variables is examined using LLC, IPS, ADF-Fisher and PP-Fisher unit root test. Table 4 shows the results of these tests for the logarithmic values of the variables. We found that LnC is not stationary at the level, LnPP and LnFP is stationary at the level, but the variables is stationary at the first difference.

Table 4. Results of the panel unit root tests.

	Level		
	IPS	ADF-Fisher	PP-Fisher
LnC	−1.154	61.805	75.653 **
LnPP	−6.528 ***	128.096 ***	43.626
LnFP	−11.934 ***	225.422 ***	14.639
	1st Difference		
	IPS	ADF-Fisher	PP-Fisher
LnC	−17.144 ***	315.742 ***	623.283 ***
LnPP	−8.740 ***	170.559 ***	250.067 ***
LnFP	−2.921 ***	83.876 ***	206.890 ***

Note: *** Statistical significance at the 1% level. ** Statistical significance at the 5% level. * Statistical significance at the 10% level.

3.2. Cointegration Test

Because all of the variables follow the first difference in the unit root tests, but the single-integer variable regression without a co-integration relationship is still false regression, we chose the Kao test and the Pedroni test with which to perform co-integration testing on the all variables. We had to determine the optimal lag length before carrying out the co-integration tests. Here, we still used AIC standards, FPE standards, AIC standards, and HQ standards to determine the optimal lag length; the results are shown in Table 5. We found the optimal lag length to be 1.

Table 5. Results of the lag length selection criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−150.382	−	0.000	0.492	0.513	0.4999
1	3142.826 *	6544.196 *	8.80×10^{-9} *	−10.035 *	−9.949 *	−10.002 *

Note: * Indicates lag order selected by the criterion.

The results of the co-integration tests are shown in Table 6. The Kao test results show that the null hypothesis without a co-integration relationship is rejected at the 1% significance level. The Pedroni test results show that Panel v-Statistic did not pass the significance test, Group ADF-Statistic passed the 5% significance test, and all other statistics rejected the null hypothesis that there is no co-integration relationship at the significance level of 1%. Therefore, based on the above test results, we found that a long-term stable co-integration relationship can be obtained between the variables.

Table 6. Results of the co-integration tests.

	Statistic Name	Statistic	<i>p</i> -Value
Kao co-integration test; Null hypothesis: no co-integration	ADF	1.701	0.044
	Panel v-Statistic	−4.927	1.000
Pedroni co-integration test; Null hypothesis: no co-integration	Panel rho-Statistic	−7.263	0.000
	Panel PP-Statistic	−19.868	0.000
	Panel ADF-Statistic	−2.376	0.000
	Group rho-Statistic	−4.518	0.000
	Group PP-Statistic	−26.574	0.000
	Group ADF-Statistic	−2.182	0.015

3.3. ARDL–PMG Estimates

On the premise that there is a co-integration relationship, we use the PMG estimation approach through an ARDL model in order to estimate the variables necessary to determine the short-term and long-term estimates. Table 7 shows the results of the PMG estimation approach.

Table 7. PMG estimation results.

Long-Term			
Dependent Variable	LnC	LnPP	LnFP
LnC	-	0.095	−0.193 ***
LnPP	−0.235 ***	-	0.599 ***
LnFP	0.276 ***	1.157 ***	-
Short-Term			
Dependent Variable	LnC	LnPP	LnFP
ΔLnC	-	−0.035	0.105 ***
ΔLnPP	0.298 ***	-	0.242 ***
ΔLnFP	−0.261 ***	−0.123 **	-
ECM(−1)	−0.195 ***	−0.327 ***	−0.259 ***

Note: *** Statistical significance at the 1% level. ** Statistical significance at the 5% level. * Statistical significance at the 10% level.

We found that LnPP and LnFP had effects on LnC in the long-term and short-term at the significance level of 1%. LnPP and LnC are negatively correlated in the long-term and positively correlated in the short-term; LnFP and LnC are positively correlated in the long-term and negatively correlated in the short-term. In the short-term, a 1% increase in LnPP will lead to a 0.298% increase in LnC, while a 1% increase in LnFP will lead to a 0.261% decrease in LnC. In the long-term, a 1% increase in LnPP will lead to a 0.235% decrease in LnC, while a 1% increase in LnFP will lead to a 0.276% increase in LnC. This occurs because the market price system cannot affect the scale of agricultural production in the short-term. In the short-term, agricultural output can only be increased by increasing the input of agricultural production factors, even if the prices of factors of agricultural production rise; however, in the long-term, agricultural production carbon emissions can be reduced through the rational allocation of production factors and the use of agricultural soil testing formulae and other technologies. In the short-term, when the price of food rises, consumers can choose to temporarily reduce consumption, leading to a decline in market demand, which in turn affects the decline in supply, and reduces agricultural carbon emissions in the short-term; however, in the long-term, the consumption of agricultural products will not decrease—with the increase in living standards, the consumption of food will further increase, which will promote the increase of agricultural carbon emissions. From the perspective of industrial scale, in the long-term, the rising price of agricultural

production factors maybe promote agriculture to adopt scale and agglomeration modes of production, reducing the number of small-scale producers; scale production can make use of advanced production technologies more quickly to reduce production costs, so as to promote carbon emissions reduction. As the price of agricultural products rises, the number of small-scale and large-scale producers will increase. At the same time, in order to achieve high income, the input of factors of production will further increase, which will increase agricultural carbon emissions.

The short-term results show that LnFP and LnPP are negatively correlated at the significance level of 5%; a 1% increase in LnFP will lead to a 0.123% decrease in LnPP ; LnC and LnPP failed the significance test. In the long-term, a 1% increase in LnFP will lead to a 115.7% increase in LnPP at the significance level of 1%; LnC and LnPP failed the significance test. In the long-term, the rise of the price of food stimulates producers to increase the use of factors of production, which increases the market demand for factors of production, leads to the rise of the price of factors of production, and thus increases the production cost.

We found that the influence of LnPP and LnC on LnFP passed the 1% significance test. In the short-term, a 1% increase in LnPP or LnC will significantly increases LnFP , by 0.242% and 0.105%, respectively. In the long-term, a 1% increase in LnPP will lead to a 0.599% increase in LnFP , while a 1% increase in LnC will lead to a 0.193% decreases in LnFP .

3.4. Granger Causality

In order to further verify the causal relationship between the variables, the method of Dumitrescu and Hurlin was used to carry out the tests; the results are shown in Table 8. These results show that the causal relationship between LnPP and LnFP passes the significance test of 1%, which indicates that the “null hypothesis” of “no causal relationship” is rejected, and that there is a two-way causal relationship between LnPP and LnFP . At the 1% significance level, LnPP is the homogeneous cause of LnC ; at the 5% significance level, LnFP is the homogeneous cause of LnC .

Table 8. Granger causality analysis.

Null Hypothesis:	W-Stat.	Zbar-Stat.	Prob.
ΔLnPP does not homogeneously cause ΔLnC	2.124	3.017	0.003
ΔLnC does not homogeneously cause ΔLnPP	1.123	0.034	0.973
ΔLnFP does not homogeneously cause ΔLnC	1.910	2.378	0.017
ΔLnC does not homogeneously cause ΔLnFP	1.498	1.153	0.249
ΔLnFP does not homogeneously cause ΔLnPP	6.924	17.308	0.000
ΔLnPP does not homogeneously cause ΔLnFP	2.148	3.087	0.002

Therefore, by combining the results of the previous models' estimation, we can obtain a relational graph of each variable, as shown in Figure 1. The promotion of the marketization of agricultural production factors and the reduction of agricultural production subsidies are conducive to the reduction of agricultural carbon emissions. The increase in the food consumption price will enhance agricultural carbon emissions, because the increase in the food consumption price will promote further investment in agricultural production factors. At the same time, the price of agricultural production factors is positively correlated with the price of food consumption, and the two will promote one another. Therefore, it is necessary to shift the direction of agricultural production subsidies, gradually moving them from the production end to the consumption end, so as to improve the current situation of agricultural carbon emissions in a two-pronged manner.

Figure 1. Diagram of the long-term causal relationship between variables.

4. Conclusions and Policy Implications

Greenhouse gas emissions are one of the most important contributors to climate change, and the price system determines demand and supply. However, analysis of the relationship between agricultural production factor prices, food consumption prices, and agricultural carbon emissions is limited in existing studies.

This study looked at the causal link between agricultural carbon emissions, prices of factors of agricultural production, and the consumer price of food using annual panel data for the 26 provinces in China between 1991 and 2018. Our findings show that all of the variables under study are co-integrated, implying that there is a long-term relationship between the variables. The PMG estimation results show: (1) In the short-term, agricultural production factor prices are positively correlated with agricultural carbon emissions, while agricultural production factor prices are negatively correlated with agricultural carbon emissions in the long-term, which verifies that agricultural carbon emissions and production factor prices are in line with EKC curve characteristics; agricultural carbon emissions first increased and then decreased with the increase of agricultural production factor prices. (2) In the short-term, food prices are negatively correlated with agricultural carbon emissions, while in the long-term, food prices are positively correlated with agricultural carbon emissions, indicating that agricultural carbon emissions and food prices conform to the U-shaped curve. (3) Whether short-term or long-term, food consumer prices are rising in response to rising the price of agricultural production elements, but the food price is negatively correlated with the price of agricultural production factors in the short-term, while in the long term the food price is positively correlated with the price of agricultural production factors. However, in the long-term, the price of agricultural production factors is positively correlated with the price of food in both directions. (4) With the increase in agricultural carbon emissions, the food consumption price increases in the short-term and decreases in the long-term, which is in line with the EKC curve. In order to further verify the causal relationship between the variables, the results of the Granger causality test show that price is the cause of agricultural carbon emissions—the price of agricultural production factors and the price of food consumption are mutually causal.

In terms of policy consequences, this reveals that price is an important determinant of carbon emissions from agriculture in China and, therefore, the importance of price in reducing carbon emissions should be extended to climate change efforts. According to the research results, this paper suggests that policymakers should use agricultural prices as a mechanism for controlling and mitigating carbon emissions. Therefore, we put forward the following suggestions: (1) The market of agricultural production factors should be further opened, the degree of marketization should be further strengthened, and the price distortion in the market of agricultural production factors should be weakened. (2) Stabilize food consumption prices, and properly consider the transfer of subsidies from the producer end to the consumer end in the formulation of agricultural subsidy policies. (3) Encourage large-scale and intensive agricultural production. These policy initiatives may help to weaken the market price distortions of agricultural production factors, optimize agricultural price subsidy policies, and reduce agricultural carbon emissions.

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