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The Impact of Food Production Comparative Advantage on Green Total Factor Productivity: The Moderating Role of Environmental Regulation

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Abstract: Guaranteeing an increase in ecologically sustainable food production is a sufficient prerequisite for the long-term development of national food security. This study's primary goal is to determine strategies for improving the nation's green total factor productivity (GTFP) of food. We begin by measuring the GTFP of food with the Global Malmquist–Luenberger (GML) index. Second, the food production comparative advantage is determined using the entropy-weighted Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) method. The food production comparative advantage is then used as a leaping point to experimentally study the pathway to enhancing the GTFP of food. The 510 sample statistics for this study come from 30 provinces in China from 2003 to 2019. The study's findings indicate that (i.) China's "food production comparative advantage" and "GTFP of Food" have shown an ascending pattern. China's Northeast and Huang–Huai–Hai regions have the greatest comparative advantages in food production. The regions with the highest food GTFP are the Northeast and Middle and Lower reaches of the Yangtze River. (ii.) Food production comparative advantage can effectively contribute to green total factor productivity, but there is a time lag. (iii.) As food production's comparative advantage rises, its contribution to GTFP becomes more apparent. (iv.) Environmental regulation moderates the influence of food production comparative advantage on GTFP. In addition, environmental regulations exert a greater moderating effect in regions with lower green total factor production rates than in regions with higher green total factor production rates. (v.) The food production comparative advantage improves the GTFP through both structural and technological effects. This study not only expands the research horizon of GTFP of food but also offers planning recommendations for technological advancement and structural adjustment in food production.

Keywords: food production comparative advantage; green total factor productivity of food; environmental regulations; structural effects; technological effects

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1. Introduction

Food security is a crucial pillar for supporting the growth of the global economy and the stability of the international community, as well as a crucial pillar for the establishment of national independence. Currently, China's expanding food production capability is coupled with an increase in negative environmental externalities [1]. Due to massive inputs of pesticides, fertilizers, and mulch, arable land has lost the capacity to restore its natural biological cycle. Between 2012 and 2021, China's total grain output grew from 612.22 million tons to 682.85 million tons, an increase of more than 11%. Simultaneously, the sown area of grain crops in China increased from 114,368 kilo hectares to 117,631 kilo hectares, an increase of 2.85%. Moreover, China's grain yield increased from 5353.12 kg per hectare to 5805 kg per hectare, an increase of 7.8%. The green total factor productivity of China's grain production, meanwhile, increased by 6.5%. In this environment, the government has given green food production a higher priority to preserve sustainable food production and provide food security [2]. In 2022, the Chinese government's "Central No. 1" document on boosting rural ecological rehabilitation recommended enhancing the complete control of agricultural surface pollution and promoting the decrease of chemical fertilizers and pesticides in food production. Improving the GTFP of food in response to China's policy calling for positive degrees is not only an important assurance for stable and sustainable food production at this time but also a crucial means of implementing the ecological civilization concept.

The key to optimizing ecological and economic advantages and increasing GTFP of food is maximizing food production while decreasing production factor inputs, particularly agricultural surface source pollution factors such as pesticides, fertilizers, and mulch [3]. The most important criteria for maximizing ecological and economic benefits are technological development and technical efficiency improvement, which is driven by technological innovation and dependent on scale expansion and enhanced field management efficiency [4]. The food production comparative advantage (including arable land advantage, labor advantage, capital advantage, and water advantage) has three effects on food production: scale growth, investment substitution, and structural optimization [5]. These effects are advantageous for both the enhancement of the environment in which food is grown and the optimization of the input structure of food production factors, taking into consideration the reduction of polluting production factors [6]. Moreover, environmental regulation is progressively becoming an important supplement to ecological food production management [7]. In light of this, the Chinese government has been enhancing the comparative advantages of regional food production while increasing the level of environmental regulation to construct a modernized system of resource-efficient and environmentally friendly food production and promote the harmonious development of resources, environment, and food production [8]. Consequently, does food production comparative advantage contribute efficiently to GTFP? Is there heterogeneity in the degree of impact across regions? What is the transmission mechanism of the impact? The answers to the aforementioned issues pertain not only to the ecologically sustainable production of food in China but also to the improvement of regional food production planning policies. Therefore, the purpose of this study is to explore the path of green total factor productivity improvement of food by taking the comparative advantage of food production as an entry point. On this basis, we further explore the moderating role of environmental regulation.

The rest of the study is organized as follows. Section 2 introduces the literature review. Section 3 introduces the theoretical hypothesis. Section 4 introduces materials and methods. Section 5 presents and discusses the empirical results. Section 6 presents the research conclusions and policy implications.

2. Literature Review

The evolution of the theory of comparative advantage, from Adam Smith's theory of absolute advantage in 1976 to David Ricardo's theory of comparative advantage in 1981, followed by Heckscher-theory Ohlin's of factor endowment by emphasizing that the heterogeneity of factor endowments among countries is the primary cause of international trade. Agricultural production is highly reliant on natural endowments, and the variation in agricultural factor endowments among nations has a significant effect on agricultural output's comparative advantage. Food production comparative advantage has been defined as the difference in the opportunity cost of countries or regions in food production and commerce due to variations in endowments such as land factor, water factor, labor factor, and capital factor [9]. The food production comparative advantage has been studied primarily from the viewpoints of factor inputs and outputs, production costs and returns [10], area and yields, cropping patterns and regional layout, and agroecosystem productivity [11]. Moreover, among the methods for measuring the food production comparative advantage, the comparative advantage index, international market share, product technical complexity, domestic resource cost method, agricultural production economic index research method, and comprehensive comparative advantage index method are most prominently displayed [9,12–16]. The integrated comparative advantage index approach, consisting of scale advantage, efficiency advantage, and effectiveness advantage, is a common method for studying the comparative advantage of regional food production [17]. Existing studies on the measurement of food production comparative advantage, however, typically only consider explicit comparative advantages such as scale advantage, efficiency advantage, and effectiveness advantage while ignoring factor resource endowment indicators such as land, labor, capital, and water resources involved in conventional comparative advantage theory.

As the problem of agricultural surface pollution has become more apparent, experts have steadily incorporated pollution components into the GTFP of food [18–24]. Most anticipated outcomes of previous studies primarily examine the economic worth of food items, thus underestimating the ecological value created by food farming. Some researchers have gradually incorporated ecological aspects into the GTFP measurement system and developed a GTFP measurement model based on ecological value maximization in recent years [25]. However, there is a paucity of research on its applicability in the sector of food production. In addition, the relationship between environmental regulation and GTFP has been the subject of scholarly investigation. The amount of environmental regulation and green total factor production have been computed using the entropy power method and the green Solow model, respectively, and the spatial spillover effects have been evaluated using the Durbin spatial model [26]. Some researchers used the SBM-GML index to evaluate GTFP in agriculture and a threshold regression model to confirm the nonlinear relationship between environmental regulations and GTFP in agriculture [27,28]. To examine the "inverted U-shaped" relationship and regional spillover impact between environmental restrictions and the GTFP of food, researchers measured the GTFP of food using the GML index [2].

In conclusion, it is evident from the available literature that food production comparative advantage and GTFP of food have been the subject of much investigation. Existing studies on the measurement of food production comparative advantage typically only consider explicit comparative advantages, such as scale advantage, efficiency advantage, and effectiveness advantage, while ignoring the factor resource endowment indicators such as land, labor, capital, and water resources involved in the traditional comparative advantage theory. In addition, most studies concentrate on the measurement of agricultural total factor productivity and its influencing factors, whereas studies on the measurement of GTFP of food with the inclusion of non-desired outputs are just emerging, and there are relatively few studies on GTFP of food that also consider the ecological value of food cultivation. Even little literature investigates the GTFP of food by beginning with the food production comparative advantage. The possible contributions of this study are: First, in terms of measuring key indicators, this study improves the comprehensive comparative advantage index method, selects 16 indicators from the advantages of land, labor, capital, and water resources, taking into account the dominant comparative advantage and potential comparative advantage, and employs the entropy-weighted Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method to make a more scientific and reasonable evaluation of the food production comparative advantage in each region. Second, as predicted outcomes in the measurement of food GTFP, food production and ecological value indicators of food cultivation are added to indicate both the ecological and economic values of food GTFP. Our study used the GML index method, which has been utilized extensively by previous researchers, to measure and assess the GTFP of food in 30 provincial administrative regions of China from 2003 to 2019. Third, based on the theory of comparative advantage, this study uses the food production comparative advantage as a starting point to explore the path of enhancing the GTFP of food. Additionally, the study investigates the moderating role of environmental regulation to provide a reference basis for enhancing the GTFP of food and the comparative advantage of regional food production.

3. Theoretical Hypothesis

3.1. Food Production Comparative Advantage and Green Total Factor Productivity

According to most academics, food production comparative advantage has a catalytic effect on food production for the four reasons listed below. First, there is no doubt that arable land quality influences food production and operation [29,30]. A definite geographical coupling exists between the amount of agricultural work and the area sown for food, and the human capital of agricultural labor (e.g., the level of education of agricultural labor), age, and feminization all have significant effects on food productivity [31,32]. In addition, the effect of capital element inputs on food cultivation is gaining prominence, with the degree of agricultural mechanization having a spatial spillover effect and making a substantial contribution to food production in nearby regions [33]. Finally, the function of water resource issues in food production, which also has a significant restricting effect on food production and so impacts food production, should not be undervalued. Comparative advantages in food production (arable land, labor, capital, and water resources advantages) increase farmers' income by reducing the cost of food production, which in turn motivates farmers to cultivate food and increases the likelihood that agricultural producers will cultivate food [34,35]. Moreover, regions with greater comparative advantages in food production are more likely to develop a trend of large-scale, specialized, and intense agriculture, hence reducing the informational and monetary costs of financing food production. In places with stronger food production comparative advantage, agricultural production element allocation is more logical, and farmers' food cultivation conduct is more effective, reducing factor input redundancy. This increases food production's economic and ecological value by reducing surface contamination from pesticides, fertilizers, agricultural films, and carbon emissions [36]. Thus, the food production comparative advantage can boost GTFP by motivating farmers to grow food and optimizing agricultural factor allocation. Consequently, the hypothesis that follows is developed.

Hypothesis 1. *Food production comparative advantage positively affects green total factor productivity.*

3.2. The Moderating Role of Environmental Regulation

Porter's famous theory, "Porter's hypothesis", claims that environmental legislation can stimulate regional industrial restructuring and is a driving force to promote regional technological innovation to eliminate backward producers [37]. When a territory's environmental regulatory intensity exceeds a particular threshold, polluting producers will shift to a location with less stringent environmental regulations; the transferred region's industrial structure will then undergo adjustment and eventual rationalization [38]. Similarly, when environmental regulation reaches a suitable frequency, it encourages producers to participate in green technology innovation, thus improving their productivity while reducing pollutant emissions [39]. The aforementioned "innovation compensation effect" provides substantial benefits to producers that will equal or even surpass the "compliance cost effect" of environmental restrictions. Long-term, environmental legislation fosters green technology innovation and displaces otherwise less productive and polluting producers, therefore enhancing national competitiveness [40,41]. Thus, by increasing the environmental cost of food production, environmental regulation drives producers in regions with low food production comparative advantage to gradually lose their capacity to operate sustainably and, ultimately, be driven off the market. In contrast, farmers in regions with a greater food production comparative advantage benefit from higher GTFP to live. Moreover, regions with stricter environmental regulations can compel producers to adopt green production technologies, such as water-fertilizer integration, which facilitates the use of high-fertility fertilizers such as water-soluble fertilizers, effectively reducing the number of total chemical fertilizers applied, therefore reducing agricultural surface pollution and carbon emissions while enhancing their ecological benefits [42]. The government's efforts to lower the marginal "compliance costs" of food producers and regions with comparative advantages in food production can reduce the marginal "compliance costs" of food producers and raise the GTFP of food [43]. The food production comparative advantage can, therefore, play a greater role in increasing GTFP as the level of environmental regulation rises. Based on the analysis presented above, we formulate our Hypothesis 2.

Hypothesis 2. *Environmental regulation moderates the impact of food production comparative advantage on green total factor productivity.*

3.3. Mediation Mechanism of Technology Effects and Structural Effects

In general, regions with a food production comparative advantage are more likely to qualify for agricultural subsidies. More adequate funds allocated for research and development of food production technologies enable the attraction of technical R&D talent and the acquisition of technical R&D equipment, which effectively increases the output of patented results in food production technologies and accelerates the rate of technological advancement and production technology innovation in food production [44]. Furthermore, the scale, intensive, and specialized forms of food production in locations with a greater food production comparative advantage are more favorable to the transformation of technological patents in food production, hence increasing the technological efficiency of food production [7]. The technological advancement aspect of the technology effect can stimulate the transformation and upgrading of food production technologies, break existing resource and usage restrictions, and make a quantum leap in the green efficiency of food production [45]. The technical efficiency aspect of the technology effect can increase the marginal productivity of food production element inputs while reducing economic and ecological costs [46], consequently giving a continuing incentive for the increase of food's GTFP. On this basis, Hypothesis 3 is proposed.

Hypothesis 3. *Food production comparative advantage positively influences green total factor productivity of food via technological effects.*

It is evident from the preceding discussion that locations with greater food production comparative advantage (i.e., regions with greater endowments of arable land, labor, capital, and water resources) are more likely to establish large-scale, intense, and specialized food production. The structural effects of this study mean that, by optimizing the structure of food cultivation, food production becomes more scaled, specialized, and intensive. In this way, it promotes the improvement of technical efficiency, which in turn enhances the food's green total factor productivity. Due to the high market demand for the three staple grains of wheat, corn, and rice, farmers' rational behavior has led to the expansion of staple grain cultivation in areas with high food production comparative advantage [47], adjusting the internal structure of food cultivation and effectively forming a large-scale, intensive, and specialized food production model that reduces factor inputs and emissions [48]. This results in structural effects. Second, the food production comparative advantage encourages food specialization by increasing the acreage of staple grains and the fraction of staple grains within the structure of food production. Specialized productive service organizations provide specialized machinery operations for the food production chain to complete the work of food production efficiently, reduce the factor inputs required per unit of food production, enhance the efficiency of food production, and reduce agricultural surface source pollution emissions [49], therefore creating structural effects. Lastly, intensive food production reduces the economic cost of food production by sharing capital, labor, and information resources [50], optimizing the allocation efficiency of production factor inputs, reducing information search costs, increasing the transparency of service prices, and promoting the diffusion, diffusion, and application of technology [51], therefore creating structural effects. The food production comparative advantage can bring the structural effect of food cultivation into play and promote the improvement of technical efficiency to reduce agricultural surface pollution and carbon emissions through large-scale production, specialized production services, and information resource-sharing mechanisms, therefore increasing the GTFP of food. On this basis, Hypothesis 4 is proposed.

Hypothesis 4. *Food production comparative advantage positively influences green total factor productivity of food via structural effects.*

4. Materials and Methods

4.1. Methodology for Measuring the Food Production Comparative Advantage

Commonly, the food production comparative advantage is measured using the complete comparative advantage technique, which selects explicit comparative advantage indicators from three perspectives: scale advantage, efficiency advantage, and effectiveness advantage. This method disregards natural endowment elements such as land advantage, labor advantage, and water advantage, which are a part of the standard comparative advantage theory and does not select measurement indicators based on the potential drivers of food production comparative advantage. This study refers to Esmaeili [12] to improve on the comprehensive comparative advantage method and selects 16 indicators (Table 1) from four aspects: land advantage, labor advantage, capital advantage, and water resource advantage, taking into account dominant comparative advantage and potential comparative advantage, which is highly systematic and scientific [52,53]. Since the food production comparative advantage is also a multi-indicator dimensional variable, the entropy-weighted TOPSIS is used to comprehensively evaluate the comparative advantage of regional food production, and the comprehensive comparative advantage index is computed as a proxy variable for the food production comparative advantage.

The measurement of the index of food production comparative advantage in this study was calculated using the entropy weight TOPSIS method. The detailed calculation process refers to Li et al. [54].

4.2. Measuring Green Total Factor Productivity of Food

Since the *GML* index can effectively balance the green development requirements of maximizing desired output and minimizing non-desired output and input factors, this study refers to Oh [35] and constructs a *GML* index model to measure the changes in total factor productivity of food ecology in 30 provincial administrative regions of China between 2003 and 2019. The specific formula for measuring is as follows.

$$\begin{gathered} GML^{t,t+1}(x^t,y^t,b^t,x^{t+1},y^{t+1},b^{t+1}) = \frac{1+D^g(x^t,y^t,b^t)}{1+D^g(x^{t+1},y^{t+1},b^{t+1})} = \frac{1+D^g(x^t,y^t,b^t)}{1+D_t(x^t,y^t,b^t)} \times \\ \frac{1+D_{t+1}(X^{t+1},Y^{t+1},B^{T+1})}{1+D^g(x^{t+1},y^{t+1},b^{t+1})} \times \frac{1+D_t(x^t,y^t,b^t)}{1+D_{t+1}(x^{t+1},y^{t+1},b^{t+1})} = \\ \frac{1+D_t(x^t,y^t,b^t)}{1+D_{t+1}(x^{t+1},y^{t+1},b^{t+1})} \times \left[\frac{\frac{1+D^g(x^t,y^t,b^t)}{1+D_t(x^t,y^t,b^t)}}{\frac{1+D^g_t(x^{t+1},y^{t+1},b^{t+1})}{1+D_{t+1}(x^{t+1},y^{t+1},b^{t+1})}} \right] = \\ \frac{TE^{t+1}}{TE^t} \times \frac{BPG^{t,t+1}_{t+1}}{BPG^{t,t+1}_t} = GEC^{t,t+1} \times GTC^{t,t+1} \end{gathered} \tag{1}$$

In Equation (1), x^t, y^t, and b^t represent input factors and desired and undesirable outputs in year t, while x^{t+1}, y^{t+1}, and b^{t+1} represent input factors, wanted, and undesirable outputs in year $t + 1$. The output distance functions of the input-output vectors (x, y, b) at periods t and $t + 1$ are denoted by D_t (x^t, y^t, b^t) and D_{t+1} (x^{t+1}, y^{t+1}, b^{t+1}), respectively. D^g (x^t, y^t, b^t) is the reference set's direction vector. TE^t and TE^{t+1} represent the combined technical efficiency in years t and $t + 1$; $BPG^{t,t+1}$ and BPG^{t+1} represent the distance between the technical reference set and the production frontier surface in years t and $t + 1$, respectively. $GEC^{t,t+1}$ and $GTC^{t,t+1}$ therefore represent the indicators of technical efficiency and technological advancement of food greening relative to period $t + 1$ produced by decomposing the $GML^{t,t+1}$ index, respectively. When the value of *GML*, *GEC*, or *GTC* is greater than 1, it indicates that food GTFP, food green technical efficiency, or food eco-technological progress is increasing from t to $t + 1$, and vice versa, it is decreasing. When the value of *GML*, *GEC*, or

GTC is equal to 1, the productivity, efficiency, or progress remains unchanged. In addition, this analysis uses 2003 as the basic year and assigns it a total factor productivity of 1 for food grown for the base era. In succeeding years, the cumulative food green total factor production is computed by cumulative multiplication concerning the base period [55].

Table 1. Indicator system for measuring the food production comparative advantage.

Target Layer	Criterion Layer	Indicator Layer	Calculation Method	Category
Food production comparative advantage	Land advantage (B1)	Arable land area (C1)	Statistics	Positive
		Arable land area per laborer (C2)	Arable land area/Number of employees in the primary sector	Positive
		Grain sown area (C3)	Statistical data	Positive
		Average area of grain sown by labor (C4)	Grain sown area/number of employees in the primary sector	Positive
	Labor advantage (B2)	Rural human capital (C5)	Average years of schooling in rural areas	Positive
		Share of the agricultural labor force (C6)	(Number of persons employed in the primary sector in the province/number of permanent residents in the province)/(Number of persons employed in the primary sector in the country/number of permanent residents in the country)	Positive
		Average labor force food production (C7)	Food production/number of employees in the primary sector	Positive
	Capital advantage (B3)	Rural transportation facilities (C8)	Total road mileage/provincial land area	Positive
		Agricultural power facilities (C9)	(Electricity consumption × value added of primary industry/GDP)/crop sown area	Positive
		Food patent output (C10)	Data collection	Positive
		Level of agricultural machinery (C11)	Total power of agricultural machinery/crop sowing area	Positive
		Rural per capita investment in fixed assets (C12)	Investment in fixed assets of farm households/number of rural population	Positive
	Water resources advantage (B4)	Precipitation density (C13)	Precipitation/Provincial Land Area	Positive
		Total water resources (C14)	Statistics	Positive
		Amount of underground water resources (C15)	Statistics	Positive
		River area (C16)	Statistics	Positive

The input factors in this study include land input, labor input, fertilizer input, pesticide input, machinery input, plastic film input, and water input in grain production, and the expected output includes grain yield and ecological value of food cultivation (measured by Kangas et al. [56]), while the non-expected output includes agricultural surface source pollution (measured by Sun et al. [57]) and carbon emission (measured by Liu and Yang [58] combined with Liu et al. [59]). Indicators and calculation methods are detailed in Table 2.

Table 2. Measurement indicators of green total factor productivity of food.

Variable Category	Variable	Calculation Method	Unit
Expected output	Ecological value of food cultivation	Measured by ESV method	None
	Food yield	Statistical data	$\times 10^4$ t
Unexpected output	Area-source pollution	Agricultural non-point source pollution × A	$\times 10^4$ t
	Carbon emission	Agriculture carbon emission amount × A	$\times 10^4$ t
Input element	Land input	Food sown area	$\times 10^3$ hm^2
	Labor input	Primary industry employees × B	$\times 10^4$ person
	Fertilizer input	Agricultural fertilizer application amount × A	$\times 10^4$ t
	Pesticide input	Amount of pesticide use × A	$\times 10^4$ t
	Mechanical input	Total power of agricultural machinery × A	$\times 10^4$ kW
	Plastic film input	Application amount of agricultural plastic film × A	$\times 10^4$ t
	Water resources input	Agriculture water consumption × A	$\times 10^8$ m^3

A = grain sown area/total crop sown area; B = (A) × (agricultural output value/total agricultural, forestry, animal husbandry, and fishery output value).

4.3. Variables Selection

The specific variable indicators and measurement methods are presented in Table 3; these variables were selected based on existing studies.

Table 3. Variables and calculation methods.

Variable Category	Variable	Symbol	Calculation Method	Unit
Dependent variable	Green total factor productivity of food	*Gtfp*	Measured by the Global Malmquist–Luenberger Index	None
Independent variable	Food production comparative advantage	*Cagp*	Obtained by entropy-weighted TOPSIS composite evaluation	None
Mediating variables	Technology effect	*Tech*	Number of food-related patents	piece
	Structural effect	*Stre*	Area planted with staple grains/area planted with other grains	None
Moderating variable	Environmental regulation	*Envi*	Investment in environmental pollution control as a proportion of GDP × C	%
Control variables	Average size of arable land per household	*Cult*	Arable land area/number of rural households	Household/hm^2
	Flood removal area	*Logg*	Statistics	$\times 10^6$ hm^2
	Industrial structure level	*Stru*	(Value added of secondary industry + value added of tertiary industry)/gross GDP	km/hm^2
	Rural fixed asset investment	*Inve*	Investment in fixed assets of rural farm households/number of rural population	$\times 10^3$ yuan/person
	Disaster rate	*Disa*	Crop disaster area/total crop sown area × 100%	None
	Food price fluctuation	*Pric*	Retail price index of food commodities	None

C = (A) × (agricultural output/GDP total).

Dependent variable: Green total factor productivity of food. We refer to Yue et al. [25] and combine the ecological value of grain cultivation with the expected output index to maximize the economic value and ecological value of food production while minimizing agricultural surface pollution, carbon emission, and other input factors to reflect the GTFP of food more scientifically, accurately, and robustly.

Independent variable: Food production comparative advantage. The measurement indexes of food production's comparative advantage are based on the traditional comparative advantage theory and the comprehensive comparative advantage index method for improvement. A total of 16 indicators (including explicit and potential indicators) are selected from four dimensions: land advantage, labor advantage, capital advantage, and water resource advantage. The entropy-weighted TOPSIS evaluates each of the four dimensions, and the overall comparative advantage index is calculated to proxy food production's comparative advantage variable.

Mediating variables: Regarding the measurement method of the structural effect (Stru), the area planted with the three staple grains of wheat, rice and corn/area planted with other grains was selected for measurement; regarding the measurement method of the technology effect (Tech), the number of food-related patents (pcs) was used for measurement, considering that the R&D investment of financial support to agriculture for food-related technologies is closely related to the output of food-related technological achievements, and the data of this variable were obtained from the database of CNKI (a website like Web of Science).

Moderating variable: Environmental regulation. This study accounts for the fact that the strength of environmental regulation of food production, which in part reflects the intensity of measures taken by local governments on the food production environment, can increase the effect of building inputs per unit of food production comparative advantage on GTFP of food. Therefore, we refer to Wang et al. [60] to assess the environmental regulatory factors in food production by selecting the ratio of environmental pollution control investment to GDP multiplied by the relevant weighting coefficients.

Control variables: The average household arable land size, de-flooded area, industrial structure level, rural fixed asset investment, disaster rate, and food price change level were chosen as the control variables in this study based on relevant research findings regarding the factors influencing GTFP [61].

4.4. Empirical Model Design

Because the GTFP (Y) data type is [0, 1] truncated data, the Tobit regression model was employed to test the following equation.

$$Y = \begin{cases} Y^*{}_{it} = \sigma + \alpha_1 D_{it} + \alpha_2 X_{z,it} + \mu_i + \varphi_t + \varepsilon_{it} & Y^*{}_{it} > 0 \\ 0 & Y^*{}_{it} \leq 0 \end{cases} \tag{2}$$

$$Y = \begin{cases} Y^*{}_{it} = \sigma + \alpha_1 D_{i(t-1)} + \alpha_2 X_{z,it} + \mu_i + \varphi_t + \varepsilon_{it} & Y^*{}_{it} > 0 \\ 0 & Y^*{}_{it} \leq 0 \end{cases} \tag{3}$$

At Equations (2) and (3): Y^* it is the explanatory variable, denoting the total factor productivity of green factors in the region i during year t. D_{it} is the core explanatory variable indicating the food production comparative advantage in region i in year t. $D_{i(t-1)}$ is the first-order lagged term of food production comparative advantage; $X_{z,it}$ is the control variable representing other factors affecting GTFP in region i in year t; z = 1, 2,. . ., 6 represent the six control variables of average household arable land size, de-flooded area, industrial structure level, rural fixed asset investment, disaster rate, and food price volatility, respectively. σ denotes the constant term of the equation; α denotes the coefficient corresponding to each variable; μ_i denotes the unobservable provincial effect in each province; φ_t denotes the fixed effect of the time trend, and ε_{it} denotes the random disturbance term. Equation (2) is the baseline model for this study to test Hypothesis H1 on the influence of food production comparative advantage on GTFP at the current time. Equation (3) incorporates the lagged term of food production comparative advantage to examine the lagging effect of food production comparative advantage on GTFP.

To overcome the effects of disturbances such as extreme values and error terms on the estimation results and to describe the stage-specific differences more objectively and thoroughly in the effects of food production comparative advantage on GTFP at different quartiles, the following two-way stationary panel quantile regression model was developed.

$$Y^*{}_{it\tau} = \sigma + \beta_{1\tau} D_{it\tau} + \beta_{2\tau} X_{z,it\tau} + \mu_{i\tau} + \varphi_{t\tau} + \varepsilon_{it\tau} \quad Y^*{}_{it\tau} > 0 \tag{4}$$

In Equation (4) τ represents the quantile, and in this investigation, quantile regression was performed with quantiles of 10%, 20%,. . ., and 90%.

In addition, approaches for boosting the GTFP of food under the specified level of food production comparative advantage will be investigated. This study seeks to examine the moderating effect of environmental regulation on the competitive advantage of food production on GTFP by developing hierarchical regression analysis models, such as Equations (5) and (6), to test Hypothesis H2.

$$Y = \begin{cases} Y^*{}_{it} = \sigma + \lambda_1 G_{it} + \lambda_2 M_{it} + \lambda_3 X_{z,it} + \mu_t + \varphi_i + \varepsilon_{it} & Y^*{}_{it} > 0 \\ 0 & Y^*{}_{it} \leq 0 \end{cases} \tag{5}$$

$$Y = \begin{cases} Y^*{}_{it} = \sigma + \xi_1 G_{it} + \xi_2 M_{it} + \xi_3 G_{it} \times M_{it} + \xi_4 X_{z,it} + \mu_i + \varphi_t + \varepsilon_{it} & Y^*{}_{it} > 0 \\ 0 & Y^*{}_{it} \leq 0 \end{cases} \tag{6}$$

M_{it} in Equation (5) denotes the environmental control in area i during year t and denotes coefficients corresponding to each equation.

To develop the mediating mechanism test model, Equations (7)–(9) are derived from the stepwise regression method. In the first step, the structural and technological implications of food production comparative advantage are evaluated (Equation (7)). In the second step, the effects of technological effect and structural effects on the total factor productivity of food greens are examined (Equation (8)). In the third stage, the impacts of food production comparative advantage and structural effect on food GTFP are investigated independently, as are the effects of food production comparative advantage and technical effect on food GTFP (Equation (9)). Three regression models were subsequently developed to evaluate Hypotheses H3 and H4.

$$T = \begin{cases} T^*{}_{k,it} = \beta + \beta_1 D_{it} + \beta_2 X_{z,it} + \mu_i + \varphi_t + \varepsilon_{it} & T^*{}_{k,it} > 0 \\ 0 & T^*{}_{k,it} \leq 0 \end{cases} \tag{7}$$

$$Y = \begin{cases} Y^*{}_{it} = \gamma + \gamma_1 T_{k,it} + \gamma_2 X_{z,it} + \mu_i + \varphi_t + \varepsilon_{it} & Y^*{}_{it} > 0 \\ 0 & Y^*{}_{it} \leq 0 \end{cases} \tag{8}$$

$$Y = \begin{cases} Y^*{}_{it} = \kappa + \kappa_1 T_{k,it} + \kappa_2 D_{it} + \kappa_3 X_{z,it} + \mu_i + \varphi_t + \varepsilon_{it} & Y^*{}_{it} > 0 \\ 0 & Y^*{}_{it} \leq 0 \end{cases} \tag{9}$$

where β, γ, κ denote the coefficients corresponding to each equation; $T^*{}_{k,it}$ denotes the technology effect (k = 1) and structural effect (k = 2) in region i in year t.

4.5. Data

The software used for data analysis in this study is STATA 17.0 and Matlab 2021b. The raw data in this paper are obtained from statistics of 30 Chinese provinces from 2003 to 2019 (Hong Kong, Macau, Taiwan, and Tibet were not included in the study sample due to missing data). It mainly contains the following statistical yearbooks. China Statistical Yearbook, China Water Resources Statistical Yearbook, China Rural Statistical Yearbook, China Water Resources Bulletin, China Agricultural Statistics, China Environmental Yearbook, China Land and Resources Statistical Yearbook, and China Fixed Asset Investment Statistical Yearbook. (Every year, the Bureau of Statistics of the People's Republic of China compiles statistics on all aspects of China's resources and makes a statistical yearbook that is openly shared with the people). Specifically, the statistics on the most important economic variables are adjusted to the price index with 2003 as the base year.

5. Results and Discussion

5.1. Analysis of Measuring Results of the Food Production Comparative Advantage and Green Total Factor Productivity

5.1.1. Analysis of Food Production Comparative Advantage Measurement Results

In China, the average value of the food production comparative advantage from 2003 to 2019 was 0.347, while the food production comparative advantage varied substantially between areas (Table 4). In addition to the 13 major grain-producing regions, 3 provinces in Guangdong, Zhejiang, and Xinjiang have a comparative advantage in grain production that is significantly more than the national average of 0.347. The majority of the 16 administrative regions at the provincial level have a high arable land factor, agricultural labor factor, agricultural capital factor, or water resource component, and hence have a great capability for food production. Hainan, Qinghai, Shaanxi, Chongqing, Ningxia, and Gansu, along with other provincial administrative regions, have a comparative advantage in grain production that is lower than the national average of 0.347. The provinces of Qinghai, Shaanxi, Ningxia, and Gansu lack arable land, agricultural manpower, agricultural capital, and water resources and hence have no food production comparative advantage. Hainan and Chongqing have more water resources, but their food production comparative advantage is diminished due to a shortage of arable land, agricultural workers, and agricultural capital. In addition, based on the growth rate of comparative advantage in grain production, the southwest administrative regions of Guizhou, Yunnan, and Chongqing in China experienced the fastest increase in food production comparative advantage from 2003 to 2019. The northeast region is dominated by Heilongjiang; the Middle and Lower Yangtze River regions are dominated by Hubei and Zhejiang; the south China region is dominated by Guangxi, and the Huang–Huai–Hai region is dominated by Jiangsu. On the one hand, it may be due to the rapid growth of agricultural capital investment in these provinces in recent years, the rapid increase in agricultural mechanization, and the continuous improvement of rural transportation facilities and comparative advantages in food production, which have substantially increased these regions' comparative advantages in food production. On the other hand, due to the proliferation of new agricultural businesses functioning on a moderate size, the output per unit of land has become more efficient.

Table 4. Regional characteristics and growth of food production comparative advantage, 2003–2019.

Area	Food Production Comparative Advantage		Area	Food Production Comparative Advantage	
	Mean	Growth Rate/%		Mean	Growth Rate/%
Beijing	0.320	1.32	Henan	0.411	5.17
Tianjin	0.299	−3.06	Hubei	0.352	31.06
Hebei	0.361	5.12	Hunan	0.396	6.42
Shanxi	0.334	2.69	Guangdong	0.421	17.45
Inner Mongolia	0.418	11.11	Guangxi	0.331	20.14
Liaoning	0.350	0.61	Hainan	0.241	3.32
Jilin	0.401	6.81	Chongqing	0.288	34.26
Heilongjiang	0.449	43.01	Sichuan	0.395	15.06
Shanghai	0.331	3.32	Guizhou	0.325	52.13
Jiangsu	0.435	19.08	Yunnan	0.332	34.94
Zhejiang	0.371	26.55	Shaanxi	0.271	25.55
Anhui	0.346	4.04	Gansu	0.301	5.63
Fujian	0.332	7.24	Qinghai	0.254	13.54
Jiangxi	0.351	12.82	Ningxia	0.296	3.75
Shandong	0.345	16.34	Xinjiang	0.369	10.56

5.1.2. Analysis of Green Total Factor Productivity of Food Measurement Results

The findings of the measurements indicate that the mean level of green total factor production of food is 1.346, indicating a significant disparity between provincial administrative regions (Figure 1). The provinces of Ningxia (0.71), Guangdong (0.739), Gansu (0.843), Guangxi (0.946), Tianjin (0.978), Qinghai (1.136), Liaoning (1.182), Hebei (1.26), and Hainan (1.26) have the lowest green total factor production of food compared to the national average (1.277). Conversely, Beijing (1.644), Hubei (1.783), and Heilongjiang are the principal locations where GTFP of food exceeds the national average (1.841).

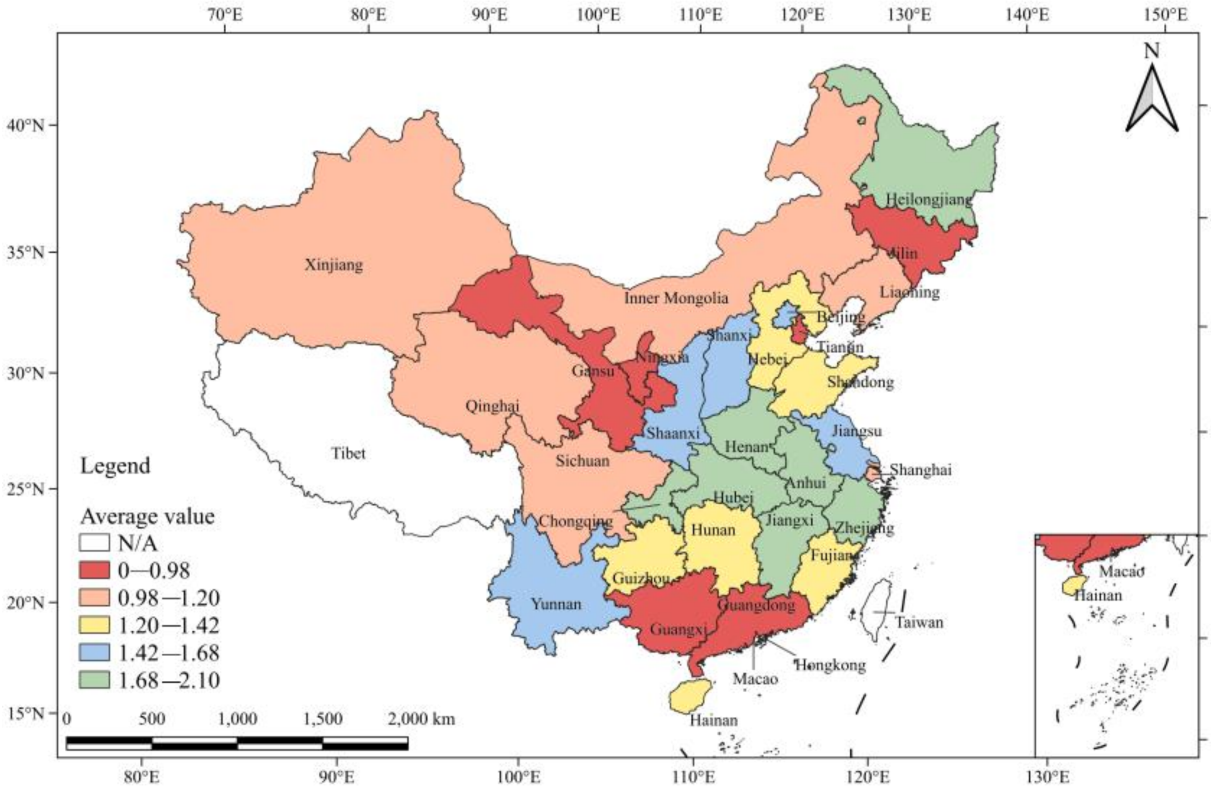

Figure 1. Regional characteristics of green total factor productivity of food, 2003–2019.

Observing the Food GTFP Index (Figure 2), the average value of the national index exhibited a fluctuating upward trend from 2003 to 2019; however, the regional growth index exhibited notable distinguishing characteristics. In particular, the GTFP index for food in the middle and lower reaches of the Yangtze River and the northeast region is greater than the national average in most years and has a higher level and a quicker growth rate than the other four regions. The cumulative growth index of GTFP of food in south China is highly volatile, exhibiting a phenomenon of ups and downs from 2003 to 2010, and then beginning to vary upwards from 2010 to 2019. The growth trends in the Southwest and Huang–Huai–Hai regions are more similar, fluctuating up and down around the national average. In contrast, the cumulative growth index of GTFP of food in the Northwest Region varies at a lower level and has a negligible increasing tendency for an extended period.

5.2. Analysis of Empirical Test Results

5.2.1. Baseline Regression Results of Food Production Comparative Advantage Affecting Green Total Factor Productivity of Food

Model (1) in Table 5 displays the control variable regression results on GTFP as a reference for other regression models. Food production comparative advantage has a favorable effect on GTFP, according to model (2). (based on Equation (2)). Each unit increase in food production comparative advantage will result in a 2.053 unit increase in GTFP. This indicates that food production comparative advantage has a positive effect on GTFP, supporting the validity of H1. This is comparable to the results of Yao et al. [61]. Inputs of food production factors are redundant relative to optimal output, and the degree of GTFP loss in food varies across factor resource endowments. In an environment with limited factor resource endowment, food production raises the environmental and resource burden while decreasing resource use efficiency [48]. In contrast, regions with greater comparative advantages in food production are more likely to encourage efficient recycling of resources and continuous optimization of resource ratios via large-scale, intensive, and specialized production methods, therefore effectively reducing the redundancy of water resources, arable land resources, and pesticide and fertilizer inputs per unit of food production. It increases the economic efficiency of food production, on the one hand [62]. On the other side, it minimizes the intensification and spread of agricultural surface source pollution and enhances the ecosystem's resilience, consequently encouraging the ongoing growth of GTFP.

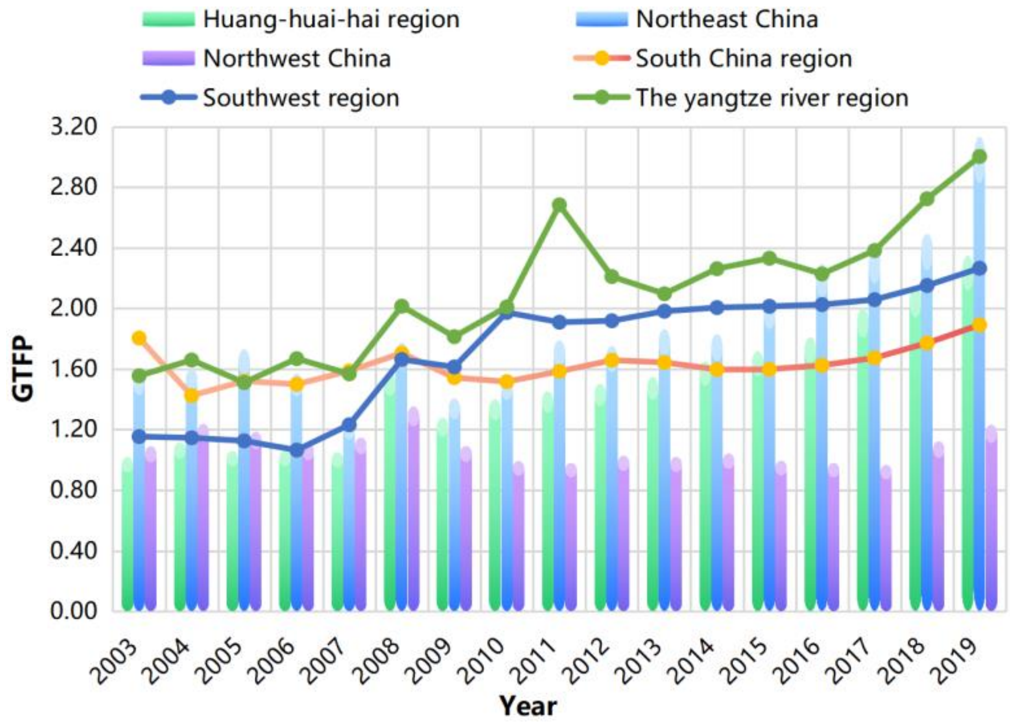

Figure 2. Regional characteristics and growth of green total factor productivity of food, 2003–2019.

The first-order lag term of food production comparative advantage is included in the regression because the transmission of the effect of food production comparative advantage on regional GTFP may take time. The regression result of the model (3) (based on Equation (3)) indicates that the effect of food production comparative advantage on GTFP is significant at the 1% level with a coefficient of 2.19%, indicating that each unit increase in food production comparative advantage will result in a 2.19% increase in GTFP the following year. Consequently, there is a time lag between food production comparative advantage and regional green total factor output. This result resembles that of Imasiku et al. [63]. It takes time for the flow of food production factors to reach the optimal allocation, even though a gain in food production comparative advantage can optimize the allocation of water and arable land resources and minimize agricultural surface pollution. Thus, the influence of food production comparative advantage on GTFP has a lag effect.

Table 5. Regression results of food production comparative advantage affecting the green total factor productivity.

	GTFP				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Cagp		2.053 *** (4.750)		2.399 *** (7.891)	2.053 *** (3.245)
L.Cagp			2.194 *** (5.147)		
Cult	1.465 *** (7.291)	1.054 *** (5.342)	1.081 *** (5.465)	0.156 *** (4.179)	1.054 *** (3.159)
Logg	0.063 (0.463)	0.003 (0.026)	−0.036 (−0.286)	0.009 (0.353)	0.003 (0.030)
Stru	−0.413 ** (−2.208)	−0.401 ** (−2.172)	−0.375 ** (−2.059)	0.156 (0.739)	−0.401 (−0.651)
Inve	−0.350 *** (−5.381)	−0.381 *** (−5.931)	−0.410 *** (−6.344)	−0.201 *** (−4.817)	−0.381 *** (−5.064)
Disa	0.016 (0.074)	0.082 (0.391)	0.274 (1.271)	−0.371 ** (−2.093)	0.082 (0.339)
Pric	−0.050 (−0.057)	0.125 (0.143)	−0.114 (−0.129)	−0.556 (−1.531)	0.125 (0.152)
_cons	0.986 (1.042)	0.515 (0.553)	0.757 (0.666)	0.331 (0.752)	0.515 (0.450)
Time	YES	YES	YES	YES	YES
Ind	YES	YES	YES	YES	YES
N	510	510	480	510	510

L.Cagp denotes the first-order lag term of Cagp. *Time* denotes time effect, and *Ind* denotes individual effect. *** and ** represent significant at the 1% and 5% levels, respectively. The number in parentheses is the z value.

In addition, the sample data may suffer from heteroskedasticity problems, which could lead to estimate bias in the typical panel Tobit model. Therefore. To adjust for estimate bias caused by heteroskedasticity and intra-group autocorrelation issues, the Poisson pseudo-maximum-likelihood (PPML) was utilized for parameter estimation in this study. PPML As demonstrated by model (4) in Table 5, food production comparative advantage has a positive influence on GTFP, which is consistent with the results of the benchmark regression. In addition, we believe that the accuracy of the parameter estimation test is tightly tied to the setting of the parameter form; nevertheless, it is difficult to assess whether the parameter model setting is right based solely on a theoretical debate. If there is a nonlinear correlation between the dummy water variable for food imports and the water stress variable for food production, the model's regression findings will be inaccurate. Thus, the robustness of the benchmark model was evaluated using nonparametric estimating Bootstrap (1000 extractions). In Table 5, the results of the nonparametric estimating model test are displayed in column model (5). Significant at the $p < 1\%$ level, the effect of food production comparative advantage on GTFP has a coefficient of 2.053. This again demonstrates that food production comparative advantage has a favorable effect on GTFP; hence, the regression results of the reference model are generally more accurate.

5.2.2. Quantile Test of the Impact of Food Production Comparative Advantage on the Green Total Factor Productivity

To exclude the influence of confounding effects such as extreme values and error terms on the estimate findings, a panel quantile regression with 10%, 20%,. . ., and 90% quantile was conducted in this study to assess inter-regional heterogeneity and test the robustness of the regression results (based on Equation (4)). Based on the regression results of Equation (4), see model (6) in Table 6, the coefficients and significance of the effect of food production comparative advantage on GTFP vary at different quartiles. Except for model 10%, which is not significant, the coefficients of model 20−90% are significantly positive, and the coefficient values of comparative advantage from 20% to 90% quartiles continue to increase rapidly.

Table 6. Regression results of the quantile of food production comparative advantage on the green total factor productivity.

	GTFP **(6)**								
	10%	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**
Cagp	−0.025 (−0.043)	1.494 ** (2.442)	1.991 *** (3.562)	2.496 *** (3.520)	2.693 *** (3.589)	2.611 *** (3.103)	3.059 *** (3.233)	3.684 *** (4.299)	5.399 *** (5.435)
Cult	0.056 (0.702)	0.005 (0.056)	0.025 (0.292)	0.154 (1.433)	0.273 ** (2.451)	0.415 *** (3.726)	0.449 *** (3.313)	0.386 ** (2.562)	0.373 * (1.914)
Logg	0.027 (0.670)	0.079 (1.548)	0.095 ** (2.436)	0.092 ** (2.154)	0.062 (1.322)	0.021 (0.370)	0.093 (1.070)	0.277 ** (2.451)	0.363 *** (3.234)
Stru	−0.022 (−0.077)	0.132 (0.402)	0.349 (0.818)	0.227 (0.365)	0.108 (0.136)	0.635 (0.698)	1.571 (1.609)	1.717 (1.443)	2.649 * (1.916)
Inve	−0.104 * (−1.660)	−0.168 * (−1.731)	−0.298 ** (−2.471)	−0.523 *** (−4.219)	−0.662 *** (−5.835)	−0.757 *** (−6.444)	−0.850 *** (−6.686)	−0.913 *** (−6.384)	−0.785 *** (−4.237)
Disa	−0.177 (−0.908)	0.214 (0.930)	0.354 (1.380)	0.264 (0.909)	0.210 (0.585)	0.159 (0.367)	0.252 (0.480)	0.321 (0.550)	0.833 (1.177)
Pric	0.026 (0.044)	−0.537 (−0.634)	−0.660 (−0.621)	−1.173 (−0.830)	−1.430 (−0.820)	−0.855 (−0.440)	−3.420 (−1.585)	−3.876 (−1.624)	−5.806 * (−1.912)
_cons	0.725 (1.109)	0.766 (0.836)	0.598 (0.518)	1.345 (0.865)	1.819 (0.946)	0.901 (0.423)	2.734 (1.149)	3.071 (1.178)	3.858 (1.133)

***, ** and * represent significant at the 1%, 5%, and 10% levels, respectively. The number in parentheses is the z value.

To visualize the findings of the quantile regression of food production comparative advantage on GTFP more intuitively. As shown in Figure 3, the coefficient of the influence of food production comparative advantage on GTFP is minor at 10% and did not pass the significance test. Due to the scarcity of arable land resources, agricultural labor resources, agricultural capital, and water resources, etc., the growth of food production comparative advantage in regions with very low food production comparative advantage (Hainan, Qinghai, Shaanxi, Ningxia, Gansu, and other provincial administrative regions) does not contribute to GTFP. The expansion of food production comparative advantage does not create optimal conditions for scale, specialization, and intensification [64]. Second, the impact coefficients of food production comparative advantage are all positive and significant in the 20–60% quantile but grow more slowly, indicating that in regions with a medium food production comparative advantage (e.g., provincial administrations such as Hubei, Fujian, Shanxi, Guangxi, and Yunnan), as food production comparative advantage increases, the effects brought about by economies of scale gradually emerge and begin to promote the promotion of exports. In regions with high food production comparative advantage (Hunan, Sichuan, Jilin, Henan, Inner Mongolia, Guangdong, Jiangsu, and Heilongjiang provincial administrative regions), the conditions for large-scale, specialized, and intensive food production are already in place, and the ecological and economic benefits of food production comparative advantage are already being realized.

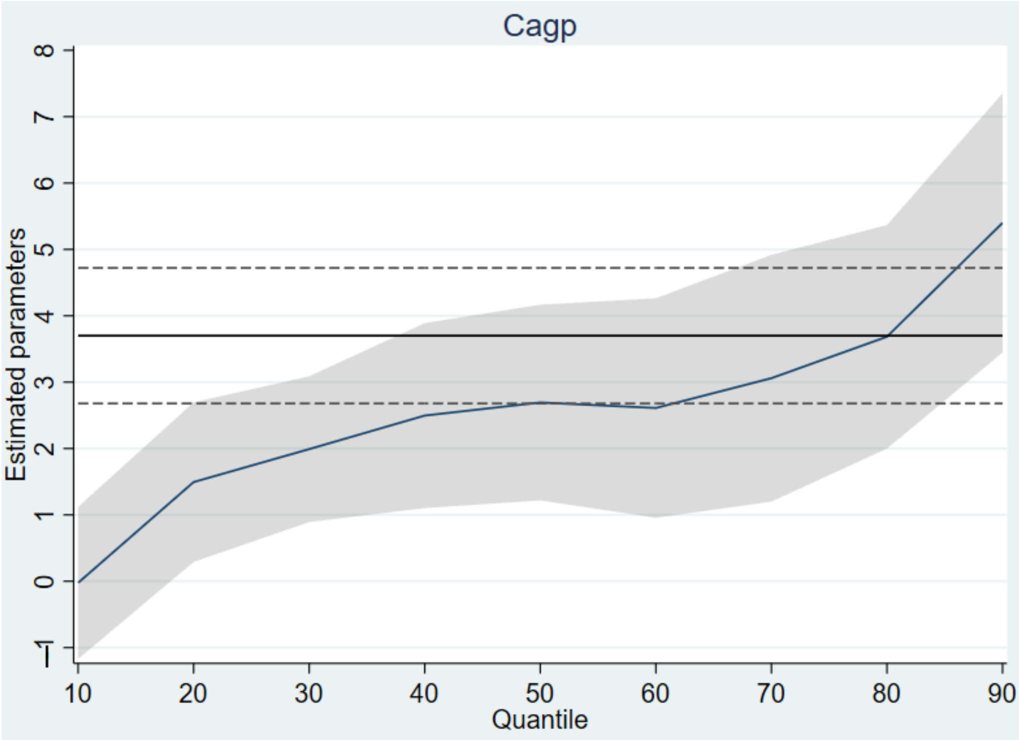

Figure 3. Quantile regression diagram of food production comparative advantage. Note: The blue curve in this figure represents the coefficient of food production comparative advantage at different loci obtained by quantile regression, and the gray area represents the 95% confidence interval of the coefficient.

5.2.3. The Test of the Moderating Role of Environmental Regulation

To further exploit its role in promoting the development of regional food GTFP in the context of existing food production comparative advantage, this study empirically examines the moderating role of environmental regulations in food production comparative advantage affecting food GTFP. Food production comparative advantage has a strong positive effect on GTFP, as shown by the model (8) in Table 7. (based on Equation (5)). After adding the interaction term between environmental regulation and food production comparative advantage to model (9), the regression coefficient of the interaction term on GTFP of food is 1.124 and passes the significance test at the 1% level, indicating that environmental regulation moderates the effect of food production comparative advantage on GTFP (based on Equation (6)) in a positive way. Assume that H2 is supported. As environmental regulation increases, so does the contribution of regions with food production comparative advantage to green total factor output.

By increasing the "compliance cost" of food production, environmental regulation forces producers with a low food production comparative advantage to gradually lose their ability to operate sustainably and be eliminated from the market, while producers with a comparative advantage benefit from higher GTFP in food production to survive [65]. It can compel producers to embrace green production techniques and lower the number of pesticides and fertilizers used, thus reducing agricultural surface pollution, carbon emissions, and water waste, therefore enhancing its ecological benefits [66]. Regions with comparative advantages in food production can use their structural effect to lower the adoption of green production technologies and emission costs, thus reducing food producers' "compliance costs" and increasing their economic efficiency [67]. As environmental regulation strengthens, regions with a competitive advantage in food production are better able to contribute to the GTFP of food.

Table 7. Regression results of the moderating effect of environmental regulation.

	GTFP			*Low Group-GTFP*			*High Group-GTFP*		
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
Cagp		3.229 *** (8.174)	1.282 *** (2.688)		3.567 *** (6.542)	−0.192 (−0.292)		1.428 *** (2.974)	1.158 ** (2.026)
Envi		0.290 *** (11.403)	−0.073 (−1.218)		0.375 *** (7.475)	−0.600 *** (−4.771)		0.214 *** (8.471)	0.162 ** (2.538)
Cagp × *Envi*			1.124 *** (6.640)			2.318 *** (8.281)			0.180 (0.868)
Cult	1.465 *** (7.291)	0.545 *** (3.393)	0.325 ** (2.099)	2.118 *** (7.433)	0.614 *** (2.832)	0.426 ** (2.429)	−0.317 (−1.381)	−0.486 ** (−2.227)	−0.517 ** (−2.311)
Logg	0.063 (0.463)	0.046 (0.438)	0.155 (1.512)	−0.041 (−0.252)	0.122 (1.105)	0.213 ** (2.292)	−0.144 (−0.637)	−0.226 (−1.220)	−0.202 (−1.064)
Stru	−0.413 ** (−2.208)	−0.368 ** (−2.223)	−0.331 ** (−2.087)	−3.744 *** (−5.441)	−3.355 *** (−5.595)	−2.345 *** (−4.293)	−0.042 (−0.267)	−0.017 (−0.119)	−0.019 (−0.137)
Inve	−0.350 *** (−5.381)	−0.473 *** (−8.160)	−0.452 *** (−8.127)	−0.291 *** (−3.465)	−0.374 *** (−5.045)	−0.282 *** (−4.215)	−0.277 *** (−3.055)	−0.398 *** (−4.863)	−0.398 *** (−4.872)
Disa	0.016 (0.074)	0.085 (0.453)	0.039 (0.217)	0.221 (0.805)	0.090 (0.371)	−0.022 (−0.100)	−0.394 (−1.393)	−0.277 (−1.089)	−0.273 (−1.073)
Pric	−0.050 (−0.057)	0.027 (0.035)	−0.227 (−0.304)	0.332 (0.307)	0.544 (0.557)	0.267 (0.307)	−1.379 (−1.024)	−1.055 (−0.886)	−1.064 (−0.895)
_cons	0.986 (1.042)	0.216 (0.259)	1.088 (1.343)	2.560 * (1.917)	1.607 (1.365)	2.409 ** (2.294)	3.709 *** (2.641)	2.804 ** (2.252)	2.888 ** (2.316)
Time	YES	YES	YES	YES	YES	YES	YES	YES	YES
Ind	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	510	510	510	255	255	255	255	255	255

***, ** and * represent significant at the 1%, 5%, and 10% levels, respectively. The number in parentheses is the z value.

In addition, it investigates the heterogeneity of the regulating role of environmental regulations in various regions with varying food GTFP. Based on the median of the regional average GTFP of food, 30 provinces in China were categorized into low and high GTFP groups in this study. We evaluated the degree of the moderating influence of environmental regulation in the two groups independently to confirm the robustness of the results while evaluating regional heterogeneity (Table 7). In the low food green TFP group, i.e., Models (10) to (12), the interaction term between environmental regulation and food production comparative advantage on green TFP has a regression coefficient of 2.318 and passes the 1% significance test. In contrast, in the high food green TFP group, i.e., Models (13) to (15), the interaction term between environmental regulation and food production comparative advantage on green TFP is not statistically significant. This indicates that environmental regulations moderate the influence of food production comparative advantage on GTFP more strongly in regions with lower GTFP than in regions with higher GTFP. This may be because the "compliance cost" environmental cost resulting from environmental regulation exerts additional pressure on producers in regions with already poor green total factor output [68]. Each unit improvement in the food production comparative advantage increases the marginal effect of lowering the cost of environmental governance. In regions with greater GTFP, however, the marginal benefit of food production comparative advantage is smaller in terms of reducing the "cost of compliance".

5.2.4. The test of the Mediating Mechanism of Food Production Comparative Advantage on Green Total Factor Productivity

In Table 8, Models (17) and (19) illustrate the regression outcomes based on Equation (7). The effect of food production comparative advantage on the technology effect passes the significance test at the 1% level, as does the effect of food production comparative advantage on the structure effect, and the regression coefficients are positive. This indicates that the food production comparative advantage benefits both technological and structural effects. The influence of the structural effect on food GTFP is significant at the 1% level, the effect of technological effect on food GTFP passes the 1% significance test, and the regression coefficients are positive. This demonstrates that both the technology effect and the structural effect have a favorable impact on the total factor productivity of food greens.

Table 8. Mediation effect of technology effects and structural effects.

	Tech		*Stre*		*GTFP*			
	(16)	**(17)**	**(18)**	**(19)**	**(20)**	**(21)**	**(22)**	**(23)**
Cagp		23.195 *** (8.245)		0.509 *** (7.220)		1.726 *** (3.800)		1.817 *** (4.030)
Tech					0.022 *** (3.604)	0.014 ** (2.245)		
Stre							0.775 *** (3.024)	0.460 * (1.742)
Cult	−0.564 (−0.697)	−2.335 *** (−3.193)	0.042 (1.461)	−0.029 (−1.136)	1.446 *** (7.297)	1.107 *** (5.535)	1.407 *** (7.174)	1.072 *** (5.448)
Logg	3.175 *** (4.752)	2.433 *** (4.618)	0.091 *** (3.629)	0.068 *** (3.358)	−0.080 (−0.579)	−0.072 (−0.558)	−0.028 (−0.203)	−0.040 (−0.309)
Stru	−0.313 (−0.224)	−0.119 (−0.091)	−0.019 (−0.584)	−0.015 (−0.465)	−0.401 ** (−2.168)	−0.395 ** (−2.153)	−0.397 ** (−2.140)	−0.393 ** (−2.137)
Inve	−1.208 ** (−2.567)	−1.418 *** (−3.225)	−0.017 (−1.478)	−0.023 ** (−2.101)	−0.329 *** (−5.102)	−0.363 *** (−5.623)	−0.339 *** (−5.250)	−0.371 *** (−5.763)
Disa	−1.327 (−0.848)	0.078 (0.053)	0.016 (0.428)	0.037 (1.054)	0.039 (0.185)	0.087 (0.413)	−0.004 (−0.019)	0.065 (0.307)
Pric	0.216 (0.033)	2.003 (0.319)	0.135 (0.884)	0.179 (1.216)	−0.073 (−0.084)	0.083 (0.096)	−0.158 (−0.181)	0.041 (0.047)
_cons	−0.093 (−0.013)	−7.127 (−1.080)	−0.143 (−0.873)	−0.275 * (−1.758)	1.074 (1.150)	0.641 (0.690)	1.131 (1.205)	0.648 (0.695)
Time	YES	YES	YES	YES	YES	YES	YES	YES
Ind	YES	YES	YES	YES	YES	YES	YES	YES
N	510	510	510	510	510	510	510	510

***, ** and * represent significant at the 1%, 5%, and 10% levels, respectively. The number in parentheses is the z value.

The results of regression based on Equation (9) are displayed in Models (21) and (22). (23). Comparing Models (2) and (21) reveals that the coefficient of the effect of food production comparative advantage on GTFP falls from 2.053 to 1.726 after the addition of the technological effect variable but still passes the significance test. This demonstrates that the effect of technology partially mediates the effect of food production comparative advantage on GTFP, therefore supporting Hypothesis H3. Comparing Model (2) to Model (23), it is discovered that the coefficient of the effect of food production comparative advantage on GTFP decreases from 2.053 to 1.817 but still passes the significance test, indicating that the structural effect partially mediates the effect of food production comparative advantage on GTFP. Assume that H4 is supported.

Nevertheless, some researchers argue that mediation effects may exist even if the coefficients β_1 and γ_1 are not statistically significant, whereas the stepwise regression method needs the coefficients β_1 and γ_1 to be statistically significant, hence diminishing the statistical power. To assess the robustness of the test results for Hypotheses H3 and H4, this research employs the Bootstrap mediation test, which has no limits on the sample distribution and excellent statistical validity. The Bootstrap test found (Table 9) that the mediating effect of technology effectively in the effect of food production comparative advantage on food GTFP was 2.282, and the mediating effect of structural effect was 4.616. Both the bias-corrected test and the percentile test value did not contain 0 at the 95% confidence interval, indicating that the effect was significant. This again confirms the accuracy of Hypotheses H3 and H4, and the results are identical to those obtained from the stepwise regression method, demonstrating that the test for the mediating effect is robust.

Table 9. Bootstrap mediation effect test results.

Path	Mediation Effect	Bias-Corrected 95% Confidence Interval		Percentile 95% Confidence Interval	
		Lower	Upper	Lower	Upper
Food production comparative advantage → Technology effects → Green total factor productivity	2.282	1.004	3.773	0.869	3.718
Food production comparative advantage → Structural effects → Green total factor productivity	4.616	3.410	5.938	3.319	5.861

6. Conclusions and Policy Implications

6.1. Conclusions

This study investigates the mechanism underlying the association between food production comparative advantage and GTFP using panel data from 30 provinces in China from 2003 to 2019. First, the entropy-weighted TOPSIS method is used to measure the food production comparative advantage. Second, the system of measuring food GTFP indicators is constructed based on the perspective of the ecological value of food cultivation and measured using the GML index. In conclusion, the Tobit panel model, Poisson pseudo-maximum likelihood, nonparametric estimation, quantile regression, mediating effect model, and moderating effect are employed to examine the influence mechanism of food production comparative advantage on GTFP. This study verifies the effect of food production comparative advantage on green total factor productivity, as well as the transmission mechanism of this effect. Previous studies on the GTFP of food have been conducted mainly from the perspectives of carbon emissions [69], surface pollution [69], and food crop consumption [3]. These studies have confirmed the important role of GTFP in ensuring national food security. This study builds on these studies to further explore and demonstrate the positive impact of food production comparative advantage on GTFP. Meanwhile, Zhai et al. argue that policy factors such as environmental regulation are the main factors affecting GTFP, which diverges from the results of this study [8]. This study finds that food production comparative advantage is the main factor affecting GTFP and that food production comparative advantage increases GTFP mainly by improving technological and structural effects. Environmental regulation, in contrast, acts as a regulator in the relationship between comparative advantage in food production and GTFP. It can be said that this study explains the mechanism of the relationship between food production comparative advantage and green total factor productivity more comprehensively while expanding the previous research on green total factor productivity. This helps to explore the ecologically sustainable production of food in China and is also useful in guiding government policy planning to further enhance the comparative advantage of regional food production. However, there are some limitations of this study that need to be explored in the future. Heterogeneity in the effect of comparative advantage on the green total factor productivity of food producers of different scales is not further considered in this study. This is because the current Chinese almanacs and statistical databases do not allow for a comprehensive collection of annual provincial panel data information for food producers of different scales, such as large, medium, small, and micro. We suggest that in the future, with the construction and improvement of the database, we can try to collect and supplement the relevant information data of food producers of different scales and, furthermore, empirically explore the heterogeneous effects of comparative advantage on the green total factor productivity of food producers in different scales.

6.2. Policy Implications

The following findings present some suggestions for improving green TFP. First, the government might enhance financial subsidies and market guidance for food scale and specialist growers to fix land fragmentation and develop field road layouts. The government should promote agricultural outsourcing services by offering preferential policy, capital, and taxation measures to optimize the level of agricultural outsourcing services and eliminate information asymmetry to attract external investment for large-scale food agriculture. Second, scientific, reasonable, and flexible environmental laws and regulations should promote environmentally friendly food production policies, advocate the use of bio-organic fertilizers and biodegradable agricultural films, and subsidize the development and application of ecological food production technologies. Various regions need different environmental regulations. Increase environmental laws in regions with poor GTFP of food (Qinghai, Jiangsu, Sichuan, Jiangxi, Shandong, and other provinces) to coordinate the ecological and economic development of food. Third, maximize structural and technical effects to boost food GTFP. Green technical efficiency and technological progress boost food GTFP. The government should optimize the internal cultivation structure of food in regions with comparative advantages in food production, promote staple food specialization, and play to the structural effects of food production to boost the GTFP of food. The government should strengthen R&D investments in food production science and technology projects in regions with comparative advantages in food production, encourage the combination of resource endowment characteristics and technological progress in food production regions, improve the conversion rate of scientific and technological achievements, and increase the GTFP of food as much as possible.

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