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Mechanism and Empirical Test of the Impact of Consumption Upgrading on Agricultural Green Total Factor Productivity in China

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Abstract: To explore the relationship between consumption upgrading and agricultural green total factor productivity in the context of green and high-quality development of agriculture in China. Based on the construction of a composite index of consumption upgrading and the Malmquist index of non-expected output in the SBM-DEA model to measure agricultural green total factor productivity, this paper uses the PVAR model and panel data from 30 Chinese provinces from 2008 to 2020 to empirically analyze the mechanism of the effect of consumption upgrading on agricultural green total factor productivity under high-quality development. The results are as follows: (1) Both the real economy and consumption upgrading are ahead of the change in agricultural green total factor productivity and have a negative short-run impact on agricultural green total factor productivity but a continuous boosting effect in the long-run. (2) In terms of specific impact paths, the real economy boosts agricultural green total factor productivity through technical efficiency and technical change paths and has a negative impact through scale efficiency, whereas consumption upgrading has inhibitory and sustained promotional effects in the short- and long-run, respectively, through technical efficiency and technical change paths and has opposite impact effects in the scale efficiency path.

Keywords: high-quality development; agricultural green production; consumption upgrading; total factor productivity

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1. Introduction and Literature Review

At present, China's comprehensive agricultural production capacity has been dramatically improved, with total grain production remaining above 1.3 trillion catties for eight consecutive years and the output of meat, eggs, vegetables, fruits, and fish ranking first in the world, ensuring that 1.4 billion Chinese people can not only be "Enough-Fed", but also "Well-Fed". This is a strong guarantee for China to cope with various risks and achieve stable economic and social development. However, behind this promising data is the environmental cost of long-run, sloppy agricultural development. The contradiction between agriculture and the carrying capacity of resources and the environment is becoming increasingly acute; ecological deterioration and environmental pollution caused by agricultural production are becoming increasingly prominent; and reliance on resource consumption to achieve quantitative growth is no longer sustainable [1–3]. All these are forcing us to accelerate the transformation of production methods, adopt scientific and technological means to improve the use of agricultural resources and economic efficiency, and drive green agricultural development with low carbon [3,4], so as to achieve green and high-quality agricultural development. The goal of green agricultural production is not only to increase yields but also to improve the quality of sustainable resource use and agro-ecological protection [2,3]. As an important engine of economic growth outside the input factors that take into account the output of environmental pollution, green total factor productivity has become a powerful evaluation indicator to judge green and sustainable agricultural development.

Regarding the factors influencing green total factor productivity in agriculture, most existing studies on the power sources of agricultural green total factor productivity have cut from the supply perspective, analyzing the effects of environmental regulation [5,6], changes in the structure of the agricultural industry [7], agglomeration of the agricultural industry [8], trade opening [1,9] and agricultural subsidies [6] on agricultural green total factor productivity. Despite the different issues explored from different perspectives, scholars have gradually developed a general understanding of agricultural green total factor productivity, namely that technological progress is the primary source driving agricultural green total factor productivity.

However, with the emergence of counter-globalization, the rise of trade protectionism, and the entire play of the advantages of the domestic mega-market, more and more scholars have begun to study the impact of consumption on agricultural green total factor productivity. Especially at present, with the improvement of quality of life, the continuous expansion and quality upgrade of people's consumption demand has raised higher expectations and requirements for agricultural production, especially the in-depth practice of the concept of green consumption, which has called for greater integration of production factors [10] and efforts to improve the agricultural green total factor productivity [2,3]. Therefore, in the process of promoting green and low-carbon development in agriculture, it is worthwhile to conduct an in-depth study on whether the opportunity of consumption upgrading can be used to promote green total factor productivity in agriculture.

Relevant studies focus on the following three aspects: The first is the impact of dietary consumption structure optimization. As China moves toward overall well-being, residents' lives have shifted from subsistence to nutrition and health [11]. Increasing attention has been paid to the balance and health of dietary structure [12,13]. The optimization of the dietary consumption structure has reduced the consumption of staple foods such as cereals and significantly increased the consumption of livestock and poultry products, fresh fruits, and vegetables, which has accelerated the optimization and transformation of the agricultural structure and led to an increase in indirect food consumption and total food consumption [11,14]. Thus, China still needs to accelerate the improvement of comprehensive agricultural production capacity and the overall competitiveness of the whole industrial chain under the basic premise of food security. Producers increase their factor inputs in a cumulative self-generated cycle according to the demand-induced innovation theory. This satisfies market demand and is driven by profit maximization and comparative competitive advantage to innovate [13,15,16] to increase agricultural productivity [4,17]. In a study on the path to high-quality agricultural development in China, Xie [18] found that the structure and scale of dietary consumption can promote agricultural structure, technological innovation, and green development through market expansion effects.

The second focus is the impact of consumption upgrading. From the perspective of China's consumption characteristics, consumption shows a continuous upgrading trend [18,19], which plays a guiding role in agricultural quality change [20]. Consumption upgrading is manifested not only in consumers' pursuit of high-end goods, but also in their desire for green, healthy, and high-quality agricultural products [12], and more so in the pursuit of other additional values beyond the basic values such as situational and humanized experiences in the consumption process [18,20]. This will prompt agricultural production and services to leap deeper, reshape the original agricultural structure model and production methods, and improve agricultural quality, efficiency, and competitiveness [2,15,16]. Notably, the strong market demand for high-value-added green agricultural by-products and their refined processed products effectively stimulates the enthusiasm and effectiveness of investment and innovation in green agriculture-related industries [16,17,21], improves the value-added capacity of agricultural products, and helps the development of agricultural industrialization.

Third, agricultural technological progress is driven by changes in consumption. From the perspective of science and technology management, changes in consumer demand stimulate the subjective initiative of producers to improve technology and increase technical efficiency, ensuring the smooth realization of technology's physical, aesthetic, and ethical effects [21]. At the microlevel, changes in consumer demand play a guiding role in innovation development. Technological innovation in response to the trend of upgrading consumer demand is essential for firms to reduce market risk and increase profits for sound development [13,16]. Studies have shown that consumption upgrading accelerates the degree of agglomeration and scale in the agricultural industry [8], promotes the promotion and application of green technologies in agricultural production, accelerates the specialized division of labor in the agricultural industry, improves labor productivity [22,23], effectively stimulates the innovation behavior of micro-entities [24], and enhances the efficiency of green production in agriculture by attracting capital inflows and enhancing the competitiveness of the industry.

These studies provide a valuable reference for analyzing the green and sustainable development of agriculture under consumption upgrading but still leave some questions to be addressed. (1) Previous empirical analyses have primarily defined and measured consumption upgrading based on consumption structure models but less on consumption patterns and philosophies [19]. However, there is still a lack of direct analyses and evidence on whether consumption upgrading affects agricultural green total factor productivity. In the context of the transformation of economic development from a "Both Abroad" to an "Internal-external Balance, Internal Focus" economy, the impact of consumption upgrading on agricultural green total factor productivity is discussed from the demand side and its mechanism is examined in depth, which can provide a new perspective for thinking about green and high-quality development in agriculture. (2) The specific paths and forms by which consumption upgrading affecting green total factor productivity are less explored in existing research. On the one hand, agricultural green total factor productivity enhancement can proceed along the paths of achievement transformation, technological imitation, or independent innovation [21]. On the other hand, agricultural green total factor productivity may come from technical efficiency and technological innovation [3,24]. Thus, consumption upgrading along different paths may bring about different forms of progress in agricultural green total factor productivity, and the exploration of the above issues may expand our understanding of agricultural green total factor productivity.

The remainder of this study is structured as follows: Part II is the analysis of the mechanism of consumption upgrading affecting agricultural green production efficiency; Part III is the construction of the econometric model and data processing; Part IV is the testing of the baseline empirical model and the interpretation of the results; Part V is the analysis of the impact mechanism and the results discussion; and Part VI is the conclusion of the whole paper.

2. Consumption Upgrading and Green Production Efficiency in Agriculture: The Mechanism of Influence

Consumption creates demand and production motives, leading to technological innovation and change, whereas technology can materialize demand [25]. From the perspective of consumption upgrading, as income rises, on the one hand, residents' consumption levels will follow Maslow's Hierarchy of Needs theory, shifting from subsistence and materialistic consumption to enjoyment and developmental consumption; on the other hand, residents will continue to improve the quality and requirements of their existing consumption products and show a higher willingness to pay for new industries and services. This will inevitably force the supply bodies in the agricultural industry chain to upgrade their technology and improve the efficiency of production materials in line with the trend of consumption. Therefore, we not only need to give full play to the power of consumption upgrading but also need to identify the path and mechanism of the impact of consumption upgrading on green total factor productivity and use this path to harness the long-term trend of high-quality agricultural development.

By decomposing agricultural green total factor productivity and summarizing and sorting out the existing literature, this study intends to analyze in detail the impact of consumption upgrading through the channels of technical efficiency, scale efficiency, and technological progress in agriculture, starting from the path of technological progress through the transformation of technological achievements and independent innovation.

First, the transformation mechanism of existing technological achievements enhances the technical efficiency of agriculture. If the rising consumer demand for agricultural products can be met only through the transformation of existing technological achievements, agricultural producers will promote the transformation of technological achievements to meet new consumer demand and profit from it. Without technological reserves or the ability to develop new technologies, the quickest way to improve technological efficiency is to imitate the technologies in competitors' or partners' products to improve their technological level, accelerate productivity, and mass produce them to meet the new demand for agricultural products and services arising from the upgrading of consumption [21]. However, the technological achievements used are readily available and do not break through the existing production frontier. Therefore, at this time, consumption upgrading only brings about an increase in the efficiency of green technology in agriculture.

Second, the mechanism of technological progress involves economies of scale. According to the Engel effect, with the growth of income and wealth levels, residents' consumption will maintain a continuous upgrading trend. Consumers will tend to buy higher-quality, more innovative agricultural products after their demand for low-elasticity agricultural products reaches saturation, leading to accelerated agricultural production and service development in scale, quality, and agglomeration. Under this development trend, labor-saving technologies and advanced and applicable technologies have become the main direction of agricultural technology selection, and the quality and proficiency of laborers are further improved, with labor productivity significantly increasing [22,23]. According to the Baumol effect, as residents' demand for highly elastic agricultural products increases with fast technological progress, the upgrading of residents' consumption will trigger the transfer of production factors such as capital from low-end traditional agricultural production to high-end agricultural production, which will lead to a continuous expansion of its scale and the realization of economies of scale and ultimately an increase in operators' profitability, thus promoting technological innovation [21].

Third, the mechanism of green technological progress resulting from innovation breakthroughs. Consumption upgrading has widened the quality of agricultural consumption and increased the level of differentiation of agricultural products. On the one hand, consumers' demand for quality and innovation inhibits or eliminates agricultural products that do not meet consumer demand and promote more adaptable agricultural products for substitution. This leads to a narrowing of profit margins for agricultural producers under the original technology and forces agricultural producers to accelerate technological innovation changes to strengthen the matching of agricultural supply and demand structures under the pressure of survival of the fittest [16,18]. On the other hand, to produce better quality or higher levels and newer agricultural products to capture the increased profits from the increase in market prices due to the increase in residents' consumption of green, ecological, and other high-value-added agricultural products, agricultural producers will increase their investment in technological research and development, continuously carry out technological innovation, improve input-output efficiency, reduce resource consumption [3,24], and eventually, break through existing production frontiers and drive overall agricultural technological progress [25,26].

The various pathways through which consumption upgrading drives green total factor productivity in agriculture are ultimately similar, and we summarize the mechanism of the impact of consumption upgrading on green total factor productivity in agriculture in Figure 1.

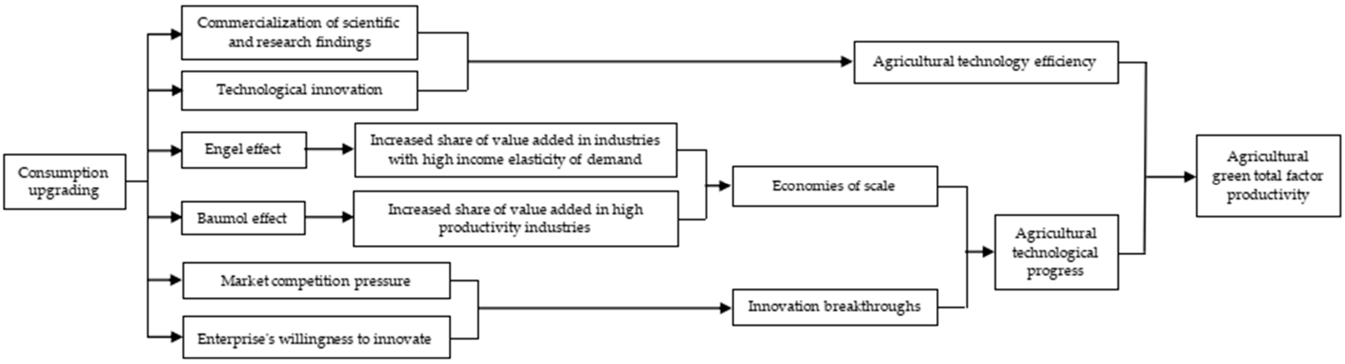


Figure 1. Mechanisms of the impact of consumption upgrading on green total factor productivity in agriculture.

3. Empirical Strategy and Data Processing

3.1. Measurement Model Settings

Holtz-Eakin proposed the vector autoregressive model (PVAR) for panel data in 1988, which expanded the VAR model from the plane to the space [27,28]. At present, the refinement of PVAR model theory is still being explored and developed, and key issues such as dimensional catastrophe, variable endogeneity, and spatial correlation still need to be addressed. However, considering that the PVAR model retains the good characteristics of the VAR model, extends the model of pure time series to the spatial direction, overcomes the requirement of the VAR model for time span, and can enrich the data from both time and regional dimensions using the panel data model, while imposing restrictions on the model by reducing the number of parameters, setting the order of variables according to economic principles, and choosing appropriate estimation methods, the PVAR model can still effectively argue and test many problems in the economic system and is widely used to accurately estimate the dynamic relationship between variables [20,25,28]. In view of this, the PVAR model shown in Equation (1) is set up to examine the impact of consumption upgrading on agricultural green total factor productivity.

$$Y_{it} = \alpha_i + \beta_0 + \sum_{j=1}^{p} \beta_j Y_{i,t-j} + \gamma_t + \mu_{it} \tag{1}$$

In Equation (1), the subscript $i = 1, 2, \cdots, 30$ represents the sample provinces; $t = 2008, 2009, \cdots, 2020$ represents the year; Y is the column vector of endogenous variables, including agricultural green total factor productivity, consumption upgrading index, and high-quality, sustainable economic development; p represents the optimal lag of the PVAR model; α_i, γ_t and μ_{it} are vectors of individual effects, time effects, and random disturbance terms, respectively.

Because the explanatory vector of the PVAR model contains lagged terms in the vector of endogenous variables and individual heterogeneity due to individual (time) effects, it has a similar econometric test to the dynamic panel model, which requires that the endogeneity of variables and individual (time) effects be dealt with effectively before the model is estimated. The data are first subjected to a "Helmert process" to remove sample time and individual fixed effects, ensuring that the transformed variables are orthogonal to the lagged variables and independent of the random disturbance terms. Finally, the parameters of the PVAR model are estimated using the generalized method of moments (GMM) estimation with the lagged variables acting as instrumental variables.

3.2. Indicator Selection and Measurement

3.2.1. Agricultural Green Total Factor Productivity

The data envelopment analysis (DEA) method has become the primary method for measuring total factor productivity, as it does not require a specific production function and avoids the effects of a biased function setting. In addition, the continuous improvement of agricultural technology in the long-run production process will lead to an increase in agricultural productivity. However, it is still inevitable that negative products, such as pollution and other undesired outputs, will be produced, and Malmquist can better reflect changes in productivity and is more adaptive when the decision unit is panel data and there are undesired outputs [1,3]. Therefore, in this study, the Malmquist index approach, which is output-oriented and variable in size, is based on the non-expected output super-efficiency slacks-based measure (SBM) DEA model, which is output-oriented and variable in size.

$$M_i(t,s) = \sqrt{\frac{\beta_t(x_i^t, y_i^{td})}{\beta_t(x_i^s, y_i^{sd})} \times \frac{\beta_s(x_i^t, y_i^{td})}{\beta_s(x_i^s, y_i^{sd})}} = \frac{\beta_t(x_i^t, y_i^{td})}{\beta_t(x_i^s, y_i^{sd})} \times \sqrt{\frac{\beta_s(x_i^t, y_i^{td})}{\beta_t(x_i^t, y_i^{td})} \times \frac{\beta_s(x_i^s, y_i^{sd})}{\beta_t(x_i^s, y_i^{sd})}} \quad (2)$$

In Equation (2), $\beta_t(x_i^t, y_i^{td})$ and $\beta_s(x_i^t, y_i^{td})$ represent the efficiency values of the decision unit i in the t period based on the SBM-DEA model of non-expected output super-efficiency, respectively, while $\beta_t(x_i^s, y_i^{sd})$ and $\beta_s(x_i^s, y_i^{sd})$ represent the efficiency values in the s period based on the t and s periods, respectively, and the reference technology. In this paper, with reference to Guo and Liu [3], a "Resource-Energy-Environment-Economy" input-output index system for green agricultural production is constructed, taking into account the resource and energy constraints and pollution emissions in agricultural production. The input indicators include labor, land, capital, energy, and water resources. Labor input is measured by the number of workers in the primary sector; land input is measured by the sum of crop sowing area and aquaculture area; capital input elements include the total power of agricultural machinery, fertilizer application, pesticide use, and agricultural film use; energy input is measured by agricultural diesel use and agricultural electricity use; energy inputs are measured by the amount of diesel used in agriculture and electricity used in agriculture; and water inputs are represented by the amount of water used in agriculture. Agricultural outputs include both desired and undesired outputs, with desired outputs represented by the total output value of agriculture, forestry, animal husbandry, and fisheries in each province over the years. Undesired outputs are defined as agricultural surface source pollution and agricultural carbon emissions, among which agricultural surface source pollution is measured by the unit survey and assessment method of Chen et al. [9]. Agricultural carbon emissions were estimated using the carbon emission estimation formula and corresponding coefficients from Guo and Liu [3].

3.2.2. Consumption Upgrading Index

Following the basic principles of systematicity, scientificity, and comparability, this study refers to relevant policy documents and draws on the research of Ye J. [19] to construct a consumption upgrading evaluation index system containing 26 indicators in five dimensions: total consumption, consumption level, consumption content, consumption pattern, and consumption concept, as shown in Table 1. The comprehensive evaluation index system not only considers the changes in the structure of the consumption object, which is the transformation of traditional "Material-Services (Spiritual)" consumption or subsistence demand for development and enjoyment demand, but also considers the changes in the consumption subject and consumption activities in the process of consumption upgrading and incorporates the changes in consumption patterns and concepts into the comprehensive evaluation of consumption upgrading. In addition, the system includes changes in consumption patterns and concepts in the comprehensive evaluation of consumption upgrading to reflect the overall improvement in consumption objects, consumption concepts and patterns, and consumption levels.

Table 1. Comprehensive evaluation index system for consumption upgrading.

Guideline Level	Specific Indicators	Indicator Attributes	Guideline Level	Specific Indicators	Indicator Attributes
Overall social consumption	Consumption rate	+	Consumer content	Per capita consumption expenditure on household equipment and services	+
	Total social consumption	+		Per capita consumption expenditure on transport and communications	+
	Growth rate of total social consumption	+		Health care consumption expenditure per capita	+
	Number of workers in the tertiary sector	+		Per capita consumption expenditure on education, culture, and entertainment	+
Consumption level of the population	Per capita consumption expenditure	+		Other consumption expenditure per capita	+
	Consumption growth rate	+		Developmental consumption as a percentage	+
	Urban to rural consumption ratio	-		Percentage of consumption for enjoyment	+
Consumption patterns	Total postal and telecommunications services	+		Consumer Upgrades	+
	Total express delivery per capita	+		Engel's coefficient	-
	Telephone penetration rate	+		Car ownership	+
	Total restaurant and accommodation business	+	Consumer Philosophy	Low carbon consumption	+
	Service Levels in Catering and Accommodation	+		Number of public transport rides per capita	+
	Number of travel agents	+		Risk management awareness	+

Note: Due to space constraints, the formulae (methods) for calculating specific indicators are not reported but are kept on file for reference.

All specific indicators were standardized using the same min-max dimensionless method as the aforementioned input-output indicators, considering the impact of the difference in magnitude of each specific indicator in the comprehensive evaluation index system. After the standardization process, the standardized indicators can be combined using the simple arithmetic average method, principal component analysis method, and entropy weighting method. Considering the degree of application of various methods in calculating the evaluation index, this study weighs the indicators using the entropy weighting method to obtain the comprehensive consumption upgrading index.

3.2.3. The Level of High-Quality Sustainable Economic Development (Real Economy)

Theory and practice have proven that the construction of a modern economic system is inseparable from a high level of the real economy, which is not only the foundation for China to achieve high-quality economic development and win the initiative in the international economy but also the key to meeting people's needs for a better life. Currently, domestic scholars believe that the real economy is the production, sale, consumption, and service of material and spiritual products in tangible materials and elements entering the market in physical form. This also includes all economic activities in operations, including manufacturing and other industries, construction, agriculture, and other tertiary industries, except for the financial and real estate industries [29]. The Federal Reserve frequently used the term "Real Economy" after the financial crisis in 2008 to include all other sectors, excluding the real estate and financial sectors. Based on this, this study uses the growth rate of the real economy, excluding the value added of the financial and real estate sectors from GDP, to represent the level of quality and sustainable development of the economy.

3.3. Study Sample and Data Sources

The empirical analysis of this study is based on provincial-level sample data with 390 samples from 30 provinces, municipalities, and autonomous regions in mainland China, excluding Tibet, from 2008–2020. The data used are mainly from the China Statistical Yearbook, China Environmental Statistical Yearbook, China Agricultural Yearbook, China Rural Statistical Yearbook, and China Energy Statistical Yearbook from 2009 to 2021, as well as some provincial statistical yearbooks, the website of the National Bureau of Statistics, and other official authoritative data, in which some indicators such as years of education per capita and industrial structure are collated from the original data and missing data are supplemented by linear interpolation or extrapolation.

4. Analysis of the Benchmark Empirical Model

Based on the PVAR model and estimation method set out above, before testing the impact of consumption upgrading on agricultural green total factor productivity, it is necessary to check the smoothness of the series of variables in the model to prevent problems such as "Pseudo-regression." In addition, based on existing research and analysis of the impact mechanism, this study ranks the variables in the PVAR model in the following order: real economy (R_Eco), consumption upgrading (CSU), and agricultural green total factor productivity (ML).

4.1. Smoothness Test

Based on robustness considerations, this study simultaneously uses three methods, namely the LLC, Fisher ADF, and Fisher PP tests, to test the smoothness of the three variables and judge the smoothness of the variables according to whether more than 50% of the methods pass the significance test. The specific test results are shown in Table 2. The original hypothesis of the existence of unit root can be rejected at the 1% significant level for variables R_Eco, CSU, and ML, from which the original series of the three variables can be judged to be smooth, indicating that there is a stable and long-run equilibrium relationship between the three endogenous variables. The PVAR model can be constructed and empirically analyzed based on the original series of each variable.

Table 2. Unit root test results for each variable.

Variables	LLC Test	Fisher ADF Test	Fisher PP Test	Conclusion
R_ECO	−6.791 ***	110.292 ***	103.616 ***	Stable
CSU	−2.738 ***	82.266 **	43.696	Stable
ML	−8.241 ***	105.332 ***	107.332 ***	Stable

Note: *** and ** denote significance at the 1% and 5% levels, respectively.

4.2. Baseline Model Analysis

4.2.1. PVAR Model Parameter Estimation Results

Regarding the choice of the optimal lag order of the PVAR model, by comparing the values of the AIC, BIC, and HQIC criteria of the PVAR model with lags 1–5, this study finds that the PVAR model with lag 1 has the smallest information criterion value; thus, building the PVAR model with lag 1 is the better choice. Table 3 presents the model estimation results.

Since PVAR, as an extended form of the VAR model, is a lack of a theoretical model, resulting in an economic interpretation of the parameter estimates that do not have much practical significance, it is difficult to evaluate the model by estimating the coefficients. Thus, this paper only presents the results of the model parameter estimation and will subsequently focus on the analysis by calculating the generalized impulse response function and variance decomposition results of the PVAR model.

Table 3. PVAR model optimal lag order and estimation results.

Panel A Results of the PVAR Model Based on GMM Estimation			
	h_R_Eco	**h_CSU**	**h_ML**
	0.411	−0.001	0.008
L.h_R_Eco	(0.121)	(0.000)	(0.003)
	−38.424	0.845	0.861
	(12.127)	(0.048)	(0.345)
	20.359	−0.105	0.009
L.h_CSU	(10.517)	(0.051)	(0.302)
	0.411	−0.001	0.008
	(0.121)	(0.000)	(0.003)
	−38.424	0.845	0.861
L.h_ML	(12.127)	(0.048)	(0.345)
	20.359	−0.105	0.009
	(10.517)	(0.051)	(0.302)
Panel B Model Optimal Lag Order Selection			
Lag order	**AIC**	**BIC**	**HQIC**
1	−9.86758 *	−8.64533 *	−9.37843 *
2	−9.11283	−7.67346	−8.53484
3	−7.25131	−5.5545	−6.56762
4	−3.88979	−1.88153	−3.07792
5	−8.4517	−6.05698	−7.48074

Note: The standard deviation of the corresponding estimates is shown in parentheses; * denotes the optimal lag order chosen for this criterion.

4.2.2. Impulse Response Analysis

Impulse response plots for the formation of each variable's change on itself and other variables' shocks were obtained after applying unit positive standard deviation shocks to each of the three variable random perturbation terms of the PVAR model and 1000 Monte Carlo simulations (Figure 2). The horizontal coordinate is the number of response periods for the shock effect, set at 20 periods; the vertical coordinate is the degree of impact of the variable; the solid line in the middle represents the impulse response value; and the dashed lines on either side indicate the confidence interval at the 5% significance level.

The impulse response of ML to a positive unit standard deviation shock to R_Eco (Figure 2) shows that ML has a small negative value in the face of a positive unit shock to R_Eco, then decreases rapidly and generates a maximum positive response in Period 1, then gradually decreases and converges to zero in Period 5, suggesting that R_Eco is not conducive to ML improvement in the short term after a positive unit shock but has a sustained positive effect in the long term. The reason for this is that, as national policy adjustments, market pressure, and ecological environment regulations become increasingly tight, the elimination of backward production capacity in the process of high-quality economic development, competition, and restructuring within the industry and the strengthening of technological innovation will break the stable relationship formed between various factors and resources in the short term, bringing innovation pains to producers. Furthermore, as industrial adjustment deepens and the pain disappears, the application of various energy-saving and clean production processes will mature, the consumption of resources and energy and the emission of pollutants will be reduced, and the competitiveness of producers, the industrial structure, and the production and economic efficiency will be gradually enhanced and optimized, thus showing a long-run promotion effect.

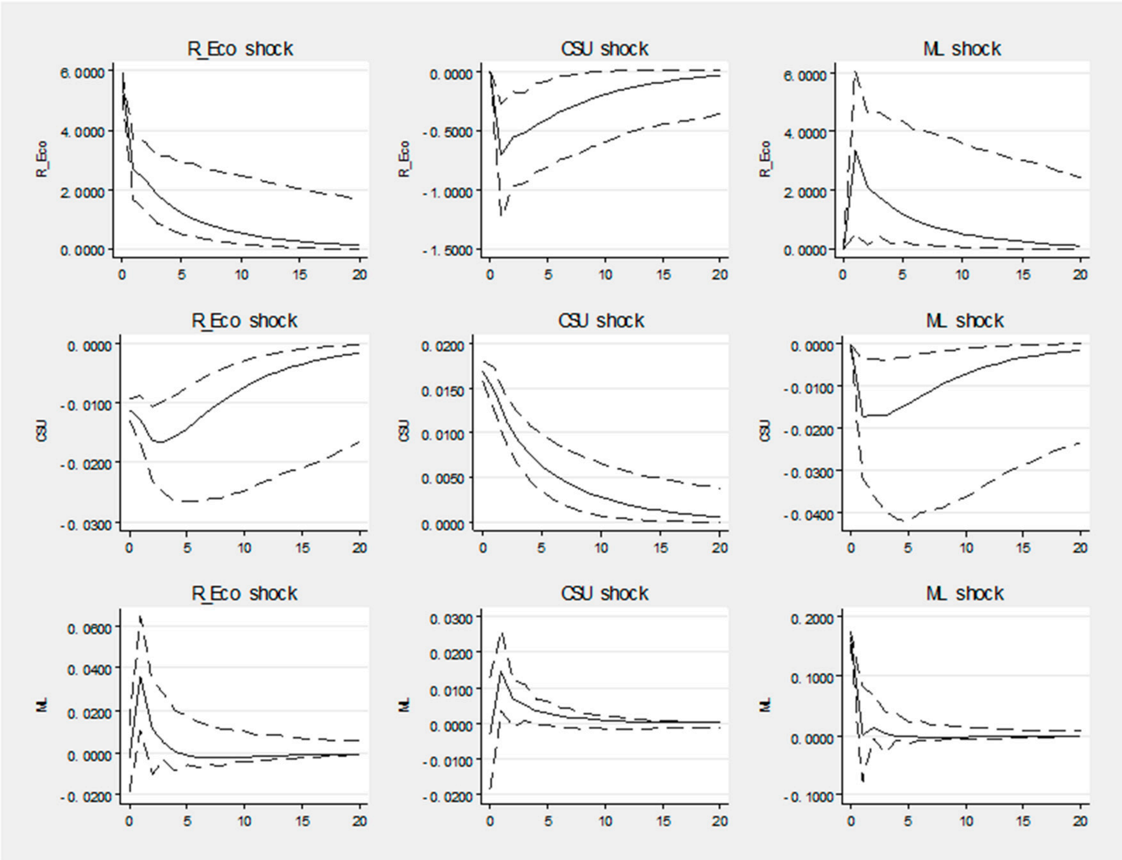


Figure 2. Impulse response diagram for Monte Carlo simulation of PVAR model.

The dynamic response process of ML after a unit positive standard deviation shock to the CSU is illustrated in Figure 2. After applying a positive unit standard deviation to the CSU, the ML forms a smaller negative response in the current period. This is mainly due to the upgrading of consumption as well as the renewal of producers' products and the emergence of substitutes, which require producers to adjust their production strategies and innovate their production technologies, while it takes some time for production factors such as capital, technology, and talent to form a reasonable allocation. With a large amount of investment and stock of assets entering the corresponding production areas, their technological level, production efficiency, and the realization of batch production, the response of ML to CSU shocks gradually appears and climbs, reaching a peak in Period 1. Subsequently, the impulse response value of ML gradually decreases and finally converges to a value around zero. Further, by comparing, we see that the dynamic effect of consumption upgrading on ML is similar to R_Eco. Therefore, the trend of consumption upgrading is ahead of the change in agricultural green total factor productivity, which has a strong long-run boosting effect on agricultural green total factor productivity, but this boosting mechanism has a specific time lag.

The dynamic response of ML to a positive shock to its unit standard deviation, given in Figure 2, shows that ML responds more immediately to a positive unit standard deviation shock in the current period. Then, the response level fluctuates gradually and converges to zero in Period 4. There is a clear "Incumbency Advantage" in agricultural green total factor productivity. The reason for this is the dynamic continuity of technological progress, as it takes a relatively long time for new technologies to be invented, put into use, and produce benefits. The rearrangement of real demand with existing technological tools can also lead to new applications of existing technologies and broaden the scope of their use of existing technologies. This, in turn, leads to an increase in agricultural green total factor productivity, which is influenced not only by its past level of development but also by its past knowledge, technology, and creativity.

4.2.3. Analysis of Variance

Based on impulse response analysis, this study continues to use variance decomposition to examine the strength of mutual explanations between variables more accurately and to measure the relative importance of various shocks to agricultural green total factor productivity. Table 4 shows the predicted variance decomposition for Periods 5, 10, 15, and 20.

Table 4. Variance decomposition results of the PVAR model.

Period	**R_Eco**			**CSU**			**ML**		
	R_Eco	**CSU**	**ML**	**R_Eco**	**CSU**	**ML**	**R_Eco**	**CSU**	**ML**
5	69.173	36.154	5.034	1.813	25.972	1.057	29.014	37.874	93.910
10	66.914	39.48	5.110	2.240	20.160	1.117	30.846	40.361	93.773
15	66.507	40.049	5.157	2.331	19.208	1.124	31.163	40.743	93.719
20	66.422	40.164	5.168	2.350	19.017	1.126	31.228	40.819	93.706

Based on the results of the variance decomposition given in Table 4, it can be seen that agricultural green total factor productivity is most affected by its shocks and is affected by its fluctuating shocks of 93.910% in Period 5, after which it has been in a small decline and drops to 93.706% in Period 20, which indicates that agricultural green total factor productivity has continuity and has a strong dependence on its past development level; thus, fluctuating shocks originate mainly from their development. The second is the shock generated by the level of the real economy: the intensity of R_Eco's shock to ML is 5.034%, and the intensity of the shock generated by R_Eco gradually strengthens and tends to be stable over time, reaching 5.168% in Period 20, indicating that the real economy can continue to exert a promoting influence on agricultural green total factor productivity in the long term, and the two can achieve a win-win effect of synergistic development, but there is a lag in the impact effect. However, similar to R_Eco, CSU has an increasing impact on ML, with the intensity of the impact increasing from 1.057% in Period 5 to 1.126% in Period 20, indicating that consumption upgrading also has a lagging, long-run, and sustained impact on agricultural green total factor productivity and that CSU and ML development can also achieve a win-win situation. On balance, the variance decomposition results are consistent with the impulse response test results; that is, in addition to being influenced by its own level of development, the green total factor productivity increase in agriculture is also affected by shocks from the real economy and consumption upgrading.

4.3. Robustness Tests

The order of variables, selection of variables, and data processing methods in the PVAR model may impact the empirical results. To ensure the reliability of the empirical results, we refer to similar literature on the selection of consumption upgrading indicators and the comprehensive evaluation index measurement methods for testing and changing the order of variables in the model.

First, we compare the indicators of consumption upgrading used in the literature. Although the impulse response functions and variance decomposition results of the two models differ from those of the benchmark model, they both show a lagged and long-run positive impact of consumption on agricultural green total factor productivity, which is consistent with the findings of the benchmark. This is consistent with the findings of the benchmark model.

Second, in constructing the comprehensive consumption upgrading index, the benchmark model in this study adopts the entropy weighting method, in which the simple arithmetic average method and principal component analysis are common methods for summing up the comprehensive index system. For this reason, this study adopts the simple arithmetic average method and the principal component analysis method to reconstruct the consumption upgrading index and replace the consumption upgrading index in the benchmark model. The main empirical analysis results are consistent with the benchmark model measurement test findings.

Finally, all other things being equal, this study examines the impact of changing the order of the three variables in the benchmark PVAR model on the impulse response and variance decomposition and finds that the main empirical results do not differ from the conclusions of the benchmark model econometric tests. On balance, the benchmark model is robust and correctly reflects the intrinsic economic logic among the variables, and the results of the empirical analysis of the model are reasonably reliable.

5. Analysis of the Mechanism of the Impact of Consumption Upgrading on Agricultural Green Total Factor Productivity and Discussion of the Results

The analysis of the theoretical mechanism shows that consumption upgrading affects agricultural green total factor productivity mainly through the channels of economies of scale, agricultural technical efficiency, and technological progress. At the same time, agricultural green total factor productivity can be decomposed into technical efficiency (AGPEC), scale efficiency (AGSEC), and technical change (AGTC), which satisfy agricultural green total factor productivity = AGPEC $\times$ AGSEC $\times$ AGTC. Therefore, this study takes AGPEC, AGSEC, and AGTC as the proxy variables of the influence path and constructs PVAR models to test the relationship between consumption upgrading and the specific relationship among the three, thus providing empirical evidence for the transmission mechanism of consumption upgrading affecting agricultural green total factor productivity.

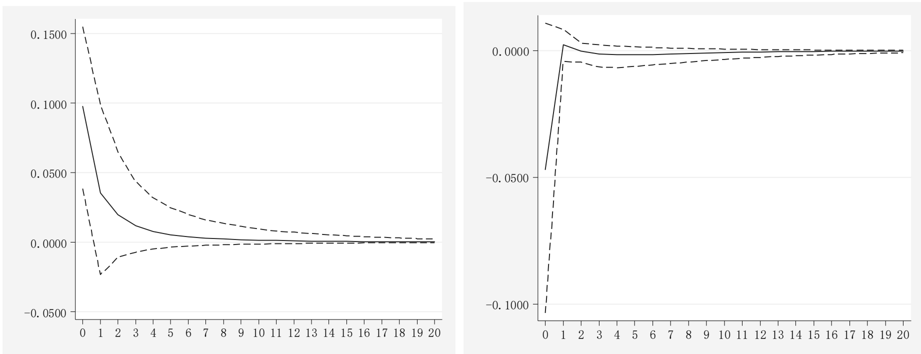
5.1. Basic Tests

The smoothness tests for AGPEC, AGSEC, and AGTC based on the three methods of LLC, Fisher ADF, and Fisher PP tests revealed that all three are smooth at the 1% significance level; that is, AGPEC, AGSEC, and AGTC are in stable equilibrium with R_Eco and CSU, respectively, in the long run. Therefore, this section will examine how the real economy and consumption upgrading affect agricultural green total factor productivity through each pathway by constructing a lag-1 PVAR model and using impulse response plots and variance decomposition as in the baseline model.

5.2. Impulse-Response Analysis

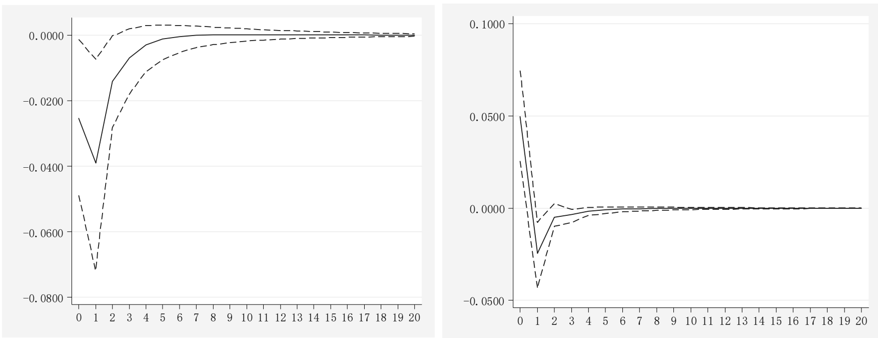
According to Figure 3, when a positive shock is applied to R_Eco, AGPEC produces a positive effect in the immediate period and starts to gradually decline after reaching a peak in the current period, but always fluctuates in a positive direction, and the shock tends to level off and converge to zero from Period 6, indicating that R_Eco produces a large positive effect on AGPEC in the short term, but the positive boosting effect gradually weakens and tends to zero as time advances. However, given a positive unit standard deviation shock to CSU, AGPEC rapidly weakens and shifts after a large negative effect in the current period and gradually converges to zero after reaching a positive direction in Period 1, indicating that CSU is detrimental to AGPEC development in the short term but has a sustained pulling effect in the long term.

In terms of the AGSEC channel path (Figure 4), AGSEC initially develops a negative response to a positive unit standard deviation shock to R_Eco and continues to grow in Period 1, after which this negative effect gradually weakens and eventually converges to zero, indicating that R_Eco not only develops an enhanced inhibitory effect on AGSEC in the short term but that the negative shock utility is characterized by long-term development. After a CSU unit standard deviation size shock, AGSEC initially generates a strong positive response and peaks at the beginning; then, the impact effect rapidly weakens and reverses to a negative value in Period 1, after which the negative impact effect rapidly decreases to a value near 0. However, the overall impact of the shock is positive; that is, consumption upgrading will boost the formation of agricultural economies of scale and accelerate the improvement of scale efficiency.



(**a**) (**b**)

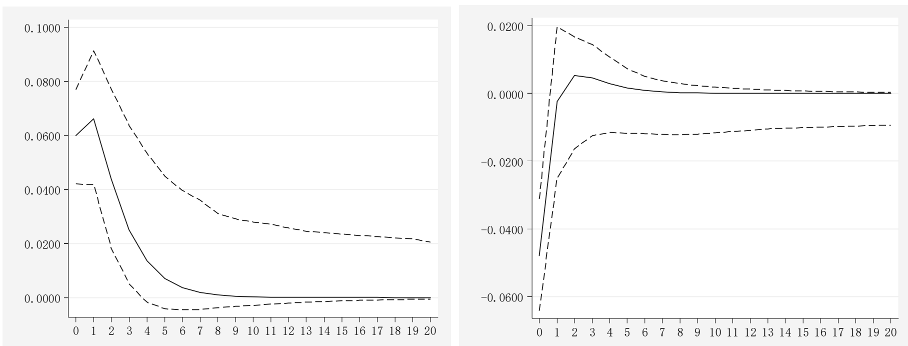
Figure 3. (**a**) R_Eco to AGPEC impulse response (**b**) CSU to AGPEC impulse response.



(**a**) (**b**)

Figure 4. (**a**) R_Eco to AGSEC impulse response (**b**) CSU to AGSEC impulse response.

For the AGTC channel path (Figure 5), applying one standard deviation shock to R_Eco generates a positive shock that reaches its maximum in Period 1, after which the positive shock gradually decreases and converges to zero, suggesting that R_Eco accelerates agricultural technological progress in the short term and that the facilitation effect is sustainable. In contrast to the above results, a unit standard deviation shock applied to the CSU produced a large negative shock to the AGTC in the current period; then, the negative effect shrank rapidly to zero in Period 1 before reversing and reaching a positive maximum in Period 2, eventually stabilizing the response function from positive, suggesting that the CSU is not conducive to innovation in agricultural technology in the short term but has a sustained facilitative effect in the long term.



(**a**) (**b**)

Figure 5. (**a**) R_Eco to AGTC impulse response (**b**) CSU to AGTC impulse response.

5.3. Variance Decomposition

Based on impulse response analysis, the contributions of R_Eco and CSU in the change process of the three impact path variables are given in Table 5. According to Panel A data, AGPEC is most affected by its own fluctuation shock, which is still at 96.421% in Period 20. The intensity of R_Eco' and CSU shocks to AGPEC maintains a stable but increasing trend in Period 20, at 2.998% and 0.582%, respectively, and the intensity of R_Eco's effect is significantly higher than that of CSU. Panel B shows that the CSU's effect on AGSEC is stronger than that of R_Eco's, and both can reach the steady state level sooner. The strengths of CSU and R_Eco on AGSEC are 4.321% and 3.369%, respectively, in the steady state, indicating that CSU and R_Eco have a stable and continuous effect on AGSEC. Panel C shows that the contribution levels of R_Eco and CSU to the channel path AGTC further increase and reach steady-state levels of 24.043% and 5.264%, respectively, for shock fluctuations in Period 10, indicating that R_Eco and CSU can produce a consistent, stable, and relatively strong shock effect on AGTC.

Table 5. Results of the variance decomposition of the impact path PVAR model.

Panel A: Path AGPEC									
Period	**R_Eco**			**CSU**			**AGPEC**		
	R_Eco	**CSU**	**AGPEC**	**R_Eco**	**CSU**	**AGPEC**	**R_Eco**	**CSU**	**AGPEC**
5	94.669	42.546	2.98	1.693	53.771	0.579	3.638	3.684	96.442
10	93.749	49.394	2.995	2.444	46.242	0.581	3.806	4.364	96.423
15	93.588	50.387	2.997	2.582	45.150	0.582	3.830	4.463	96.421
20	93.559	50.557	2.998	2.607	44.964	0.582	96.421	4.480	96.421
Panel B: Path AGSEC									
Period	**R_Eco**			**CSU**			**AGSEC**		
	R_Eco	**CSU**	**AGSEC**	**R_Eco**	**CSU**	**AGSEC**	**R_Eco**	**CSU**	**AGSEC**
5	87.863	50.806	3.367	0.393	36.554	4.319	11.744	12.641	92.314
10	87.170	55.841	3.369	0.724	30.203	4.321	12.106	13.956	92.310
15	87.051	56.555	3.369	0.790	29.304	4.321	12.159	14.142	92.310
20	87.030	56.677	3.369	0.801	29.149	4.321	92.310	14.173	92.310
Panel C: Path AGTC									
Period	**R_Eco**			**CSU**			**AGTC**		
	R_Eco	**CSU**	**AGTC**	**R_Eco**	**CSU**	**AGTC**	**R_Eco**	**CSU**	**AGTC**
5	89.926	39.125	23.931	3.962	38.933	5.265	6.111	21.942	70.804
10	86.664	46.133	24.043	5.329	31.669	5.264	8.006	22.197	70.693
15	85.983	47.418	24.043	5.618	30.418	5.264	8.399	22.165	70.693
20	85.825	47.701	24.043	5.685	30.143	5.264	70.693	22.156	70.693

5.4. Results Discussion

From the empirical results, R_Eco is not conducive to ML upgrading in the short-run but can produce a continuous positive promotion impact in the long-run, and the impact intensity gradually increases and tends to be stable. It can be seen that although R_Eco develops faster than ML upgrading, strengthening R_Eco is conducive to continuously promoting ML upgrading. As highlighted by Xie [21] and Asheim et al. [30], the severe external environment brought by economic transformation will "Force" enterprises to continuously improve their innovation capability, which is the so-called "Eel Effect". With the rapid improvement of the quality of real economy development in our country, the "Eel Effect" in agricultural green innovation has already emerged. However, R_Eco has a heterogeneous impact on ML in different paths, with positive impacts in both the AGPEC and AGTC paths, and the strength of the latter's impact is significantly higher than that of the former, indicating that R_Eco has a stronger impact on the development and application of advanced green technologies by stimulating agricultural operators to increase their innovation inputs. In the AGSEC pathway, R_Eco has a stimulating impact on AGSEC in the short-run but a persistently inhibiting impact in the long-run, indicating that R_Eco development is not conducive to the agglomeration of agricultural industries and the realization of economies of scale.

Similar to R_Eco, CSU has a lagging and sustained positive contribution to ML, indicating that although the level and quality of agricultural production are inadequate in responding to CSU, CSU can effectively lead the innovation of agricultural green technology and the improvement of production efficiency. Further, through the impact paths, CSU has a suppressive impact on ML in the short-run through paths AGPEC and AGTC, while it has a continuous promotion impact in the long-run, and the intensity of the impact on the former is significantly higher than that on the latter; while in the AGSEC path, CSU has a positive promotion impact on ML in both the short- and long-run, but the intensity of the impact is lower than that on AGTC.In summary, CSU plays a positive role in all three impact paths on ML in China, but the impact on AGPEC and AGSEC is relatively stronger, indicating that CSU mainly promotes ML enhancement through promoting the application of existing technological achievements and the formation of agricultural economies of scale.

The empirical results also show that in addition to being influenced by R_ECO and CSU, ML not only has a direct inverse impact on R_ECO and CSU but also has an indirect inverse impact on CSU or R_ECO through the mediating variable R_ECO or CSU. Moreover, the development of R_Eco, CSU, and ML is all significantly correlated with their previous levels, reflecting the inherited and cumulative nature of economic development.

Taken together, both R_Eco and CSU can promote ML improvement but have differential impacts through different paths. Specifically, R_Eco mainly produces positive impacts through the AGTC and AGPEC paths, while it produces negative impacts through AGSEC; CSU produces inhibitory impacts in the short-run through paths AGPEC and AGTC and has facilitating impacts in the long-run, and the impact of path AGPEC is higher than that of path AGTC, while the path AGSEC contributes to an overall stronger positive impact.

6. Conclusions and Insights

Based on the construction of a comprehensive evaluation index of consumption upgrading and the calculation of agricultural green total factor productivity based on the Malmquist index method of the non-expected output super-efficiency SBM-DEA model, this study uses the PVAR model to analyze the impact effect of consumption upgrading on agricultural green total factor productivity in the context of high-quality economic development based on panel data from 30 provinces from 2008 to 2020 and further decomposes total factor productivity into agricultural technical efficiency, scale efficiency, and agricultural technological progress to explore the impact of different paths of consumption upgrading on agricultural green total factor productivity. The main findings are as follows: agricultural green total factor productivity is characterized by a significant dependence on its inertia, but the real economy and consumption upgrading also constitute important influencing factors for its change, and both are ahead of agricultural green total factor productivity change. Although it is not conducive to agricultural green total green factor productivity growth in the short run, it has a continuous positive effect in the long run, and the role of the real economy is stronger than that of consumption upgrading. In terms of impact paths, the real economy and consumption upgrading show differential effects in the three paths, with the development of the real economy promoting the commercialization of scientific and research findings, the formation of economies of scale in agriculture, and the improvement of technical efficiency with no change in the production frontier, but not promoting technological innovation and breaking through the existing production frontier. Consumption upgrading shows completely different impacts in different paths and stages, with the short term only contributing to the expansion of the agricultural industry and the formation of economies of scale, while in the long term, it mainly promotes the transformation of technological achievements and technological innovations that break through the production frontier to enhance agricultural green total factor productivity.

The above results show that in the context of China's high-quality economic development, how to use the opportunity of consumption upgrading to promote the improvement of agricultural green total factor productivity needs more comprehensive consideration. It is generally believed that the development of the real economy and consumption upgrading may have an overall pulling effect on the increase of agricultural green total factor productivity, but this paper finds that the current real economy and consumption upgrading have heterogeneous mechanisms of action in different paths and that there are some shortcomings. Conditions need to be created to further exploit the positive effect of consumption upgrading on the agricultural green total factor productivity in the context of high-quality economic development. (1) Comply with the new trend of economic transformation and consumption upgrading, especially the trend of green consumption; accelerate the green and low-carbon upgrading of traditional agriculture; and build a green agricultural development technology system to realize the circular connection between the green agricultural production and living system, so as to better play the role of promoting green agriculture through consumption upgrading and meet the requirements of high-quality economic development. (2) Strengthen the protection of intellectual property rights, promote the introduction and cooperation of international technology and the commercialization of scientific and research findings, and take advantage of the opportunity of consumption upgrading and China's own advantages as a large country to steadily increase the agricultural land output rate based on green technology, while significantly improving agricultural labour productivity and resource utilization, and promoting the agricultural green total factor productivity. (3) Actively build agricultural industry clusters of appropriate scale and strong radiation capacity by relying on advantageous resources so as to fully stimulate the vitality of agricultural business entities and enable them to better realize technological innovation, transformation, and application in the context of consumption upgrading. (4) Reasonably define the positioning of the government and enterprises in science and technology innovation and give full play to the government's leading and supporting roles in basic and strategic science and technology innovation, while effectively stimulating the independent innovation capacity of agricultural business entities under consumption upgrading by taking market demand as the guide.

In addition, there are still some limitations in this study that need further analysis and research. (1) This study does not analyze the regional differences in the mechanism of the effect of consumption upgrading on agricultural green total factor productivity, which may have some influence on the conclusions and insights. (2) This study assumes that the research samples are independent of each other and does not consider the horizontal spatial influence between samples brought about by the flow of people, logistics, and information between samples. (3) Due to data availability, this study does not analyze in depth the impact of the more micro-level city and county level consumption upgrading on agricultural green total factor productivity, which is a direction that needs further analysis in the future.

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