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The Impact of Technological Innovation on Agricultural Green Total Factor Productivity: The Mediating Role of Environmental Regulation in China

Lihuan Huang and Ying Ping *

School of Economics and Management, Shanghai Ocean University, Shanghai 201306, China; melodyhlh@163.com
* Correspondence: yping@shou.edu.cn

Abstract: This study delves into the effects of agricultural technological innovation on agricultural green total factor productivity (AGTFP) and the intermediating role of environmental regulation (ER) in 30 Chinese provinces from 2010 to 2021. Employing mediation analysis methods such as the three-step approach, Sobel–Goodman test, and Bootstrap methods, the findings are robust: technological innovation significantly enhances AGTFP, as evidenced by a 1% level significant coefficient of 0.030. Additionally, ER acts as a potent mediator, where its inclusion as an independent variable alongside agricultural technological innovation (AST) boosts the coefficient to 0.031, further confirming its synergistic effect on AGTFP. These data points underline the importance of innovation in agricultural sustainability and the reinforcing role of environmental regulation. Consequently, this study advocates for intensified agricultural innovation support, tailored environmental regulation policies, augmented environmental education, and a meticulous evaluation system for environmental legislation to foster sustainable agricultural practices.

Keywords: China; agricultural sustainability; technological innovation; environmental regulation; mediation analysis

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1. Introduction

As China's modernization accelerates, green development in agriculture has become essential for high-quality growth in this sector. China's agriculture faces challenges including low farming returns, inefficient land use, and non-point source pollution, hindering its green transition [1]. The 20th National Congress of the Communist Party emphasized shifting from quantity to quality in agricultural development, highlighting the importance of technological innovation and labor quality improvement. President Xi Jinping stressed enhancing innovation, competitiveness, and overall quality in agriculture. This underscores the imperative to facilitate green development within the agriculture sector by leveraging technological innovation to enhance the efficiency and sustainability of agricultural production, thereby improving agricultural green total factor productivity (AGTFP). Environmental regulation, a key tool for controlling pollution, plays a significant role in this transformation. Despite its positive contributions, the specific impact of environmental regulation on the relationship between technological innovation and agricultural sustainability needs further exploration. Delving into how technological innovation enhances AGTFP and the nuanced role of environmental regulation is essential for fostering agricultural green development.

Existing literature on agricultural technological innovation, environmental regulation, and agricultural green total factor productivity (AGTFP) primarily focuses on three areas. Firstly, researchers utilize various methods to measure AGTFP to more comprehensively reflect the environmental costs and resource efficiency of agricultural production. Ge et al. and Yang et al. use the SBM-DDF method and Dagum Gini coefficient to analyze AGTFP from temporal and spatial differentiation perspectives, revealing regional disparities and drivers of China's agricultural green efficiency [2,3]. Further studies by Guo et al. and Liu et al. have refined these calculations using improved EBM models and the undesired MinDS super-efficiency MetaFrontier-Malmquist model, discussing their dynamic changes and spatial convergence [4,5]. Additionally, Alem's 2023 study on Norwegian dairy farms incorporates CH4 emissions into the productivity models, providing a novel perspective for evaluating AGTFP with environmental outputs [6]. Studies indicate that AGTFP improvement is influenced by various factors. Wu et al. found that mechanization levels, human capital stocks, and fiscal expenditure levels significantly positively affect AGTFP in the Yangtze Economic Belt, whereas disaster rates and irrigation facility levels have negative impacts [7]. Further studies by Ma et al. and Li et al. explore the impact of environmental regulation and rural financial development on AGTFP, noting a dual threshold effect of environmental regulation, while enhancements in the scale, structure, and efficiency of financial development significantly boost AGTFP [8,9]. Secondly, the impact of agricultural technological innovation on AGTFP is significant. Sun et al. emphasize that technological innovation enhances resource efficiency and environmental protection, thus effectively increasing AGTFP [10]. Chen et al. explore how the digital economy and green technological innovations synergistically enhance AGTFP [11]. Wu et al. examine how green innovation can boost AGTFP through the technological distance framework [12]. Barath's 2024 study analyzes the ecological efficiency impacts on Hungarian field crop farmers participating in agricultural environmental schemes, highlighting the potential limitations of policy tools in fostering sustainable agricultural practices [13]. Thirdly, the impact of environmental regulation on green agricultural development is widely analyzed. Research by Ma et al. using data from China's 30 provinces demonstrates that environmental regulation has significant spatial spillover effects on AGTFP, with the urban–rural income gap playing a mediating role [14]. This indicates that environmental regulation and economic structural adjustments need to be coordinated to achieve more effective green agricultural development. Li et al. explore how technological innovation interacts with environmental regulation to affect AGTFP, finding a dual threshold effect where stronger regulation significantly enhances the positive impacts of innovation within certain limits [15]. These findings suggest that policy design should consider the synergy between innovation and regulation and the specific environmental and economic conditions of different regions. Complementing these insights, Staniszewski's 2023 research offers a broader view by highlighting the structural conditions for sustainable agriculture enhancement within the European Union, using FADN regional data to demonstrate how local characteristics impact sustainability [16]. Although focused on the EU, his methods and findings provide valuable references for formulating regionally differentiated environmental regulation policies in countries like China.

The existing literature extensively explores agricultural green total factor productivity (AGTFP) from various angles but falls short of fully deciphering how technological innovation in agriculture influences AGTFP and the intricate mediating role environmental regulation might play. Addressing this gap, our study leverages data from 2010 to 2021 across 30 Chinese provinces to develop a regression model. The study verifies the positive contribution of technological innovation to AGTFP, offering fresh empirical evidence on its role in boosting efficiency and sustainability in agricultural practices. It also elaborates on the nuanced role of environmental regulation, highlighting its significance in the interaction between technological innovation and AGTFP. Through a detailed spatiotemporal analysis, we uncover regional disparities and trends in AGTFP, laying a foundation for crafting precise regional policies for green agricultural development. The findings provide empirical backing for enhancing AGTFP through agricultural innovation and effective environmental policies.

2. Theoretical Mechanism

2.1. Relationship between Agricultural Technological Innovation and Agricultural Green Total Factor Productivity

Agricultural technological innovation plays a pivotal role in promoting sustainable agricultural development. Adopting new technologies and improving cultivation and management methods not only enhances agricultural production efficiency but also strengthens ecosystem sustainability. Technological innovations contribute positively to the environment by reducing reliance on chemical fertilizers and pesticides, improving soil health, promoting biodiversity, and enhancing crop yield and quality. Additionally, innovation includes optimizing resource use within agricultural production processes, such as water conservation and efficient energy use, significantly impacting agricultural green total factor productivity. Technological advancement serves as a key support for modern agricultural development and transformation, facilitating improvements in AGTFP. It promotes greener efficiency, reduces carbon emissions, and increases resource utilization and agricultural waste management efficiency [17]. Gao et al. have highlighted that technological progress has a significant positive effect on AGTFP, especially in Eastern China [18], aligning with research by Li et al. [19] and He et al. [20], which indicates that technological progress significantly fosters green agricultural production, thereby enhancing AGTFP. Based on these insights, we propose the following hypothesis:

Hypothesis 1. *Agricultural technological innovation has a significant positive effect on agricultural green total factor productivity.*

2.2. Relationship between Agricultural Technological Innovation, Environmental Regulation, and Agricultural Green Total Factor Productivity

Environmental regulation plays a key role in shaping the impact of agricultural technological innovation on AGTFP [10,21]. It serves as a critical policy mechanism, guiding agricultural practices toward sustainability by implementing standards for emissions, promoting green technologies, and providing subsidies for innovation [22]. Theoretically, environmental regulations foster the introduction and implementation of agricultural innovations by establishing emission standards, promoting green technologies, and providing innovation subsidies. These measures motivate producers to adopt eco-friendly technologies and methods, increase the costs of pollution emissions, and encourage investment in the development of environmentally friendly technologies. Technological innovations directly enhance AGTFP by improving resource efficiency, reducing emissions, and increasing yields. Environmental regulation indirectly strengthens the positive effects of technological innovation on AGTFP by ensuring these innovations meet environmental standards and objectives. Moreover, studies have shown that environmental regulation also impacts AGTFP positively. Picazo-Tadeo et al. [23] found positive effects of Chinese environmental policies on AGTFP, and Zhan and Xu [24] reported that proper environmental regulations significantly elevate AGTFP. Therefore, we posit environmental regulation as a mediator that intensifies the effect of technological innovation on AGTFP, leading to the formulation of the following hypothesis:

Hypothesis 2. *The impact of agricultural technological innovation on AGTFP is mediated by environmental regulation.*

3. Research Design

3.1. Variable Selection and Data Sources

3.1.1. Dependent Variable: Agricultural Green Total Factor Productivity (AGTFP)

In line with the methodologies proposed by Ma et al. [14] and extended by Yang et al. [25], this study applies the Slack-Based Measure (SBM) and Global Malmquist-Luenberger (GML) index to measure agricultural green total factor productivity (AGTFP). This non-parametric approach, rooted in the Data Envelopment Analysis (DEA) framework introduced by Tone (2003) [26], affords us a holistic measure of AGTFP, encompassing a comprehensive range of inputs and outputs as detailed in Table 1.

Table 1. Input and output indicators for AGTFP.

Indicator Type	Name	Description	Unit
Input	Land Use	Cropped area	Thousand hectares
	Labor Input	Number of agricultural workers	Thousands
	Machinery Input	Total machinery power	Thousand kilowatts
	Fertilizer Input	Fertilizer use	Thousand tons
	Water Input	Agricultural water use	Billion cubic meters
Output	Desired Output	Total agricultural output	Billion Yuan
	Undesired Output	Carbon emissions from agriculture	Thousand tons

Distinguished from conventional total factor productivity measures, the SBM-GML index adeptly manages a diverse array of inputs while specifically accounting for undesirable outputs such as carbon emissions from agriculture. This nuanced analysis enhances our ability to gauge environmental efficiency and the sustainability of agricultural practices accurately. The approach not only evaluates the improvements in agricultural production efficiency but also delineates the potential environmental impacts of agricultural activities, thereby advocating for green development within the sector. The SBM model formula employed in our analysis is:

$$\min\rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1 - \frac{1}{s1+s2}\left(\sum_{r=1}^{s1}\frac{s_r^+}{y_{rk}^+} + \sum_{t=1}^{s2}\frac{s_t^b}{y_{tk}^b}\right)}$$

Here, s_i^-, s_r^+, and s_t^b represent slack in inputs, desirable outputs, and undesirable outputs, respectively, highlighting areas where efficiency gains are possible.

Furthermore, the GML index illustrates temporal variations in AGTFP, capturing both technological progress and efficiency changes over time, as expressed by:

$$\mathrm{GML}^{t,t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; x^t, y^t, b^t\right) = \frac{1 + D_G^T\left(x^t, y^t, b^t\right)}{1 + D_G^T\left(x^{t+1}, y^{t+1}, b^{t+1}\right)}$$

This index provides a comparative view of the distance functions across consecutive periods, shedding light on productivity dynamics, including environmental considerations.

It is essential to acknowledge the inherent limitations associated with employing DEA-based methods in regression analysis. The efficiency scores produced by DEA may not fulfill the traditional regression prerequisites, such as normality and independence, potentially skewing the results. Therefore, while the SBM-GML index yields significant insights, interpretations of the resultant regression analyses must be approached with caution, given these methodological constraints.

3.1.2. Explanatory Variable: Level of Agricultural Technological Innovation (AST)

We use the number of agricultural science and technology patents in each province as a proxy for agricultural technological innovation, applying logarithmic transformation for data normalization as per Zhang et al. [27]. This metric reflects the intensity and outcomes of agricultural technological innovation efforts across regions, revealing regional disparities in innovation capabilities and their potential influence on AGTFP.

3.1.3. Mediating Variable: Environmental Regulation (ER)

Environmental regulation (ER) is assessed using the frequency of environment-related terms in provincial government reports, following the methodology described by Chen et al. [28], with data log-transformed to ensure consistency. This measure approximates the vigor of local environmental governance. Recognizing that policy impacts often manifest with a delay, our analysis employs values lagged by two periods—a practice supported by findings in the literature that demonstrate the delayed effects of such policies [29,30].

3.1.4. Control Variables

Informed by the literature [8,10], our study incorporates several control variables to accurately assess AGTFP. The agricultural mechanization level (AM) indicates that higher mechanization could elevate energy use and environmental costs, potentially reducing AGTFP. Agricultural financial support (ASP) is gauged by the ratio of agricultural fiscal expenditure to total fiscal expenditure, reflecting governmental emphasis on agricultural advancement and support for technological innovation. The agricultural industrial structure adjustment index (ASI) is calculated as one minus the proportion of agricultural output to total output from agriculture, forestry, animal husbandry, and fisheries, suggesting a move towards a diversified agricultural structure. The industrial labor productivity ratio (IPR) compares the productivity of the primary industry to the secondary and tertiary industries, with a lower IPR possibly hindering AGTFP. Lastly, the rural consumption proportion (RCP) measures the share of rural retail sales in total retail sales, indicating the rural market's capacity to drive demand for high-quality and environmentally sustainable production, thereby positively affecting AGTFP. These variables together offer a comprehensive framework for understanding the multifaceted factors influencing agricultural productivity and sustainability.

3.1.5. Data Source

This study utilizes panel data from 2010 to 2021 for 30 provinces in China, sourced from the China City Statistical Yearbook, China Energy Statistical Yearbook, China Statistical Yearbook, China Agricultural Yearbook, and China Rural Statistical Yearbook. Table 2 presents descriptive statistics for the variables.

Table 2. Descriptive statistics of variables.

Type	Variable	Symbol	Mean	Std Dev	Min	Max
Dependent Variable	Agricultural Green Total Factor Productivity	AGTFP	1.074	0.104	0.765	2.362
Explanatory Variable	Agricultural Technological Innovation	AST	2719	3005	24	16,651
Mediating Variable	Environmental Regulation	ER	4826	6402	47	45,140
Control Variables	Agricultural Mechanization Level	AM	3397	2920	94	13,353
	Agricultural Financial Support	ASP	0.482	0.0908	0.0940	0.689
	Agricultural Industrial Structure Adjustment Index	ASI	0.482	0.0908	0.0940	0.689
	Industrial Labor Productivity Ratio	IPR	0.4197	0.1403	0.0977	0.8145
	Rural Consumption Proportion	RCP	34.5397	10.5436	6.2	60.5

3.2. *Econometric Model Specification*

To test the hypotheses proposed in this study, we established the following regression models:

$$\mathrm{AGTFP}_{it} = \alpha_0 + \alpha_1 \mathrm{AST}_{it} + \alpha_2 \sum\nolimits_m \alpha_m \mathrm{Control}_{it} + \varepsilon_{it} \tag{1}$$

$$\mathrm{ER}_{it-2} = \beta_0 + \beta_1 \mathrm{AST}_{it} + \beta_2 \sum\nolimits_j \beta_j \mathrm{Control}_{it} + \varepsilon_{it} \tag{2}$$

$$\mathrm{AGTFP}_{it} = \gamma_0 + \gamma_1 \mathrm{AST}_{it} + \gamma_2 \mathrm{ER}_{it-2} + \gamma_3 \sum\nolimits_k \beta_k \mathrm{Control}_{it} + \varepsilon_{it} \tag{3}$$

Model (1) examines the impact of agricultural technological innovation on agricultural green total factor productivity (AGTFP), aiming to validate Hypothesis 1. Models (2) and (3) investigate the mediating effect of environmental regulation, addressing Hypothesis 2. The dependent variable in these models is AGTFP, the explanatory variable is the level of agricultural technological innovation (AST), and the mediating variable is environmental regulation (ER), with Control representing control variables. Recognizing the lagged nature of environmental regulation as a policy variable, we apply a two-period lag to ER based on prior research demonstrating similar delayed impacts. This approach helps mitigate endogeneity concerns due to reverse causality, ensuring more accurate estimates of ER's effects. The empirical analysis is conducted using Stata 17 software.

3.3. Temporal and Spatial Analysis of AGTFP in China

Figure 1 presents the trend of China's agricultural green total factor productivity (AGTFP) from 2010 to 2021, showing steady growth overall. The national AGTFP ranged from a low of 1.018 in 2010 to a high of 1.136 in 2020, indicating notable improvements in agricultural efficiency and sustainability across the decade. Regionally, the eastern area saw AGTFP fluctuate within a range of 1.026 to 1.155, denoting consistent advances in agricultural innovation and efficiency. The central region's AGTFP growth was more stable, moving from 1.022 to 1.091, reflecting steady productivity increases through technological upgrades. The western region experienced the most significant AGTFP rise, from 1.009 in 2010 to 1.137 in 2021, peaking at 1.208 in 2020, suggesting substantial progress in sustainable agricultural practices. Since 2016, all three regions have shown an upward AGTFP trend, coinciding with the green development concept introduced at the CPC's 18th Central Committee's 5th Plenary Session in October 2015. This highlights the region's efforts to enhance AGTFP in response to national calls, achieving notable results. Overall, the national and regional AGTFP remained above 1, indicating positive growth in environmental sustainability and efficiency in China's agricultural production.

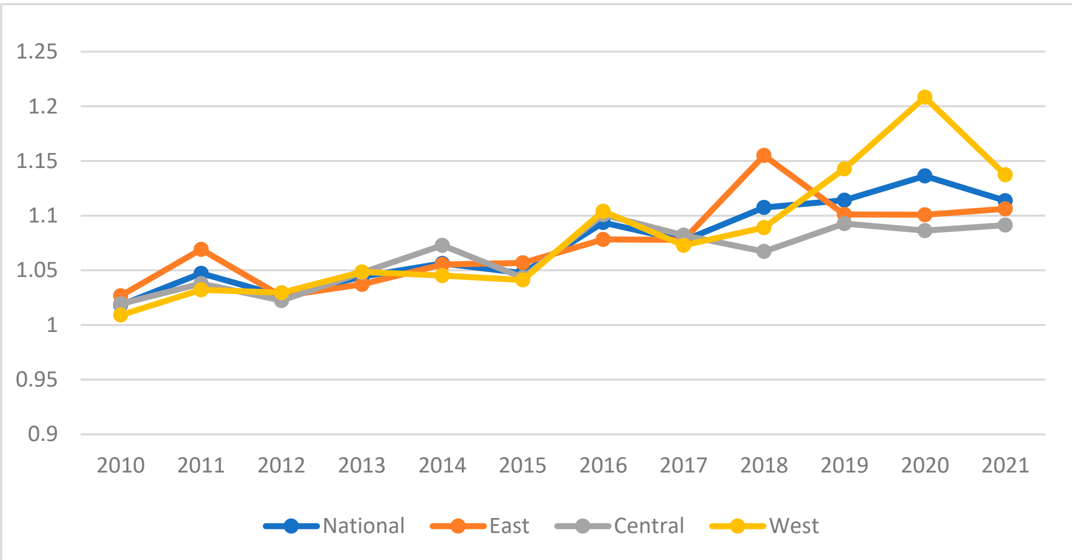

Figure 1. Development trend of China's agricultural green total factor productivity (AGTFP), 2010–2021.

Across China, AGTFP averages demonstrate regional variations, indicating differing levels of progress in enhancing agricultural efficiency and greening production processes, see Figure 2. Qinghai Province leads with the highest average AGTFP (1.2317), attributed to its unique geographical and climatic conditions favoring sustainable agricultural practices, alongside regional policy support and ecological civilization efforts. However, Qinghai's low agricultural output base may exaggerate AGTFP improvements. Eastern and central provinces like Tianjin, Jiangxi, Fujian, Shandong, and Henan also show higher AGTFP averages, reflecting advancements in agricultural innovation and ecological efficiency, likely due to higher economic development and strong agricultural technology support. Conversely, urbanized provinces like Beijing and Shanghai exhibit lower AGTFP averages, correlating with their smaller share of agricultural output in the economy. Western provinces such as Yunnan and Gansu display moderate AGTFP averages, suggesting effectiveness in agricultural development strategies to improve productivity yet indicating room for further progress in greening agricultural processes. Nationwide, while AGTFP averages generally exceed 1, indicating positive growth in efficiency and sustainability, regional imbalances persist, calling for differentiated development strategies to further promote green agricultural transformation and balanced regional growth towards ecological civilization goals.

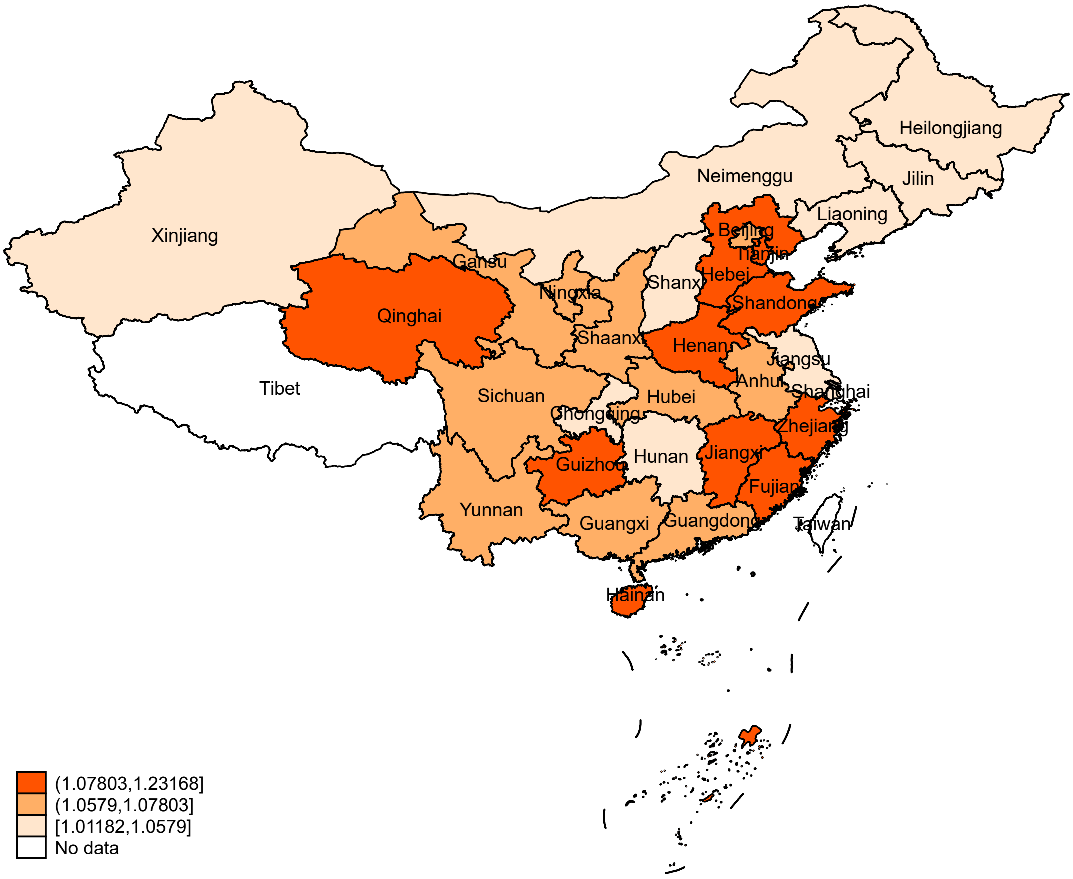

Figure 2. Distribution of average AGTFP by province in China, 2010–2021.

4. Empirical Analysis

4.1. Baseline Regression

In our baseline regression analysis, Table 3 reports the impact of agricultural technological innovation (AST) on agricultural green total factor productivity (AGTFP) using the fixed effects (FE) regression model. This model selection was based on the outcomes of a rigorous Hausman test, which yielded a statistic of 57.56 and a p-value of 0.0000. The test strongly rejects the null hypothesis of no systematic difference between the fixed effects and random effects models' coefficients. This finding confirms that provincial unobservable heterogeneity significantly influences AGTFP, indicating that the FE model provides a more accurate representation of these effects, which show a significant positive effect of AST on AGTFP at the 1% level, with a coefficient of 0.030.

Table 3. Fixed effects results of agricultural technological innovation on AGTFP.

Variable	$AGTFP_{it}$
AST_{it}	0.030 ***
	(6.700)
AM_{it}	−0.000 ***
	(−3.576)
ASI_{it}	−0.106
	(−1.491)
ASP_{it}	0.006 **
	(2.485)
RCP_{it}	0.003 **
	(2.539)
IPR_{it}	0.092
	(1.276)
_cons	0.772 ***
	(12.325)
Observations	360
R^2	0.268
F statistic	19.79

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

This study utilizes the traditional three-step method for mediating effect analysis to explore how environmental regulation (ER) serves as a mediator in the relationship between agricultural technological innovation (AST) and AGTFP. Fixed effects (FE) models address unobservable heterogeneity in panel data, ensuring robustness. Given the panel covers multiple provinces with potential autocorrelation at different times, cluster-robust standard errors are applied to enhance the robustness of regression analysis, effectively controlling for provincial heterogeneity and autocorrelation, thereby increasing the reliability of the estimates [31].

Table 4 shows that without considering ER as a mediator, AST significantly boosts AGTFP at the 1% level with a coefficient of 0.030, indicating that agricultural technological innovation significantly improves AGTFP under constant conditions. When ER is the dependent variable and AST the independent variable, AST significantly influences ER at the 1% level with a coefficient of 0.453, suggesting that agricultural technological innovation substantially strengthens environmental regulation, aligning with theoretical expectations. In the final column, considering both AST and ER as independent variables with AGTFP as the dependent variable, the positive impact of AST on AGTFP slightly increases to 0.031 and remains significant at the 1% level. This suggests that agricultural technological innovation indirectly enhances AGTFP by strengthening environmental regulation. The regression results indicate a direct positive effect of agricultural technological innovation on AGTFP, with a slight enhancement when considering environmental regulation as a mediator, demonstrating that agricultural technological innovation indirectly promotes AGTFP by improving environmental regulation levels.

The Sobel–Goodman test, integrating Sobel's (1982) [32] and Goodman's (1960) [33] approaches, was used to assess the direct, indirect, and total effects of agricultural technological innovation (AST) on AGTFP, factoring in environmental regulation (ER) as a mediator. While the indirect effect was near-significant ($Z = 1.904$, $p = 0.057$), suggesting a substantial contribution to the total effect, the direct effect was highly significant ($Z = 4.179$, $p = 0.000$), as was the total effect ($Z = 5.152$, $p = 0.000$). Environmental regulation mediated 14.2% of the total effect of AST on AGTFP, highlighting the significant role of enhanced environmental regulation in conveying the positive impact of technological innovation on AGTFP (Table 5).

Table 4. Regression results for agricultural green total factor productivity and environmental regulation in China.

Variable	$AGTFP_{it}$	ER_{it-2}	$AGTFP_{it}$
AST_{it}	0.030 ***	0.453 ***	0.031 ***
	(6.344)	(7.308)	(3.266)
AM_{it}	−0.001 ***	−0.001	−0.001 ***
	(−5.733)	(−1.220)	(−5.154)
ASI_{it}	−0.106	2.451 *	−0.176 **
	(−1.275)	(1.858)	(−2.093)
ASP_{it}	0.006 **	0.028	0.006 **
	(2.634)	(0.593)	(2.401)
RCP_{it}	0.003 **	0.007	0.003 *
	(2.199)	(0.369)	(2.035)
IPR_{it}	0.092	−0.303	0.164
	(0.948)	(−0.191)	(1.202)
ER_{it-2}			0.011 **
			(2.570)
_cons	0.772 ***	3.182 **	0.677 ***
	(7.113)	(2.107)	(4.954)
Observations	360	300	300
R^2	0.268	0.218	0.234
F statistic	18.47	12.44	14.09

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Sobel–Goodman test for mediating effect.

	Coefficient	Std. Error	Z-Value	*p*-Value
Indirect Effect	0.005	0.003	1.904	0.057
Direct Effect	0.031	0.007	4.179	0.000
Total Effect	0.036	0.007	5.152	0.000
Ratio of Indirect to Direct Effect			0.165	
Proportion of Mediating Effect in Total Effect			0.142	

Given the strict normal distribution assumption of the Sobel–Goodman test, a Bootstrap test with 1000 samples was conducted to robustly assess the mediating effect, overcoming the limitation of non-normal distribution of coefficient products. The Bootstrap test confirmed the mediating effect's significance [34], as the confidence intervals for the indirect effect did not include zero. Specifically, the mediating effect accounted for 14.1% of the total effect, closely aligning with the Sobel–Goodman findings and underscoring the crucial role of environmental regulation in linking agricultural technological innovation to AGTFP improvements (Table 6).

Table 6. Bootstrap test results.

	Estimate	Bias	Bootstrap Std. Error	95% Confidence Interval for Indirect Effect	
Indirect Effect	0.0051	0.0001	0.0028	0.0002	0.0112 [P]
				0.0001	0.0111 [BC]
Direct Effect	0.0311	0.0007	0.0071	0.0173	0.0453 [P]
				0.0186	0.0463 [BC]

4.2. Robustness Test

This study conducts a robustness test by lagging the explanatory variable, agricultural technological innovation (AST), by one period to re-examine its impact on agricultural green total factor productivity (AGTFP) and explore the potential mediating role of environmental regulation (ER). Table 7 presents the regression results from the fixed effects model analysis.

Table 7. Robustness analysis of environmental regulation's mediating effects on AGTFP.

Variable	$AGTFP_{it}$	ER_{it-2}	$AGTFP_{it}$
AST_{it-1}	0.030 ***	0.488 ***	0.032 ***
	(5.340)	(7.664)	(3.908)
AM_{it}	−0.001 ***	−0.001	−0.001 ***
	(−5.611)	(−1.073)	(−5.135)
ASI_{it}	−0.098	2.512 *	−0.160 *
	(−1.110)	(2.015)	(−1.901)
ASP_{it}	0.005 **	0.021	0.006 **
	(2.245)	(0.431)	(2.230)
RCP_{it}	0.002 *	0.001	0.002 *
	(1.930)	(0.028)	(1.894)
IPR_{it}	0.141	−0.419	0.159
	(1.193)	(−0.272)	(1.153)
ER_{it-2}			0.008 *
			(1.853)
_cons	0.772 ***	3.287 **	0.705 ***
	(6.758)	(2.241)	(5.291)
Observations	330	300	300
R^2	0.245	0.270	0.248
F statistic	13.84	12.22	13.88

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Model (1) shows that the one-period lagged AST significantly impacts AGTFP (coefficient = 0.030, significant at 1%), reinforcing the positive effect of agricultural innovation on AGTFP. Model (2) examines the impact of one-period lagged AST on ER lagged by two periods, with the AST coefficient being 0.488, significant at 1%, indicating that agricultural innovation significantly strengthens environmental regulation. In Model (3), considering both AST and ER's effects on AGTFP, the coefficient for AST slightly increases to 0.032, significant at 1%, while ER shows a significant impact at the 10% level with a coefficient of 0.008. These results not only reaffirm the direct positive influence of agricultural innovation on AGTFP but also provide evidence of ER's mediating role between agricultural innovation and AGTFP. The consistency with previous regression outcomes further validates the robustness of the study's findings.

5. Conclusions and Recommendations

This study, utilizing data from 2010–2021 across 30 Chinese provinces, meticulously examines the direct impact of agricultural technological innovation on agricultural green total factor productivity (AGTFP) and the mediating role of environmental regulation (ER). Using mediation analysis techniques such as the traditional three-step approach, Sobel–Goodman test, and Bootstrap methods, the findings underscore that firstly, agricultural technological innovation significantly boosts AGTFP, highlighting its critical role in enhancing agricultural efficiency and sustainability. Secondly, environmental regulation positively impacts AGTFP both directly and as a mediator, amplifying the effect of technological innovation on AGTFP. Based on these findings, the following policy recommendations are proposed:

1. Enhance Support for Agricultural Innovation. Governments and relevant institutions should increase investment in agricultural R&D, especially in technologies that improve resource efficiency and reduce environmental pollution. Promoting collaboration between academia, research, and industry is crucial for the rapid transformation and application of research outcomes. Establishing innovation platforms and incubators can provide resources and support for innovation teams, facilitating the commercialization of technological achievements and offering more support and training opportunities for agricultural producers.

2. Implement Effective Environmental Regulation Policies. Given the critical role of environmental regulation in stimulating technological innovation and enhancing AGTFP, further refinement of environmental protection laws is recommended, ensuring agricultural practices meet sustainability standards. Adopting flexible management measures tailored to the environmental capacity and agricultural development level of each region, alongside incentives such as tax breaks and subsidies, can encourage producers to adopt eco-friendly technologies and practices, achieving a green transformation in agriculture.
3. Strengthen Environmental Awareness and Science Education. To raise awareness of environmental protection and enhance the understanding and application of modern agricultural technologies among farmers and the public, the government should guide public education and outreach activities. Customized training programs in rural areas can teach agricultural technology knowledge and raise awareness of sustainable practices. Utilizing digital platforms can extend education coverage, enabling farmers in remote areas to access the latest knowledge and information, thus accelerating the adoption of green agricultural technologies.
4. Monitor and Evaluate the Effects of Environmental Regulation. Establishing a comprehensive monitoring and evaluation system is vital for assessing the effectiveness of environmental regulation policies periodically. Advanced monitoring technologies, such as remote sensing and geographic information systems (GIS), can provide accurate data for policymakers. By incorporating feedback from farmers, businesses, and environmental organizations, policymakers should adjust and optimize environmental regulation policies based on evaluation results and social feedback, ensuring their scientific validity and effectiveness, thereby maximizing the positive impact of environmental regulation.

6. Limitations of the Study and Future Work

While this study offers important insights into the effects of agricultural technological innovation and environmental regulation on agricultural green total factor productivity (AGTFP), several inherent limitations need recognition. Firstly, the scope of this research is confined to 30 provinces in China, spanning from 2010 to 2021. Consequently, the applicability of the results to other regions or differing time frames may be restricted. Future research endeavors should look to broaden both the geographical and temporal range to further substantiate the current study's conclusions. Secondly, although the application of mediation analysis provides a refined comprehension of the interplay between the variables, it does not establish causation. Potentially influential unobserved confounders may have impacted the results. Subsequent investigations would benefit from the employment of longitudinal data and experimental designs to ascertain causal linkages. Lastly, this investigation is based on data aggregated at the provincial level, potentially obscuring local discrepancies. Future research initiatives could leverage more detailed, municipal-level data to gain a more nuanced understanding of the variables at play.

Further studies should also consider the dynamic interplay between agricultural innovation and environmental regulation, taking into account the progressive nature of both technological advancements and regulatory landscapes. Exploring the influence of other potential mediators and moderators, including market dynamics and the repercussions of climate change, would likely yield a more expansive perspective of the forces shaping AGTFP.

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