



OPEN ACCESS

EDITED BY

Alex Oriol Godoy,
University for Development, Chile

REVIEWED BY

Maria Isabel Miguel,
University of Coimbra, Portugal
Hamza Taoumi,
Sidi Mohamed Ben Abdellah University,
Morocco

*CORRESPONDENCE

Zhihua Zeng,
✉ 22210201050002@hainanu.edu.cn

RECEIVED 25 August 2024

ACCEPTED 27 November 2024

PUBLISHED 16 December 2024

CITATION

He G and Zeng Z (2024) The impact of productive services on the technological complexity of agricultural exports and the moderating role of environmental regulations. *Front. Environ. Sci.* 12:1486254. doi: 10.3389/fenvs.2024.1486254

COPYRIGHT

© 2024 He and Zeng. This is an open-access article distributed under the terms of the [Creative Commons Attribution License \(CC BY\)](https://creativecommons.org/licenses/by/4.0/). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

The impact of productive services on the technological complexity of agricultural exports and the moderating role of environmental regulations

Guoping He and Zhihua Zeng*

School of International Business, Hainan University, Haikou, China

The integration of socialized services and green development are two major trends shaping modern agriculture. Similarly, the increasing technological complexity of exports has become a defining characteristic of contemporary agricultural trade. However, the relationship between agricultural services and the technological complexity of agricultural exports, as well as the potential influence of environmental regulations on this relationship, remains underexplored. This study utilizes provincial panel data from mainland China spanning 2007 to 2022 to investigate the impact of agricultural productive services on the technological complexity of agricultural exports. It also examines the mechanisms behind this impact and the moderating effects of different types of environmental regulations. The findings reveal that agricultural productive services significantly and robustly enhance the technological complexity of agricultural exports by fostering agricultural technological Advances and alleviating financial constraints. Furthermore, the study identifies varying moderating effects of environmental regulations. Command-and-control and voluntary public environmental regulations significantly amplify the positive impact of productive services on export complexity, whereas market-based environmental regulations show no significant effect. These findings suggest that promoting the development of agricultural services and optimizing environmental regulation policies are critical to enhancing the technological sophistication and sustainability of agricultural exports.

KEYWORDS

productive services, agricultural products, technological complexity of exports, technological advancement, agricultural financial constraints, environmental regulation

1 Introduction

The technological complexity of exports is a crucial indicator of the quality and efficiency of export products, reflecting their technological content and position in the global value chain (Bas and Strauss-Kahn, 2015; Ma et al., 2024; Yang et al., 2022). Since the 21st century, China's agricultural exports have grown rapidly. In 2001, the value of agricultural exports was \$16.07 billion, and by 2023, it had reached \$98.93 billion—an increase of 516%, with an average annual increase of 23.45%. This increase has positioned China as the fifth-largest agricultural exporter globally. Despite this progress, the technological complexity of these exports remains significantly lower than that of

developed agricultural countries (Yin and Tian, 2013). China's exports are dominated by primary agricultural products, limiting the sophistication of its exports. Given the country's large population and limited *per capita* agricultural resources, relying on primary agricultural exports is unsustainable. Therefore, improving the technological complexity of agricultural exports is essential for sustainable growth.

The 2024 Central Document No. 1 emphasizes the need to strengthen agricultural social services platforms and systems to build a modern agricultural management framework. Agricultural productive services are social services that directly or indirectly support various stages of agricultural production, from pre-production to post-production. These services play a crucial role in fostering new agricultural and rural economic activities, as well as in building a modern agricultural industrial, production, and management system. Green development, which aims to harmonize environmental protection with economic growth, is essential for achieving sustainable development. As an extension of the sustainable development concept, green development has been central to China's agricultural economic policies in the 21st century. Guided by this green philosophy, China has introduced several environmental regulations aimed at promoting sustainable agricultural practices. Given this context, it is important to examine how agricultural productive services influence the technological complexity of agricultural exports and whether this effect is moderated by environmental regulations. Understanding these dynamics is crucial for enhancing export sophistication and ensuring the long-term sustainability of agricultural exports. However, research exploring the combined impact of agricultural productive services and environmental regulations on the technological complexity of agricultural exports is relatively scarce (See Section 2). This study, based on provincial-level panel data from mainland China between 2007 and 2022, investigates the impact and mechanisms through which agricultural productive services affect the technological complexity of agricultural exports, as well as the moderating effects of different types of environmental regulations.

This paper contributes in two key ways. First, it extends the study of productive services' impact on export technological complexity to the agricultural sector, offering a detailed analysis of the pathways through which these services influence export complexity. Second, this research introduces environmental regulation as a moderating variable, exploring how different types of environmental regulations—command-and-control, market-based incentives, and voluntary public regulations—moderate the relationship between agricultural productive services and the technological complexity of agricultural exports. This provides valuable insights for policymakers aiming to support the development of agricultural productive services and adjust environmental regulations.

The structure of the paper is as follows: Section 2 reviews relevant literature and outlines the research theme; Section 3 provides a theoretical analysis of how productive services may influence export complexity and the potential moderating role of environmental regulations, and presents the research hypotheses; Section 4 measures the technological complexity of China's agricultural exports; Section 5 introduces the data sources, variable settings, and statistical descriptions of the sample;

Section 6 empirically tests the research hypotheses proposed in Section 3; Section 7 summarizes the study's conclusions; and Section 8 discusses the policy implications of the findings.

2 Literature review

2.1 Research on the impact of agricultural services on agricultural production

Existing literature on the role of agricultural productive services mainly examines their impact on agricultural production. Most studies have found that agricultural productive services help reduce production costs (Tang et al., 2018; Li et al., 2023), optimize resource allocation efficiency, and increase crop yields (Wu A. et al., 2024; Yitayew et al., 2023) and agricultural productivity (Niu and Li, 2024). Agricultural extension services, a key component of agricultural productive services (Kidd et al., 2000), have been extensively studied worldwide. For instance, Djurava et al. (2023) found that agricultural extension services improved technical efficiency and enhanced the economic benefits of wheat production for 323 wheat farmers in Uzbekistan. Similarly, Manda et al. (2024) analyzed data from 429 farmers in Tanzania and found that agricultural extension services significantly accelerated the adoption and level of new technologies. Alam et al. (2024) showed that agricultural extension services not only increased the adoption rate of technologies but also reduced production risks, with this effect being more pronounced among wealthier households.

As research progresses, some scholars have also identified a positive impact of agricultural productive services on green agricultural development. Studies have shown that agricultural productive services promote green total factor productivity in agriculture (Jiang et al., 2024) and low-carbon agricultural production (Wang et al., 2022; Lu et al., 2023), with the effect on agricultural carbon efficiency becoming more pronounced as urbanization increases (Shi et al., 2024). In terms of intermediary mechanisms, agricultural productive services primarily promote green development by fostering technological advancements and optimizing planting structures (Zhu et al., 2022; Wu B. et al., 2024). Xu et al. (2024) further found that agricultural productive services significantly enhanced agricultural environmental benefits by correcting factor misallocation. When agricultural factors are misallocated, the level of marketization plays a positive moderating role in this process.

Regarding different types of agricultural productive services, agricultural green finance services have been shown to significantly promote high-quality agricultural development by providing funding support for agricultural enterprises and alleviating research and development funding constraints. This effect is more pronounced in regions with higher levels of agricultural development and exhibits spatial spillover effects (Yuan et al., 2024; Bai and Li, 2024). Agricultural insurance services reduce the risk for farmers adopting green production technologies, alleviate financial constraints, and encourage increased investment in green technologies, thereby improving green total factor productivity in agriculture (Fang et al., 2021). The impact of agricultural insurance services strengthens as farm size increases

(Makate et al., 2019). Agricultural machinery services, by promoting non-farm employment and expanding farm scale, significantly increase farmers' adoption of green technologies, such as organic fertilizer, straw return, and no-tillage practices (Qing et al., 2023).

2.2 Research on the impact of agricultural productive services on the technological complexity of agricultural product exports

There has been limited exploration of the impact of agricultural productive services on the technological complexity of agricultural exports. For instance, Yao (2014) found that between 1980 and 2012, agricultural productive services did not significantly affect the technological complexity of China's agricultural exports. On the other hand, Lang and Liu (2019) found that agricultural productive services enhanced the technological complexity of agricultural exports in their sample countries. Among these services, those related to technology development had the most significant impact, followed by transportation, logistics, and storage services. Zhang and Lang (2024) studied provincial-level data from China between 2011 and 2020 and found that financial services significantly increased the technological complexity of China's agricultural exports by promoting technological innovation, industry integration, and human capital development. They noted that the marginal effect was increasing, though the spatial spillover effect was negative. The impact of financial services varied depending on agricultural product type, financial regulatory intensity, and the level of digital rural development. Li and Wang (2024) found that digital financial services significantly increased the technological complexity of agricultural exports, with this effect being notably stronger in the eastern region compared to the central and western regions. Additionally, the role of digital financial services was amplified by the internet and openness to foreign trade. They also examined the mediating role of marketization in this relationship.

2.3 Research on the impact of environmental regulations on agricultural production and export trade

Neoclassical economics posits that strict environmental regulations limit individual behaviors, increase production costs, and reduce industry competitiveness or productivity (Stephens and Denison, 1981; Gollop and Roberts, 1983). However, the "Porter Hypothesis" suggests that strict environmental regulations can promote the adoption of green technologies, thereby improving production efficiency. Many scholars have tested the "Porter Hypothesis" in the agricultural sector.

Research on the impact of environmental regulations on agricultural production has shown, from a micro perspective, that such regulations can increase farmers' willingness to adopt new technologies (Lu et al., 2021), particularly among village leaders' families and large-scale farming operations (Zeng et al., 2024). Guo et al. (2022) found that different types of environmental regulations influence farmers' adoption of green agricultural technologies differently, with the impact being stronger when social capital

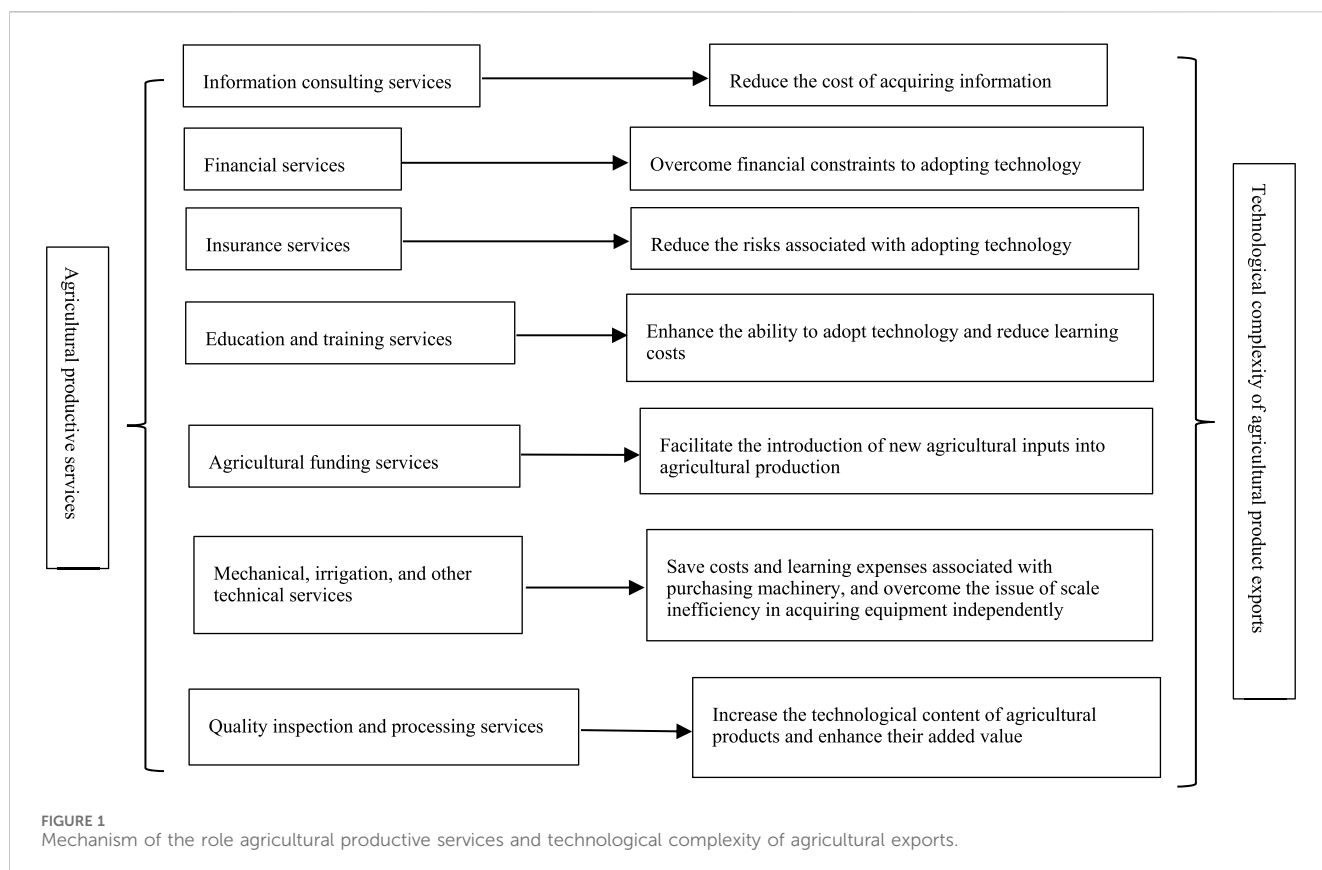
moderates farmers' attitudes. On a macro level, environmental regulations have been shown to improve agricultural productivity (Bokusheva et al., 2012). Both formal and informal environmental regulations significantly enhance companies' green total factor productivity, although the impact differs depending on the type of regulation (command-control vs. market-based incentives) (Liu et al., 2022). Huang et al. (2024), using the Super-SBM model to assess agricultural green growth in G20 countries, found that environmental regulations have a significant impact on agricultural technological innovation and green growth. The results indicate an inverted "U" relationship between environmental regulations and agricultural green growth, with a time lag in their effects.

In terms of environmental regulations' impact on agricultural exports, Runge and Nolan (1990) highlighted that as environmental and sanitary regulations increasingly shape international trade, their effects vary across countries, with developing nations disproportionately experiencing negative impacts (Pastiphatkul et al., 2021). Li and Zhu (2021) examined the certification process for agricultural products on e-commerce platforms under environmental regulations and developed a production function to assess their effects. Their research revealed that environmental regulations influenced the quality of agricultural products exported through the China-Pakistan Economic Corridor and shaped the competitiveness of export enterprises. Furthermore, strict environmental regulations have been linked to rising export prices and declining export volumes of Chinese horticultural products, leading to reduced international competitiveness (Peng et al., 2014). Conversely, other studies suggest a positive correlation between environmental regulations and agricultural export competitiveness (Xiong, 2020). Empirical evidence also indicates that in both the short and long term, stricter environmental regulations significantly boost agricultural export volumes (Yang, 2015).

As discussed earlier, much of the existing literature has focused on the effects of agricultural production services on agricultural production and the influence of environmental regulations on agricultural production and trade. However, there has been insufficient attention to how agricultural production services affect the technological complexity of agricultural exports, particularly regarding the role of environmental regulations in this relationship. This study aims to use provincial panel data from mainland China for the period 2007–2022 to analyze the impact and mechanisms of agricultural production services on the technological complexity of agricultural exports, especially examining the role of environmental regulations in this effect. The goal is to provide insights for policymakers in formulating relevant policies.

3 Theoretical analysis

Hausmann and Rodrik (2003) first introduced the concept of export technological complexity. He argued that in an open trade environment, countries naturally develop a trade pattern where high-tech nations export products with higher technological content, while low-tech nations export products with lower technological content. Export technological complexity reflects



the technological content of export products. In 2007, Hausmann et al. (2007) expanded this concept, indicating that export technological complexity is a comprehensive measure reflecting the technological content, export productivity, and added value of export products. Higher export technological complexity corresponds to higher technological content, added value, and export competitiveness. Rodrik (2006) further noted that the technological complexity of exports reflects a country's position in the international division of labor—the higher the complexity, the higher the country's position in the global value chain. Thus, export technological complexity is a comprehensive indicator of an economy's export product technology, added value, export competitiveness, and international division of labor status.

Traditional agriculture is mainly self-sufficient or semi-self-sufficient (He et al., 2022), with a narrow market scope. Producers generate their own seeds, fertilizers, and feed, and they primarily purchase simple tools like plows, hoes, and sickles from local markets while selling a small amount of primary agricultural products. The transactions are small-scale and infrequent, involving numerous trading partners with low transaction costs due to minimal monopolistic behavior.

However, as urbanization progresses, agricultural markets expand, leading to the development of long-distance transportation, contract transactions, and agricultural technology advancements. The introduction and widespread use of high-quality seeds, chemical fertilizers, pesticides, and agricultural machinery (Perelman, 1973; Vasil'ev, 1969; Qian et al., 2022), along with increasing consumer demands for higher-quality and processed agricultural products, have driven agricultural specialization.

Agricultural input production, agricultural services, and agricultural product processing and transportation have gradually separated from traditional agricultural production, giving rise to specialized agricultural input production organizations, agricultural product processing organizations, and agricultural service organizations. Producers have become specialized in primary agricultural production. The technological complexity of agricultural exports relies on the supply of new inputs, technologies, and production methods, as well as the adoption of these by operators (Eck and Huber, 2016). Small-scale farmers, in particular, often face constraints in adopting new inputs, technologies, and production methods due to limitations in information, capital, risk, human capital, and scale of operations. As shown in Figure 1, agricultural productive services influence the technological complexity of agricultural exports through several pathways:

- (1) Information consulting services: Specialized agricultural service organizations have a clear advantage in collecting and analyzing information. This enables producers to stay informed about new inputs, technologies, and production methods, helping them make timely decisions on whether to adopt these innovations. Information consulting services support producers in selecting the most suitable technologies, thereby improving agricultural productivity. Additionally, these services provide valuable feedback to researchers, allowing them to refine and enhance agricultural technologies based on the needs and experiences of producers (Varshney et al., 2022; Yitayew et al., 2023).

- (2). **Financial Services:** Financial services help overcome capital constraints faced by agricultural operators, particularly small farmers, enabling them to adopt new inputs, technologies, and production methods. [Abate et al. \(2016\)](#), through their study of Ethiopian farmers, found that financial services not only alleviate the funding constraints faced by farmers by providing them with capital to purchase advanced inputs, but also enhance their willingness to adopt modern technologies.
- (3). **Insurance Services:** Agricultural insurance plays a crucial role in mitigating the risks associated with both natural and socio-economic instability, particularly in risk transfer and compensation for losses from natural disasters. On one hand, agricultural insurance reduces the research and development risks for technology firms, providing a safeguard for agricultural technological progress ([Fu et al., 2024](#); [Luo and Wei, 2023](#); [Hao, 2015](#)). On the other hand, agricultural insurance helps reduce the risks faced by farmers, especially smallholders, when adopting new inputs, technologies, and production methods. By reducing income uncertainty, it helps maintain farmers' enthusiasm for agricultural production, thereby supporting the sustainable development of agriculture ([Zhang et al., 2020](#)).
- (4). **Education and Training Services:** Service organizations improve producers' ability to adopt new inputs, technologies, and production methods through education and training. This not only directly enhances their capacity but also reduces the learning costs associated with adopting innovations. Additionally, trained farmers often exhibit spillover effects, as they use their social networks to encourage other farmers to participate in training, thereby increasing the willingness and ability of a broader group of farmers to adopt new technologies.
- (5). **Supply of Agricultural Funding:** Agricultural inputs are essential for increasing production and income in farming. Service organizations have a distinct advantage in the procurement and promotion of agricultural inputs, facilitating the rapid integration of new inputs into farming practices. These organizations provide farmers with direct access to manufacturers, offer tailored solutions, and ensure the delivery of high-quality, cost-effective, and environmentally friendly inputs that enhance efficiency and productivity.
- (6). **Machinery, Irrigation, and Other Technical Services:** The adoption of agricultural mechanization, modern irrigation, and some modern agricultural technologies requires significant capital investment and higher human capital, and is constrained by operational scale. For instance, when operational scale is small, purchasing large machinery may not be economically viable ([Thapa and Gaiha, 2014](#)). Service organizations provide machinery, irrigation, and technical services (such as drip and sprinkler irrigation, soil testing and fertilizer recommendations, resource utilization of animal waste, and integrated pest management), saving producers the cost of purchasing equipment and learning, and overcoming the inefficiency of purchasing large machinery.
- (7). **Quality Inspection and Processing Services for Agricultural Products:** Quality inspection and processing services not only enhance the technological content of agricultural products but also significantly increase their added value ([Si et al., 2018](#)), improving product competitiveness and positioning in the international division of labor.

Based on the above analysis, the following research hypotheses can be proposed:

Hypothesis 1. Agricultural productive services have a positive impact on the technological complexity of agricultural exports.

Hypothesis 2. Agricultural productive services enhance the technological complexity of agricultural exports by promoting advancements in agricultural technology.

Hypothesis 3. Agricultural productive services also increase the technological complexity of agricultural exports by alleviating financial constraints in agriculture.

Pursuing the “servitization” and “greening” of agricultural production is a key strategy for achieving sustainable agricultural development in China. Environmental regulation refers to the constraints imposed by the government to protect the environment through direct or indirect interventions in resource utilization by producers via administrative regulations, economic incentives, and environmental awareness initiatives ([Gibbs et al., 2000](#)). Within the framework of the “Porter Hypothesis,” in the industrial sector, the entities subject to environmental regulation are also those responsible for technological innovation. Thus, the costs of complying with environmental regulations are closely linked to corporate technological innovation, leading to both “compliance cost” effects and “innovation compensation” effects ([Barbera and McConnell, 1990](#); [Porter and Van der Linde, 1995](#)). In the agricultural sector, however, the primary entities subject to environmental regulation are farmers, while the responsibility for agricultural technological innovation typically falls on the government, agricultural extension services, and other related organizations. Agricultural service organizations play a crucial role in providing farmers with advanced inputs, production methods, and technologies. Environmental regulations, in turn, influence the research and development investments of these service organizations in agricultural technology and production methods, thereby moderating the impact of agricultural productive services on the technological complexity of agricultural exports.

On the one hand, environmental regulation exerts a “compliance cost” effect. The costs associated with environmental management, including the purchase of clean production inputs, pollution control, and environmental restoration, are borne jointly by farmers and agricultural service organizations. For farmers, increased environmental management costs may crowd out investments in agricultural machinery services, human capital training services, and agricultural product processing services ([Shadbegian and Gray, 2005](#)), thereby reducing the technological

content of agricultural products and leading to a decline in the technological complexity of agricultural exports. For agricultural service organizations, the large upfront investments and long development cycles required for clean production technologies (Boyd and McClelland, 1999) can impose short-term financial burdens, potentially affecting the quality of other productive services.

On the other hand, environmental regulation also exhibits an “innovation compensation” effect. As the intensity of environmental regulation increases, agricultural service organizations are compelled to address issues such as low resource utilization efficiency and high pollution emissions in their production processes. This drives them to develop and provide new production technologies that optimize resource allocation, reduce emissions, and enhance product value. In the long term, stricter environmental regulations encourage agricultural producers to adopt cleaner and greener production technologies, which, by increasing the added value and technological content of agricultural products, improve the technological complexity of agricultural exports (Hamamoto, 2006; Larrán Jorge et al., 2015). Based on these considerations, the following hypothesis is proposed:

Hypothesis 4. The environmental regulation plays a moderating role in the impact of agricultural productive services on the technological complexity of agricultural exports.

4 Estimation of the technical complexity of agricultural exports

4.1 Estimation method

Currently, there are two main methods for measuring the technological complexity of exports. The first is the absolute share-weighting method proposed by Spraos and Michaely (1985), which is based on the theory of comparative advantage. The second is the relative share-weighting method, introduced by Dani et al. (2006) and Hausman et al. (2007), which is grounded in the theory of revealed comparative advantage. Both methods assume a strong correlation between the technological content of export products and the national income level. The absolute share-weighting method uses the share of export products in the international market as the weight. However, this approach may underestimate the technological complexity of exports from smaller countries that have a comparative advantage in specific products, even if their overall export volumes are low. In contrast, the relative share-weighting method addresses this issue by calculating the relative share of products using the revealed comparative advantage index. This method corrects for potential underestimation of export technological complexity in smaller countries and reduces bias arising from uneven regional distribution. Therefore, this paper follows the approach of Xu et al. (2022) and adopts the relative share-weighting method to measure export technological complexity. This method involves three steps:

The first step and second steps are to calculate the revealed comparative advantage index for products, as described in Formulas 1, 2.

$$EXRCA_{ij} = \frac{EX_{ij}/EX_j}{\sum_{j=1}^m EX_{ij} / \sum_{j=1}^m EX_j} \quad (1)$$

In Formula 1, $EXRCA_{ij}$ represents the relative weight of product i in region j , EX_{ij} is the export value of product i in region j , EX_j is the total export value of products in region j , and m is the number of sample regions.

$$EXTSI_j = \sum_{j=1}^m EXRCA_{ij} \times GDP_j \quad (2)$$

The indicators in Formula 2 have the same meanings as those in Formula 1.

The third step is to calculate the export technological complexity at the regional level, as described in Formula 3.

$$EXPYIT_j = \sum_{i=1}^n \frac{EX_{ij}}{\sum_{i=1}^n EX_{ij}} \times EXTSI_j \quad (3)$$

In Formula 3, $EXPYIT_j$ represents the export technological complexity of region j ; n is the number of products; the meanings of the other indicators are the same as those in Formula 2.

4.2 The technological complexity of agricultural exports in Chinese provinces

This study uses data from the General Administration of Customs of China, covering HS01-HS24, HS51, and HS52 product codes, to calculate the technological complexity of agricultural exports from China’s provincial regions for the years 2007–2022. Due to data limitations, Beijing, Shanghai, and Xizang are excluded, leaving a total of 28 provinces, autonomous regions, and municipalities.

As shown in Figure 2, the overall technological complexity of China’s agricultural exports has demonstrated a steady upward trend, increasing from 19.261 thousand yuan in 2007 to 77.703 thousand yuan in 2022, representing a 303% growth. The growth rate was relatively high from 2007 to 2011, with an average annual increase exceeding 15%. However, there was a notable decline in 2009 due to the impact of the global financial crisis. From 2012 to 2020, the growth rate trended downward, falling from 10.8% in 2012 to 2.7% in 2020. In 2021, as the global economy began to recover following the COVID-19 pandemic, there was a small peak in the growth rate of agricultural export technological complexity, reaching 12.7%.

From a provincial distribution perspective, as shown in Figure 3, by 2022, Jiangsu and Zhejiang in the Yangtze River Delta region, along with Hainan, which focuses on tropical crops and aquatic products, ranked highest with values of 85.92 thousand yuan, 85.91 thousand yuan, and 83.21 thousand yuan, respectively. Conversely, Guizhou, primarily mountainous, had the lowest value at 66.72 thousand yuan. Regarding the average growth rate

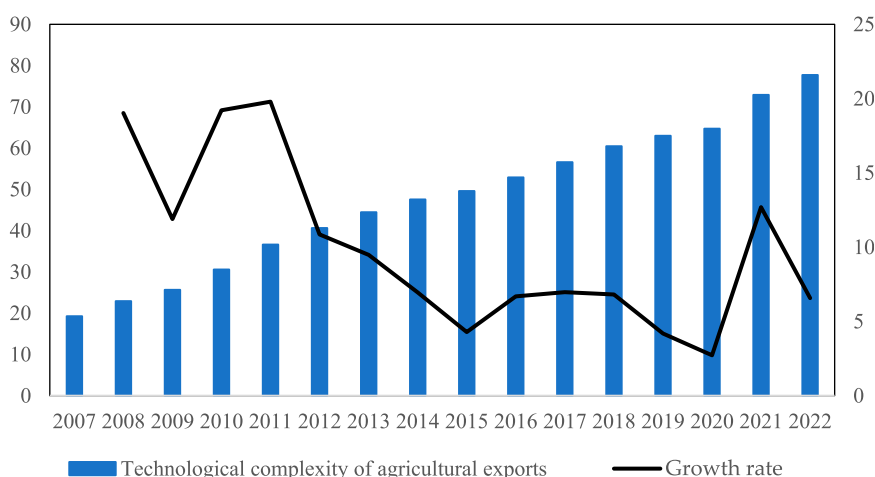


FIGURE 2 Changes in the technological complexity of China’s agricultural product exports. Note: The left axis represents the technological complexity of agricultural exports. The right axis represents the growth rate.

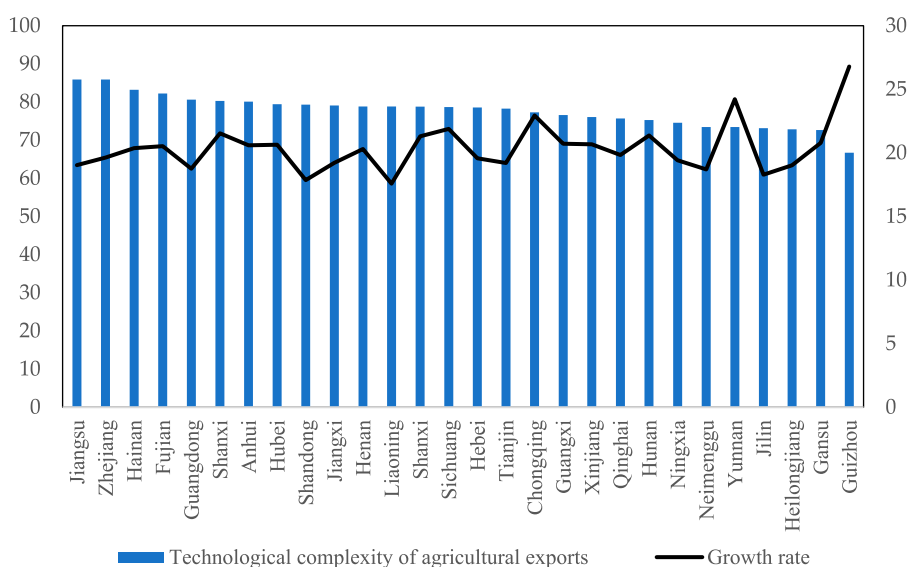


FIGURE 3 Technological Complexity of Agricultural Exports and Average Annual Growth Rate by Province in China. Note: The left axis represents the technological complexity of exports in 2022. The right axis represents the average annual growth rate.

from 2007 to 2022, Guizhou experienced the fastest growth at 26.79%, followed by Yunnan at 24.22%. Provinces such as Liaoning, Shandong, and Jilin had more moderate growth rates, at 17.58%, 17.86%, and 18.28%, respectively.

5 Data and variable

5.1 Data sources

This study utilizes provincial-level panel data from China for the period 2007–2022. Due to significant data missing for Beijing,

Shanghai, and Tibet, and difficulties in obtaining data for Hong Kong, Macau, and Taiwan, the research scope is limited to 28 provincial-level administrative regions, excluding Beijing, Shanghai, Tibet, and Hong Kong, Macau, and Taiwan. Specifically, data on agricultural trade are sourced from the General Administration of Customs of China; agricultural R&D investment data are obtained from the “China Science and Technology Statistical Year-book”; rural loan data are from the “China Rural Financial Services Report”; data on agricultural technology patents are retrieved from the China National Knowledge Infrastructure (CNKI) patent database; data on environmental protection-related administrative penalties and

public complaints are from the “China Environmental Yearbook”; and data on primary industry employment, arable land area, crop sowing area, effective irrigation area, total output value of agriculture, forestry, animal husbandry, and fishery, and fixed asset investment in agriculture, forestry, animal husbandry, and fishery are sourced from the “China Business Statistical Yearbook,” the “China Statistical Yearbook,” the “China Rural Statistical Yearbook,” and various provincial statistical yearbooks.

5.2 Variable definitions and statistical description

5.2.1 Dependent variable

Export technological complexity of agricultural products (Expyit), measured using the relative share weighting method (see Section 4 for details). In the sample, the mean value of agricultural exports technological complexity is 51.352 thousand yuan, with a maximum of 94.798 thousand yuan and a 256 minimum of 16.987 thousand yuan.

5.2.2 Independent variable

Agricultural Productive Service Level (Ser), Currently, there is a lack of systematic statistics on agricultural productive services for Chinese provinces (including autonomous regions and municipalities). Previous studies have used the output value of agriculture, forestry, animal husbandry, and fishery services as a proxy. This study adopts the approach of Zhang and Guo (2021), using the ratio of total output value of these services to total crop planting area to reflect the level of agricultural productive services. In the sample, the mean value is 2.994 thousand yuan per hectare, with a maximum of 15.927 thousand yuan per hectare and a minimum of 0.298 thousand yuan per hectare.

5.2.3 Control variables

Agricultural Research and development Investment (R&D), This is a key factor influencing agricultural technology supply and thus impacts the technological complexity of agricultural exports (Wang and Wei, 2008). The mean value of agricultural R&D investment in the sample is 5.5884 billion yuan, with a maximum of 30.3844 billion yuan and a minimum of 6.1009 billion yuan.

Agricultural Fixed Asset Investment Intensity (Invest), This is measured as the total fixed asset investment in agriculture, forestry, animal husbandry, and fishery divided by the total crop planting area. Higher investment intensity indicates greater capital and technological intensity in agriculture. The mean value is 14.929 thousand yuan per hectare, with a maximum of 125.019 thousand yuan per hectare and a minimum of 0.646 thousand yuan per hectare.

Rural Human Capital Level (Hum), This is measured by the nominal *per capita* human capital in rural areas, with data from “The China Human Capital Report.” Higher human capital level enhance the adoption of new inputs, technologies, and production methods, influencing the technological complexity of agricultural exports (Che and Zhang, 2018). The mean value is 480.87 thousand

yuan, with a maximum of 1,092.16 thousand yuan and a minimum of 146.34 thousand yuan.

Agricultural Labor Input Intensity (Lab), This is measured as the number of laborers in primary industry divided by the crop planting area. The scarcity of agricultural labor leads to higher labor costs. Consequently, producers are more inclined to adopt more capital and advanced technologies to replace labor, thus enhancing the technological complexity of their products. Therefore, agricultural labor input significantly influences the technological complexity of agricultural exports. The mean value is 16.308 thousand persons per hectare, with a maximum of 36.327 thousand persons per hectare and a minimum of 3.254 thousand persons per hectare.

Irrigation Conditions (Inst), This is measured by the proportion of effective irrigation area to the total crop planting area (%). Better irrigation conditions can reduce agricultural production costs and adjustment costs, potentially affecting the technological complexity of agricultural exports. The mean value is 41.426%, with a maximum of 99.362% and a minimum of 17.191%.

5.2.4 Mediating variables

Agricultural technological progress (Tech), This is reflected by the number of agricultural technology patents. Patent numbers are a leading indicator of technological advancement and can reflect the level of scientific and technological progress in society (Griliches, 1990). The mean in the sample is 23.673, with a maximum value of 166.51 and a minimum value of 0.06.

Effect of Agricultural Productive Services on Alleviating Funding Constraints (Fina), Measured by the amount of loans used per unit of total agricultural output value. The mean value is 0.645 billion yuan per billion yuan of agricultural output, with a maximum of 6.634 billion yuan and a minimum of 0.039 billion yuan.

5.2.5 Moderating variables

Environmental regulations can be classified into three categories: command-control regulations, market-based regulations, and public-voluntary regulations (Blackman et al., 2010). This study investigates how each type of environmental regulation moderates the impact of agricultural productive services.

Command-Control Environmental Regulations (Ger) are quantified by the number of administrative penalty cases related to environmental protection. This metric reflects the extent of enforcement and regulatory authority as established by national standards and is a key indicator of the rigor of environmental laws and management practices (Cole et al., 2008). In the sample, the average number of cases is 41.617 hundred, with a maximum of 451.4 and a minimum of 0.26.

Market-Based Environmental Regulations (Mer) are evaluated based on the implementation of carbon trading markets across different provinces, given the lack of official data on pollution fees and environmental protection expenditures in agriculture. Following Yang et al. (2017), a value of 1 is assigned if a carbon trading market is operational in the province, and 0 otherwise.

Public-Voluntary Environmental Regulations (Per) are assessed by the number of public complaints and reports concerning environmental issues, as adapted from Dasgupta and Wheeler

TABLE 1 Summary statistics.

Variable	Mean	Standard deviation	Minimum	Maximum
Expyit	51.352	18.286	16.987	94.798
Ser	2.994	2.316	0.298	15.927
R&D	55.884	61.099	0.064	303.844
Invest	14.929	17.385	0.646	125.019
Hum	48.087	19.051	14.634	109.216
Lab	16.308	6.603	3.254	36.37
Inst	41.426	15.894	17.191	99.362
Tech	23.673	30.013	0.06	166.51
Fina	0.645	0.668	0.039	6.634
Ger	41.617	60.025	0.26	451.4
Mer	0.103	0.304	0	1
Per	85.491	138.221	0.5	1,153.92

TABLE 2 Basic regression results.

	(1)	(2)
Ser	0.686 *** (0.104)	0.469 *** (0.104)
R&D		0.014 *** (0.005)
Invest		0.017 *** (0.009)
Hum		0.028 (0.027)
Lab		-0.003 (0.004)
Inst		0.009 (0.019)
Constant	49.297 *** (0.321)	47.775 *** (1.426)
N	448	448
Control	No	Yes
Year	Yes	Yes
Region	Yes	Yes
R-squared	0.159	0.224

Notes: Robust standard errors are shown in parentheses; * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

(1997). In the sample, the average is 85.491 hundred cases, with a maximum of 1,153.92 and a minimum of 0.5.

The statistical description of each variable is shown in Table 1.

6 Empirical results

6.1 Model setting

Given that the data in this study comprises unbalanced provincial panel data, we follow the approach of Custódio and Metzger (2014) and apply the Hausman test to determine the appropriate model between fixed effects and random effects. The test results show a p-value of less than 0.001, indicating that the null hypothesis of choosing a random effects model is rejected at the 1% significance level. Therefore, the fixed effects model is deemed appropriate for regression estimation in this study:

$$Expyit_{it} = \alpha_0 + \beta_1 Ser_{it} + \beta_2 Control_{it} + \vartheta_i + \mu_t + \varepsilon_{it} \quad (4)$$

In this model (Equation 4), $Expyit_{it}$ represents the technological complexity of agricultural exports in province i during year t . The explanatory variable Ser_{it} denotes the level of productive services in province i during year t . $Control_{it}$ is a vector of control variables. ϑ_i , μ_t and ε_{it} represent the individual fixed effects, time fixed effects, and random disturbance term, respectively.

6.2 Basic regression

As shown in Table 2, agricultural productive services (Ser) have a positive impact on the technological complexity of agricultural exports (Expyit) at the 1% significance level, aligning with the research hypothesis 1. An increase of 1,000 yuan/hectare in agricultural productive services input corresponds to an average increase of 0.469 thousand yuan in the technological complexity of agricultural exports (see Model (2)).

Regarding control variables, both agricultural R&D investment (R&D) and agricultural fixed asset investment (Invest) have positive impacts on the technological complexity of agricultural exports at the 1% and 5% significance level, respectively. This is because

TABLE 3 Robustness test results.

	(1)	(2)	(3)
Ser	0.469 ** (0.187)	0.448 *** (0.001)	0.479 *** (0.104)
Contant	20.844 *** (2.171)	48.482 *** (2.119)	48.079 *** (1.301)
N	448	448	448
Control	Yes	Yes	Yes
Year	Yes	Yes	Yes
Region	Yes	Yes	Yes
R-squared	0.224	0.187	0.224

Notes: Robust standard errors are shown in parentheses; * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

agricultural R&D investment is a crucial factor influencing the supply of agricultural technology, and higher agricultural fixed asset investment intensity indicates greater capital and technological intensity in agriculture. Rural human capital level (Hum) and irrigation conditions (Inst) also positively impact the technological complexity of agricultural exports, whereas agricultural labor input intensity (Lab) has a negative impact, though none of these effects are statistically significant. This lack of significance may be attributed to the relatively small variations in rural human capital level, irrigation conditions, and agricultural labor input intensity across most Chinese provinces, leading to data distributions that are too concentrated to demonstrate distinct impacts on the technological complexity of agricultural exports.

6.3 Robustness test

6.3.1 Cluster-robust standard errors

As shown in Table 3, Model (1), the regression results using cluster-robust standard errors indicate that the level of agricultural productive services continues to have a positive impact on the technological complexity of agricultural exports at the 5% significance level.

6.3.2 Exclusion of special years

By excluding data from the 2008–2009 financial crisis and the 2020–2021 COVID-19 pandemic, a new regression was conducted, as seen in Table 3, Model (2). The results demonstrate that agricultural productive services still positively influence the technological complexity of agricultural exports at the 1% significance level, with minimal changes in the coefficient size.

6.3.3 Winsorization of variables

To account for potential outliers in the sample, all continuous variables were winsorized at the 1% level on both tails before regression. The results, shown in Table 3, Model (3), reveal that the level of agricultural productive services remains positively significant at the 1% level, with little change in the coefficient size.

6.3.4 Quantile regression

To explore whether the effect of agricultural productive services on the technological complexity of agricultural exports differs across various levels, we apply the quantile regression technique introduced by Koenker and Bassett (1978). We analyze four quantiles of agricultural productive services (0.25, 0.5, 0.75, and 0.9). The results, detailed in Table 4, demonstrate that agricultural productive services positively influence the technological complexity of agricultural exports at all quantiles (0.25, 0.5, 0.75, and 0.9) with statistical significance at the 1% level. In conclusion, the evidence supports the robustness of the finding that agricultural productive services exert a significant positive effect on the technological complexity of agricultural exports, consistent across different quantile levels and methodological approaches.

6.4 Endogeneity test

Two-Stage Least Squares (2SLS) Methodology: To address endogeneity concerns, we adopt the method proposed by Zhang and Guo (2021), using one-period lagged agricultural productive services (L1.Ser) as an instrumental variable. The results from the 2SLS estimation are summarized in Table 5. **First-Stage Results:** The instrument, L1.Ser, shows a strong correlation with the core explanatory variable at the 1% significance level, meeting the relevance criterion for an instrumental variable. **Second-Stage Results:** Both the K-P LM statistic and the Wald F statistic reject the null hypothesis with high significance, confirming the validity of the instrumental variable. The coefficient for agricultural productive services is estimated at 0.511, remaining significantly positive at the 1% confidence level. This result is consistent with the baseline regression findings, reinforcing the robustness of our conclusions.

6.5 Mechanism analysis

6.5.1 Testing methods

As mentioned earlier, agricultural productive services increase the technological complexity of agricultural exports through two main channels: promoting agricultural technological advancements

TABLE 4 Quantile regression test.

	0.25	0.5	0.75	0.9
Ser	0.464***	0.469 **	0.448 ***	0.479 ***
	(0.139)	(0.187)	(0.001)	(0.104)
N	448	448	448	448
Control	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes

Notes: Robust standard errors are shown in parentheses; * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

TABLE 5 Endogeneity test.

	First-stage	Second-stage
Ser		0.511 ***
		(0.111)
L1.Ser	1.098 ***	
	(0.048)	
K-P LM		32.428 ***
		(0.001)
Wald F		522.406
N	420	420
Control	Yes	Yes
Year	Yes	Yes
Region	Yes	Yes
R-squared		0.2359

Notes: Robust standard errors are shown in parentheses; * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

and alleviating financial constraints in agriculture (see Hypotheses 2 and 3 in Section 2). To test these hypotheses, we use the three-step method proposed by Baron and Kenny (1986) and construct the following econometric model. We construct the following econometric model Equations 5–9:

Step 1: Examining the Impact of Agricultural Productive Services on Technological Complexity of Agricultural Exports.

$$Expyit_{it} = \alpha_0 + \beta_1 Ser_{it} + \beta_2 Control_{it} + \vartheta_i + \mu_t + \varepsilon_{it} \quad (5)$$

Step 2: Examining the Impact of Agricultural Productive Services on Technological Advances and alleviation of agricultural financial constraints.

$$Tech_{it} = \alpha_0 + \beta_1 Ser_{it} + \beta_2 Control_{it} + \vartheta_i + \mu_t + \varepsilon_{it} \quad (6)$$

$$Fina_{it} = \alpha_0 + \beta_1 Ser_{it} + \beta_2 Control_{it} + \vartheta_i + \mu_t + \varepsilon_{it} \quad (7)$$

Step 3: Examining the Impact of Technological Advances and alleviation of agricultural financial constraints on Agricultural Export Technological Complexity.

$$Expyit_{it} = \alpha_0 + \beta_1 Ser_{it} + \beta_1 Tech_{it} + \beta_2 Control_{it} + \vartheta_i + \mu_t + \varepsilon_{it} \quad (8)$$

$$Expyit_{it} = \alpha_0 + \beta_1 Ser_{it} + \beta_1 Fina_{it} + \beta_2 Control_{it} + \vartheta_i + \mu_t + \varepsilon_{it} \quad (9)$$

In the above, $Tech_{it}$ and $Fina_{it}$ represent Technological Advances and alleviation of agricultural financial constraints for province i at time t , respectively. All other variables remain consistent with the baseline model.

6.5.2 Mediation effect test of agricultural technological advances

As shown in Table 6, agricultural productive services significantly promote agricultural technological advancements at the 5% significance level (see Column 2). Furthermore, technological advancements significantly increase the technological complexity of agricultural exports at the 5% significance level (see Column 3). This confirms Hypothesis 2 proposed in Section 2, indicating that agricultural technological progress is an important mediator through which agricultural productive services affect the technological complexity of agricultural exports.

6.5.3 Mediation effect test of alleviating financial constraints

As shown in Table 7, agricultural productive services significantly alleviate agricultural financing constraints (at the 5% significance level, see Column 2); the alleviation of financial constraints significantly enhances the technological complexity of agricultural exports (at the 1% significance level, see Column 3). This confirms Hypothesis 3 proposed in Section 3, indicating that alleviating agricultural financial constraints is an important mediator through which agricultural productive services affect the technological complexity of agricultural exports.

6.6 Moderating effect analysis

Theoretical analysis suggests that environmental regulations may have a moderating effect on the relationship between agricultural productive services and the technological complexity of agricultural exports. Therefore, a regression test is conducted to examine the moderating effect of environmental regulations. To reduce the impact of multicollinearity and improve the reliability of the empirical results, agricultural productive services (Ser) and the three types of environmental regulations—command-and-control

TABLE 6 Mediation effect test results of agricultural technological advances.

	(1)	(2)	(3)
	Expyit	Tech	Expyit
Ser	0.469 ***	1.184 **	0.449 ***
	(0.104)	(0.611)	(0.103)
Tech			0.016 **
			(0.008)
Contant	47.775 ***	-2.673	47.817 ***
	(1.426)	(14.294)	(1.353)
N	448	448	448
Control	Yes	Yes	Yes
Year	Yes	Yes	Yes
Region	Yes	Yes	Yes
R-squared	0.224	0.275	0.267

Notes: Robust standard errors are shown in parentheses; * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

TABLE 7 Mediation effect test results of alleviating financial constraints.

	(1)	(2)	(3)
	Expyit	Fina	Expyit
Ser	0.469 ***	0.043 **	0.399 ***
	(0.104)	(0.023)	(0.096)
Fina			1.644 ***
			(0.173)
Contant	47.775 ***	1.114 ***	45.943
	(1.426)	(0.347)	(1.309)
N	448	448	448
Control	Yes	Yes	Yes
Year	Yes	Yes	Yes
Region	Yes	Yes	Yes
R-squared	0.224	0.172	0.312

Notes: Robust standard errors are shown in parentheses; * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

(Ger), market-based incentives (Mer), and voluntary public regulations (Per)—are centered before regression. The regression results are presented in Table 8.

Column (1) shows the regression results for command-control environmental regulations (Ger). The interaction term ($c_Ser \times c_Ger$) has an estimated coefficient of 0.001, which is significant at the 1% level, indicating a positive moderation effect on the relationship between agricultural productive services and the technological complexity of agricultural exports. Command-control environmental regulations are government-imposed measures that specify pollution standards for agricultural producers through laws

and regulations, increasing the input costs for farmers and agricultural service organizations. The positive coefficient suggests that the “compliance cost” effect of command-control environmental regulations in China is currently less than the “innovation compensation” effect. This means that the economic benefits of R&D and innovation in green production methods and clean technologies by agricultural service organizations exceed the costs, and the economic benefits for farmers from adopting green production methods also surpass the costs. Consequently, this strengthens the role of agricultural productive services, leading to increased technological content and added value of agricultural products.

TABLE 8 Moderating effect analysis.

	(1)	(2)	(3)
	Command-control	Market-based	Public-voluntary
c_Ser	0.479 *** (0.129)	0.521 *** (0.097)	0.595 *** (0.133)
c_Ger	-0.001 (0.001)		
c_Ser × c_Ger	0.001 *** (0.000)		
c_Mer		0.598 ** (0.306)	
c_Ser × c_Mer		-0.069 (0.107)	
c_Per			0.001 (0.001)
c_Ser × c_Per			0.001 *** (0.000)
Contant	43.084 *** (1.829)	49.419 *** (1.539)	43.018 *** (1.801)
N	364	448	364
Control	Yes	Yes	Yes
Year	Yes	Yes	Yes
Region	Yes	Yes	Yes
R-squared	0.192	0.229	0.199

Notes: Robust standard errors are shown in parentheses; * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Column (2) presents the regression results for market-based environmental regulations (Mer). The interaction term ($c_Ser \times c_Mer$) is not significant. This may be due to the relatively short history of the carbon emissions trading market in China, the limited number of participating provinces, and the imperfect market mechanism. As of 2021, only Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Fujian were participating in the carbon trading market, with other provinces joining only gradually. According to the “China Carbon Balance Trading Framework Research Report,” agricultural carbon sinks account for 20% of the total and are steadily increasing, indicating significant potential for emissions reduction. However, China’s agricultural carbon market is still in its early stages of development, and thus, the moderating effect of market-based environmental regulations on agricultural productive services is not yet significant. As the agricultural carbon market develops, the positive moderating effect of market-based environmental regulations is expected to improve.

Column (3) shows the regression results for public voluntary environmental regulations (Per). The interaction term ($c_Ser \times c_Per$) is positive and significant at the 1% level, indicating a positive moderating effect. Although the proportion of public voluntary

environmental regulations is currently low, as an informal institution, voluntary environmental regulations often yield high returns with relatively low investments. Increased public awareness of environmental protection and pollution not only enhances the willingness to adopt green technologies but also creates a “spillover effect.” As awareness of agricultural green development improves in a region, it promotes higher levels of green development awareness in surrounding areas, thus increasing the adoption of green technologies and strengthening the role of agricultural productive services.

7 Conclusion

The development of agricultural “servitization” and “greening” is key to achieving sustainable agricultural development. While much of the existing literature has focused on the role of agricultural productive services in agricultural production and the impact of environmental regulations on agricultural production and trade, the effect of agricultural productive services on the technological complexity of agricultural exports has not received sufficient attention. Moreover, the role of environmental regulations

in this process remains largely unexplored. This paper uses provincial panel data from mainland China between 2007 and 2022 to examine the impact and mechanisms through which agricultural productive services influence the technological complexity of agricultural exports, as well as the moderating effects of different types of environmental regulations.

The study finds that agricultural productive services have a significant and robust positive impact on the technological complexity of agricultural exports. The promotion of agricultural technological progress and the alleviation of financial constraints are key pathways through which agricultural productive services influence export complexity. Furthermore, different types of environmental regulations have varying moderating effects on this relationship. Specifically, command-and-control and voluntary public environmental regulations significantly strengthen the positive effect of agricultural productive services on the technological complexity of agricultural exports, whereas market-based environmental regulations have no significant effect. Additionally, investment in agricultural fixed assets and research and development contributes to increasing the technological complexity of agricultural exports, while labor input in agriculture negatively impacts export complexity.

8 Policy implications

Based on the findings of this study, the following policy implications are proposed:

First, Leverage the Promoting Role of Agricultural Productive Services on Export Technological Complexity. The government should continue to advance the high-quality development of agricultural productive services. Relevant preferential policies should be implemented, and financial and credit support measures should be adopted to support the development of various agricultural service organizations. Additionally, strengthening the construction of agricultural internet and big data infra-structure to improve the information acquisition capabilities of agricultural practitioners is crucial. Guidance on reasonable use of land and property for mortgages to address funding difficulties in purchasing agricultural productive services should also be provided.

Second, Increase Investment in Agricultural Productive Service Infrastructure and Optimize Service Structure. Address infrastructure weaknesses by accelerating the integration of industrial and agricultural sectors and supporting infrastructure development in rural education, technology, and information. The government should facilitate collaboration between agricultural machinery enterprises and service organizations, provide subsidies for machinery purchases, and promote the use of advanced agricultural equipment such as smart tractors, efficient combine harvesters, and agri-cultural irrigation drones to enhance the quality of agricultural productive services.

Third, Enhance the Professionalization of Agricultural Productive Service Providers. Given that current providers are primarily surplus rural labor with generally low educational and technical levels, government investment in education and training for service providers should be increased, with rewards for those

who participate. At the same time, attracting knowledgeable and capable professionals is necessary to improve service quality.

Fourth, Standardize Command-control Environmental Regulations. Agri-cultural laws and regulations are relatively outdated, often based on industrial point-source pollution characteristics. Agricultural pollution is predominantly non-point source, broad, and complex to manage. Therefore, the government should develop regulations tailored to the characteristics of agricultural production to rein-force the role of agricultural productive services.

Fifth, Stimulate the Effectiveness of Market-Based Environmental Regulations. The agricultural carbon trading market should be standardized by learning from pilot regions and gradually improving market mechanisms. Detailed regulations for agricultural carbon emissions trading should be issued, and activities to familiarize agricultural practitioners with the market should be organized to enhance market efficiency.

Sixth, Increase Public Environmental Awareness and Leverage Public Voluntary Environmental Regulations. The government should improve information disclosure on environmental protection and establish channels for public supervision. Promotion of energy-saving, emission-reducing, and low-carbon production concepts should be strengthened, particularly among agricultural practitioners, to reduce pollution from the source. Green production sharing sessions should be organized to encourage cross-regional communication among enterprises and farmers, maximizing the “spill-over effect” of public voluntary environmental regulations.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: <https://www.stats.gov.cn/>.

Author contributions

GH: Conceptualization, Formal Analysis, Investigation, Methodology, Project administration, Resources, Validation, Visualization, Writing—original draft, Writing—review and editing. ZZ: Data curation, Software, Supervision, Writing—original draft, Writing—review and editing.

Funding

The author(s) declare that no financial support was received for the research, authorship, and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated

organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

- Abate, G. T., Rashid, S., Borzaga, C., and Getnet, K. (2016). Rural finance and agricultural technology adoption in Ethiopia: does the institutional design of lending organizations matter? *World Dev.* 84, 235–253. doi:10.1016/j.worlddev.2016.03.003
- Alam, M. J., Sarma, P. K., Begum, I. A., Connor, J., Crase, L., Sayem, S. M., et al. (2024). Agricultural extension service, technology adoption, and production risk nexus: evidence from Bangladesh. *Heliyon* 10 (14), e34226. doi:10.1016/j.heliyon.2024.e34226
- Bai, Z. M., and Li, C. X. (2024). The impact of agricultural productive services on agricultural green total factor productivity: local effects and spatial spillovers. *China Agric. Resour. Regional Plan.*, 1–10.
- Barbera, A. J., and McConnell, V. D. (1990). The impact of environmental regulations on industry productivity: direct and indirect effects. *J. Environ. Econ. Manag.* 18 (1), 50–65. doi:10.1016/0095-0696(90)90051-Y
- Baron, R. M., and Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. *J. Personality Soc. Psychol.* 51 (6), 1173–1182. doi:10.1037/0022-3514.51.6.1173
- Bas, M., and Strauss-Kahn, V. (2015). Input-trade liberalization, export prices and quality upgrading. *J. Int. Econ.* 95 (2), 250–262. doi:10.1016/j.jinteco.2014.12.005
- Blackman, A., Lahiri, B., Pizer, W., Rivera Planter, M., and Muñoz Piña, C. (2010). Voluntary environmental regulation in developing countries: Mexico's Clean Industry Program. *J. Environ. Econ. Manag.* 60 (3), 182–192. doi:10.1016/j.jeem.2010.05.006
- Bokusheva, R., Kumbhakar, S. C., and Lehmann, B. (2012). The effect of environmental regulations on Swiss farm productivity. *Int. J. Prod. Econ.* 136 (1), 93–101. doi:10.1016/j.ijpe.2011.09.017
- Boyd, G. A., and McClelland, J. D. (1999). The impact of environmental constraints on productivity improvement in integrated paper plants. *J. Environ. Econ. Manag.* 38 (2), 121–142. doi:10.1006/jjeem.1999.1082
- Che, Y., and Zhang, L. (2018). Human capital, technology adoption and firm performance: impacts of China's higher education expansion in the late 1990s. *Econ. J.* 128 (614), 2282–2320. doi:10.1111/ecoj.12524
- Cole, M. A., Elliott, R. J. R., and Wu, S. (2008). Industrial activity and the environment in China: an industry-level analysis. *China Econ. Rev.* 19 (3), 393–408. doi:10.1016/j.chieco.2007.10.003
- Custódio, C., and Metzger, D. (2014). Financial expert CEOs: CEO's work experience and firm's financial policies. *J. Financial Econ.* 114 (1), 125–154. doi:10.1016/j.jfineco.2014.06.002
- Dasgupta, S., and Wheeler, D. (1997). *Citizen complaints as environmental indicators: evidence from China*. Policy Research Working Paper Series. Available at: <http://elibrary.worldbank.org/doi/book/10.1596/1813-9450-1704>.
- Djurava, M., Bobojonov, I., Kuhn, L., and Glaubens, T. (2023). The impact of agricultural extension type and form on technical efficiency under transition: an empirical assessment of wheat production in Uzbekistan. *Econ. Analysis Policy* 77, 203–221. doi:10.1016/j.eap.2022.11.008
- Eck, K., and Huber, S. (2016). Product sophistication and spillovers from foreign direct investment. *Can. J. Economics/Revue Can. d'économique* 49 (4), 1658–1684. doi:10.1111/caje.12247
- Fang, L., Hu, R., Mao, H., and Chen, S. (2021). How crop insurance influences agricultural green total factor productivity: evidence from Chinese farmers. *J. Clean. Prod.* 321, 128977. doi:10.1016/j.jclepro.2021.128977
- Fu, L.-S., Qin, T., Li, G.-Q., and Wang, S.-G. (2024). Efficiency of agricultural insurance in facilitating modern agriculture development: from the perspective of production factor allocation. *Sustainability* 16 (14), 6223. doi:10.3390/su16146223
- Gibbs, D., and Jonas, A. E. G. (2000). Governance and regulation in local environmental policy: the utility of a regime approach. *Geoforum* 31 (3), 299–313. doi:10.1016/S0016-7185(99)00052-4
- Gollop, F. M., and Roberts, M. J. (1983). Environmental regulations and productivity growth: the case of fossil-fueled electric power generation. *J. Political Econ.* 91 (4), 654–674. doi:10.1086/261170
- Griliches, Z. (1990). *Patent statistics as economic indicators: a survey*. Cambridge, MA: National Bureau of Economic Research (NBER Working Paper No. w3301). Available at: <http://www.nber.org/papers/w3301.pdf>.
- Guo, Z., Chen, X., and Zhang, Y. (2022). Impact of environmental regulation perception on farmers' agricultural green production technology adoption: a new perspective of social capital. *Technol. Soc.* 71, 102085. doi:10.1016/j.techsoc.2022.102085
- Hamamoto, M. (2006). Environmental regulation and the productivity of Japanese manufacturing industries. *Resour. Energy Econ.* 28 (4), 299–312. doi:10.1016/j.reseneeco.2005.11.001
- Hao, A. M. (2015). The impact of agricultural producer services on the contribution of agricultural technological progress. *J. South China Agric. Univ. Soc. Sci. Ed.* 14 (2), 8–15. doi:10.7671/j.issn.1672-0202.2015.01.002
- Hausmann, R., Hwang, J., and Rodrik, D. (2007). What you export matters. *J. Econ. Growth* 12 (1), 1–25. doi:10.1007/s10887-006-9009-4
- Hausmann, R., and Rodrik, D. (2003). Economic development as self-discovery. *J. Dev. Econ.* 72 (2), 603–633. doi:10.1016/S0304-3878(03)00124-X
- He, K., Wang, H., and Zhang, J. (2022). Pathways of agricultural transformation under the “dual carbon” target: from the market to the “market”. *J. Huazhong Agric. Univ. Soc. Sci. Ed.* 1, 1–9. doi:10.13300/j.cnki.hnwkxb.2022.01.001
- Huang, L., Zhou, X., Chi, L., Meng, H., Chen, G., Shen, C., et al. (2024). Stimulating innovation or enhancing productivity? The impact of environmental regulations on agricultural green growth. *J. Environ. Manag.* 370, 122706. doi:10.1016/j.jenvman.2024.122706
- Jiang, Y., Han, G., and Yu, D. (2024). Digital finance and agricultural green total factor productivity: the mediating role of digital village development. *Finance Res. Lett.* 67, 105948. doi:10.1016/j.frl.2024.105948
- Kidd, A. D., Lamers, J. P. A., Ficarelli, P. P., and Hoffmann, V. (2000). Privatising agricultural extension: caveat emptor. *J. Rural Stud.* 16 (1), 95–102. doi:10.1016/S0743-0167(99)00040-6
- Koenker, R., and Bassett, G. (1978). Regression quantiles. *Econometrica* 46 (1), 33–50. doi:10.2307/1913643
- Lang, D. N., and Liu, H. M. (2019). Research on the contribution of productive services to the division of global value chains in agriculture: a sectoral perspective based on export value-added. *Int. Trade Econ. Explor.* 35 (9), 18–34. doi:10.13687/j.cnki.gjijmts.2019.09.002
- Larrán Jorge, M., Herrera Madueño, J., Martínez-Martínez, D., and Lechuga Sancho, M. P. (2015). Competitiveness and environmental performance in Spanish small and medium enterprises: is there a direct link? *J. Clean. Prod.* 101, 26–37. doi:10.1016/j.jclepro.2015.04.016
- Li, X. Y., and Wang, W. M. (2024). Mechanisms of digital finance enabling the quality of agricultural exports. *J. South China Agric. Univ. Soc. Sci. Ed.* 23 (2), 55–67. doi:10.7671/j.issn.1672-0202.2024.02.006
- Li, X., and Zhu, B. (2021). Influence of Environmental Regulation on Cross-Border E-commerce Export of Agricultural Products. *Journal of Environmental Protection and Ecology*, 22(3), 1347–1357.
- Li, Y., Huan, M., Jiao, X., Chi, L., and Ma, J. (2023). The impact of labor migration on chemical fertilizer use of wheat smallholders in China—mediation analysis of socialized service. *J. Clean. Prod.* 394, 136366. doi:10.1016/j.jclepro.2023.136366
- Liu, Y., She, Y., Liu, S., and Lan, H. (2022). Supply-shock, demand-induced or superposition effect? The impacts of formal and informal environmental regulations on total factor productivity of Chinese agricultural enterprises. *J. Clean. Prod.* 380, 135052. doi:10.1016/j.jclepro.2022.135052
- Lu, H., Chen, Y. J., and Hu, H. (2021). Can agricultural socialized services promote farmers' adoption of environmentally friendly agricultural technologies? *Agric. Technol. Econ.* 3, 36–49. doi:10.13246/j.cnki.jae.2021.03.003
- Lu, H., Duan, N., and Chen, Q. (2023). Impact of agricultural production outsourcing services on carbon emissions in China. *Environ. Sci. Pollut. Res.* 30 (13), 35985–35995. doi:10.1007/s11356-022-24771-2
- Luo, M. Z., and Wei, B. H. (2023). The carbon emission reduction effect of agricultural producer services: effect and mechanism. *Econ. Geogr.* 40 (4), 58–68. doi:10.15931/j.cnki.1006-1096.2023.04.001
- Ma, D., Zhu, Y., and Yang, Y. (2024). How Green finance affects export production quality: fresh evidence from China. *Energy Econ.* 131, 107381. doi:10.1016/j.eneco.2024.107381
- Makate, C., Makate, M., Mutenje, M., Mango, N., and Siziba, S. (2019). Synergistic impacts of agricultural credit and extension on adoption of climate-smart agricultural technologies in southern Africa. *Environ. Dev.* 32, 100458. doi:10.1016/j.envdev.2019.100458
- Manda, J., Feleke, S., Mutungi, C., Tufa, A. H., Mateete, B., Abdoulaye, T., et al. (2024). Assessing the speed of improved postharvest technology adoption in Tanzania: the role of social learning and agricultural extension services. *Technol. Forecast. Soc. Change* 202, 123306. doi:10.1016/j.techfore.2024.123306

- Niu, Q. C., and Li, G. C. (2024). Farmers' off-farm employment, agricultural productive services, and agricultural production efficiency: evidence from China's rural fixed observation points. *J. Huazhong Agric. Univ. Soc. Sci. Ed.* (5), 72–81. doi:10.13300/j.cnki.hnwxkb.2024.05.007
- Pastiphatkul, P., Chalermphol, J., and Khampan, A. (2021). "Environmental regulations and agricultural product trade: the case of Thailand," in *Natural resource governance in asia* Eds R. Ullah, S. Sharma, M. Inoue, S. Asghar, and G. Shivakoti (Elsevier), 315–323.
- Peng, K. M., Xi, L. Q., and Peng, K. L. (2014). Empirical analysis of the impact of stringent environmental regulations on the export competitiveness of Chinese horticultural products: calculation based on the environmental input-output table. *J. Industrial Eng. Manag.* 28 (2), 26–38. doi:10.13587/j.cnki.jieem.2014.02.018
- Perelman, M. (1973). Mechanization and the division of labor in agriculture. *Am. J. Agric. Econ.* 55 (3), 523–526. doi:10.2307/1239138
- Porter, M. E., and Van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *J. Econ. Perspect.* 9 (4), 97–118. doi:10.1257/jep.9.4.97
- Qian, L., Lu, H., and Gao, Q. (2022). Household-owned farm machinery vs. outsourced machinery services: the impact of agricultural mechanization on the land leasing behavior of relatively large-scale farmers in China. *Land Use Policy* 115, 106008. doi:10.1016/j.landusepol.2022.106008
- Qing, C., Zhou, W., Song, J., Deng, X., and Xu, D. (2023). Impact of outsourced machinery services on farmers' green production behavior: evidence from Chinese rice farmers. *J. Environ. Manag.* 327, 116843. doi:10.1016/j.jenvman.2022.116843
- Rodrik, D. (2006). What's so special about China's exports? *China and World Econ.* 14 (5), 1–19. doi:10.1111/j.1749-124X.2006.00038.x
- Runge, C. F., and Nolan, R. M. (1990). Trade in disservices: environmental regulation and agricultural trade. *Food Policy* 15 (1), 3–7. doi:10.1016/0306-9192(90)90019-V
- Shadbegian, R. J., and Gray, W. B. (2005). Pollution abatement expenditures and plant-level productivity: a production function approach. *Ecol. Econ.* 54 (2–3), 196–208. doi:10.1016/j.ecolecon.2004.12.029
- Shi, R., Shen, Y., Du, R., Yao, L., and Zhao, M. (2024). The impact of agricultural productive service on agricultural carbon efficiency—from urbanization development heterogeneity. *Sci. Total Environ.* 906, 167604. doi:10.1016/j.scitotenv.2023.167604
- Si, R. S., Lu, Q., Zhang, Q. Q., and Liang, H. (2018). The impact of land transfer on farmers' demand for socialized agricultural services—an empirical analysis based on the PSM model. *Resour. Sci.* 40 (9), 1762–1772. doi:10.18402/resci.2018.09.07
- Spraos, J., and Michaely, M. (1985). Trade, income levels, and dependence. *Econ. J.* 95 (380), 1123–1125. doi:10.2307/2233286
- Stephens, J. K., and Denison, E. F. (1981). Accounting for slower economic growth: the United States in the 1970s. *South. Econ. J.* 47 (4), 1191. doi:10.2307/1058200
- Tang, L., Liu, Q., Yang, W., and Wang, J. (2018). Do agricultural services contribute to cost saving? Evidence from Chinese rice farmers. *China Agric. Econ. Rev.* 10 (2), 323–337. doi:10.1108/CAER-06-2016-0082
- Thapa, G., and Gaiha, R. (2014). "Smallholder farming in asia and the pacific: challenges and opportunities," in *New directions for smallholder agriculture*. Editors P. B. R. Hazell and A. Rahman (Oxford University Press), 25–56.
- Varshney, D., Joshi, P. K., Kumar, A., Mishra, A. K., and Kumar Dubey, S. (2022). Examining the transfer of knowledge and training to smallholders in India: direct and spillover effects of agricultural advisory services in an emerging economy. *World Dev.* 160, 106067. doi:10.1016/j.worlddev.2022.106067
- Vasil'ev, N. (1969). The distribution of agricultural enterprises and increased specialization of agriculture. *Problems Econ.* 11 (12), 37–46. doi:10.2753/PET1061-1991111237
- Wang, R., Zhang, Y., and Zou, C. (2022). How does agricultural specialization affect carbon emissions in China? *J. Clean. Prod.* 370, 133463. doi:10.1016/j.jclepro.2022.133463
- Wang, Z., and Wei, S.-J. (2008). *What Accounts for the Rising Sophistication of China's Exports?*. National Bureau of Economic Research. Available at: <https://papers.ssrn.com/abstract=1091406>.
- Wu, A., Elahi, E., Cao, F., Yusuf, M., and Abro, M. I. (2024). Sustainable grain production growth of farmland—a role of agricultural socialized services. *Heliyon* 10 (5), e26755. doi:10.1016/j.heliyon.2024.e26755
- Wu, B., Guo, Y., Chen, Z., and Wang, L. (2024). Do agricultural productive services impact the carbon emissions of the planting industry in China: promotion or inhibition? *Sustainability* 16 (16), 6850. doi:10.3390/su16166850
- Xiong, R. C. (2020). An empirical analysis of the impact of environmental regulations on Jiangxi's agricultural exports. *Commer. Econ. Res.* (21), 172–174.
- Xu, B., Baležentis, T., Štreimikienė, D., and Shen, Z. (2024). Enhancing agricultural environmental performance: exploring the interplay of agricultural productive services, resource allocation, and marketization factors. *J. Clean. Prod.* 439, 140843. doi:10.1016/j.jclepro.2024.140843
- Xu, Z., Feng, Y., and Wei, H. (2022). Does geographical indication certification increase the technical complexity of export agricultural products? *Front. Environ. Sci.* 10, 892632. doi:10.3389/fenvs.2022.892632
- Yang, X. Y. (2015). A study on the co-integration mechanism of environmental regulation and agricultural exports: taking Shandong Province as an example. *J. Zhejiang Agric.* 27 (1), 128–132.
- Yang, Y., Wang, Q., Gao, Y., and Zhao, L. (2022). Does environmental regulation promote the upgrade of the export technology structure: evidence from China. *Sustainability* 14 (16), 10283. doi:10.3390/su141610283
- Yang, Z., Fan, M., Shao, S., and Yang, L. (2017). Does carbon intensity constraint policy improve industrial green production performance in China? A quasi-DID analysis. *Energy Econ.* 68, 271–282. doi:10.1016/j.eneco.2017.10.009
- Yao, Z. Q. (2014). Developing productive service industries and enhancing the international competitiveness of Chinese industries. *Study Explor.* 4, 93–99.
- Yin, Z. C., and Tian, T. (2013). Changes in the export competitiveness of Chinese agricultural products and international comparison—analysis based on export technological complexity. *Agric. Technol. Econ.* 1, 77–85. doi:10.13246/j.cnki.jae.2013.01.009
- Yitayew, A., Abdulai, A., and Yigezu, Y. A. (2023). The effects of advisory services and technology channeling on farm yields and technical efficiency of wheat farmers in Ethiopia. *Food Policy* 116, 102436. doi:10.1016/j.foodpol.2023.102436
- Yuan, X., Zhang, J., Shi, J., and Wang, J. (2024). What can green finance do for high-quality agricultural development? Fresh insights from China. *Socio-Economic Plan. Sci.* 94, 101920. doi:10.1016/j.seps.2024.101920
- Zeng, Y., He, K., Zhang, J., and Li, P. (2024). Impacts of environmental regulation perceptions on farmers' intentions to adopt multiple smart hog breeding technologies: evidence from rural Hubei, China. *J. Clean. Prod.* 469, 143223. doi:10.1016/j.jclepro.2024.143223
- Zhang, C., and Lang, L. H. (2024). New financial support for building an agricultural power: digital inclusive finance and international competitiveness of Chinese agricultural products. *World Econ. Res.* (8), 16–28+135. doi:10.13516/j.cnki.wes.2024.08.002
- Zhang, H., and Guo, X. (2021). Development of producer services and improvement of total factor productivity in agriculture: regional differences and spatial effects. *Agric. Technol. Econ.* 5, 93–107. doi:10.13246/j.cnki.jae.2021.05.007
- Zhang, W., Huang, Y., and Tan, Y. (2020). Policy choices for precise poverty alleviation through rural finance in disaster-affected and impoverished areas: agricultural credit or agricultural insurance? *Insur. Stud.* (1), 21–35. doi:10.13497/j.cnki.is.2020.01.002
- Zhu, Y., Deng, J., Wang, M., Tan, Y., Yao, W., and Zhang, Y. (2022). Can agricultural productive services promote agricultural environmental efficiency in China? *Int. J. Environ. Res. Public Health* 19 (15), 9339. doi:10.3390/ijerph19159339