frontiers | Frontiers in Sustainable Food Systems

TYPE Original Research
PUBLISHED 13 February 2026
DOI 10.3389/fsufs.2025.1740649

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OPEN ACCESS

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RECEIVED 06 November 2025
REVISED 19 December 2025
ACCEPTED 23 December 2025
PUBLISHED 13 February 2026

CITATION
Luo C, Wen J and Li X (2026) Specialty agriculture, farming efficiency, and resource reallocation: an empirical and quantitative analysis of China.
Front. Sustain. Food Syst. 9:1740649.
doi: 10.3389/fsufs.2025.1740649

Specialty agriculture, farming efficiency, and resource reallocation: an empirical and quantitative analysis of China

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Based on a quasi-natural experiment arising from China's policy of designating Advantageous Zones for Specialty Agricultural Products, this study employs panel data from 566 Chinese counties between 2011 and 2021 and applies a multi-period difference-in-differences approach to identify the causal effect of specialty agriculture development on county-level agricultural production efficiency. The findings reveal that the specialized development of specialty agriculture significantly enhances county-level agricultural production efficiency. Mechanism analysis indicates that the policy promotes agricultural production efficiency through three non-obvious channels: curbing the expansion of inefficient agricultural industries, optimizing the brand structure of agricultural products, and narrowing the income disparity among farmers. Further heterogeneity analysis shows that the policy effects are more pronounced in regions with lower levels of financial development and weaker transportation infrastructure. This study provides a new perspective for understanding the efficiency mechanisms of specialty agriculture policies and offers important implications for developing countries seeking to promote agricultural modernization through regional industrial policies.

KEYWORDS

agricultural branding, agricultural productivity, multi-period DID, quantitative analysis, specialty agriculture

1 Introduction

Against the backdrop of continued global population growth and increasingly severe constraints on natural resources such as arable land and water, improving agricultural production efficiency has become a core strategy for countries worldwide to ensure food security, promote rural development, and achieve the United Nations Sustainable Development Goals (Chowdhuri and Pal, 2025; Tan et al., 2025). This challenge is particularly acute for developing countries, which urgently need to identify effective policy instruments that can simultaneously increase output, enhance efficiency, and raise farmers' incomes under limited resource endowments (Baig et al., 2025; Lun et al., 2024). In this context, developing specialty agriculture based on regional comparative advantages—driving productivity growth through geographical agglomeration, specialization, and brand value addition—has emerged as a widely recognized policy pathway globally (Lu et al., 2024).

International experience shows that various forms of regional specialty agriculture policies have achieved significant success in improving industrial efficiency. In Europe, France's "Appellation d'Origine Contrôlée" (AOC) system strictly defines production areas, regulates techniques and quality standards, not only preserving cultural heritage but also notably increasing the added value and supply-chain efficiency of wine through differentiated branding (Januário et al., 2025). Similarly, Italy's "Denominazione di Origine

Controllata e Garantita" (DOCG) system implements detailed regulations on grape cultivation and winemaking, promoting specialization and technological innovation within production regions (Vaquero-Piñeiro et al., 2025). The Netherlands, through its highly intensive "horticultural cluster" model, has established a complete and efficient industrial chain from breeding and production to logistics and marketing, serving as an exemplar of enhancing land and resource productivity via technology-intensive specialization (Lichy et al., 2023). In Asia, Japan's "One Village, One Product" movement represents a classic top-down case of fostering local specialty industries; by leveraging local resources, building regional brands, and expanding market access, it has effectively improved agricultural productivity (Gugerell et al., 2017). Thailand's government-led "One Tambon, One Product" (OTOP) project supports rural specialty crafts and agricultural products, achieving standardization and branding that facilitate industrial upgrading (Nagashima and Kato, 2025). Furthermore, in many developing countries, regionally specialized production models based on natural resource endowments have become integral to improving agricultural returns. These cross-national practices reveal a common logic: regional agricultural specialization can foster the sharing of technology and infrastructure, capture market premiums through quality certification and brand building, and ultimately enhance agricultural production efficiency (Slijper et al., 2023; Barghusen et al., 2022).

While international experience offers valuable insights, rigorous empirical evidence on whether large-scale, government-led specialty agriculture policies can systematically enhance agricultural production efficiency remains scarce in the academic literature (Zheng et al., 2025; Zhong et al., 2025; Zhang et al., 2024; He and Liu, 2024). Existing studies primarily focus on two aspects. First, much of the research consists of case studies of individual cities or counties. Although such studies provide valuable preliminary evidence suggesting that developing specialty agriculture improves production efficiency, the generalizability of their findings is limited (Zhou Q. et al., 2025). The lack of econometric analysis based on large-sample, multi-year panel data makes it difficult to establish a robust causal relationship between specialty agriculture and agricultural production efficiency (Zhong et al., 2025). Second, most studies focus on the role of specialty agriculture in boosting farmers' income and county-level economic growth (Zhou Z. et al., 2025). Discussions regarding agricultural production efficiency are often only treated as a potential outcome or supplementary analysis within these core relationships, lacking direct and in-depth theoretical frameworks and empirical tests that specifically center on production efficiency as the core variables (Zhou Q. et al., 2025; He and Liu, 2024). In the specific context of China, no study has yet examined the impact of China's Designated Advantageous Zones for Specialty Agricultural Products policy on agricultural production efficiency. Existing discussions are mostly confined to case analyses of specific regions. While insightful, these studies are constrained by sample size and methodological approaches, making it difficult to address endogeneity concerns or provide causal inferences with general statistical significance (Tang et al., 2025; Lu et al., 2025). Therefore, key questions—whether specialty agriculture policies can indeed affect agricultural production efficiency, through which channels, and whether the effects vary across different market environments—remain unanswered (Dong et al., 2025; Zhang et al., 2025).

In this context, China's Advantageous Zones for Specialty Agricultural Products policy provides a valuable natural experiment for investigating the above questions. As the world's largest agricultural producer and consumer, China has long prioritized improving agricultural productivity as a national strategic goal. Since 2017, the Chinese government has implemented the Designated Advantageous Zones for Specialty Agricultural Products policy, delineating specific regions for developing specialty agricultural products based on local ecological endowments and historical advantages. The policy aims to integrate the production, processing, and marketing chains while promoting standardized production and technology adoption. China's unique institutional context and policy implementation model offer distinct advantages for this study (Dong et al., 2025; Zhang et al., 2025). Unlike the origin protection systems in regions like the EU, which are often based on historical tradition (Guareschi et al., 2023), China's Designated Advantageous Zones policy represents a proactive, top-down industrial planning initiative with clear designation criteria and dynamic management rules (Mulya and Hudalah, 2024). Implemented in batches across different regions over time, the policy creates temporal variation between treated (designated) and control (non-designated) counties, creating conditions for employing a multi-period difference-in-differences approach to identify causal effects. Furthermore, the availability of rich socio-economic data at the county level in China enables large-sample panel analysis.

Therefore, this study utilizes panel data from 566 Chinese counties between 2011 and 2021, measures agricultural production efficiency using the stochastic frontier approach, and employs the policy designating Advantageous Zones for Specialty Agricultural Products as a quasi-natural experiment. A multi-period difference-in-differences model is applied to empirically examine the impact of specialty agriculture development on county-level agricultural production efficiency, and to investigate its underlying mechanisms and heterogeneity. Compared to the existing literature, the marginal contributions of this study are threefold. First, it constructs a large-sample county-level dataset and employs a rigorous causal identification strategy to provide scientific evidence on the agricultural production efficiency effects of specialty agriculture development, thereby introducing a new determinant to the research on agricultural production efficiency. Second, it investigates the mechanisms through which specialty agriculture development affects county-level agricultural production efficiency from three specific aspects: optimizing the brand structure of agricultural products, curbing disorderly expansion of agricultural industries, and narrowing farmers' income disparity. Furthermore, it conducts heterogeneity analysis focusing on financial support and transportation infrastructure. These aspects provide certain innovations in understanding the mechanistic pathways and conditional contexts through which specialty agriculture development enhances agricultural production efficiency, offering theoretical insights for government decision-making. Third, unlike existing studies that analyze the impact of geographical indications on local economic development at the city level, this study employs county-level panel data. The expanded sample size helps mitigate potential estimation bias. Simultaneously, the application of the difference-in-differences method helps address endogeneity concerns arising from the implementation of the Advantageous Zones policy. Moreover, this study accounts for the issue of heterogeneous treatment effects in multi-period DID models, thereby further enhancing the reliability of the findings.

2 Policy background and research hypotheses

2.1 Policy background

In April 2017, the Ministry of Agriculture and Rural Affairs of China issued the "Notice on Carrying out the Work of Creating Advantageous Zones for Specialty Agricultural Products," officially launching the establishment and designation process for National Advantageous Zones for Specialty Agricultural Products (AZSAP). The AZSAP policy follows a "first establish, then designate" procedure, aiming to support the development of specialized agricultural industrial zones through standardized and institutionalized management processes, incorporating them into a regularized supervision system. The AZSAP policy delineates stringent establishment criteria and application procedures. Applicant regions must meet basic conditions including unique natural resource endowments, distinctive varieties and techniques, and relatively high brand recognition (Raimondi et al., 2024). The application process involves: voluntary applications from local governments, selection and recommendation by provincial-level departments, and a final joint expert review organized by the Ministry of Agriculture and Rural Affairs, the National Development and Reform Commission, and the National Forestry and Grassland Administration, with official designation granted upon approval (Guareschi et al., 2023).

The designation process not only provides inclined support to central and western regions and poverty-stricken areas but also offers targeted resource assistance to regions that show strong potential but have not yet met all standards, helping them achieve qualification before designation. Designated regions receive the title of Advantageous Zones for Specialty Agricultural Products along with supporting policy benefits. Concurrently, national-level Advantageous Zones for Specialty Agricultural Products are subject to a dynamic assessment mechanism. Zones that fail evaluations, experience serious quality issues, ecological damage, or harm to farmers' interests will have their titles revoked and are ineligible to reapply for 3 years, thereby maintaining policy effectiveness. The application procedure is illustrated in Figure 1.

In December 2017, China designated the first batch of 62 regions as Advantageous Zones for Specialty Agricultural Products. Subsequent designations occurred in January 2019 (second batch, 84 regions), February 2020 (third batch, 83 regions), and December 2020 (fourth batch, 79 regions). By 2021, China had designated a total of 308 Advantageous Zones for Specialty Agricultural Products across four batches. According to the "Construction Outline for Advantageous Zones for Specialty Agricultural Products," the target

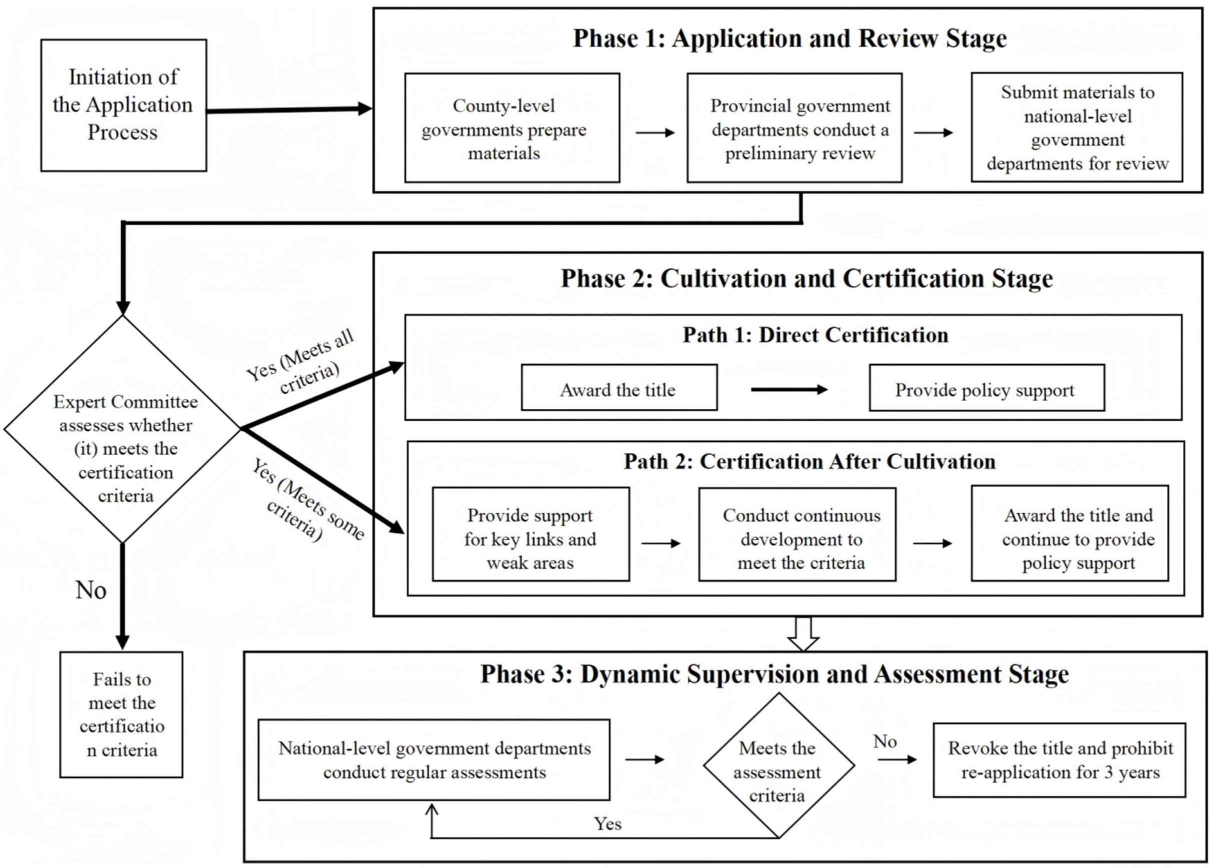

FIGURE 1
Application process for national advantageous zones for specialty agricultural products.

of designating 308 national-level Advantageous Zones for Specialty Agricultural Products had been achieved by the end of 2020. These cover five major categories of agricultural products: specialty grain and economic crops, specialty horticultural products, specialty livestock products, specialty aquatic products, and forestry specialty products. Among these, specialty horticultural product zones are the most numerous (179), accounting for 58.12% of the total, followed by specialty grain and economic crops (53 zones, 17.21%). Specialty aquatic product zones are the fewest (21), representing only 6.82% of the total. While these advantageous zones achieve comprehensive coverage at the provincial level, their distribution exhibits significant regional disparities. These Advantageous Zones for Specialty Agricultural Products are specific rural areas endowed with natural resources and industrial scale, which fully utilize and leverage regional advantages to drive the agglomeration of specialized industries into clusters, forming large-scale and systematic industrial agglomerations for specialty agricultural products. These zones not only develop regional specialty agricultural products but also transform them into thriving industries, significantly enhancing agricultural productivity. Therefore, this study treats the AZSAP designation policy as a quasi-natural experiment to investigate the impact of specialty agriculture development on county-level agricultural productivity.

The core identification strategy of this study lies in utilizing the designation of China's Advantageous Zones for Specialty Agricultural Products as a quasi-natural experiment to examine the causal relationship between specialty agriculture development and agricultural productivity. To ensure the reliability of causal inference, it is first necessary to carefully consider potential endogeneity issues, particularly the challenge of reverse causality—that is, whether there exists selection bias whereby counties with higher agricultural productivity are more likely to be selected as Advantageous Zones for Specialty Agricultural Products. This paper argues that the likelihood of reverse causality between AZSAP designation and contemporaneous productivity is low, based primarily on the following three aspects: First, the design philosophy of the selection mechanism for China's AZSAP policy emphasizes innate endowment rather than contemporaneous efficiency, thereby avoiding efficiency-oriented selection at the source. Second, this policy is essentially an induced institutional change aimed at enhancing agricultural productivity. Notifications issued by the Ministry of Agriculture and Rural Affairs explicitly state that the policy aims to cultivate agricultural industries in underdeveloped western regions. The underlying logic is to guide the reallocation of production factors and improve agricultural productivity through the "policy signal" of designation status, rather than rewarding past efficiency performance. Third, the pattern of government behavior in Chinese policy implementation further weakens the channel for reverse causality. An important motivation for local governments to apply for various demonstration zones is to compete for superior policy resources based on their unique exogenous resource endowments (such as distinctive climate, soil conditions, or geographical indication products) that are difficult to replicate (Zhang et al., 2025; Zhang et al., 2022). These endowments are historical and geographical in nature, and are conceptually and measurably separable from contemporaneous productivity, which is endogenously determined by technical efficiency and management levels. In summary, the AZSAP designation policy theoretically approximates a "policy shock" based on exogenous endowments, making reverse causality with contemporaneous agricultural productivity highly improbable (Guareschi et al., 2023; Raimondi et al., 2024).

2.2 Research hypotheses

2.2.1 Specialty agriculture development and agricultural production efficiency

The promotion of specialty agriculture through targeted policies to enhance regional agricultural production efficiency is a common strategy adopted by many countries, particularly developing economies (Rathore et al., 2024). China's policy of designating Advantageous Zones for Specialty Agricultural Products integrates a suite of government instruments, including direct investment in agricultural infrastructure, targeted financial credit services, and fiscal subsidies (He et al., 2021). These measures play a crucial role in fostering local specialty agriculture and, consequently, boosting agricultural production efficiency.

First, by investing in and improving infrastructure—such as transportation, irrigation, and cold chain logistics within production zones—the policy significantly reduces agricultural production risks and transaction costs (Chang et al., 2025). This enhancement strengthens farmers' willingness and capacity to cultivate specialty crops. Superior infrastructure not only expands market accessibility for agricultural products but also improves water and fertilizer use efficiency and disaster resilience (Rong et al., 2025). Consequently, it improves the marginal output of production factors at the micro level, contributing to higher efficiency in specialty agricultural production. Second, within China's unique Administrative Subcontract system, policies formulated by central departments provide macro-level guidance for provincial and municipal governments (Su et al., 2024). Provincial governments typically refine these central directives into more actionable local regulations to ensure effective implementation at the grassroots level (Shah et al., 2023). Taking the Advantageous Zones policy as an example, provincial and municipal governments have generally established corresponding supportive measures within the overall administrative framework (Su et al., 2024). Through resource allocation tools like financial support and fiscal subsidies, a selective support system for potential advantageous zones has been constructed. Such resource infusion effectively incentivizes farmers and agribusinesses to increase investment in new technologies, intelligent equipment, and modern management practices, helping to alleviate the capital constraints and technological inertia prevalent in traditional agriculture (Zhao et al., 2025; Ruzhani and Mushunje, 2025). This promotes a gradual shift in agricultural production methods towards an intensive development path reliant on technological and managerial innovation, thereby enhancing agricultural production efficiency. Third, the implementation of the Advantageous Zones policy can foster cross-regional industrial chain integration and synergistic cooperation. Once a county achieves significant gains in agricultural production efficiency through this policy, its policy design and implementation experience—such as land transfer models and organized management schemes—are often adopted and promoted more widely by provincial and municipal governments (Xu et al., 2025). These higher-level governments utilize their administrative capacity to coordinate and promote collective action, organizing multiple county governments to jointly invest in infrastructure, operate unified regional public brands, and collaboratively develop sales channels. Such administrative interventions help reduce redundant construction and resource misallocation, facilitating the optimal allocation of capital, technology, and talent across a broader scale, thereby improving the resource allocation efficiency of the entire agricultural economic zone (Deng and Gibson, 2019). Based on the above analysis, the following research hypothesis is proposed:

> *H1*: The development of specialty agriculture can promote county-level agricultural production efficiency.

2.2.2 Mechanism pathway analysis

The designation policy for Advantageous Zones for Specialty Agricultural Products establishes stringent entry criteria, creating a screening mechanism for industries based on regional comparative advantages, thereby curbing the disorderly expansion of agricultural production scale at its source. The policy explicitly requires that specialty products demonstrate superiority in quality and resource characteristics, rather than relying solely on the scale of production. This process essentially constitutes a signaling game model. The Chinese Ministry of Agriculture and Rural Affairs acts as the sender, transmitting credible information about product attributes to provincial, municipal, and county-level agricultural departments as receivers (Rong et al., 2025; Chang et al., 2025). This ensures that only products with genuine comparative advantages receive certification, thereby guiding production factors toward high-efficiency regions. Ultimately, this promotes the formation of a spatially concentrated agricultural industrial structure and effectively restrains the unchecked expansion of extensive farming practices.

Furthermore, as the world's largest developing country, China possesses unique agricultural resource endowments and institutional characteristics. This distinctiveness is particularly evident in the 566 county-level samples examined in this study. Most of these counties are nationally designated poverty-stricken counties with relatively lagging agricultural development stages, dominated by smallholder farming. Unlike urban areas in developed countries, the main agricultural operators in these counties are fragmented, small-scale farmers rather than modern large-scale agribusinesses (Aldieri et al., 2021; Adom and Adams, 2020). Within such a smallholder-dominated agricultural system, factor markets—particularly for labor, land, and credit—are underdeveloped, and the expansion of industrial scale is often accompanied by diminishing marginal efficiency. The implementation of the policy for Advantageous Zones for Specialty Agricultural Products optimizes the allocation of production factors. High-efficiency farmers, upon gaining access to more resources, can fully leverage their advantages in meticulous management and technology application, thereby enhancing overall production efficiency. This mechanism aligns closely with China's specific institutional context and differs fundamentally from the scale-productivity relationship formed through market self-regulation in countries with private land ownership. Within the context of collective land ownership, policy-induced scale convergence is not merely a reduction in size but creates favorable conditions for improving agricultural production efficiency by optimizing the structure of operating entities.

Based on the above analysis, this paper proposes the following theoretical hypothesis:

> *H2*: The designation policy for Advantageous Zones for Specialty Agricultural Products enhances county-level agricultural production efficiency by curbing the disorderly expansion of agricultural industrial scale.

The policy designating China's Advantageous Zones for Specialty Agricultural Products enhances the concentration of production factors in superior regions by identifying and supporting agricultural areas with significant resource endowments and industrial foundations, thereby promoting agricultural specialization, scale, and standardization (Anh et al., 2025; Barghusen et al., 2022). In this process, the policy significantly influences the regional agricultural product identification system, particularly through the structural regulation of the number of geographical indications (GIs). While an increase in GIs is generally viewed as a positive signal of agricultural branding, uncontrolled proliferation without coordination may lead to overlapping identifiers, blurred brand recognition, and resource fragmentation, which can ultimately constrain overall industrial efficiency. By systematically integrating regional agricultural resources and strengthening public brand development, the designation policy effectively guides the GI system from "quantity expansion" to "quality improvement," reducing inefficient and redundant GI registrations (Lichy et al., 2023). This lays an institutional and organizational foundation for enhancing agricultural production efficiency.

Specifically, the policy optimizes the layout of GIs and promotes agricultural production efficiency through the following pathways: First, resource integration and standardization under policy guidance help mitigate homogeneous competition and marketing inefficiencies caused by excessive and disorderly GIs. This allows producers to focus more on quality improvement and process control, thereby increasing land productivity and resource utilization. Second, the streamlining and refinement of GIs enhance the recognition and authority of regional public brands, driving production towards standardization and intensification (Xu et al., 2025; Shah et al., 2023; Baig et al., 2025). This reduces the costs of technology extension and quality supervision, thereby improving total factor productivity. Third, the fiscal and technological support accompanying the policy tends to be concentrated in leading industries and core brands, prompting a more rational allocation of production factors. This elevates the application levels of mechanization and intelligence, further unleashing economies of scale and specialization. Thus, the policy does not simply suppress the development of GIs but restructures the regional agricultural brand ecosystem through structural optimization and quality enhancement, reducing resource misallocation and efficiency losses caused by identifier redundancy (Ray and Ghose, 2014). The rational adjustment in the number of GIs under policy guidance essentially reflects the maturation of the regional agricultural governance system, establishing a solid foundation for building an efficient and synergistic modern agricultural industrial system, which ultimately significantly promotes the sustained improvement of county-level agricultural production efficiency.

Based on the above analysis, this paper proposes the following research hypothesis:

> *H3*: The designation of China's Advantageous Zones for Specialty Agricultural Products enhances county-level agricultural production efficiency by reducing the number of inefficient geographical indications and optimizing the agricultural brand structure.

The policy designating China's Advantageous Zones for Specialty Agricultural Products effectively narrows income disparities among farmers by shaping regional public brands and restructuring value chain distribution, thereby generating a significant positive impact on agricultural production efficiency (Mulya and Hudalah, 2024; Raimondi et al., 2024). First, by establishing regional public brands, the policy effectively mitigates the "lemons market" problem in agricultural products, transforming potential resource endowment advantages into market competitiveness and price premiums. The unified quality standards, traceability systems, and marketing promotions established under policy endorsement collectively build strong regional brand equity. This brand premium primarily and initially benefits small and medium-sized farmers (SME farmers), who are relatively disadvantaged in traditional market structures. The reason is that large farmers or agribusinesses often already possess certain market development capabilities and proprietary brand foundations, whereas the public brand of the Advantageous Zones precisely provides "credit guarantees" and "quality signals" for SME farmers lacking such capital. This enables them to share in the brand's benefits, thereby achieving a significant increase in per-unit agricultural product sales revenue. This process essentially enhances the bargaining power and profit share of disadvantaged participants in the value chain, effectively reducing the income gap between SME farmers engaged in the specialty industry within the zone and large farmers who grow other crops or already possess scale advantages (Raimondi et al., 2024; Tang et al., 2025). Second, the narrowing of income disparities among farmers can serve as an important driver for enhancing agricultural production efficiency by reshaping the behavior of microeconomic agents. On one hand, the reduction in income disparity, mainly manifested through the stabilization and growth of operating income and cash flow among SME farmers, further enhances their willingness to make productive investments and improves their credit accessibility. This alleviates the long-standing credit rationing constraints they face (Song et al., 2025; Yun and Jia, 2025). The simultaneous improvement in investment willingness and capacity encourages farmers to increase investments in improved production factors (such as efficient agricultural machinery, water-saving facilities, and high-quality seeds), thereby driving gains in agricultural production efficiency. On the other hand, a more homogeneous farming community in terms of income distribution exhibits higher "homogeneity" in risk preferences, information processing capabilities, and willingness to adopt new technologies. This homogeneity significantly reduces the extension costs for agricultural technology dissemination systems. Under the guidance of municipal and county-level agricultural departments, extension personnel can conduct standardized training more effectively. Innovations such as new crop varieties and farming techniques can be widely adopted within the region at lower marginal costs and with faster diffusion speeds, thereby promoting agricultural production efficiency.

Based on the above analysis, this paper proposes the following theoretical hypothesis:

> *H4*: The policy designating China's Advantageous Zones for Specialty Agricultural Products enhances county-level agricultural production efficiency by narrowing income disparities among farmers.

3 Research design

3.1 Sample selection and data sources

To examine the impact of specialty agriculture development on agricultural productivity at the county level, this study compiles panel data for 566 Chinese counties from 2011 to 2021. Given the special administrative status of municipalities directly under the central government, county-level districts belonging to these municipalities are excluded from the sample. Additionally, counties with missing data are omitted. The data sources are as follows: The list of National Advantageous Zones for Specialty Agricultural Products is obtained from the website of the Ministry of Agriculture and Rural Affairs. The number of geographical indications for agricultural products is compiled from registration announcements published on the official website of the Ministry of Agriculture and Rural Affairs. The distance from each county to the provincial capital is calculated using 2019 administrative division data. Data for other control variables are sourced from the National Bureau of Statistics of China.

3.2 Variable selection and description

3.2.1 Dependent variable

This study draws on the stochastic frontier approach (SFA) incorporating a time-varying technical inefficiency index to measure agricultural productivity (Ghani, 2025). Compared to data envelopment analysis (DEA), the stochastic frontier model accounts for both the production function and random factors, making it more suitable for characterizing agricultural production (Barbier, 2025; Chen and Gao, 2025). The general form of the model is shown in the following equation:

$$Y_{it} = f\left(X_{it};\beta\right)\exp\left(v_{it} - u_{it}\right) \tag{1}$$

In Equation 1: Y_{it} represents the output of region i in period t; f(·) denotes the deterministic frontier output, i.e., the production frontier; X_{it} is a vector of input factors; β is a vector of coefficients to be estimated; v_{it} is the random error term, assumed to follow a normal distribution, capturing the effects of various stochastic factors and statistical errors on the production frontier; and u_{it} represents the technical inefficiency term, assumed to follow a truncated normal distribution.

Given its flexible functional form, absence of additional restrictions on returns to scale, and ability to capture nonlinear relationships between inputs and output, the translog production function is selected for incorporation into the stochastic frontier model to estimate regional technical efficiency levels (Lun et al., 2024; Lu et al., 2024; Yadava et al., 2025). The translog production function is specified as in Equation 2:

$$\begin{aligned} \ln Y_{it} &= \alpha_0 + \alpha_L \ln L_{it} + \alpha_A \ln A_{it} + \alpha_E \ln E_{it} \\ &+ \alpha_{LA} \ln L_{it} \times \ln A_{it} + \alpha_{LE} \ln L_{it} \times \ln E_{it} \\ &+ \alpha_{AE} \ln A_{it} \times \ln E_{it} + \alpha_{L^2} \ln^2 L_{it} + \alpha_{A^2} \ln^2 A_{it} \\ &+ \alpha_{E^2} \ln^2 E_{it} + \alpha_{Lt} \ln L_{it} \times t + \alpha_{At} \ln A_{it} \times t \\ &+ \alpha_{Et} \ln E_t \times t + \alpha_t t + \alpha_{t^2} t^2 + v_{it} - u_{it} \end{aligned} \tag{2}$$

In Equation 2: Y_{it} denotes the value-added of the primary industry, serving as the agricultural output variable in the model. For input variables X_{it}, this study selects three agricultural input factors: labor (number of employees in the primary industry, Lit), land (total sown area of crops at year-end, A_{it}), and mechanical power (total power of agricultural machinery, E_{it}). Technical efficiency level TE_{it} is used to express the ratio of the producer's expected output to the stochastic frontier output, comprehensively reflecting changes in agricultural productivity (Yadava et al., 2025). Accordingly, this study adopts TE_{it} as the proxy variable for agricultural productivity. The calculation of TE_{it} is given by:

$$TE_{it} = \frac{\exp\left[\ln f\left(X_{it}\right) + v_{it} - u_{it}\right]}{\exp\left[\ln f\left(X_{it}\right) + v_{it}\right]} = \exp\left(-u_{it}\right) \tag{3}$$

TABLE 1 Estimation results of the stochastic frontier model with time-varying technical inefficiency.

Parameter	Coefficient	Std. Err.	*z*-value
Constant (α_0)	3.617	0.7126	5.08***
Labor input coefficient (α_L)	1.1074	0.0658	16.83***
Land input coefficient (α_A)	−0.7309	0.0194	−37.62***
Machinery input coefficient (α_E)	0.2594	0.0174	14.87***
Mean of technical inefficiency term (μ)	3.3644	0.6459	5.21***
Time-varying decay coefficient (η)	0.0099	0.0017	5.97***
Total variance (σ^2)	0.4253	0.0623	−5.84***
Share of inefficiency variance (γ)	0.9542	0.0072	18.42***
Log-likelihood value	598.24***		
Wald test statistic	2160.48***		

***Indicates significance at the 1% level. The model is specified as a translog stochastic frontier production function with time-varying decay. The *z*-values are test statistics for parameter significance.

The variables in Equation 3 are defined consistently with Equation 1.

Based on panel data from 566 counties, we estimated a stochastic frontier production function model. The estimation results are presented in Table 1.

Table 1 presents the estimation results of the stochastic frontier analysis (SFA) model with time-varying technical inefficiency. The Wald test statistic is 2160.48 and significant at the 1% level, indicating that the model has strong overall explanatory power. The relatively high log-likelihood value (598.24) suggests a good model fit. The γ coefficient is 0.954 and statistically significant at the 1% level, indicating that approximately 95.4% of the deviation of actual output from the production frontier is attributable to technical inefficiency, while only about 4.6% stems from random noise. This strongly justifies the use of the stochastic frontier model.

3.2.2 Core explanatory variable

This study employs the implementation of China's Advantageous Zones for Specialty Agricultural Products (AZSAP) policy as a proxy variable for regional specialty agriculture development. Counties designated as Advantageous Zones for Specialty Agricultural Products are considered to have higher levels of specialty agriculture development. Thus, we define the interaction term in the difference-in-differences model as $D_{it} = treat_i \times post_t$. Here, $treat_i$ represents the treatment group dummy variable, which takes the value of 1 if the county is designated as an AZSAP and 0 otherwise; $post_t$ represents the time dummy variable, which takes the value of 1 for the year of designation and all subsequent years, and 0 otherwise. The coefficient of this interaction term captures the impact of AZSAP designation on county-level agricultural productivity, reflecting the agricultural productivity effect of specialty agriculture development.

3.2.3 Mechanism variables

The theoretical analysis presented in the preceding section indicates that the development of specialty agriculture can indirectly enhance county-level agricultural production efficiency through three channels: curbing the disorderly expansion of agricultural industry scale, reducing the number of inefficient agricultural product brands, and narrowing the rural income gap. Accordingly, this study introduces three mediating variables for mechanism analysis: agricultural industry scale, the number of agricultural product brands, and the degree of rural income inequality. Agricultural industry scale is measured by the value-added of the primary industry. The number of agricultural product brands is measured by the count of geographical indications for agricultural products. The degree of rural income inequality is measured using an indicator of farmer income inequality derived from the Kakwani index (Ray and Ghose, 2014; Anh et al., 2025; Yang L. et al., 2025; Barbier, 2025).

3.2.4 Control variables

To control for other factors affecting county-level common prosperity, this study selects the following control variables. (1) Capital accumulation level. Given that asset investment is closely associated with local agricultural infrastructure, which may influence agricultural production efficiency, this paper uses the ratio of fixed asset investment to the year-end total population to represent the regional capital accumulation level (Han et al., 2024). (2) Education level. The proportion of secondary school students in the total population is employed to control for the impact of educational attainment (Zhang et al., 2023). (3) Employment level. This is measured by the share of employed individuals in formal units within the county's year-end total population. (4) Technological innovation level. The number of patents granted per 10,000 people in the county serves as a proxy for technological innovation. (5) Communication infrastructure level. The ratio of landline telephone subscribers to the year-end total population indicates the level of regional communication infrastructure (Abbas Khan et al., 2025). (6) Geographical location. This is measured by the interaction term between a county's distance to its provincial capital (logged in the regression) and a time trend (Bernard et al., 2025). (7) Fiscal service level. This is measured by the share of local government general budgetary expenditure in the county's gross regional product. Additionally, time and region fixed effects are controlled for Wang et al. (2024). The definitions and descriptive statistics of the main variables are presented in Table 2.

3.3 Empirical specification

This study treats the designation of Advantageous Zones for Specialty Agricultural Products (AZSAP) as a quasi-natural experiment and employs a difference-in-differences (DID) approach

TABLE 2 Definitions and descriptive statistics of main variables.

Variable type	Variable	Variable meaning	Measurement method	Obs	Mean	Std. dev.	Min	Max
Dependent variable	APE	Agricultural productivity	Agricultural technical efficiency measured using the stochastic frontier approach	5,889	1.206654	0.5750663	0.2151393	11.69142
Core explanatory variable	SPD	Specialty agriculture development level	Dummy variable equal to 1 for county i in year t and subsequent years after designation as an AZSAP, and 0 otherwise	5,889	0.0830362	0.2759603	0	1
Mechanism variables	AISE	Agricultural industrial scale	Value-added of primary industry (billion yuan)	5,889	12.01649	0.9401109	8.385489	14.20112
	APBL	Number of agricultural product brands	Number of geographical indications for agricultural products	5,889	1.235014	1.736885	0	12
	FIID	Rural income inequality	Kakwani index measuring rural income inequality	5,889	0.2082361	0.1456242	0	0.6956101
Control variables	CAL	Capital accumulation level	Per capita fixed asset investment (10,000 yuan/person)	5,889	4.371468	4.143761	0.3758205	21.98624
	EL	Education level	Proportion of secondary school students in total population	5,889	0.0467117	0.0156027	0.0066153	0.1128836
	EML	Employment level	Proportion of employed persons in total population	5,889	0.0969331	0.0872266	0.0165764	0.4995291
	TIL	Technological innovation level	Patent grants per 10,000 people	5,889	3.997708	7.094395	0	72.38889
	CIL	Communication infrastructure level	Ratio of landline telephone subscribers to total population	5,889	0.0933324	0.0627723	0.0072444	0.5550461
	GLC	Geographical location characteristic	Interaction term between distance to provincial capital and time trend	5,889	30.38043	17.2091	2.175285	80.03851
	FSL	Fiscal service level	Local government budgetary expenditure as proportion of GDP	5,889	0.2499543	0.1530782	0.0281244	1.358199

to estimate the impact of specialty agriculture development on county-level agricultural productivity (Guareschi et al., 2023; Raimondi et al., 2024). Counties designated as Advantageous Zones for Specialty Agricultural Products constitute the treatment group, while other counties form the control group. This design controls for other differences before and after the AZSAP designation, thereby isolating the genuine policy effect. The baseline regression model is specified as follows:

$$APE_{it} = \alpha_0 + \beta_1 D_{it} + \theta_1 Control_{it} + \varphi_i + v_t + \varepsilon_{it} \tag{4}$$

In Equation 4: APE_{it} represents the dependent variable, comprising the agricultural productivity of county i in year t, which serves as the measure of county-level agricultural productivity. D_{it} indicates the level of specialty agriculture development, taking the value of 1 if county i is designated as an AZSAP in year t, and 0 otherwise. $Control_{it}$ denotes a set of control variables, specifically including capital accumulation level, education level, employment level, technological innovation level, communication infrastructure level, geographical location, and fiscal service level. φ_i and v_t represent county fixed effects and year fixed effects, respectively. ε_{it} is the error term, α denotes the intercept, and β_1 and θ_1 represent parameters to be estimated.

To further examine the mechanism through which specialty agriculture development affects county-level agricultural productivity, this study constructs mechanism variables and establishes a regression model analyzing the impact of specialty agriculture development on these mechanism variables. The model is specified as follows:

$$M_{it} = \alpha_0 + \beta_2 D_{it} + \theta_2 Control_{it} + \varphi_i + v_t + \omega_{it} \tag{5}$$

In Equation 5, M_{it} represents the three mechanism variables: agricultural product branding, agricultural industry scale expansion, and farmer income inequality. ω_{it} denotes the error term, β_2 and θ_2 represent parameters to be estimated, and all other variables remain consistent with Equation 4.

TABLE 3 Baseline regression results.

Variable name	(1)	(2)
SPD	0.116*** (0.042)	0.098** (0.041)
CAL		0.008* (0.004)
EL		−1.762*** (0.652)
EML		−0.477** (0.203)
TIL		0.003 (0.003)
CIL		0.101 (0.153)
GLC		0.011*** (0.002)
FSL		−0.433*** (0.160)
_cons	1.198*** (0.007)	1.060*** (0.087)
County FE	Yes	Yes
Year FE	Yes	Yes
N	5,703	5,703
Adj. R^2	0.432	0.435

*, **, and *** indicate significance at the 10, 5, and 1% levels, respectively. Robust standard errors are shown in parentheses.

4 Results analysis and discussion

4.1 Baseline regression results

Table 3 presents the baseline regression results examining the impact of specialty agriculture development on county-level agricultural production efficiency. The dependent variable in both columns (1) and (2) is agricultural production efficiency. Column (1) reports the regression results with only the specialty agriculture development variable as the explanatory factor, while controlling for year and region fixed effects. The initial results suggest a statistically significant positive effect of specialty agriculture development on agricultural production efficiency. Building on column (1), column (2) introduces a set of control variables. The coefficient for specialty agriculture development remains statistically significant and positive, indicating that specialty agriculture development significantly enhances agricultural production efficiency in these regions. Therefore, Hypothesis H1 is confirmed.

4.2 Robustness checks

4.2.1 Parallel trends test

From the perspective of policy designation criteria, the establishment requirements for China's Advantageous Zones for Specialty Agricultural Products emphasize unique resource endowments, solid industrial foundations, high-quality and safe products, and strong demonstration effects, without specifically highlighting the enhancement of agricultural productivity. Theoretically, it can be assumed that at the time of designation, these regions did not exhibit significant differences in agricultural productivity compared to other areas. From a statistical testing perspective, this study employs an event study approach to conduct ex ante parallel trends testing. The model is specified as follows:

$$APE_{it} = \alpha_0 + \sum_{s=1}^{4} \beta_s D_s + \theta_3 Control_{it} + \varphi_i + v_t + \delta_{it} \tag{6}$$

In Equation 6: β_s and θ_3 are coefficients to be estimated; the event study methodology primarily focuses on βs, which captures differences in time trends between treatment and control groups. When s equals 0, it represents the year of AZSAP policy implementation; when s is negative, it represents years before policy implementation; when s is positive, it represents years after policy implementation. Additionally, this study uses the period immediately before policy implementation as the baseline, thus setting the coefficient for the preceding period to 0. δ_{it} denotes the model error term. All other variables remain consistent with Equation 4.

Considering that the two-way fixed effects (TWFE) estimator for multi-period difference-in-differences may suffer from weighting bias, including potential negative weights that could affect the unbiasedness of results, this study treats the initial AZSAP designation as the treatment event and computes the interaction-weighted estimator to identify the dynamic effects of the AZSAP policy on agricultural productivity (Hong and Li, 2025; Aguilar-Loyo, 2025). The parallel trends test results based on both the TWFE estimator and interaction-weighted estimator are shown in Figure 2. Before policy implementation, the effects of specialty agriculture development are

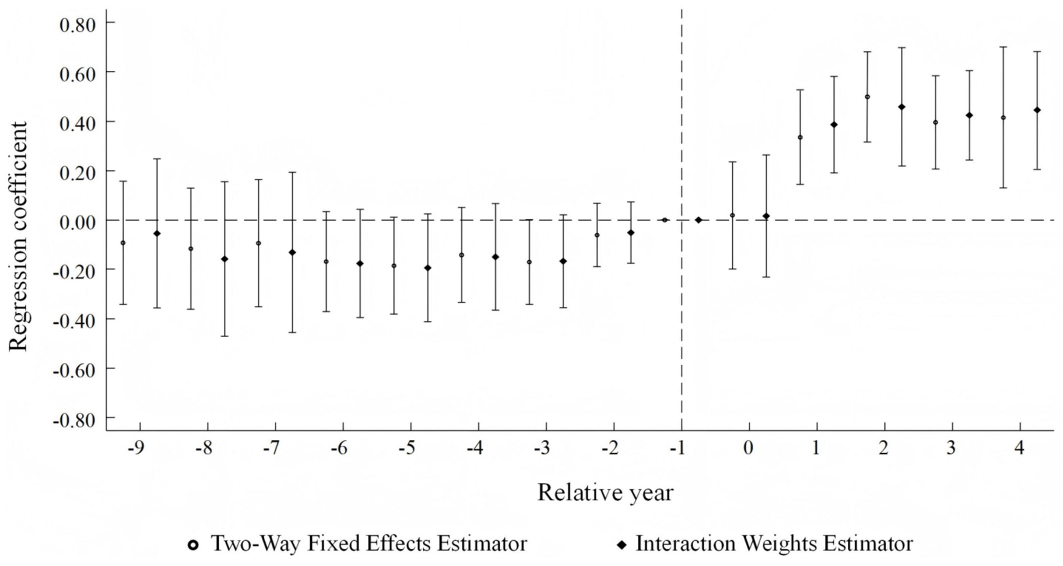

FIGURE 2
Parallel trends test.

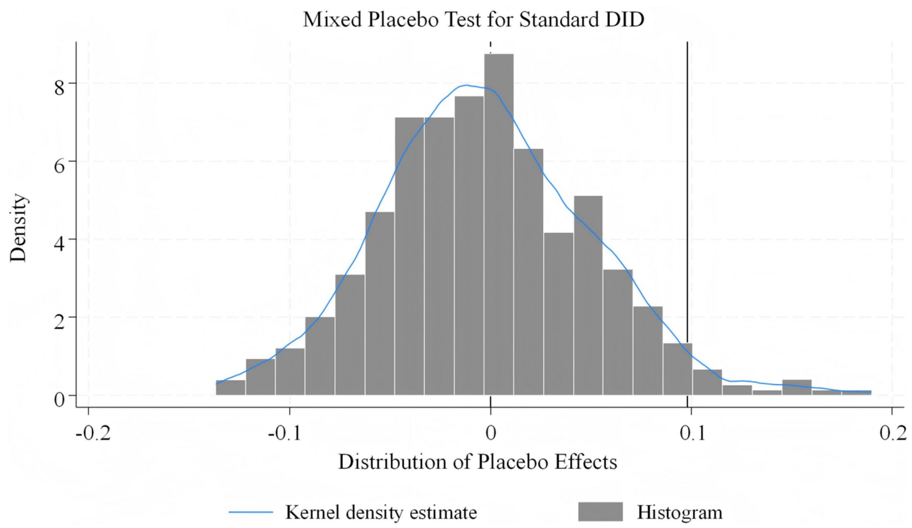

FIGURE 3
Placebo test.

statistically insignificant. One year after policy implementation, specialty agriculture development shows a significant positive effect on agricultural productivity. This indicates that, on one hand, treatment and control groups followed parallel trends before policy implementation, satisfying the parallel trends assumption. On the other hand, after policy implementation, specialty agriculture development significantly enhances agricultural productivity.

4.2.2 Placebo test

To exclude the potential influences of non-random policy shocks and regional heterogeneity on the research conclusions, this study conducts a placebo test. The results, as shown in Figure 3, indicate that the mean coefficient estimated from randomized samples is distributed normally around zero and is distinctly separated from the baseline regression coefficient. This suggests that the observed impact of specialty agriculture development on county-level agricultural productivity is not driven by other policy shocks or random factors, thereby confirming the robustness of our main findings.

4.2.3 Stable unit treatment value assumption test

Beyond the parallel trends assumption, the stable unit treatment value assumption (SUTVA) represents another crucial prerequisite for the difference-in-differences approach, requiring that the policy does not affect other control units. To address this, we examine whether the AZSAP designation policy generates spillover effects on neighboring counties (Qiu and Tong, 2021; Coutts, 2022). Specifically, this study treats counties adjacent to policy-implementing counties as the treatment group, while counties without policy implementation and not adjacent to implementing counties serve as the control group. The following model is established for testing:

$$APE_{it} = \alpha_0 + \beta_3\, Adjacent_i \times post_t + \theta_t\, Control_{it} + \varphi_i + \nu_t + \kappa_{it} \quad (7)$$

In Equation 7: Adjacenti indicates whether county i is adjacent to a policy-implementing county. $Adjacent_i \times post_t$ represents the interaction term between the policy shock and adjacent areas, serving as the core explanatory variable for policy spillover effects; β_3 and θ_4 denote coefficients to be estimated; κ_{it} is the model error term; all other variables remain consistent with Equation 4. The stable unit treatment value assumption primarily focuses on β_3, which reflects the policy's spillover effects. If β_3 is statistically significantly different from zero, it indicates the presence of spillover effects; otherwise, it suggests no such effects. The regression results presented in Table 4 show that the interaction term between policy shock and adjacent areas is statistically insignificant. This indicates that the AZSAP designation policy does not generate significant spillover effects on counties adjacent to the policy-implementing counties.

4.2.4 Goodman-Bacon decomposition test

In a staggered Difference-in-Differences (multi-period DID) design, where units receive treatment at different times, the traditional Two-Way Fixed Effects (TWFE) estimator may suffer from bias due to heterogeneous treatment effects. A particular concern is the potential for negative weighting arising from "problematic control groups"—where earlier-treated units serve as controls for later-treated units (Goodman-Bacon, 2021). To examine whether our baseline results are affected by this issue, we conduct the Goodman-Bacon decomposition test. This method decomposes the overall TWFE estimator into a weighted average of all possible pairwise comparisons, including "treated versus never-treated groups," "earlier-treated versus later-treated groups," and "later-treated versus earlier-treated groups."

TABLE 4 Stable unit treatment value assumption test results.

Variable name	(1)
adjacent_post	0.000 (0.023)
CAL	0.001 (0.004)
EL	−1.847*** (0.596)
EML	−0.707*** (0.215)
TIL	0.004 (0.003)
CIL	0.349** (0.152)
GLC	0.013*** (0.002)
FSL	−0.829*** (0.121)
_cons	1.094*** (0.076)
County FE	Yes
Year FE	Yes
N	4,164
Adj. R^2	0.470

*, **, and *** indicate significance at the 10, 5, and 1% levels, respectively. Robust standard errors are shown in parentheses.

TABLE 5 Goodman-bacon decomposition results.

Control group type	Weight	Estimate
Treated vs. never-treated	0.861	0.104
Earlier-treated vs. later-treated	0.111	0.277
Later-treated vs. earlier-treated	0.028	−0.015

This table reports the Goodman-Bacon decomposition results. The weights sum to one.

Table 5 reports the decomposition results. It shows that among all pairwise comparisons constituting the total estimate, those using the "never-treated group" as the control (i.e., "treated versus never-treated") dominate the weighting, accounting for approximately 86.1% of the total. In contrast, the potentially problematic comparisons, where "earlier-treated groups" serve as controls for "later-treated groups" (i.e., "later-treated versus earlier-treated"), carry a weight of only 2.8%, implying a minimal influence on the overall estimate. This indicates that the positive effect of the Designated Advantageous Zones policy on agricultural production efficiency primarily stems from valid comparisons between the treated groups and the control groups that never received the policy shock, rather than from problematic between-group comparisons. Therefore, our baseline regression results are unlikely to be substantially biased by the "problematic control group" issue arising from heterogeneous treatment effects, supporting the reliability of the staggered DiD estimates employed in this study.

4.2.5 Controlling for predetermined variables

The designation of Advantageous Zones for Specialty Agricultural Products is not random and may be correlated with a region's inherent agricultural resource endowments and development potential. To mitigate the potential selection bias arising from this non-random assignment, we follow the related literature and introduce a predetermined variable into our baseline regression model. Specifically, we argue that whether a region is designated earlier or more easily may be highly correlated with its initial agricultural resource endowment. Therefore, we use the value-added of the primary industry in the initial year of our sample (2011) as a proxy for the initial scale of the agricultural economy. We then construct its interaction term with a time trend and include it in the model as a predetermined control.

The regression results after including this predetermined variable are presented in Table 6. The coefficient of our core explanatory variable, SPD, remains positive and statistically significant at the 5% level, and its magnitude is close to the baseline estimate. This indicates that the positive effect of specialty agriculture development on agricultural production efficiency holds even after controlling for the time trend of initial conditions that may influence policy assignment, confirming the robustness of our baseline findings.

4.2.6 Policy exclusivity test

During the study period, besides the Designated Advantageous Zones for Specialty Agricultural Products policy, other national-level agricultural and regional development policies implemented concurrently could also affect county-level agricultural production efficiency. To ensure that the identified effect primarily stems from the

TABLE 6 Regression results with a predetermined control.

Variable name	(1)
SPE	0.099** (0.040)
CAL	0.001 (0.004)
EL	−0.431 (0.631)
EML	−0.205 (0.192)
TIL	0.004 (0.002)
CIL	0.268* (0.153)
GLC	0.005** (0.002)
FSL	−0.381** (0.157)
init_agri_trend	−0.034*** (0.003)
_cons	3.044*** (0.198)
N	5,703
Adj. R^2	0.465

*, **, and *** indicate significance at the 10, 5, and 1% levels, respectively. Robust standard errors are shown in parentheses.

TABLE 7 Policy exclusivity test.

Variable name	(1)	(2)	(3)
	Only IIDPZ	Only NASDEZ	Both
SPE	0.098** (0.042)	0.099** (0.042)	0.099** (0.042)
CAL	0.008* (0.004)	0.008* (0.004)	0.008* (0.004)
EL	−1.781*** (0.652)	−1.778*** (0.655)	−1.795*** (0.655)
EML	−0.494** (0.203)	−0.478** (0.203)	−0.494** (0.203)
TIL	0.003 (0.003)	0.002 (0.003)	0.003 (0.003)
CIL	0.097 (0.153)	0.101 (0.153)	0.097 (0.153)
GLC	0.011*** (0.002)	0.011*** (0.002)	0.011*** (0.002)
FSL	−0.432*** (0.160)	−0.431*** (0.160)	−0.430*** (0.160)
IIDPZ policy	−0.098* (0.054)		−0.097* (0.054)
NASDEZ policy		−0.030 (0.039)	−0.028 (0.039)
_cons	1.063*** (0.087)	1.062*** (0.087)	1.065*** (0.087)
N	5,703	5,703	5,703
Adj. R^2	0.436	0.435	0.435

*, **, and *** indicate significance at the 10, 5, and 1% levels, respectively. Robust standard errors are shown in parentheses.

Designated Advantageous Zones policy rather than interference from other policies, we conduct a policy exclusivity test. Following the existing literature, we specifically control for the following two policies that were gradually implemented during the sample period and are potentially relevant to agricultural development. The first is the Integrated Development of Primary, Secondary, and Tertiary Industries in Rural Areas Pilot Zone policy, implemented since 2017, which aims to enhance the comprehensive agricultural production capacity and modernization by building a high-quality agricultural supply system. The second is the National Agricultural Sustainable Development Experimental Demonstration Zone policy, a significant initiative launched after 2017 that profoundly influences rural industrial development through measures such as industrial poverty alleviation and infrastructure investment. We construct dummy variables for each of these policies (taking a value of 1 for the year the policy begins and all subsequent years, and 0 otherwise) and include them as additional control variables in the baseline regression model.

The results are presented in Table 7. In columns (1) and (2), where the Integrated Development Pilot Zone (IIDPZ) or the National Agricultural Sustainable Development Experimental Zone (NASDEZ) variable is included separately, the coefficient and significance level of the core variable SPD remain largely unchanged. In column (3), where both policy control variables are included simultaneously, the coefficient of SPD remains positive and statistically significant. This demonstrates that the independent positive effect of the Designated Advantageous Zones for Specialty Agricultural Products policy on improving agricultural production efficiency remains robust after controlling for the influence of other major concurrent agricultural support policies.

4.2.7 Instrumental variable approach

To address potential endogeneity concerns in analyzing the impact of specialty agriculture development on county-level agricultural production efficiency, this study employs an instrumental variable approach. The instrumental variable is constructed as the number of agricultural heritage systems in the county dating back to the year 2000, with estimation performed using the two-stage least squares (2SLS) method. Regarding relevance, the count of agricultural heritage systems reflects a region's historical accumulation in specialty crop cultivation and local genetic resource development, which constitutes the historical foundation and resource potential for specialty agriculture development, thus being strongly correlated with contemporary specialty agriculture development levels (Shakya and Vagnarelli, 2024; Liu et al., 2025). Furthermore, since policies such as the Designation of Advantageous Zones for Specialty Agricultural Products typically emphasize regional agricultural cultural resources in their planning, this variable also possesses policy indicative significance, satisfying the relevance condition for instrumental variables. In terms of exogeneity, as historical legacies primarily influenced by local cultural traditions, agricultural heritage systems bear no direct relationship with current agricultural production efficiency, thus meeting the exogeneity requirement. The regression results are presented in Table 8. The regression results show that the instrumental variable has a statistically significant positive effect on specialty agriculture development. The Kleibergen-Paap rk LM statistic of 515.38 ($p < 0.01$) rejects the null hypothesis of underidentification, indicating a strong correlation between the instrumental variable and the endogenous variable. The Cragg-Donald Wald F statistic of 1073.78 ($p < 0.01$) suggests no weak instrument problem. The second-stage estimation results remain significant after addressing endogeneity, demonstrating the robustness of our previous findings.

4.3 Mechanism analysis

4.3.1 Agricultural industry scale

Column (1) of Table 9 presents the mechanism regression results examining the impact of specialty agriculture development on agricultural industry scale. The results show that the coefficient for

TABLE 8 Instrumental variable test results.

Variable name	First	Second
	(1)	(2)
	SPD	APE
The number of agricultural heritage systems	0.1488852*** (0.0062315)	
SPD		0.1171* (0.079)
Kleibergen-Paap rk LM statistic	515.38	
Cragg-Donald Wald F statistic	1073.78	
N	5,720	5,720
Control variables	Yes	Yes
County FE	Yes	Yes
Year FE	Yes	Yes

*, **, and *** indicate significance at the 10, 5, and 1% levels, respectively. Robust standard errors are shown in parentheses.

TABLE 9 Mechanism test results.

Variable name	(1)	(2)	(3)
	Agricultural industry scale	Agricultural product brand	Rural income inequality
SPD	−0.027*** (0.009)	−0.115** (0.057)	−0.010*** (0.002)
CAL	0.003* (0.002)	0.005 (0.007)	0.003*** (0.000)
EL	0.722*** (0.212)	−12.829*** (1.358)	−0.689*** (0.061)
EML	0.100* (0.060)	1.448*** (0.373)	0.050*** (0.012)
TIL	0.001 (0.001)	0.000 (0.003)	−0.000*** (0.000)
CIL	0.304*** (0.054)	0.590* (0.323)	−0.037*** (0.013)
GLC	0.008*** (0.001)	0.059*** (0.005)	−0.001*** (0.000)
FSL	−0.578*** (0.044)	−0.157 (0.202)	0.031*** (0.012)
_cons	11.821*** (0.032)	−0.131 (0.157)	0.260*** (0.007)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	5,889	5,889	5,889
Adj. R^2	0.983	0.810	0.955

*, **, and *** indicate significance at the 10, 5, and 1% levels, respectively. Robust standard errors are shown in parentheses.

specialty agriculture development is statistically significant and negative, indicating that specialty agriculture development curbs the expansion of agricultural industry scale. Our mechanism test reveals that while the implementation of specialty agriculture policies reduces agricultural industry scale, it simultaneously enhances agricultural production efficiency. Thus, Hypothesis H2 is supported. This finding highlights an important policy transmission mechanism: the positive effect of specialty agriculture development on production efficiency is achieved not through traditional scale expansion but alongside a contraction in industry scale. A plausible explanation for this result is that the Designated Advantageous Zones policy, by establishing strict quality and geographical access standards, creates an industry screening mechanism. This mechanism likely curbs extensive production expansion based merely on quantitative growth. It guides production factors to shift away from low-value-added, homogeneous production sectors toward more distinctive and market-potential sectors. Consequently, while the overall scale is contained, the allocation of resources is optimized, leading to gains in production efficiency. This aligns with the policy's original design intention of concentrating production factors in advantageous regions, suggesting a potential pathway for improving efficiency by correcting resource misallocation.

4.3.2 Number of agricultural product brands

Column (2) of Table 9 presents the mechanism regression results for the impact of specialty agriculture development on the number of agricultural product brands. The results indicate a statistically significant negative coefficient for specialty agriculture development, supporting Hypothesis H3. This mechanism test reveals a non-traditional transmission path through which specialty agriculture enhances production efficiency. The policy intervention does not work by increasing the number of agricultural brands; instead, it optimizes brand structure by selecting superior ones and eliminating inferior ones, thereby curbing low-level redundant construction and ultimately improving agricultural production efficiency. An increase in the sheer number of geographical indications does not necessarily translate to enhanced brand competitiveness and may sometimes lead to resource dispersion and market recognition confusion. The rational reduction in brand quantity following policy implementation may indicate that, under the joint guidance of government and market selection, resources are released from maintaining numerous scattered and inefficient brands. These resources can then be more concentrated on improving the quality, standards, and technological levels of specific advantageous products. This streamlining of the brand system helps reduce marketing inefficiencies and regulatory costs within the region, thereby establishing an organizational and institutional foundation for improvements in agricultural production efficiency.

4.3.3 Rural income inequality

Column (3) of Table 9 presents the mechanism regression results for the impact of specialty agriculture development on rural income inequality. The results demonstrate a statistically significant negative coefficient for specialty agriculture development, indicating that specialty agriculture development effectively reduces rural income disparity and thereby enhances agricultural total factor productivity. Thus, Hypothesis H4 is verified. Specifically, by fostering specialty industries and constructing regional public brands, the policy likely creates opportunities for small and medium-sized households widely participating in the industry to share the value-added benefits from the industrial chain, thus helping to narrow the income gap among farmers within the region. A more balanced income distribution helps mitigate issues such as insufficient production investment and divergent willingness to adopt technology, which can arise from severe income polarization. This contributes to creating a more stable micro-level operational environment, which is conducive to the promotion of agricultural technology and the improvement of overall resource allocation efficiency, ultimately driving gains in agricultural productivity.

4.4 Heterogeneity analysis

4.4.1 The impact of different financial development levels

Regions with more developed financial systems provide a more favorable external environment for specialty agriculture development, enabling agricultural enterprises to expand financing scale and acquire modern production equipment, ultimately enhancing agricultural production efficiency (Yang Y. et al., 2025; Bagci et al., 2025; Yun and Jia, 2025). This study employs the year-end loan balance of financial institutions in each county to divide the sample into high (top 50%) and low (bottom 50%) financial development groups for regression analysis. As shown in Table 10, specialty agriculture development significantly improves agricultural production efficiency in regions with lower financial development, while this effect is insignificant in regions with higher financial development.

This finding can be interpreted through the lens of the "government-market substitution relationship." In regions with underdeveloped financial systems, market failures are prevalent, and both traditional farmers and new agricultural entities face severe credit constraints. Under these circumstances, the policy of designating Advantageous Zones for Specialty Agricultural Products essentially functions as a "market substitute" through various measures including government credit endorsement, targeted credit support, and risk-sharing mechanisms. This compensates for deficiencies in formal financial institutions, effectively unleashes potential investment demand and technology adoption willingness, and consequently generates significant efficiency improvements. Conversely, in regions with higher financial development, market mechanisms can allocate resources relatively efficiently, resulting in limited marginal gains from policy intervention, which reflects a substitution boundary between government intervention and market functions.

4.4.2 The impact of different transportation infrastructure levels

Transportation infrastructure plays a crucial role in mediating the impact of specialty agriculture development on agricultural production efficiency (He et al., 2024). This study further examines whether the productivity-enhancing effect of specialty agriculture development varies across different levels of transportation infrastructure. The sample is divided into high and low transportation infrastructure groups for subgroup analysis. Table 11 shows that specialty agriculture development significantly promotes agricultural production efficiency in regions with inferior transportation infrastructure, while this effect is insignificant in regions with superior transportation infrastructure.

This phenomenon can be understood from the perspective of "public goods complementarity." Regions with poor transportation conditions fall into a "location disadvantage trap" due to limited market accessibility and high transaction costs. The policy of designating Advantageous Zones for Specialty Agricultural Products provides crucial complementary public investments through supporting cold chain logistics, establishing e-commerce platforms, and facilitating production-marketing linkages, significantly reducing institutional costs in agricultural product circulation and transforming potential resource advantages into actual market competitiveness. This indicates that in regions with weak transportation infrastructure, the policy demonstrates a more pronounced "critical breakthrough effect," highlighting strong synergistic complementarity between government guidance and infrastructure development. In contrast, in regions with well-developed transportation infrastructure, where hard constraints on market access have been largely eliminated, policy intervention yields insignificant marginal benefits.

TABLE 10 Heterogeneity analysis results by financial development level.

Variable name	(1)	(2)
	High financial development level	Low financial development level
SPD	0.026 (0.029)	0.153** (0.068)
CAL	0.009* (0.005)	−0.004 (0.005)
EL	−0.788 (0.633)	−2.039** (0.993)
EML	−0.084 (0.169)	0.096 (0.347)
TIL	−0.000 (0.002)	0.007 (0.007)
CIL	0.075 (0.142)	−0.234 (0.253)
GLC	0.008*** (0.003)	0.004 (0.004)
FSL	−1.005*** (0.151)	−0.431** (0.194)
_cons	1.107*** (0.099)	1.340*** (0.138)
County FE	Yes	Yes
Year FE	Yes	Yes
N	2,298	3,360
Adj. R^2	0.665	0.414

*, **, and *** indicate significance at the 10, 5, and 1% levels, respectively. Robust standard errors are shown in parentheses.

TABLE 11 Heterogeneity analysis results by transportation infrastructure level.

Variable name	(1)	(2)
	High transportation infrastructure level	Low transportation infrastructure level
SPD	−0.026 (0.065)	0.119*** (0.046)
CAL	0.012 (0.011)	0.006 (0.004)
EL	−0.761 (1.620)	−1.980*** (0.699)
EML	−0.612** (0.309)	−0.368 (0.224)
TIL	0.021*** (0.004)	−0.005* (0.003)
CIL	0.498* (0.294)	0.031 (0.172)
GLC	0.019*** (0.006)	0.009*** (0.003)
FSL	−1.666*** (0.272)	−0.381** (0.168)
_cons	0.914*** (0.165)	1.119*** (0.096)
County FE	Yes	Yes
Year FE	Yes	Yes
N	766	4,937
Adj. R^2	0.586	0.432

*, **, and *** indicate significance at the 10, 5, and 1% levels, respectively. Robust standard errors are shown in parentheses.

TABLE 12 Heterogeneity analysis results by agricultural development level.

Variable name	(1)	(2)
	High agricultural development level	Low agricultural development level
SPD	0.285*** (0.063)	−0.063 (0.063)
CAL	−0.000 (0.005)	0.024** (0.011)
EL	−2.142** (0.967)	−2.532** (1.055)
EML	0.372* (0.208)	−1.355*** (0.415)
TIL	−0.002 (0.003)	−0.001 (0.004)
CIL	−0.150 (0.189)	−0.073 (0.262)
GLC	0.009*** (0.003)	0.001 (0.006)
FSL	0.207 (0.263)	−0.699*** (0.205)
_cons	0.924*** (0.113)	1.513*** (0.176)
County FE	Yes	Yes
Year FE	Yes	Yes
N	3,148	2,440
Adj. R^2	0.480	0.420

*, **, and *** indicate significance at the 10, 5, and 1% levels, respectively. Robust standard errors are shown in parentheses.

4.4.3 Impact of different agricultural development levels

Given substantial variations in agricultural development levels across counties and differences in the agglomeration of specialty agriculture industries, the productivity effects of specialty agriculture development may exhibit heterogeneity (Cao et al., 2025; Dong et al., 2025; Zhou Z. et al., 2025). To address this, we employ the gross output value of agriculture, forestry, animal husbandry, and fishery per capita to divide the sample into high agricultural development level (top 50%) and low agricultural development level (bottom 50%) groups, separately estimating the impact of specialty agriculture development on county-level agricultural productivity. The results presented in Table 12 indicate that specialty agriculture development significantly enhances agricultural productivity in regions with higher agricultural development levels. This suggests that in areas with more advanced agricultural development, agricultural operators typically possess greater physical capital, human capital, and technological reserves. Farmers and agricultural enterprises in these regions demonstrate stronger capabilities in adopting yield-enhancing and efficiency-improving technologies such as water-saving irrigation, green pest control, and quality grading systems, enabling faster technological progress and efficiency gains. Additionally, regions with higher agricultural development levels benefit from better-established industrial chains, facilitating easier integration from production to processing and marketing within the value chain, thereby realizing economies of scale and scope.

5 Conclusion and discussion

5.1 Conclusion

This study systematically examines the impact of specialty agriculture development on county-level agricultural production efficiency by leveraging the quasi-natural experiment of China's designation of Advantageous Zones for Specialty Agricultural Products and employing panel data from 566 counties between 2011 and 2021. The main findings are threefold. First, specialty agriculture development significantly enhances county-level agricultural production efficiency, a conclusion that remains robust after a series of tests including instrumental variable and placebo analyses. Second, mechanism analysis reveals three distinct pathways that diverge from conventional understanding: (1) the policy optimizes agricultural factor allocation by curbing disorderly expansion of agricultural industry scale and redirecting resources from inefficient homogeneous production activities; (2) rather than simply increasing brand quantity, the policy enhances agricultural production efficiency by optimizing the brand structure of agricultural products, manifested through the reduction of inefficient geographical indications; (3) through shaping regional public brands and reconstructing value chains, the policy effectively narrows the income disparity among farmers, and this more inclusive growth pattern ultimately translates into improved agricultural production efficiency by enhancing human capital and promoting technology diffusion. Third, heterogeneity analysis indicates that the policy's efficiency-enhancing effects are more pronounced in regions with lower financial development and weaker transportation infrastructure. This suggests that government policy interventions can effectively compensate for market failures in areas with insufficient market-based institutional support. Additionally, the policy demonstrates stronger effects in regions with higher agricultural development levels, indicating that existing industrial foundations and human capital stocks are crucial for absorbing and transforming policy dividends.

5.2 Discussion

The core findings of this study challenge the conventional wisdom that views "economies of scale" and "brand quantity" as the sole pathways to efficiency gains. Our results indicate that, within specific institutional and market structures, moderate scale suppression and brand streamlining can, in fact, serve as drivers for improving agricultural production efficiency. This finding engages in a meaningful dialog and comparison with diverse international models of specialty agriculture development, highlighting the critical importance of aligning policy instruments with national conditions.

First, regarding brand governance and scale control, the policy effects identified in this study share similarities with the European "origin protection" model. For instance, France's Appellation d'Origine Contrôlée (AOC) system strictly delimits production zones and regulates production methods and output, thereby curbing the unchecked expansion of agricultural scale. Through substantial quality premiums and technological standardization, it significantly enhances industrial efficiency. Similarly, Japan's "One Village, One Product" movement emphasizes differentiated and premium development based on local uniqueness rather than pursuing homogeneous expansion, ultimately achieving rural industrial revitalization. These cases collectively demonstrate that constraining production within the optimal resource endowment through rigorous institutional design is key to achieving high-quality, high-efficiency development. This stands in sharp contrast to the path dominant in the United States, which is characterized by large-scale specialized operations and association/cooperative models. The distinctive feature of the Chinese policy lies in its government-led “designation” process, which combines the stringent standards of the European model with the regional focus of the Japanese model, leveraging strong governmental administrative power to rapidly reconfigure the allocation of agricultural production factors.

Second, regarding the pathway of industrial chain integration, the Dutch flower industry provides another exemplary model. As a resource-limited country, the Netherlands—through long-term, sustained industrial policy support, substantial R&D investment, and close collaboration among government, enterprises, and research institutions—has achieved global leadership in greenhouse technology, breeding innovation, and intelligent equipment. It has constructed a complete and efficient industrial chain from R&D to global logistics, thereby attaining remarkable agricultural productivity. This validates another potential pathway for enhancing efficiency in specialty agriculture: overcoming natural resource constraints by deepening technology and capital investment. In contrast, as a developing country, China’s policy focuses more on leveraging existing technological levels and resource endowments to tap efficiency potential by optimizing organizational methods and resource allocation. This reflects the differentiated policy approaches of countries at different stages of socioeconomic development.

Finally, the mechanism identified in this study—"reducing farmer income inequality promotes productivity”—aligns with the theory of “pro-poor growth” in development economics and finds confirmation in international practices. For example, within fair-trade value chains for Kenyan tea or Peruvian coffee, ensuring that smallholders receive a fairer share of profits incentivizes their long-term investment in land improvement and sustainable technologies, ultimately enhancing the productivity and resilience of the entire industry cluster. The uniqueness of the Chinese policy lies in its systematic design of inclusive mechanisms through the creation of regional public brands within a large-scale, top-down national industrial policy framework, offering an institutional innovation to address the potential trade-off between efficiency and equity.

Utilizing the quasi-natural experiment of national-level Designated Advantageous Zone designation, this study provides causal evidence from a large Chinese sample for the productivity effects of specialty agriculture development. It deepens the understanding of the complex relationship between agricultural specialization and efficiency, offering a theoretical basis for how governments can implement precise policies under different developmental stages and regional conditions. Future research could employ more micro-level household data to examine the differential behavioral responses of farmers of varying scales to the policy. Alternatively, comparative cross-national studies could be conducted to systematically analyze the effectiveness and boundaries of specialty agriculture support policies under different political-economic systems, thereby contributing to a more universal theory of agricultural development policy.

Data availability statement

The datasets presented in this article are not readily available because the county-level panel data used in this study were provided by the Government Department under a strict confidentiality agreement. Due to the sensitive nature of the data and legal restrictions, the raw data are not available for public sharing. However, the process of data collection, variable construction, and all statistical analyses are described in full detail in the manuscript. The Stata do-files for replicating all tables and figures are available from the corresponding author upon reasonable request. For verification purposes, qualified researchers may contact the corresponding author to discuss the possibility of accessing a de-identified or aggregated version of the data under a non-disclosure agreement, subject to approval by the data provider. Requests to access the datasets should be directed to CL, chengdiluo786@163.com.

Author contributions

CL: Writing – original draft, Writing – review & editing. JW: Writing – review & editing. XL: Writing – review & editing.

Funding

The author(s) declared that financial support was received for this work and/or its publication. This research was funded by Guangxi Philosophy and Social Science Research Program Key Project of “People’s Congress Theory and Practice Research” (Grant No. 25RDA004), the Key Project of Nanning Social Science Think Tank (Grant No. NNSkZK202503), General Report on the Preliminary Research of the 15th Five-Year Plan for Agricultural and Rural Development in Guangxi (Grant No. GXZC2024-C3-005884-JZZB), Research on Rural Construction and Governance and the Construction of Target index System for Rural Development during the 15th Five-Year Plan Period (Grant No. GXZC2024-C3-005884-JZZB), Guangxi Federation of Social Science Associations for Municipal and County-level Societies (General Project) (Grant No. Sxsklkt2024-77).

Acknowledgments

The author sincerely thanks Huishan Huang for continuous guidance and constructive criticism during writing.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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