

Can quality and safety governance improve cultivated land green utilization efficiency? A quasi-natural experiment based on the national agricultural product quality and safety pilot program

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Abstract

The national agricultural product quality and safety pilot (APQS) is not only related to food safety but may also affect agricultural green transformation by changing agricultural production practices. Using panel data from Chinese prefecture-level cities over the period 2010 – 2021, this study applies a multi-period difference-in-differences approach to assess the effects of this policy on cultivated land green utilization efficiency (LGUE) and further examines its effects on outcomes related to the resource, market, and technology dimensions. The results indicate that the pilot policy significantly improves LGUE, and this finding remains robust across staggered DID estimation and other robustness checks. The subgroup estimates show heterogeneous patterns across samples defined by agricultural functional zones, regions, and terrain conditions. Further analysis suggests that the pilot policy improves irrigation coverage and irrigation support conditions, promotes geographical indication certification for agricultural products, and is positively associated with agricultural patent application activity.

Keywords: National agricultural product quality and safety pilot; Cultivated land green utilization efficiency; Agricultural resource utilization efficiency; Agricultural product branding level; Agricultural technological innovation capacity

1. Introduction

Cultivated land underpins human survival and advancement, occupying a non-substitutable role in food production and ecological preservation. As the world population keeps rising and climate change worsens, balancing food security and ecological sustainability within constrained land resources has emerged as a critical issue confronting the global community (Mahmood et al. 2024). In China, this conflict is especially evident: the overall area of farmland is constrained, while the amount of cultivated land available per capita remains relatively limited. From 2005 to 2024, China's cultivated land area per capita fluctuated overall, reaching a temporary peak of 1.48 mu in 2013 before declining to 1.38 mu in 2024 (Fig. 1). This trend highlights the structural constraint imposed by limited cultivated land resources per capita. On the other hand, agriculture has long depended on fertilizers and pesticides. These inputs secure food supply to some extent, but they also reduce efficiency, spread non-point pollution, and cause ecological degradation (Rad et al. 2022). Under these conditions, relying only on more inputs is no longer viable. Instead, enhancing LGUE becomes essential, as it connects output growth with environmental sustainability and provides a key pathway for agricultural green transformation.

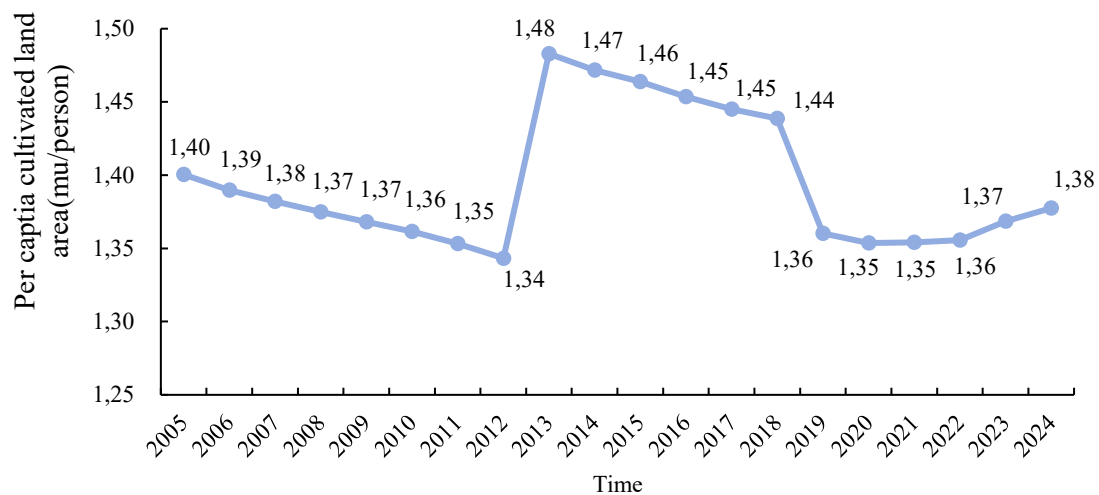


Fig. 1. Per capita cultivated land area, 2005–2024

In recent years, China has vigorously advanced the APQS. The core aim is to improve quality standards by strengthening source control, refining production norms and origin certification, and establishing systems for traceability and risk monitoring (Huo et al. 2022). Although the original purpose of this policy was to ensure food safety, its implementation has reshaped rules on input use, process supervision, and behavioral constraints, gradually altering the incentives and constraints of agricultural production. This institutional effect has not only standardized agricultural production practices but also provided new institutional support and pathways for improving LGUE.

At the same time, research on LGUE has continued to deepen. A relatively systematic analytical framework has gradually taken shape. Existing studies focus mainly on three aspects. First, in terms of measurement, scholars generally include agricultural carbon emissions and non-point source pollution as undesirable outputs. They often use models such as the super-efficiency SBM to assess efficiency (Fu et al. 2023; S. Li et al. 2024). Second, in spatial and temporal patterns, studies find that efficiency levels have risen slowly nationwide and in key regions. However, regional disparities have widened, with clear spatial clustering, path dependence, and periodic fluctuations (Ke et al. 2023; J. Zhang et al. 2024). Third, in terms of mechanisms, the effects of different factors vary. Agricultural services and digital development usually promote efficiency and create spatial spillovers (Huang et al. 2024; Tang and Chen 2022). By contrast, the role of urbanization is more complex, and its effects change in direction and strength across development stages. In general, the literature mainly addresses measurement and spatial distribution of LGUE. A few works analyze the mechanisms, but causal tests of institutional policy impacts are scarce. This gap provides the entry point for this study, which uses the quasi-natural experiment of the APQS.

The existing literature has examined agricultural product quality and safety governance across different stages and dimensions. Standardization can enhance control over agricultural production processes, with standardized production bases generally exhibiting better product quality and safety performance than dispersed smallholders (Yuhong Liu et al. 2024). Quality certification and geographical indications can mitigate information asymmetry, improve agricultural products' access to higher-quality market segments, and enable producers to obtain

price premiums (Berihun and Gutema 2025; X. Li et al. 2022). Traceability mechanisms can improve pricing and profit allocation while strengthening the stability and sustainability of agricultural supply chains (J. Jiang et al. 2024). Advances in digital monitoring and intelligent early-warning tools have increasingly connected risk identification, information integration, collaborative decision-making, and response actions, while environmental early warning has evolved from risk prediction toward dynamic response and intelligent governance (Shao and Zhang 2026). These developments provide a new technological foundation for dynamic monitoring of agricultural product quality risks and related regulatory decision-making. Agricultural socialized services can reduce the use of fertilizers and pesticides while facilitating the diffusion of green production practices through cross-regional service provision and rural social networks (C. Jiang et al. 2025; C. Yang et al. 2022). Overall, quality and safety governance may facilitate agricultural green transformation through production standardization, market incentives, and technical services, thereby providing a foundation for this study to examine the effects of APQS on LGUE.

To address the gaps in prior studies, this paper uses panel data covering 273 prefecture-level cities across China from 2010 to 2021. LGUE is evaluated using the super-efficiency SBM model. Subsequently, a multi-period difference-in-differences method combined with an event-study design is employed. Controlling for city and year fixed effects, the analysis identifies the policy effect and further tests the parallel trend assumption as well as the influence of phased implementation.

Relying on this research design, this study contributes chiefly in two respects. First, this study extends the research on LGUE from an institutional policy perspective. Existing studies on LGUE have mainly examined the effects of resource endowments, production conditions, technological progress, and environmental constraints, while the impacts of institutional policies such as agricultural product quality and safety governance on agricultural green efficiency remain insufficiently explored. Unlike conventional agricultural green policies that mainly emphasize input reduction, pollution control, or technology promotion, APQS focuses on quality and safety governance. Through institutional arrangements such as production standardization, quality certification, traceability system development, and market incentives, APQS connects production process regulation with agricultural product value realization, providing a new institutional pathway for agricultural green transformation. Using APQS as a quasi-natural experiment, this study examines the impact of quality and safety governance policies on LGUE and integrates agricultural product quality governance and agricultural green efficiency improvement into a unified analytical framework, thereby extending existing LGUE research from an institutional policy perspective. Second, this study extends research on how agricultural product quality and safety policies influence agricultural green development by examining their potential impact channels. Existing research on agricultural product quality and safety policies has largely focused on food quality improvement, market performance, and adjustments in production behavior. However, there is still limited systematic evidence on how quality and safety governance may further influence agricultural resource utilization, market incentives, and agricultural technological innovation. From the resource, market, and technology dimensions, this study examines the effects of APQS on agricultural resource utilization efficiency, agricultural product branding level, and agricultural technological innovation capacity, respectively. The results provide additional evidence for understanding the resource-, market-, and technology-related components through

which quality and safety governance may be connected to agricultural green development.

2 Theoretical analysis and research hypotheses

2.1 Direct effect

The APQS serves as an institutional tool to standardize agricultural production and circulation, with the goal of improving product safety. According to institutional regulation theory, external regulation can change the incentive and constrain structure of producers. This encourages adjustments in input choices and management practices, thereby improving both efficiency and environmental outcomes. First, production standardization. The APQS enforces uniform input standards and operational guidelines, imposes strict requirements on fertilization and pesticide application, and limits excessive use of polluting inputs, thereby alleviating environmental stress on farmland (L. Zhang et al. 2018). Second, information transparency. With the help of traceability systems, production is monitored. The higher penalty for violations encourages producers to adjust their input structure and field practices, which raises LGUE (Huo and Liu 2024; J. Jiang et al. 2024). Third, institutionalized support. The program builds testing platforms, strengthens training, and offers fiscal support. By reducing the threshold for green production and encouraging the use of green technologies, these measures ultimately improve LGUE (Han et al. 2025; Yu et al. 2024). Accordingly, the following hypothesis is proposed:

H1. The APQS significantly improves LGUE.

2.2 Impact channels

From the perspectives of institutional regulation and sustainable value creation, APQS may reshape the decision-making environment of agricultural producers through resource allocation, market incentives, and technological innovation, thereby influencing LGUE. Accordingly, this study examines the effects of APQS from the resource, market, and technology dimensions.

2.2.1 Agricultural resource utilization efficiency

APQS may improve the conditions for agricultural resource utilization through the resource allocation channel. Regarding input management, the pilot policy strengthens the regulation of agricultural inputs such as water, fertilizers, and pesticides through institutional arrangements including production standards, quality traceability, and monitoring and inspection, thereby encouraging producers to reduce inefficient input use and resource waste (S. Zhang et al. 2024). Regarding production support, standardized production requirements and complementary support measures may encourage local governments to improve farmland irrigation infrastructure and agricultural production services, thereby strengthening stable irrigation support for agricultural production (Rathore et al. 2025). Greater effective irrigation coverage can improve the alignment of irrigation resources with agricultural production needs while providing the necessary conditions for resource-saving practices such as water-saving irrigation and precision fertilization. This can reduce inefficient input use and alleviate the effects of water resource constraints and fluctuations in production conditions on cultivated land utilization. Accordingly, by regulating agricultural inputs, improving irrigation support conditions, and optimizing resource allocation, APQS may enhance irrigation coverage and resource security in agricultural production while creating favorable conditions for the adoption of resource-saving practices such as water-saving irrigation and precision fertilization, thereby contributing to more efficient and rational use of agricultural resources. Based on this reasoning, the following hypothesis is formulated:

H2. APQS contributes to improving the conditions for agricultural resource utilization.

2.2.2 Agricultural product branding level

APQS may promote agricultural product branding by strengthening market incentives. Quality certification, geographical indications, and brand labels can signal product quality to the market, mitigate information asymmetry between producers and consumers, and facilitate access to higher-quality market segments, enabling agricultural products to obtain price premiums and more stable sales channels (J. Jiang et al. 2024; X. Li et al. 2022). As product quality becomes more recognizable and gains greater market acceptance, producers may obtain more stable economic returns from standardized production, thereby strengthening their incentives to adjust input practices and sustain green production (Yuying Liu et al. 2019; H. Yang et al. 2023). Accordingly, by strengthening quality signaling and market returns, APQS may encourage agricultural product certification and branding activities. In line with the above discussion, the following hypothesis is advanced:

H3. APQS contributes to improving the agricultural product branding level.

2.2.3 Agricultural technological innovation capacity

APQS may promote agricultural technological innovation by stimulating technological demand and providing policy support. Higher quality standards and stricter production requirements may increase demand for the development of technologies related to precision fertilization, water-saving irrigation, quality monitoring, and pest and disease control, thereby encouraging research institutions, agricultural enterprises, and production service organizations to engage in technological R&D and patent application activities (Luo et al. 2024). Meanwhile, technical training, research collaboration, and agricultural production services associated with the pilot program may facilitate the accumulation of agricultural technological knowledge and the diffusion of innovation outcomes (Hien and Chi 2023). Such innovation activities may provide the technological foundation for reducing inefficient input use, optimizing resource allocation, and improving agricultural production practices, thereby creating favorable conditions for improving LGUE. On this basis, the following hypothesis is established:

H4. APQS contributes to improving agricultural technological innovation capacity.

3 Data and models

3.1 Research framework

Fig. 2 illustrates the analytical framework of this study. This study first examines the policy effects of APQS on LGUE and analyzes its underlying logic from three dimensions: production standardization, information transparency, and institutionalized support. Second, this study conducts heterogeneity analysis across agricultural functional zones, regions, and terrain conditions to identify variations in policy effects under different spatial contexts and agricultural development conditions. The analysis then examines the effects of APQS on agricultural resource utilization efficiency, agricultural product branding level, and agricultural technological innovation capacity. Finally, drawing on the empirical findings, this study summarizes the conclusions and discusses relevant policy implications.

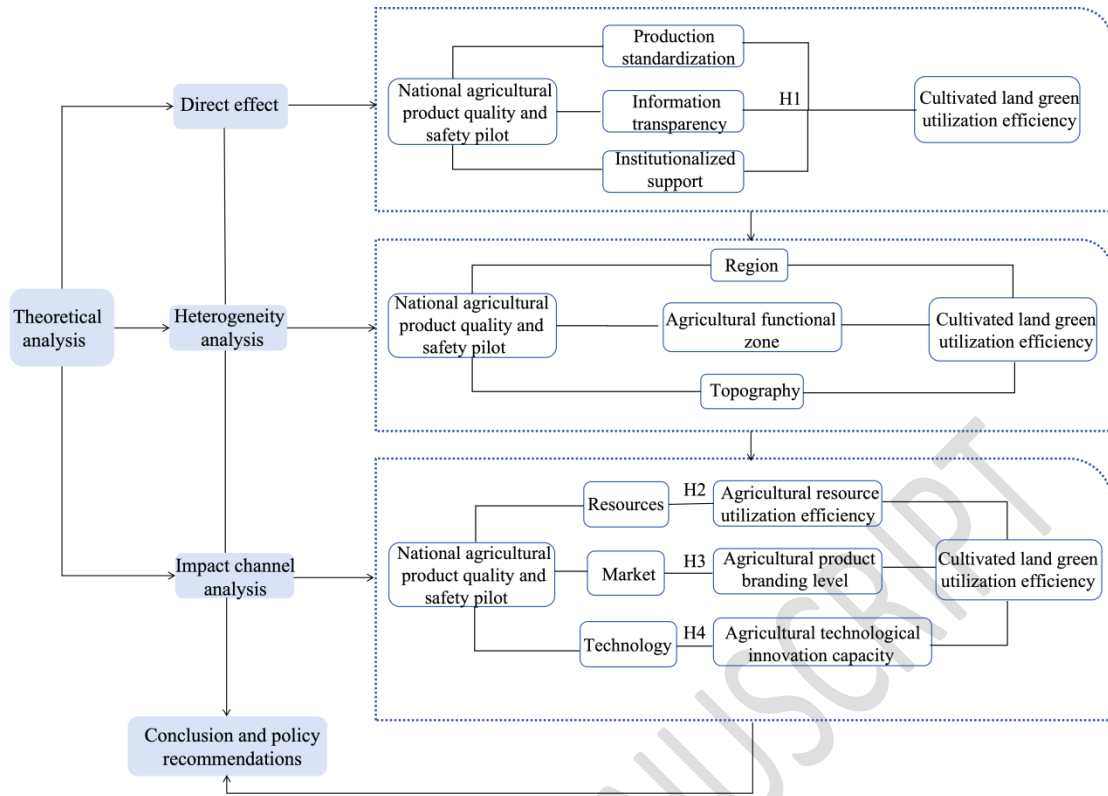


Fig. 2. Research framework

3.2 Data and variables

3.2.1 Dependent variable

This study employs the Super-SBM model to estimate LGUE at the prefecture-level city level. The model simultaneously incorporates inputs, desirable outputs, and undesirable outputs and allows further differentiation among decision-making units on the efficiency frontier, thereby addressing the limitation of the conventional SBM model in which multiple efficient units receive an efficiency score of 1. Given regional differences in agricultural production scale, natural conditions, and factor inputs, this study performs the efficiency estimation under the assumption of variable returns to scale. To construct the efficiency frontier, this study treats all city-year observations over 2010–2021 as decision-making units and uses the pooled panel data to construct a common production frontier. Each city-year LGUE score is evaluated relative to the same production frontier, providing a consistent benchmark for efficiency comparisons across years and facilitating the analysis of temporal changes in LGUE. The model is specified as follows:

$$LGUE = \frac{1}{m} \sum_{i=1}^m \frac{\bar{x}_i}{x_{i0}} / \left(\frac{1}{s_1 + s_2} \left(\sum_{q=1}^{s_1} \frac{\bar{y}_q^w}{y_{q0}^w} + \sum_{q=1}^{s_2} \frac{\bar{y}_q^b}{y_{q0}^b} \right) \right) \quad (1)$$

$$s. t. \quad \begin{cases} \bar{x} \geq \sum_{j=1, j \neq k}^n \theta_j x_j \\ \bar{y}^w \leq \sum_{j=1, j \neq k}^n \theta_j y_j^w \\ \bar{y}^b \geq \sum_{j=1, j \neq k}^n \theta_j y_j^b \\ \bar{x} \geq x_0, 0 \leq \bar{y}^w \leq y_0^w, \bar{y}^b \geq y_0^b, \theta \geq 0 \end{cases}$$

In equation (1), $LGUE$ represents cultivated land green utilization efficiency, with θ as the weight vector. x_{i0} 、 y_{q0}^w 、 y_{q0}^b represent the input indicators, desirable outputs, and undesirable

215 outputs, respectively; $\bar{x}_i$, $\bar{y}_{q0}^q$, $\bar{y}_{q0}^b$ denote the corresponding slack variables; and m , s_1 , s_2 , n
 216 denote the numbers of inputs, desirable outputs, undesirable outputs, and decision-making units,
 217 respectively. Following the relevant literature (Xie et al. 2018), LGUE is constructed using crop
 218 sown area, total agricultural machinery power, fertilizer and pesticide application, and
 219 employment in the primary industry as inputs; grain output and agricultural output value as
 220 desirable outputs; and agricultural carbon emissions as the undesirable output. This study
 221 primarily accounts for carbon emissions associated with fertilizer and pesticide application,
 222 agricultural film use, and farmland irrigation in crop production. Specifically, carbon emissions
 223 are calculated as $CE_{it}=0.896F_{it}+4.934P_{it}+5.18M_{it}+20.476I_{it}$, where F_{it} , P_{it} , M_{it} , and I_{it}
 224 represent fertilizer application, pesticide application, agricultural film use, and effective irrigated
 225 area, respectively. The corresponding carbon emission coefficients are 0.896 kg/kg, 4.934 kg/kg,
 226 5.18 kg/kg, and 20.476 kg/hm² (Qinghua and Guangsheng 2023). Total agricultural machinery
 227 power is included as an input indicator to capture the level of agricultural mechanization
 228 equipment. Owing to the limited availability of prefecture-level data on energy consumption, such
 229 as agricultural diesel use, emissions associated with agricultural machinery operation are not
 230 included in the carbon accounting. Accordingly, the agricultural carbon emission indicator
 231 captures emissions from crop production within the accounting boundary defined above. Within
 232 this indicator system, fertilizer and pesticide use is incorporated into the efficiency evaluation
 233 framework from both resource input and environmental impact perspectives. As input indicators,
 234 they capture the actual consumption of chemical inputs in agricultural production, whereas their
 235 associated carbon emissions are incorporated into the undesirable output to reflect the
 236 environmental costs generated by these input activities. The Super-SBM model therefore evaluates
 237 the potential to reduce agricultural inputs and environmental burdens while maintaining given
 238 levels of grain output and agricultural output value, thereby providing an integrated measure of the
 239 economic output, resource consumption, and environmental impacts associated with cultivated
 240 land utilization. Fig. 3(a1)–(a4) illustrate the spatial distribution of LGUE. From 2010 to 2021,
 241 LGUE in China showed an overall upward trend, with substantial improvements in the eastern,
 242 central, and northeastern regions. In contrast, the western region continued to lag behind,
 243 indicating persistent regional disparities.

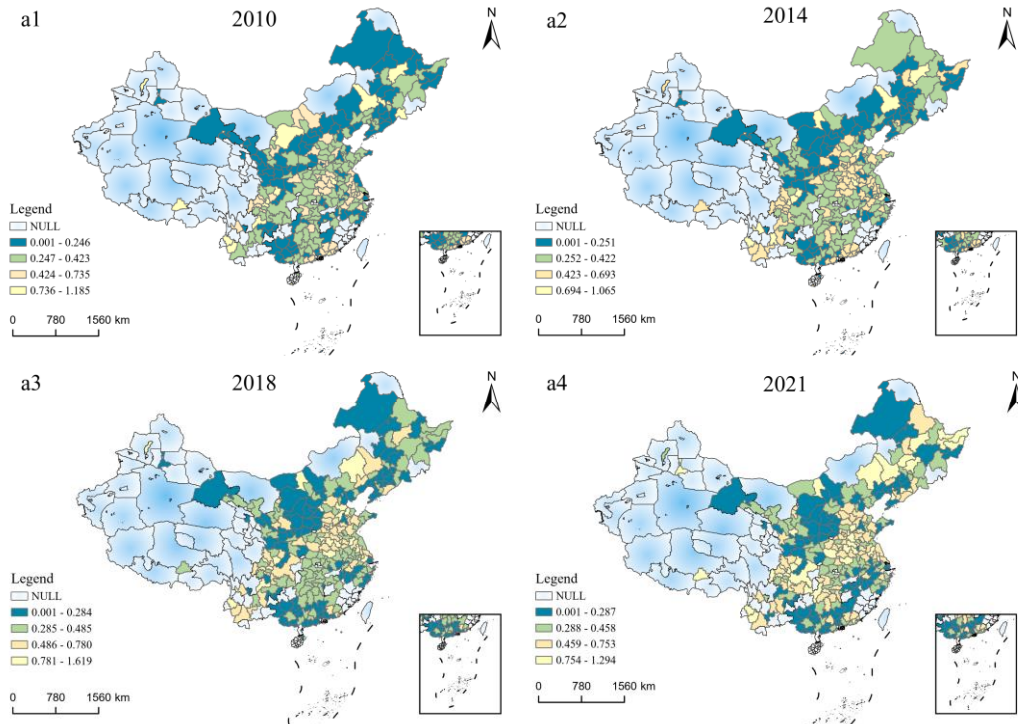


Fig. 3. Spatial distribution of LGUE

Note: The base map is derived from the standard map (GS(2024)0650) provided by the Ministry of Natural Resources of China and cannot be modified.

3.2.2 Independent variable

To identify the policy effects, this study constructs a treatment dummy variable, “Treated”. If a prefecture-level city is selected as an APQS pilot city during the study period, “Treated” takes the value of 1; otherwise, it takes the value of 0. Given that APQS was introduced in staggered batches, this study defines the policy activation variable “Time” according to the year in which each city first became an APQS pilot city. For the first batch of pilot cities in 2015, “Time” equals 1 from 2015 onward and equals 0 before 2015. For the second batch of pilot cities in 2017, “Time” equals 1 from 2017 onward and equals 0 before 2017. Cities that were not selected as APQS pilots are assigned a value of 0 throughout the entire sample period. Based on this definition, this study constructs the interaction term $Treated \times Time = DID$ and applies a multi-period difference-in-differences model to estimate the impact of APQS on LGUE.

3.2.3 Channel variables

Agricultural resource utilization efficiency is measured using the ratio of effective irrigated area to total crop-sown area as a proxy. This indicator primarily captures effective irrigation coverage and irrigation support conditions in agricultural production. A higher value indicates that crop production has greater access to reliable irrigation and relatively better water resource support conditions. Agricultural product branding level is measured by the number of geographical indication certifications for agricultural products, capturing the extent of regional agricultural product certification and brand development. Applicant addresses are obtained from geographical indication certificate application records and used to assign each certification to the corresponding prefecture-level city. For certifications involving multiple regions, geographic attribution is determined based on the applicant’s registered address. Agricultural technological innovation capacity is measured by the logarithm of the total number of agricultural patent

applications, capturing the intensity of regional agricultural technology R&D and patent application activity. Agricultural patents are identified using Class A01 of the International Patent Classification (IPC) and assigned to the corresponding prefecture-level cities based on the addresses of patent applicants.

3.2.4 Control variables

Following related studies (Z. Li et al. 2021; L. Wang et al. 2022), this paper selects several control variables covering population, economy, technology, and resource utilization. Urbanization level is assessed by the share of urban permanent residents within the total resident population. Industrial structure is captured by the proportion of regional GDP contributed by value added in the tertiary sector. Internet penetration rate is captured by the number of internet users for every 100 residents. Human capital level is assessed using the ratio of students enrolled in regular higher education institutions to the total resident population at year-end. Agricultural mechanization level is assessed by dividing the aggregate power of agricultural machinery by cultivated land area. The science and technology level is measured by the share of local fiscal expenditure on science and technology in total local fiscal expenditure.

3.2.5 Data

APQS was introduced in three batches in 2015, 2017, and 2021. This study focuses on the first two batches of pilots, as the third batch was initiated in 2021, which coincides with the end of the sample period. The insufficient post-treatment observation period prevents reliable identification of its policy effects and dynamic evolution. Moreover, the measurement of LGUE requires multidimensional city-level indicators related to agricultural inputs, outputs, and environmental conditions, while data for some administrative units have been persistently unavailable. To maintain sample continuity, this study removes administrative units with substantial missing data that prevent the construction of a continuous panel. The final sample covers 273 cities during 2010–2021, including 172 APQS pilot cities and 101 non-pilot cities, with Beijing, Shanghai, Tianjin, and Chongqing included as the four municipalities directly under the central government. For isolated missing values in the retained sample, linear interpolation is conducted within each city using valid observations from the adjacent years before and after the missing year. The interpolated observations account for less than 5% of the total observations for the relevant variables, mainly involving agricultural input indicators, and are scattered across different cities and years rather than concentrated in particular locations or periods. The data are primarily collected from *the China Rural Statistical Yearbook*, *the China City Statistical Yearbook*, provincial and municipal statistical yearbooks and statistical bulletins, local government information disclosure platforms, and relevant announcements issued by the State Administration for Industry and Commerce, the General Administration of Quality Supervision, Inspection and Quarantine, the China National Intellectual Property Administration, and the Ministry of Agriculture and Rural Affairs. Table 1 presents the descriptive statistics of the main variables.

Table 1. Descriptive statistics

Variable	Symbol	Mean	SD	N
Cultivated land green utilization efficiency	LGUE	0.385	0.246	3276
Agricultural product quality and safety pilot	APQS	0.306	0.461	3276
Agricultural mechanization level	AMC	1.005	0.777	3276
Urbanization level	UBL	0.552	0.152	3276

Variable	Symbol	Mean	SD	N
Industrial structure	IDS	0.421	0.103	3276
Internet penetration rate	IPE	22.02	13.36	3276
Human capital level	HCP	0.020	0.026	3276
Science and technology level	STH	0.016	0.017	3276
Agricultural resource utilization efficiency	ARUE	0.406	0.240	3276
Agricultural product branding level	APBL	3.520	5.189	3276
Agricultural technological innovation capacity	ASIC	2.655	4.967	3276

3.3 Model design

3.3.1 Multi-period difference-in-differences model

The implementation of APQS provides a “quasi-natural experiment” for this study. Given the staggered implementation of APQS and variation in the timing of pilot adoption across cities, this study employs a multi-period difference-in-differences (DID) model with city and year fixed effects for the baseline estimation. This specification controls for time-invariant city-level characteristics and common annual shocks while providing a consistent estimation framework for the subsequent impact channel and heterogeneity analyses. The baseline model is specified as follows:

$$LGUE = \beta_0 + \beta_1 DID_{it} + \beta_2 Control_{it} + \delta_i + \sigma_t + \varepsilon_{it} \quad (2)$$

In equation (2), the dependent variable is *LGUE*. β_0 represents the constant term. *DID* reflects the APQS, with β_1 measuring the policy impact. *Control_{it}* is the vector of control variables, and β_2 indicates the estimated coefficients. City and year fixed effects are also taken into account. ε_{it} denotes the stochastic error term in the model.

3.3.2 Impact channel analysis model

To further examine the potential impact channels through which APQS may affect *LGUE*, this study considers three dimensions—agricultural resource utilization, market incentives, and technological innovation—and uses agricultural resource utilization efficiency, agricultural product branding level, and agricultural technological innovation capacity as the corresponding channel variables. Within the multi-period difference-in-differences framework, the effects of APQS on these variables are estimated separately to examine changes in the corresponding production conditions, market activities, and technological innovation activities following policy implementation. The model is specified as follows:

$$M_{it} = \gamma_0 + \gamma_1 DID_{it} + \sum \gamma_k control_{it} + \rho_i + \mu_t + \varepsilon_{it} \quad (3)$$

In equation (3), *M* denotes the channel variables, including agricultural resource utilization efficiency, agricultural product branding level, and agricultural technological innovation capacity.

4 Empirical results

4.1 Baseline regression

Using the DID framework, the paper performs baseline regression with a two-way fixed effects model. Table 2 reports the results. Column (1) includes city fixed effects but does not include time fixed effects, and the DID coefficient remains significantly positive, indicating a preliminary positive association between the policy and *LGUE*. Column (2), which incorporates control variables while retaining city fixed effects, shows that the result remains stable. Column (3)

removes the control variables but retains both city and year fixed effects. In column (4), both time and city fixed effects are controlled together with control variables. The results stay consistent. Overall, the results indicate that APQS significantly improves LGUE, thereby supporting Hypothesis 1.

Table 2. Baseline regression results

	(1)	(2)	(3)	(4)
APQS	0.071*** (0.007)	0.022*** (0.009)	0.033*** (0.010)	0.030*** (0.010)
AMC		-0.017** (0.007)		-0.018*** (0.007)
UBL		0.134** (0.060)		0.124* (0.067)
IDS		0.202*** (0.064)		0.279*** (0.079)
IPE		0.001*** (0.000)		0.001** (0.000)
HCP		0.732* (0.436)		0.543 (0.439)
STH		-0.624** (0.307)		-0.640** (0.310)
_Cons	0.363*** (0.003)	0.206*** (0.032)	0.375*** (0.004)	0.186*** (0.052)
Year FE	No	No	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	3276	3276	3276	3276
R ²	0.669	0.679	0.677	0.681

Note: The symbols ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels in sequence.

Same applies to the following table.

4.2 Robustness tests

4.2.1 Parallel trend test

Before estimating the policy effects of APQS using the difference-in-differences approach, this study employs an event-study framework to examine dynamic changes surrounding policy implementation. Let G_i denote the year in which city i first entered the APQS pilot program, with $G_i=2015$ for the first batch of pilot cities and $G_i=2017$ for the second batch. Event time is defined as the current year minus the policy implementation year, such that $e_{it}=t-G_i$. Accordingly, $e_{it}<0$, $e_{it}=0$, and $e_{it}>0$ correspond to the pre-treatment period, the year of policy implementation, and the post-treatment period, respectively. Event time is not defined for cities that never entered the pilot program; their event-time dummy variables are set to 0 in all periods, and these cities are included in the estimation as the control group. In the estimation, this study constructs event-time dummy variables for years 7 through 1 before policy implementation and years 1 through 4 after policy implementation. Observations from the year of policy implementation (event time 0) are excluded from the event-study estimation, and hence no coefficient is estimated or reported for this period. Drawing on the event-study framework (Beck et al. 2010), the event-study

specification is as follows:

$$LGUE_{it} = \beta_0 + \sum_{k=-7}^{-1} \alpha_k E_{it}^k + \sum_{k=1}^4 \alpha_k E_{it}^k + \varphi' X_{it} + \delta_i + \sigma_t + \varepsilon_{it} \quad (4)$$

In equation (4), $LGUE_{it}$ denotes the LGUE of city i in year t . E_{it}^k denotes the event-time dummy variable, which equals 1 if the event time for pilot city i in year t is k , and 0 otherwise. The coefficient α_k captures the dynamic evolution of LGUE across event periods surrounding the implementation of APQS.

Given the 2010–2021 sample period, the number and cohort composition of observations contributed by the 2015 and 2017 pilot batches differ at event times farther from policy implementation. In particular, observations for event times five to seven years before implementation are mainly contributed by the later-treated 2017 cohort, whereas observations from the fifth post-treatment year onward come exclusively from the 2015 cohort. To enhance comparability across the two policy cohorts and prevent distant event-time estimates from being dominated by a single cohort, Figure 4 presents the dynamic effects within an event-time window of $[-4, +4]$. Because observations from the implementation year are excluded from the event-study estimation, no coefficient is displayed for event time 0. Importantly, observations outside this display window remain in the regression sample. Specifically, the event-time dummies for five to seven years before implementation remain in the model and contribute to the estimation, although their coefficients are not shown in Figure 4 to preserve graphical clarity and cross-cohort comparability. Observations from the fifth post-treatment year onward are likewise retained in the regression sample, but separate event-time dummies are not specified for these more distant post-treatment periods. Thus, $[-4, +4]$ refers only to the display range in Fig. 4 and does not represent a truncation of the regression sample period. Fig. 4 presents the dynamic effect estimates from the event-study analysis. Before APQS implementation, none of the event-time coefficients displayed in the figure are statistically different from zero, and their confidence intervals all include zero. A joint significance test of the pre-treatment coefficients likewise fails to reject the null hypothesis that they are jointly equal to zero. This result indicates no detectable systematic differences in pre-treatment trends and is consistent with the parallel trends assumption. Because local applications and preparatory activities may precede formal pilot designation, some anticipatory adjustment by producers cannot be entirely ruled out. Nevertheless, neither the individual pre-treatment estimates nor the joint test indicates significant changes, suggesting no clear evidence of systematic anticipation effects in the sample. Following policy implementation, the estimated coefficients gradually turn positive and increase with time since adoption, suggesting that the effects of APQS may accumulate over time.

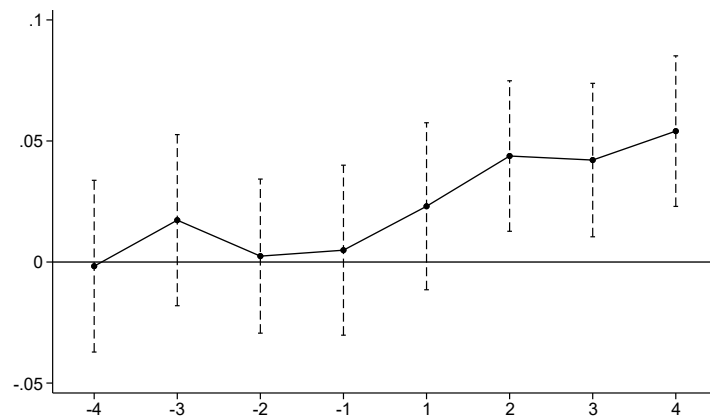


Fig. 4. Parallel trend test

Note: The horizontal axis represents event time, defined as $e_{it}=t-G_i$, where G_i denotes the year in which a city first entered the APQS pilot program. Observations from the implementation year (event time 0) are excluded from the event-study estimation, so no coefficient is reported for event time 0. The regression includes event-time dummies for each of the seven years preceding policy implementation and each of the first four years following implementation. Distant event periods are not binned at the endpoints of the display window. The coefficients for event times -7 to -5 are included in the estimation but not displayed, whereas observations from the fifth post-treatment year onward remain in the regression sample without separate event-time dummies. The joint test of the pre-treatment coefficients yields $F(7, 2975) = 0.94$, $p = 0.4752$, so the null hypothesis that these coefficients are jointly equal to zero cannot be rejected. The dashed lines indicate 95% confidence intervals.

4.2.2 Placebo test

This research applies a placebo test to further assess the robustness of the baseline results. In conducting the placebo test, a total of 172 prefecture-level cities are randomly selected to constitute the pseudo-treatment group. This process is repeated 1,000 times, producing the placebo distribution shown in Fig. 5, which is largely centered around zero. In contrast, the actual estimated coefficient of 0.03 is located in the upper tail of the placebo distribution, indicating that the baseline result is unlikely to be driven by random assignment.

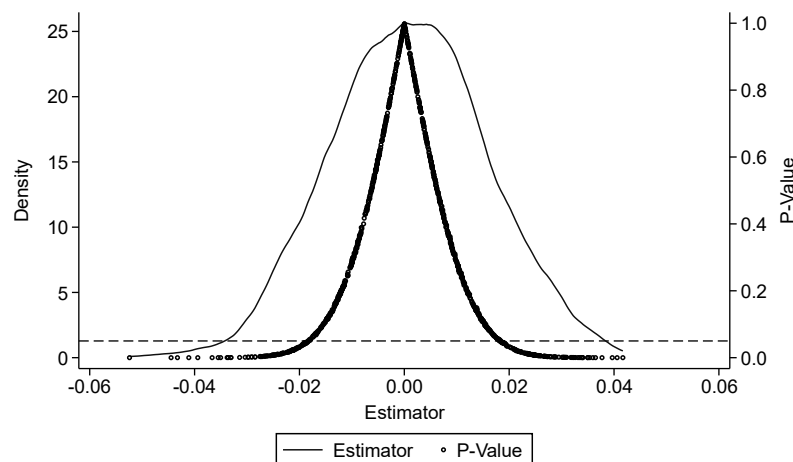


Fig. 5. Placebo test

4.2.3 Excluding other similar policy interference

To ensure that the estimation results are not confounded by other similar policies, the study additionally controls for three initiatives: the low-carbon city pilot, the agricultural green development pilot zone, and the national modern agriculture demonstration zone. Regression findings are shown in Table 3. The low-carbon city pilot is added in Column (1), the agricultural green development pilot zone in Column (2), and the national modern agriculture demonstration zone in Column (3). As shown, regardless of which policy variable is introduced, the results remain significantly positive at the 1% level. This indicates that the promotion effect of the APQS on LGUE does not stem from the overlapping effects of other policies, and the conclusion is highly robust.

Table 3. Results after excluding policy interference

	(1)	(2)	(3)
	Low-carbon city	National pilot zone for green	National modern agricultural

	(1)	(2)	(3)
		agricultural development	demonstration zone
APQS	0.030*** (0.010)	0.031*** (0.010)	0.031*** (0.010)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
_Cons	0.220*** (0.052)	0.185*** (0.052)	0.188*** (0.052)
N	3276	3276	3276
R ²	0.681	0.682	0.681

4.2.4 PSM-DID

Given that the selection of APQS pilot cities may involve non-random factors, this study further applies the propensity score matching difference-in-differences (PSM-DID) approach as a robustness check. This study applies 1:3 nearest-neighbor matching to construct matched samples between the treatment and control groups, using the control variables in the baseline model as covariates to reduce systematic differences in observable characteristics. As shown in Fig. 6, the differences in the distributions of covariates between the treatment and control groups are significantly reduced after matching, suggesting that the matching procedure improves the comparability of the samples. Based on these matched samples, the PSM-DID estimates reported in column (1) of Table 4 show that the coefficient of the policy interaction term is 0.030 and significantly positive at the 1% level, consistent with the baseline regression results. This finding suggests that after accounting for observable differences between the treatment and control groups, the positive association between APQS and improved LGUE remains robust, providing additional evidence for the baseline results. Therefore, these results are primarily used to assess whether the baseline findings remain stable after adjustment for observable characteristics and should be interpreted only within this context.

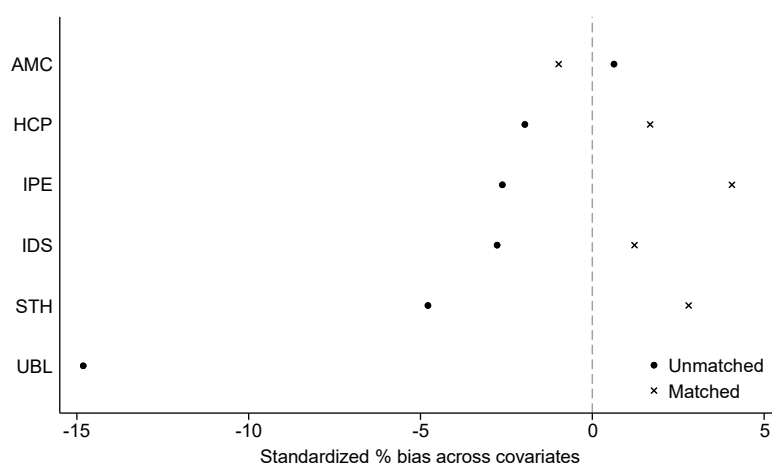


Fig. 6. Standardized bias of variables

449 Table 4. Other robustness tests

	(1)	(2)	(3)	(4)
	PSM-DID	DML	Excluding Municipalities	Staggered DID
DID	0.030*** (0.011)	0.022** (0.011)	0.034*** (0.010)	
ATT				0.036** (0.016)
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	—
City FE	Yes	Yes	Yes	—
_Cons	0.241*** (0.058)	0.003 (0.003)	0.185*** (0.052)	
N	2700	3276	3228	3276
R ²	0.695		0.679	

450 Note: City and year fixed effects are not separately reported for the staggered DID estimator because it is based on
451 group-time average treatment effects rather than a conventional two-way fixed-effects specification.

452 4.2.5 DML

453 This study further employs the double machine learning (DML) approach as an additional
454 estimation strategy. Compared with conventional regression approaches, DML flexibly models the
455 relationships between control variables, treatment variables, and outcome variables using machine
456 learning algorithms, which helps mitigate potential estimation bias arising from functional form
457 misspecification and provides an alternative framework for evaluating the baseline findings. This
458 study adopts the random forest algorithm for estimation and implements five-fold cross-fitting to
459 reduce the potential overfitting risk associated with machine learning models. As reported in
460 column (2) of Table 4, the estimated coefficient of the APQS policy variable is 0.022 and
461 significantly positive at the 5% level, which is consistent with the baseline results. This suggests
462 that the positive association between APQS and LGUE improvement remains robust when using
463 an alternative estimation framework, further strengthening the reliability of the conclusions.

464 4.2.6 Excluding municipalities

465 Column (3) of Table 4 presents the estimation results after excluding the four municipalities
466 directly under the central government. Since the baseline sample contains Beijing, Shanghai,
467 Tianjin, and Chongqing, which differ from other cities in terms of administrative status, resource
468 allocation, and policy implementation conditions, this study excludes these municipalities and
469 conducts the estimation again. The results indicate that the estimated coefficient of the policy
470 interaction term is 0.034 and significantly positive at the 1% level, consistent with the baseline
471 findings. This suggests that the positive association between APQS and LGUE improvement
472 remains robust after excluding municipalities directly under the central government, providing
473 additional evidence supporting the reliability of the baseline estimates.

474 4.2.7 Staggered DID

475 APQS was introduced in separate batches in 2015 and 2017, and the event-study results
476 suggest that its effects may evolve over time. This raises the possibility of heterogeneous policy
477 effects across pilot cohorts and stages of implementation. To further accommodate variation in

treatment timing and potential treatment-effect heterogeneity, this study supplements the baseline analysis with the staggered DID approach proposed by Callaway and Sant'Anna (2021). Specifically, cities are grouped into treatment cohorts according to the year of their first APQS adoption. Group-time average treatment effects are estimated using the doubly robust inverse probability weighting method (dripw), with not-yet-treated cities serving as the control group. As reported in column (4) of Table 4, the overall average treatment effect on the treated (ATT) is 0.036 and statistically significant at the 5% level. This indicates that the positive effect of APQS on LGUE remains evident after accounting for variation in treatment timing and potential heterogeneity across cohorts and periods. The staggered DID results are consistent with the baseline TWFE-DID estimates in both sign and statistical significance. However, the coefficient magnitudes are not directly comparable because the two approaches differ in their estimands, comparison groups, and weighting schemes. Taken together, the two estimation approaches provide consistent evidence that APQS improves LGUE. Nevertheless, the overall ATT should not be interpreted as implying homogeneous treatment effects across different pilot cohorts.

5 Further discussion

5.1 Impact channel analysis

5.1.1 Agricultural resource utilization efficiency

Regarding agricultural resource utilization efficiency, column (1) of Table 5 reports a DID coefficient of 0.022, which is positive and statistically significant at the 1% level, indicating a significant increase in the ARUE indicator following APQS implementation. In light of how ARUE is measured, this finding primarily reflects greater effective irrigation coverage and improved irrigation support conditions in agricultural production. Better irrigation conditions can enhance water resource support for agricultural production and provide a foundation for adopting resource-saving practices such as water-saving irrigation and precision fertilization, thereby improving the conditions for agricultural resource utilization (Saad et al. 2020).

5.1.2 Agricultural product branding level

Regarding agricultural product branding level, column (2) of Table 5 reports a DID coefficient of 0.607, which is positive and statistically significant at the 1% level, indicating that APQS significantly promotes regional agricultural product certification and brand development. Quality certification and geographical indications can signal product quality to the market, enhance the market recognition of agricultural product quality, and help create stable market incentives for high-quality agricultural products (Danko and Nifatova 2022).

5.1.3 Agricultural technological innovation capacity

Regarding agricultural technological innovation, column (3) of Table 5 reports a DID coefficient of 0.315, which is positive and statistically significant at the 10% level. In light of how ASIC is measured, this finding primarily indicates that regional agricultural patent application activity becomes more active following APQS implementation. Higher quality standards and strengthened production requirements may stimulate R&D demand for technologies such as precision fertilization, water-saving irrigation, and integrated pest management, while providing policy incentives for agricultural technological innovation activities (Meng et al. 2024).

520 Table 5. Results of impact channel analysis

	(1)	(2)	(3)
	ARUE	APBL	ASIC
APQS	0.022*** (0.007)	0.607*** (0.136)	0.315* (0.165)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
_Cons	0.456*** (0.039)	3.567*** (0.730)	6.020*** (0.890)
N	3276	3276	3276
R ²	0.808	0.858	0.770

521 5.2 Heterogeneity analysis

522 5.2.1 Heterogeneity analysis across agricultural functional zones

523 To examine the effects of APQS across different agricultural functional zones, this study
524 divides the sample into major grain-producing and non-major grain-producing areas and conducts
525 separate regressions. As reported in Table 6, the estimated APQS coefficients are 0.022 for major
526 grain-producing areas and 0.032 for non-major grain-producing areas, both of which are positive
527 and statistically significant. Major grain-producing areas bear important responsibilities for
528 maintaining stable grain production and supply, meaning that policy implementation needs to
529 balance quality and safety requirements, production factor allocation, and grain production
530 objectives (Xu et al. 2025). By contrast, agricultural product structures and industrial
531 configurations are relatively diverse in non-major grain-producing areas, where quality
532 certification and branding may be more readily aligned with local resource endowments and
533 market demand. Overall, the estimated effects of APQS are positive in both agricultural functional
534 zone subsamples.

535 Table 6. Heterogeneity across agricultural functional zones

	(1)	(2)
	Major grain areas	Non-major grain areas
APQS	0.022* (0.013)	0.032** (0.015)
Control variables	Yes	Yes
Year FE	Yes	Yes
City FE	Yes	Yes
_Cons	0.336*** (0.069)	0.132 (0.089)
N	2004	1272
R ²	0.660	0.704

536 5.2.2 Regional heterogeneity analysis

537 To examine the regional patterns of APQS effects, this study conducts separate regressions
538 for the eastern, central, and western regions. As reported in Table 7, the estimated APQS

coefficient is 0.073 in the eastern region and is positive and statistically significant at the 1% level. The corresponding coefficient is 0.032 in the western region and is positive and significant at the 10% level, whereas the coefficient for the central region is -0.039 and is negative and significant at the 1% level. These results indicate that the estimated effects of APQS vary across regional subsamples, suggesting that its policy performance may depend on regional agricultural production functions, industrial foundations, and implementation conditions. The eastern region is characterized by a relatively high degree of agricultural industrialization and comparatively well-developed agricultural product markets and quality regulatory systems, which may facilitate closer alignment between quality and safety governance and green production (Yifang Liu et al. 2020). The central region bears substantial responsibility for maintaining stable grain production and supply, where the coordination of quality and safety requirements, production costs, and grain production objectives may be more complex (D. Liu et al. 2021). The positive estimate for the western region suggests that APQS may still generate positive effects in regions with different levels of agricultural development. Overall, the regional patterns of APQS effects may reflect the combined influence of agricultural production foundations, policy implementation conditions, and the capacity of agricultural producers to adapt to policy requirements.

Table 7. Regional heterogeneity

	(1)	(2)	(3)
	Eastern region	Central region	Western region
APQS	0.073*** (0.017)	-0.039*** (0.014)	0.032* (0.018)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
_Cons	0.160* (0.094)	0.426*** (0.100)	0.156* (0.089)
N	1308	924	1044
R ²	0.591	0.750	0.747

5.2.3 Topographic heterogeneity analysis

To examine whether the effects of APQS vary across terrain conditions, this study divides the sample into plain and hilly areas and conducts separate regressions. As reported in Table 8, the estimated APQS coefficient is positive and statistically significant in plain areas, whereas the estimate for hilly areas is not statistically significant, indicating different patterns of estimated policy effects across the two terrain subsamples. These differences may be associated with the agricultural production conditions characterizing the two types of terrain. Plain areas generally have more favorable conditions for agricultural machinery use, farmland infrastructure, and contiguous farming, which may facilitate standardized production, coordinated regulation, and agricultural technology diffusion. By contrast, hilly areas face constraints arising from uneven terrain and cultivated land fragmentation, which increase the costs of agricultural operations, mechanized farming, and large-scale production and may constrain the implementation of quality and safety policies (Y. Wang et al. 2020). Accordingly, the differences in estimates across terrain subsamples may reflect variation in agricultural production foundations and policy implementation conditions, although their specific roles require further investigation.

Table 8. Topographic heterogeneity

	(1)	(2)
	Plain area	Hilly area
APQS	0.037*** (0.011)	0.013 (0.019)
Control variables	Yes	Yes
Year FE	Yes	Yes
City FE	Yes	Yes
_Cons	0.250*** (0.063)	0.140 (0.097)
N	2268	996
R ²	0.641	0.741

Note: The terrain-based subsamples include only plain and hilly areas. Observations from the Tibetan Plateau are excluded from the subgroup regressions, resulting in a combined number of observations across the two groups that is slightly smaller than the baseline sample.

6. Conclusions and policy recommendations

6.1 Conclusions

Using panel data from 273 prefecture-level cities over the period 2010–2021, this study employs a multi-period difference-in-differences approach to assess the effects of APQS on LGUE. The results indicate that both the baseline TWFE-DID and staggered DID estimates show a significant positive effect of APQS on LGUE, with the finding remaining robust across other robustness checks. Further analysis suggests that the pilot policy improves irrigation coverage and irrigation support conditions, promotes geographical indication certification and branding activities for agricultural products, and is positively associated with agricultural patent application activity. The heterogeneity analysis reveals different patterns of APQS estimates across agricultural functional zones, regions, and terrain conditions. Notably, the central region exhibits a negative and statistically significant estimate, suggesting that the effects of quality and safety governance on LGUE may depend on regional agricultural production functions and the conditions under which local production systems adapt to policy requirements. In regions bearing responsibilities for maintaining stable grain production and supply, the coordination of quality and safety standards, production costs, and green transformation requirements may be particularly important for policy effectiveness.

6.2 Policy recommendations

Drawing on these results, several policy implications can be outlined:

First, agricultural product quality and safety governance should be advanced in a context-specific manner. Given the variation in APQS estimates across regional and terrain subsamples, differentiated policy measures should be adopted according to regional development levels, agricultural functional roles, and natural resource endowments. In eastern and plain regions, efforts should focus on further improving quality standards and regulatory systems while utilizing their advantages in industrial foundations and large-scale agricultural production. For central and hilly regions, more attention should be given to improving agricultural infrastructure, technical

support services, and policy implementation capacity, so as to reduce the costs of quality and safety governance and enhance policy adaptability and effectiveness.

Second, the policy effectiveness of APQS should be further improved by strengthening the resource, market, and technology dimensions. In the resource dimension, efforts should be made to strengthen the standardized management and process monitoring of agricultural inputs, such as fertilizers and pesticides, promote resource-saving practices including water-saving irrigation and precision fertilization, and improve agricultural resource utilization conditions. In the market dimension, geographical indications, regional public brands, quality certification, and information disclosure systems should be further improved to strengthen quality signaling and brand value of high-quality agricultural products, thereby enhancing market incentives for green production. In the technology dimension, cooperation among research institutions, agricultural extension agencies, and production entities should be strengthened to facilitate the development and application of green agricultural technologies, thereby providing technological support for green agricultural production.

Finally, efforts should be made to enhance complementary policy systems and establish long-term governance mechanisms. Building on the existing quality standards, regulatory frameworks, and traceability systems, complementary policies related to financial support, market incentives, and technical services should be further strengthened to improve the continuity and stability of APQS. Meanwhile, interregional knowledge exchange and policy coordination should be enhanced. The demonstration and diffusion of effective regional governance practices should be strengthened, with their application adapted to local agricultural development conditions and resource endowments, thereby promoting coordinated progress between agricultural product quality and safety governance and agricultural green transformation.

6.3 Research limitations

This study has several limitations that should be acknowledged. First, constrained by the availability of prefecture-level data on agricultural inputs, outputs, and environmental indicators, the sample period extends only through 2021. Because the third batch of APQS pilots was launched in 2021, coinciding with the end of the sample period, the available post-treatment period is insufficient to reliably identify its policy effects and dynamic evolution. Accordingly, this study focuses on the effects of the first two pilot batches, while the applicability of the findings to subsequent batches and longer-term policy effects remains to be further examined. Second, although this study examines the effects of APQS on agricultural resource utilization efficiency, agricultural product branding level, and agricultural technological innovation capacity, it does not further estimate how these variables affect LGUE. The current analysis therefore does not identify the specific causal transmission process through which APQS influences LGUE. Future research could draw on richer micro-level data and causal mediation methods to provide more rigorous tests of the underlying mechanisms. Third, the agricultural carbon accounting in this study primarily covers emissions associated with fertilizer and pesticide application, agricultural film use, and farmland irrigation. Owing to the limited availability of prefecture-level data on energy consumption, particularly agricultural diesel use, emissions associated with agricultural machinery operation are not included in the accounting. This omission may result in some underestimation of total carbon emissions from crop production. Future research could incorporate data on agricultural diesel use and machinery energy consumption to broaden the accounting boundary for agricultural carbon emissions.

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