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Article

The impact of gene editing technology on agricultural economic efficiency Biomechanical Applications: An empirical analysis based on international CRISPR patent data

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Abstract: Gene editing technology, particularly CRISPR has revolutionized the field of biology, agriculture and biomechanics, significantly enhancing the global agricultural economic efficiency and enabling advancements in biomechanical research. CRISPR technology has emerged since around 2012, and has rapidly become a hotspot for research on gene editing technology. Utilizing the precise and efficient genome editing capability of CRISPR, the technology has made breakthroughs in enhancing crop resistance to insect pests, improving drought resistance, and increasing the nutritional value, and enhanced agricultural economic benefits. In parallel, CRISPR has also enabled innovative applications in biomechanics, such as the development of genetically modified organisms (GMOs) with optimized musculoskeletal structures for improved mechanical performance and the study of gene functions in biomechanical systems. In this study, we integrated CRISPR patent data from 13 countries and regions with different regions and development levels from 2015–2022, constructed the Agricultural Economic Index (AEI) through principal component analysis, and used regression models to quantitatively assess the economic benefits of CRISPR technology, while also exploring its potential impact on biomechanical research and applications. The results of the study show that there is a significant positive correlation between the number of CRISPR patents and agricultural economic efficiency, validating its key role in promoting agricultural transformation and sustainable development. This study highlights the dual impact of gene editing technology in promoting economic growth and fostering bio-innovation, while also exploring its potential impact on biomechanical research and applications. This research provides empirical evidence of CRISPR's strategic value in agriculture and biomechanics, emphasizing the importance of technological innovation f enhancing economic efficiency and advancing scientific frontiers.

Keywords: gene editing technology; CRISPR; agricultural economy; biomechanics; patent; regression analysis

1. Introduction

1.1. Introduction to research

Agriculture, as a vital component of the global economy, not only bears the responsibility of ensuring food security but also plays a critical role in addressing climate change and promoting sustainable development. However, traditional agricultural production models face challenges in meeting future demands for food quantity and quality, particularly under constraints of limited land resources and increasing environmental pressures. The advent of gene editing technology, particularly CRISPR-Cas9, has provided unprecedented breakthroughs for agricultural innovation. The gene editing technology of CRISPR/Cas9 has become an important and significant technical tool for research in the fields of plant gene function study and genetic breeding [1].

In 1987, a Japanese research group discovered the repeat structure of CRISPR in the flanking sequence of the iap gene of E. coli K12 [2]. After continuous research and exploration, in 2002 scientists formally named it CRISPR in order to reflect the structural characteristics of this type of repetitive sequences [3]. In 2007, a study found that the spacer sequences of CRISPR are extra-chromosomal sequences from plasmids or phages, etc., and experimentally confirmed that the CRISPR system can equip hosts, such as bacteria, with a unique defence against invasion by foreign DNA immunity [4], in 2008, it was found that the bacterial CRISPR system can prevent the transfer of exogenous genes, the first experimental confirmation of the CRISPR system function [5], in 2013, the researchers found that the CRISPR system crRNA specific recognition of the target sequences, guiding the Cas nuclease to accurately locate the target genes and carry out precise cutting of this feature, so that the CRISPR/Cas system more widely known [6].

CRISPR/Cas gene editing technology is a kind of gene editing technology through single Sq RNA to identify the target site, use Cas nuclease to cut the specific target sequence to produce DNA double strand break (DSB), and then through non-homologous end joining (non-homologous end joining, NHEJ) or homology-directed repair HDR to repair the breaks. After DSBs are generated, insertion or deletion of random DNA fragments occurs through non-homologous end joining (NHEJ) or homology-directed repair (HDR), or the corresponding gene fragments are inserted or replaced during homology-directed repair, thus realizing the gene editing technology of genome sequence mutation. CRISPR/Cas system only needs to design sequences complementary to the target site, and can edit one or more DNA or RNA sequences at the same time, which is easy to operate, with high mutation efficiency and high specificity. The application of this technology in crop genetic breeding can introduce one or several excellent traits into crops to obtain new varieties in a shorter period of time without cross-breeding, and obtain good results in improving the quality of many crops.

CRISPR is a revolutionary technology that enables precise editing of specific DNA sequences. Its efficiency, simplicity, and scalability have rapidly made it a cornerstone in agricultural science, with applications such as improving crop resistance to adverse conditions, increasing crop yields, and optimizing nutritional content. Since its discovery by the scientific community, CRISPR technology has seen exponential growth in research and application, with a significant surge in patent filings across various countries. In plants, CRISPR/Cas9-based gene editing comprises multiple steps, including selection of target sites, design and synthesis of SgRNAs, delivery of transformation vectors or CRISPR/Cas9 ribonucleoproteins, in plant cells, transformation, and screening of gene-edited plants [7].

CRISPR/Cas systems are divided into two major classes, Class I and Class II. Class II requires multiple Cas protein complexes to target exogenous DNA, while Class I requires only a single Cas protein for interference. CRISPR/Cas9 is the most widely used CRISPR/Cas system in current research. protospacer-adjacent motif site to recognize the target DNA sequence and subsequently base-pair with DNA under the guidance of SG RNA, Cas9 produces a double-stranded break 3 bp upstream of the PAM site. CRISPR/Cas9 has a serious drawback, i.e., the off-target effect near the target gene during gene editing results in non. The off-target effect near the target gene during the gene editing process resulted in the cleavage of non-target sequences and the generation of unwanted mutations. In addition, the specificity and efficiency of PAM sites affect the cutting efficiency of CRISPR/Cas9. Therefore, more precise CRISPR editing techniques have emerged: Single-base editing and guided gene editing.

Despite the widely acknowledged potential of gene editing in agriculture, there remains a notable gap in evaluating its economic benefits. Most existing studies focus on biological mechanisms or case analyses of specific regions, lacking systematic economic research based on multi-national data. Therefore, examining the comprehensive impact of CRISPR technology on agricultural economics, particularly by quantifying the contribution of technological innovation through patent data, is of substantial importance.

This study selects data from China, the United States, Australia, Japan, the European Union, Brazil, and Canada between 2015 and 2022 to analyze the influence of CRISPR technology on agricultural economic efficiency. By incorporating indicators such as the share of agricultural output in GDP, agricultural employment ratio, and crop production value, a composite Agricultural Economic Index (AEI) was constructed. Using regression analysis, this study investigates the mechanisms through which patent innovation affects agricultural economic efficiency. The findings not only provide empirical support for assessing the economic benefits of CRISPR technology but also offer theoretical insights and practical recommendations for policymakers aiming to advance agricultural technology and promote sustainable agricultural development.

1.2. Literature review

It is already a mature research method to evaluate the development process of an industry with patent data. In terms of selecting patent data, Wang et al. [8] built a core patent recognition index system to screen core patents in the field of artificial intelligence from the perspective of behavioral effects and motivation. Xie et al. [9] built a comprehensive value index system for core patents to identify core patents in the field of wind energy. Luo et al. [10] analyzed the correlation between various patent attribute indexes and core patents through multiple regression models, and identified the core patents in the field of new energy vehicle devices. In terms of the combination of patents and agriculture, Yang et al. [11] identified the key technologies of crop breeding technology through patent co-citation clustering and combination analysis.

Some scholars have used patent statistics to describe the international distribution and transfer of environmental technologies [12] and the distribution and change of climate change mitigation technologies [13], and conducted empirical studies on specific fields and problems of green technology innovation. In agricultural patents, Luo et al. [14] studied the R&D investment and patent protection of agricultural biotechnology in the United States. Through statistical analysis of patent data, Zou [15] analyzed the global development trends of agricultural biotechnology from a macro level and multiple angles, and used patent portfolio analysis and other methods to dig patent data, calculate the comprehensive competitive position of agricultural biotechnology in major countries, and made diagnostic analysis of the target market and technical field layout of each country. The patent competition in agricultural biotechnology in major countries in the world is introduced, which also mentions the application of new gene editing technology patents in agriculture, but the data is only recorded in 2018. In addition, Zhu et al. [16] used literature for analysis.

In terms of the evaluation of agricultural development level, Li et al. [17] evaluated and analyzed the development level of modern agriculture in Hebei Province, Zhangjiakou City and Zhuolu County from 2005 to 2012 through entropy weight method and linear weighting method. Zhong et al. [18] used the data of Jiangxi Province from 2000 to 2012 to build an evaluation index system of agricultural socialized service, and measured the level of agricultural socialized service in Jiangxi province by using the entropy weight method. Du et al. [19] constructed a three-level indicator system containing 23 specific indicators, and collected the specific values of 23 specific indicators in each province in 2015 according to relevant statistical yearbooks and statistical websites. By referring to the agricultural monitoring and evaluation method and comparing the relevant data of foreign developed agricultural countries, the specific values of each index when basically realizing agricultural modernization and fully realizing agricultural modernization are given, and then the numerical scores of each specific index are scored by a linear equation. Finally, the total scores and rankings of agricultural modernization degree in the country and provinces and the scores and rankings of each level index are calculated. Hu [20] and others analysed agricultural factor performance based on empirical data from 90 countries from 1995 to 2020, Yu [21] measured the agricultural economic indicators of Chinese provinces using a comprehensive evaluation method, Sun [22] analysed the impact of the digital economy on the income of farmers by using principal component analysis, in addition, Liu [23] and others analysed the impact of weather extremes on the agricultural economy which shows that other objective factors should be considered, Xu [24] and others analysed the relationship between agricultural economy and talent return, which reflects the social utility, and the study of Zhao [25] and Yang [26] show that the level of agricultural economy is related to investment, which help me to construct the indicators of AEI.

After trying various indicators, this paper finally selected seven indicators to determine the agricultural economic index AEI by using principal component analysis method, obtained the number of patents of gene editing technology from WIPO by referring to different methods in patent screening, and analyzed the impact of gene editing technology on agricultural economic benefits by establishing regression equations.

2. Research methods

2.1. Data sources

In order to measure the economic efficiency of agriculture, Agricultural Economic Indicators (AEI) were constructed with reference to other literatures that measure the level of agricultural development, seven sets of data were selected for the construction of AEIs in this study, with the vast majority of the data coming from the Food and Agriculture Organization of the United Nations (FAOSTAS), the sources of which are listed below **(Table 1)**:

Table 1. Parameter data and sources.

Variable	Meaning	Sources
Value added	Proportion of annual increase in agricultural output value to total output value	FAOSTAT
Value	Total value of annual agricultural production	FAOSTAT
Emission	Annual carbon dioxide emissions	FAOSTAT
Export	Annual value of agricultural exports	FAOSTAT
Area with irrigator	Area of agricultural land with irrigation facilities	FAOSTAT
Employment	Proportion of agricultural employed population in total employed population	FAOSTAT
Government investment	Annual Government agricultural investment	FAOSTAT

In addition to constructing the AEI, this paper also collected other data when constructing the regression model. Among them, the patent data comes from WIPO and patent database Incopat, whose relevant data are integrated, and the method of collection is to search for patents containing CRISPR during 2012–2022, and collect statistics according to the countries, among which, the relevant data belonging to PCT (Patent Cooperation Treaty) are classified into the relevant countries according to the nationalities of the patent inventors. Among them, the data related to PCT (Patent Cooperation Treaty) is classified into relevant countries according to the nationality of the patent inventor, and the patent data of patent number A01 is selected, and the countries are selected according to the region and development status **(Table 2)**:

Table 2. Selected countries.

Country	Continent	Development status
USA	North America	Developed country
Canada	North America	Developed country
China	Asia	Developing country
Japan	Asia	Developed country
Brazil	Latin America	Developing country
Australia	Oceania	Developed country
Korea (South)	Asia	Developed country
India	Asia	Developing country
Israel	Asia	Developed country
Russia	Europe	Developing country
Mexico	Latin America	Developing country
Argentina	Latin America	Developing country
EU	Europe	

According to the data, the number of patents by country shows the following trend in **Figure 1**:

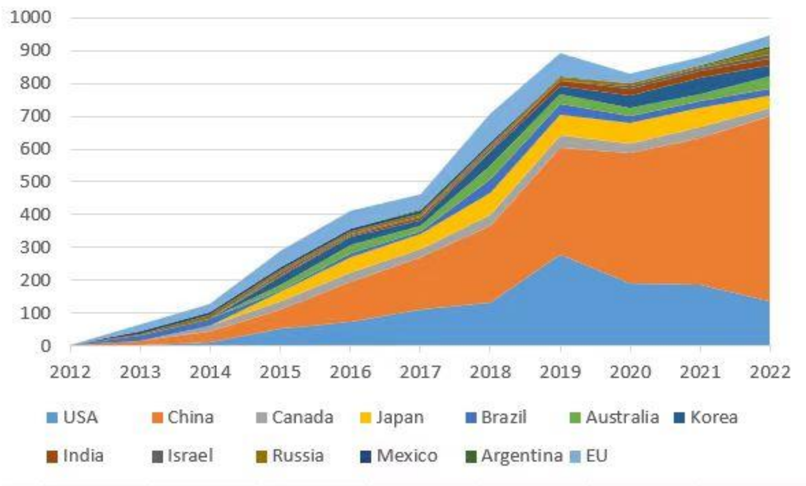

Figure 1. CRISPR patent data by country.

In addition to this, the following variables were selected for constructing the model and the data are as follows **(Table 3)** :

Table 3. Variable data and sources.

Variable	Meaning	Sources
Temperature Change	Average monthly land temperature change	FAOSTAT
GDPp	GDP per capital	World Bank
Area	Agricultural area, including urban and associated areas	FAOSTAT

Data compilation and cleaning were performed using Excel, while data processing was conducted using Stata 17.

2.2. Construction of Agricultural Economic Indicators (AEI)

The data in **Table 1** were used to construct the AEI. The data were first standardized using the following formula:

$$x_N = \frac{x_i - \bar{x}}{\sigma} \tag{1}$$

where x_N represents the standardized result, $\bar{x}$ denotes the mean value, and σ stands for the standard deviation.

Principal Component Analysis (PCA) is a statistical technique used for dimensionality reduction while preserving as much variability as possible in large datasets. It transforms the original set of variables into a new set of uncorrelated variables known as principal components, which are ordered by the amount of variance they explain. Using the standardized results, principal component analysis (PCA) was conducted on the seven parameters to determine their correlation with AEI.

AEI is a comprehensive measure of a country's or region's agricultural development from the perspectives of crop production, economic efficiency, scientific and technological agriculture, and social efficiency, etc. Based on the calculations, the AEI for each country is as follows **(Table 4)**:

Table 4. AEI for selected countries.

Country	AEI average
China	−1.128485961
USA	−1.418828617
Canada	0.070850586
Japan	−1.322337725
Brazil	5.551080184
Australia	0.697581161
Korea	3.550232736
Inida	−1.684955326
Israel	−1.308217287
Russia	−1.374609785
Mexico	−0.833507576
Argentina	−0.840425936
EU	0.041623588

2.3. Research ideas

Having already obtained the AEI, the Agricultural Economic Indicator (AEI) was first defined as the dependent variable, relying on four independent variables: Nmber of patents, area, GDP per capita and temperature change.

In terms of model construction, regression equations were first constructed using these independent variables and basic regression analyses were performed. After the initial establishment of the regression model, I performed a test of covariance and a test of heteroscedasticity on the data. The covariance test is used to rule out the problem of multicollinearity that may be caused by high correlation between independent variables, while the heteroskedasticity test ensures that the error terms in the regression model have homoskedasticity, further verifying the robustness of the model.

After the initial regression model analysis, the lagged effect of the number of patents (Patents) is examined by introducing a lagged term (1 to 3 years). By analyzing the results of the lagged variables, it is found that the lagged effect of the number of patents is not significant on the AEI, indicating that the immediate effect of the number of patents on the AEI is greater than its lagged effect. In order to explore the possible interaction between the number of patents and other variables, the interaction term model of the number of patents and other independent variables is constructed to analyze their common effects. This analysis helps to reveal the joint effects between the number of patents and each factor, further deepening the understanding of the factors influencing the AEI. Based on the results of the model, a comprehensive analysis is carried out and the main influence paths and conclusions of each factor on the agricultural economic indicators are summarized.

3. Experimental contents

3.1. Constructing the model

Based on the Agricultural Economic Indicators (AEI) as the dependent variable and relying on the four independent variables of number of patents, area, GDP per capita and temperature change, the regression model was constructed as follows:

$$AEI_{it} = \beta_0 + \beta_1 Patent + \beta_2 GDPp_n + \beta_3 Area_n + \beta_4 Tem_n + \varepsilon_{it} \quad (2)$$

AEI_{it} represents the agriculture index of country i in year t. β_1, β_2, β_3, β_4 show the effect of the number of patents, GDP per capita, agriculture area and average temperature change on the AEI, while ε_{it} is the error term.

3.2. Model testing

The Vif value of the multicollinearity test is 1.30 and the model is free from the problem of multicollinearity.

The model was tested for heteroskedasticity and subsequently the model was subjected to robust standard errors.

3.3. Analyzing the lagged effect

The generation of patents may not have a significant impact on the agricultural benefits of the current year, and it may take some time from the generation of patents to their application. Therefore, the lag variables are designed to explore the impact of patents on AEI 1–3 years after their generation.

The lagged utility was added to the data on the number of patents to separately analyze their impact on AEI at 1–3 years after the patent was created, constructing the formula as follows:

$$AEI_{it} = \beta_0 + \beta_1 Patent + \beta_2 GDPp_n + \beta_3 Area_n + \beta_4 Tem_n + \beta_5 Patent_{t-lag} + \varepsilon_{it} \quad (3)$$

where β_5 responds to the effect of patent data on the AEI when lagged lag years, that is, what lag years after the patent was created do to the AEI.

3.4. Interact effect

The effect of patent data alone may not be complete, considering the interaction of patent data with several other variables. Interactive variables were generated between patent data and per capita GDP, temperature change and agricultural area respectively, and the comprehensive impact of patent generation on agricultural economic benefits under different conditions was tested. The construction equation is as follows:

$$AEI_{it} = \beta_0 + \beta_1 Patent + \beta_2 GDPp_n + \beta_3 Area_n + \beta_4 Tem_n + \beta_5 Patent\_Area + \varepsilon_{it} \quad (4)$$

$$AEI_{it} = \beta_0 + \beta_1 Patent + \beta_2 GDPp_n + \beta_3 Area_n + \beta_4 Tem_n + \beta_5 Patent\_GDPp + \varepsilon_{it} \quad (5)$$

$$AEI_{it} = \beta_0 + \beta_1 Patent + \beta_2 GDPp_n + \beta_3 Area_n + \beta_4 Tem_n + \beta_5 Patent\_Temp + \varepsilon_{it} \quad (6)$$

In Equation (4), β_5 reflects the interaction between patent data and agricultural area, in Equation (5) reflects the interaction between patent data and per capita GDP, and in Equation (6) reflects the joint impact of patent data and temperature change.

4. Analysis results

After processing, the results of the preliminary regression analyses were as follows (**Table 5**):

Table 5. Multiple regression analysis results.

Variable	Coefficient	Std. Err.	*t*-value	*p*-value
Patents	0.0061277	0.0013596	4.51	0.000
GDPp_*n*	−1.0747270	0.0881478	−12.19	0.000
Temp_*n*	−0.3469650	0.0894861	−3.88	0.000
Area_*n*	1.1865690	0.1106646	10.72	0.000
Intercept	−0.2403947	0.1026884	−2.34	0.021
R-squared	0.7581			
Prob > *F*	0.000			

After robust standard errors, the final results are as follows (**Table 6**):

Table 6. Results after robust standard errors.

Variable	Coefficient	Std. Err.	*t*-value	*p*-value
Patents	0.0061277	0.0010246	5.98	0.000
GDPp_*N*	−1.074727	0.1046209	−10.27	0.000
Area_*N*	1.186568	0.111336	10.66	0.000
Temp_*N*	−0.346965	0.0875808	−3.96	0.000
Intercept	−0.2403947	0.1038772	−2.31	0.022
R-squared	0.7581			
Prob > *F*	0.000			

According to the results, the regression equation is as follows:

$$AEI_{it} = \beta_0 + 0.0061277Patent - 1.074727GDPp_n + 1.186568Area_n - 0.346965Temp_n + \varepsilon_{it} \quad (7)$$

The R^2 value of the model is 0.7581, indicating that the regression model can explain about 75.81% of the variability of agricultural economic index (AEI), which indicates that the model has a good fitting effect and can accurately describe the changing trend of AEI. Among them, the coefficient of patent number is positive and statistically significant ($p < 0.01$), indicating that there is a positive relationship between patent number and agricultural economic indicators. That is, for every unit increase in the number of patents, the agricultural economic index will increase by about 0.0061 units, which means that the increase in the number of patents has a promoting effect on the development of agricultural economy. The per capita GDP coefficient is negative and statistically significant ($p < 0.01$), which means that the increase of per capita GDP has a negative impact on agricultural economic indicators. Specifically, with each unit of per capita GDP growth, the agricultural economic indicator will decline by about 1.075 units. This result may indicate that in some countries or regions, too high per capita GDP may mean accelerated urbanization, which has a depressing effect on the agricultural economy. The coefficient of agricultural area was positive and statistically significant ($p < 0.01$), indicating that there was a strong positive correlation between agricultural area and agricultural economic indicators. That is, for every unit increase in agricultural area, the agricultural economic index AEI will increase by about 1.187 units. This shows that larger agricultural area can effectively promote the development of agricultural economy. The coefficient of temperature change was negative and statistically significant ($p < 0.01$), indicating that temperature change had a negative impact on agricultural economy. Each unit of temperature change will cause the agricultural economic indicator AEI to decrease by about 0.347 units. This indicates that climate change, especially abnormal temperature changes, may have adverse effects on the stable development of agricultural economy. The influence of each factor on AEI conforms to the conventional cognition.

After the patent data is set to lag effect, the results are as follows:

According to **Table 7**, the effect is not obvious after the addition of lagging variables, and the *p*-values are all greater than 0.1, or even very close to 1, with no statistical significance. Therefore, the effect of patent data on agricultural economy is not obvious 1–3 years after the generation of patent data.

Table 7. Results with patents lag.

Variable	**Coefficient**	**Std. Err.**	***t*-value**	***p*-value**
Patents	0.0078917	0.0042698	1.85	0.068
Patents_lag1	−0.0000719	0.0063147	−0.01	0.991
Patents_lag2	−0.0030698	0.0063988	−0.48	0.633
Patents_lag3	0.0014456	0.0055444	0.26	0.795
GDPp_*N*	−1.085219	0.1064012	−10.2	0.000
Area_*N*	1.139104	0.1485776	7.67	0.000
Temp_*N*	−0.3456626	0.1111054	−3.11	0.002
Intercept	−0.2638426	0.1360269	−1.94	0.055
R-squared	0.777			
Prob > *F*	0			

Create an interaction term with the patent data and several other variables to test the interaction results. The results are as follows:

According to the results in **Table 8**, the effect of the interaction model between patent data, per capita GDP and agricultural area is not significant, and the *p*-value is greater than 0.1, which is not statistically significant. The interaction effect between patent data and temperature change is significant, and p is less than 0.05, when the coefficient is positive. In countries and regions with large temperature changes, patent data has a greater positive impact on agricultural economic level.

Table 8. Results of interactive data processing.

Variable	Coefficient	Std. Err.	*t*-value	*p*-value
Patents_GDPp	−0.0001967	0.0002414	−0.81	0.417
Patents_Area	−0.0002666	0.0003926	0.68	0.49
Patents_Temp	0.0006388	0.0002553	2.5	0.014

5. Conclusion

This study examines the impact of CRISPR-related patent activity on agricultural economic efficiency, taking into account variables such as agricultural area, GDP per capita, and temperature change. Through regression analysis, the study provides key insights into the drivers behind agricultural economic performance and highlights the role of gene editing technology in advancing agricultural modernization.

The results show that the number of CRISPR-related patents has a positive impact on agricultural economic indicators, with a statistical significance coefficient of 0.0061. This suggests that technological innovations, particularly in gene editing, can significantly improve agricultural productivity and economic efficiency. Patents contribute to the development of new crop varieties, increase resistance to environmental pressures, optimize resource utilization, and provide considerable economic benefits to the agricultural sector.

However, the analysis also found that per capita GDP has a negative impact on agricultural economic efficiency, with a coefficient of −1.075. This finding is consistent with the observation that high-income economies often undergo structural shifts in urbanization and industrialization, which can inhibit the relative contribution of agriculture to overall economic activity. These results highlight the need to explore diversified strategies to balance economic growth with the preservation and enhancement of agricultural values.

Agricultural area is another key factor, with a positive coefficient of 1.187. This highlights the fundamental role of land resources in agricultural economic growth. Expanding agricultural land or making its use more efficient remains a key strategy to boost agricultural output and economic contribution, especially in regions where arable land is a limiting factor.

The negative coefficient of temperature change is −0.347, which reflects the adverse effect of climate change on agricultural production performance. Temperature fluctuations disrupt growing conditions, reduce yields, and challenge the stability of agricultural production systems. The study highlights the urgency of climate adaptation measures, including the development of climate-resilient crops and the adoption of precision agriculture techniques, to mitigate these negative impacts.

An exploration of the lagging effect of patent activity found no statistically significant results, suggesting that the effects of CRISPR-related patents were immediate rather than delayed. This highlights the rapid integration of gene-editing technology into agricultural practices and the direct impact of innovation on economic outcomes.

The interaction term analysis shows that the interaction effect between patent activity and GDP per capita or agricultural area is not significant. However, the interaction between patents and temperature change shows a significant positive effect, suggesting that technological innovation plays a greater role in mitigating climate challenges in regions with greater temperature fluctuations. This highlights the importance of deploying cutting-edge technologies to improve agricultural sustainability in the country most vulnerable to climate change.

This study confirms the critical role of CRISPR-related innovations in improving economic efficiency in agriculture, especially in the face of climate change. The findings highlight the importance of supporting technological advances, improving land use efficiency, and implementing targeted climate adaptation strategies. Policymakers should prioritize investments in agricultural research and development, incentivize the application of advanced technologies, and develop policies that promote sustainable agricultural practices to ensure long-term economic and environmental benefits.

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