

Article

Empowered or Negative? Research on the Impact of Industrial Agglomeration on the Development of Agricultural New Quality Productive Forces: Evidence from Shandong Province, China

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Abstract: Realizing the SDGs is a core issue of global development. In this regard, China has put forward a new quality productive forces development path with innovative thinking, providing systematic solutions for sustainable transformation through factor allocation optimization and whole-chain innovation drive. In the agricultural sector, industrial agglomeration is one of the factors affecting the development of new quality productive forces, with a spatial layout that can improve the efficiency of agricultural production and the effective utilization of resources. This paper investigates the impact of agricultural industry agglomeration on new quality productive forces by using the spatial Durbin model (SDM) to measure the relevant data of 16 prefecture-level cities in Shandong, China, from 2010 to 2022. The results show the following: (1) The spatial patterns of agricultural industry agglomeration and new quality productive forces in Shandong Province have been evolving, showing an obvious spatial correlation and “high in the south and low in the north” and “high in the north and low in the south” spatial patterns, respectively. (2) From a global perspective, industrial agglomeration has significant negative direct and indirect effects on the development of agricultural new quality productive forces, and this conclusion still holds after robustness testing. (3) From a local perspective, the impact of agricultural industry agglomeration on new quality productive forces is regionally heterogeneous. In the central economic zone, the impact is positive, while in the western and eastern economic zones, it is negative. This research provides a theoretical basis for optimizing the spatial layout of the agricultural industry and constructing a sustainable productivity system.



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Keywords: industrial agglomeration; agricultural new quality productive forces; spatial spillover effect; spatial Durbin model; entropy method

1. Introduction

As a result of intensifying global climate change and the contradiction between food security and ecological protection, sustainable agricultural development has become a key battleground for realizing the United Nations’ 2030 Agenda (SDGs) [1]. China’s sustainable development ground is in the upper-middle level of the world [2], and new quality productive forces have emerged on this basis. The new quality productive forces aim to promote intelligent and intensified agricultural production through the reconstruction of factor production and organization modes, with scientific and technological innovation, digital synergy, and green and low-carbon methods as the core [3]. The essence of new quality productive forces is strategically coupled with clean energy, industrial innovation, and

sustainable production in the United Nations sustainable development goals (SDGs) [4]. Moreover, agriculture is the foundation of China's statehood, the tool for the country's rise, and the basis of its strength [5]. Thus, agricultural new quality productive forces are the focus of future development. New quality productive forces will become a key engine for the agricultural industry to break through its resource constraints and reshape its competitiveness, which could help in the modernization, intelligence, and greening of agriculture, improve agricultural production efficiency, and lay a solid foundation for achieving rural revitalization. As a driver of spatial organization and industrial chain integration, agricultural industrial agglomeration can leverage geographic advantages to accelerate the dissemination of effective information, promote the cross-regional flow of innovation factors, and provide spatial radiation to the surrounding areas. This spillover effect has a certain practical significance in breaking traditional agricultural production boundaries and optimizing the efficiency of regional resource allocation. As a large agricultural province in China, Shandong Province has been modernizing its agriculture at a relatively fast pace and has a rich agricultural industry. Areas such as the Shouguang Vegetable Industry Cluster and Jiaodong Peninsula Intelligent Agricultural Belt show not only the impact of industrial agglomeration in improving local productivity but also the synergistic effects of technology spillover, factor sharing, and other mechanisms on neighboring regions, providing typical samples for an analysis of spatial spillover effect paths. By studying the spatial spillover effect of new quality productive forces and agricultural industry agglomeration, this paper can explore the nonlinear impact of industrial agglomeration on regional agricultural new quality productive forces, providing a decision-making basis for constructing cross-regional synergistic development mechanisms and promoting the high-quality development of agriculture.

There is a wealth of research related to agricultural industrial agglomeration, with many scholars focusing on exploring its impacts on the economy, ecological environment, and sustainable development. Agricultural industry agglomeration is a phenomenon in which factors of agricultural production flow into a specific region due to natural conditions, policy guidance, or market mechanisms [6]. In terms of economic benefits, industrial agglomeration can promote regional agricultural growth through the scale effect [7]. However, the direct enhancement of farmers' income is controversial [8–10]. In terms of environmental effects, industrial agglomeration and rural surface pollution affect each other and have an N-shaped fluctuating relationship [11]. By using the "combination of planting and breeding mode (CPB)" to achieve industrial synergy and waste resource utilization, pollution from planting, livestock, and poultry breeding can be reduced. Industrial clustering can also reduce pollution from planting and livestock breeding [12]. However, industrial agglomeration has a threshold effect, with moderate agglomeration possibly promoting the green transformation of industry, while excessive concentration leads to resource overload [13]. Therefore, the new energy technology formed by industrial agglomeration will have negative effects on sustainable development if it is detached from locally adapted factor conditions and hardware facilities [14]. Existing research on industrial agglomeration provides a multidimensional theoretical framework and methodological reference for our research, revealing the role of the agglomeration effect's boundaries through the multiple perspectives of economy, ecology, and sustainable development, and laying the foundation for exploring the regional synergy mechanism. Other scholars' applications of spatial econometric modeling also provide a methodological reference for us to quantify the spatial spillover effect.

The concept of new quality productive forces is relatively new, and most of the existing research focuses on its characteristics, the construction of the evaluation index system, and practical applications. In terms of concepts and characteristics, new quality

productive forces overcome the limitations of traditional productivity that relies on resource consumption and scale expansion, creating a productivity form with new elements such as knowledge, technology, and data as the core driving forces [15,16]. In terms of measurement, many scholars have constructed a three-dimensional indicator system. It mainly includes labor materials, labor objects, and laborers. These are combined with the entropy value method and others to achieve dynamic assessment and cross-regional comparison [17,18]. In terms of practical applications, they reveal the dynamic mechanism at the level of economic development, inputs of factors of production, and other threshold conditions [19,20]. Existing results on new quality productive forces lay an important theoretical foundation for subsequent research, which this paper used to analyze the essential differences between traditional productivity and new quality productive forces. The results also provide a method for constructing a multidimensional indicator system, which can provide a reference for dynamic measurements and cross-regional comparative research.

Although there has been an abundance of research on agricultural industrial agglomeration and new quality productive forces, no scholars have yet analyzed the two together, and there are still gaps in the research field. However, there is a connection between the theoretical mechanism of agricultural industrial agglomeration and new quality productive forces. As the local agricultural industry agglomeration increases, a large number of talents, capital, resources, and technologies will pour in, creating a siphon effect [21]. These factors are indispensable for the development of new quality productive forces. Factor agglomeration can increase the efficiency of factor production, reduce the cost of innovation, accelerate the transfer of information, and provide a material basis for freeing new productivity from traditional factor dependence. Therefore, the combined analysis of the two has a theoretical basis. This is a novel approach in this paper.

In this paper, in order to improve the scientific validity of the study, we also refer to the framework, ideas, and methods of related articles [22–24] and their application to the investigation of the impact of agricultural industry agglomeration on new quality productive forces.

In summary, there is a relatively rich body of domestic and international scientific research that provides guidance for the theoretical framework of this study. Three new aspects of this study are of particular value: (1) The study of China's agricultural industrial development is useful to other developing countries, as it can inspire these countries to explore a development model suitable for their national conditions. (2) Although there is a large amount of studies in the literature on agricultural industrial agglomeration in China, it should follow the trend in the development during this time and analyze the relationship between agricultural industrial agglomeration and new quality productive forces from the perspective of new quality productive forces in order to fill the current research gap. (3) The system of indicators of new quality productive forces has not yet been harmonized. The existing indicators can be updated according to different research needs to provide a basis for subsequent research. Using spatial econometric models, the relevant data of 16 prefecture-level cities in Shandong, China, from 2010 to 2022 were analyzed to study the spatial spillover effect of agricultural industrial agglomeration on new quality productive forces, providing a direction for improving the future development of new quality productive forces.

2. Research Hypotheses and Model Construction

2.1. Research Hypotheses

In a specific region, once the agricultural industrial agglomeration reaches a certain level, market competition effects, knowledge spillover effects, and economy-of-scale effects will emerge [25]. (1) In terms of market competition effects, when industries agglomer-

ate in the same region, the competitive pressure among them will prompt enterprises to continuously increase investment in science and technology and optimize product quality, so as to promote the overall development to a higher level [26]. Weifang, Shandong Province, is a large agricultural city, in which the Shouguang Vegetable Industry Cluster operates through the improvement of varieties and brand competition, forcing the reform and upgrading of related enterprises in the region and forming a good market competition effect. (2) In terms of knowledge spillover effects, a large number of empirical analyses show that the spatial agglomeration effect of agricultural industry clusters can bring about technology and knowledge spillover through the construction of a specialized division of a labor collaboration network and a resource-sharing mechanism [27]. This can contribute to accelerating the dissemination of agricultural information in the region, increase opportunities for agricultural operators to communicate and learn from one another, advance technological innovation, and promote the application of research and development results. The Qingdao Smart Agriculture Demonstration Park in Shandong Province has implemented a collaborative network of industry, academia, and research institutes, facilitating the proliferation of technologies such as plant protection drones in Shandong, and allowing for the spatial spillover of knowledge and technology, with far-reaching impacts on the development of agriculture throughout the province. (3) In terms of economy-of-scale effects, agricultural industry agglomeration can improve the efficiency of local production factor allocation, reduce the operating costs of enterprises, and gradually form economies of scale, which can strongly promote the development of the agricultural industry in the region [28]. The agricultural machinery industry cluster in the city of Weifang has reduced the unit production cost and driven the continuous improvement of Weifang's overall agricultural output value through centralized purchasing and shared cold chain logistics. It can be seen that the formation and development of industrial agglomeration in the region also changes the direction of the industrial structure and the direction of the economy in the neighboring areas through the radiation-driven effect [29]. Based on this, this paper proposed the following hypothesis:

H1. *The agricultural industrial agglomeration in Shandong Province has spatial correlation.*

When agricultural industrial agglomeration reaches a certain level, it can also produce negative effects [30,31]. The number of enterprises that a region can support with its natural resources and its social and economic development level is limited. When industrial agglomeration exceeds a reasonable threshold, excessive competition and factor crowding effects will emerge. This will not only weaken its economic efficiency but may even turn the agglomeration effect from positive to negative, resulting in diseconomies of scale [32]. On the one hand, as the scale of industry continues to expand, the prices of agricultural factors of production and the amount of inputs will change, leading to environmental pollution, population crowding, and the excessive concentration of resources, making the crowding effect in the region greater than the scale effect [33]. The agricultural industry in Weifang is currently suffering from a shortage of land resources due to the over-concentration of enterprises, while the overuse of pesticides and chemical fertilizers has caused a significant increase in the rate of soil crusting, which has slowed down the process of green agricultural development. On the other hand, industrial agglomeration attracts large resource flows, creating a siphon effect, leading to a lack of labor force and material resources in adjacent regions, which is not conducive to agricultural development [34]. Cities in the east of Shandong Province, such as Qingdao and Yantai, have absorbed most of the young and strong labor force in the surrounding counties and cities by virtue of their own superior resource supply, resulting in the western cities (such as Heze) and other traditional agricultural areas facing the "hollowing out" dilemma. The problem of diseconomies of scale has thus been

highlighted. To date, many scholars have proven the adverse consequences of excessive concentration of a single industry, such as crowding effects, widening regional development gaps, and slowing social and economic development [35–37]. It can be seen that agricultural industrial agglomeration does not have a linear positive impact on agricultural development, and there are also many negative problems: a nonlinear effect. Based on this, this paper proposed the following hypothesis:

H2. *The impact of agricultural industrial agglomeration in Shandong Province on the development of agricultural new quality productive forces is nonlinear.*

The input structure of agricultural resource factors is influenced by the resource endowments and economic development levels of each region. Shandong Province covers a relatively large area and faces the sea to the east. There are differences in agricultural resource endowments, regional economic development levels, and urbanization processes between cities, leading to spatial heterogeneity in agricultural production levels across Shandong Province [38]. According to the “gradient theory” [39], Shandong Province can be divided into an eastern economic belt, a central economic belt, and a western economic belt. Cities such as Weihai, Yantai, Qingdao, Weifang, and Rizhao are included in the scope of the eastern economic belt. The central economic belt includes five major cities: Jinan, Zibo, Tai’an, Dongying, and Linyi (the city of Laiwu was merged into Jinan in 2019). Six major cities, including Heze, Liaocheng, Binzhou, Zaozhuang, Dezhou, and Jining, belong to the western economic belt. Similarities within the region can promote resource agglomeration, while differences between regions are the basis for the regional division of labor, cooperation, and common development [40]. The three major economic zones in Shandong Province differ significantly in terms of natural resource endowment and the level of economic development [41]. This causes differences in the industrial agglomeration and the development levels of agricultural new quality productive forces in different regions, and their geographical proximity has resulted in the existence of spatial correlations. Different regions should adopt different development strategies to capture the similarities and differences in the development of each region and to improve resource utilization efficiency and productivity levels. It is very meaningful to measure and analyze the impact of the degree of industrial agglomeration in each economic zone of Shandong Province. Based on this, this paper proposed the following hypothesis:

H3. *The impact of agricultural industrial agglomeration in Shandong Province on the development of agricultural new quality productive forces is regionally heterogeneous.*

Based on the above analysis, this paper proposed three hypotheses: the agricultural industrial agglomeration in Shandong Province has a spatial correlation, agricultural industrial agglomeration has a nonlinear impact on the development of agricultural new quality productive forces, and the impact of agricultural industry agglomeration on new quality productive forces exhibits regional heterogeneity. Figure 1 illustrates the theoretical framework of the spatial spillover effects of agricultural industry agglomeration on new quality productive forces in Shandong Province.

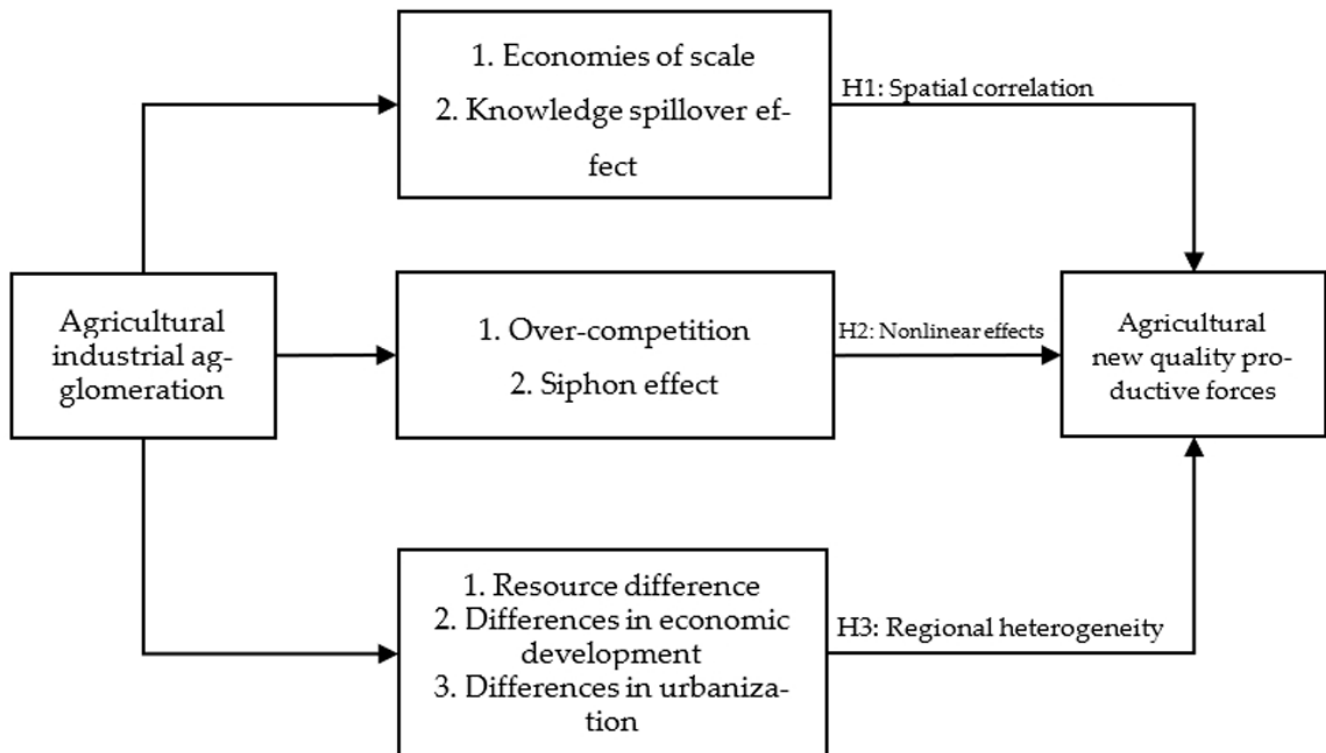


Figure 1. Theoretical framework.

2.2. Model Construction

2.2.1. Entropy Value Method Model

The explained variable in this study is agricultural new quality productive forces (NQPFs). Clarifying the connotations of agricultural new quality productive forces is the basis for measuring it scientifically. Relevant scholars believe that [42] agricultural new quality productive forces represent a leap in agricultural productivity led by scientific and technological innovation, consisting of new quality laborers, new quality labor objects, and new quality labor materials. The core of this concept lies in the organic combination of “new” and “quality”. New quality agricultural laborers are individuals with advanced skills and knowledge in the modern agricultural system, who can enhance agricultural production efficiency through scientific management and information technology. New quality agricultural labor materials emphasize the application of innovative technologies and intelligent equipment in agricultural production to promote the optimal allocation of resources. New quality agricultural labor objects focus on the concept of sustainable development, emphasizing the production and consumption of eco-friendly agricultural products, and reflecting the dual concern of agricultural development for environmental and social responsibilities. As a relatively new concept, the agricultural new quality productive forces have a relatively small system of relevant evaluation indicators, and standards have not yet been formed. Therefore, this study constructed an evaluation index system from three aspects. At the same time, based on the research of other scholars, this paper organized and merged 13 secondary indicators and established corresponding measurement methods [43–45]. The details are shown in Table 1.

Table 1. Indicator system for agricultural new quality productive forces.

Criteria Layer	Primary Indicator	Secondary Indicator	Measurement Method	Attribute
New Quality Agriculture Workers	Quality of workers	Education level	Education expenditure in the local general public budget expenditure	Positive
		Number of higher education talents	Number of students in regular higher education institutions	Positive
	Labor productivity	Per capita output of the primary industry	Output of the primary industry/number of employees in the primary industry	Positive
		Per capita income of rural residents	Per capita disposable income of rural residents	Positive
	Employment concept of workers	Rural employment rate	Rural workforce/rural population	Positive
New Quality Agriculture Labor Objects	Ecological environment	Green environmental protection	Greening coverage rate	Positive
			Energy-saving and environmental protection fiscal expenditure/government public fiscal expenditure	Positive
	New quality industry	Green development	Pure fertilizer consumption per unit area/crop total sown area	Negative
		Innovation status	Pesticide application per unit area/crop total sown area	Negative
		Level of mechanization in agricultural operations	Number of patents obtained by research institutions Comprehensive mechanization level of major crops' planting and harvesting	Positive
New Quality Agriculture Labor Materials	Tangible labor materials	Intelligent agricultural machinery	Rural electricity consumption/total agricultural, forestry, animal husbandry, and fishery output value	Positive
			Total agricultural machinery power/rural population	Positive
		Digital labor tools	Number of computers per hundred rural households Number of mobile phones per hundred rural households	Positive Positive
	Intangible labor resources	Agricultural technology innovation	Scientific and technological expenditure/government public financial expenditure × (agricultural, forestry, animal husbandry, and fishery total output value/regional GDP)	Positive
		Agricultural R&D funding input intensity	R&D expenditure × (agricultural, forestry, animal husbandry, and fishery total output value/regional GDP)	Positive

To reduce and avoid subjectivity when determining weights, this paper drew on the practice of related scholars in measuring high-quality agricultural development [46,47]. After assigning values to each indicator through the entropy method, the weighted average summation method was used to measure the development level of agricultural new quality productive forces in 16 prefecture-level cities in Shandong, China. In this process, since the differences in the magnitude and dimensions of the indicators interfere with the specific data, the data had to be standardized to reduce the interference. The specific formulae are as follows:

$$\text{Positive indicators : } x_{itj} = \frac{x_{itj} - \min(x_{tj})}{\max(x_{tj}) - \min(x_{tj})} \quad (1)$$

$$\text{Negative indicators : } x_{itj} = \frac{\max(x_{tj}) - x_{itj}}{\max(x_{tj}) - \min(x_{tj})} \quad (2)$$

where i represents the region, t represents the year, and j represents a core indicator used to quantify the development of agricultural new quality productive forces. $\min(x_{tj})$ is the minimum value of the indicator j among all regions in year t , and $\max(x_{tj})$ is the maximum value.

The explanatory variable in this study is agricultural industrial agglomeration (LQ). In previous research, some scholars have pointed out that the location entropy index eliminates scale differences between regions and realistically reflects the spatial distribution of geographical factors [48]. Based on this, this study applies the location entropy model to measure it. This method quantifies the degree of agricultural industry agglomeration in geospatial space by constructing a regional industrial specialization index, which is specifically expressed as the ratio of the output value of the primary industry in a prefecture-level city to that of Shandong Province, divided by the ratio of the economic gross product of the prefecture-level city to that of Shandong Province [49,50]. The formula is as follows:

$$LQ_{it} = \frac{Q_{it} / \sum_{i=1}^{16} Q_{it}}{G_{it} / \sum_{i=1}^{16} G_{it}} \quad (3)$$

where LQ_{it} represents the degree of agricultural industrial agglomeration in region i in year t . Q_{it} and G_{it} represent the output value and gross product of agriculture, forestry, animal husbandry, and fishery in region i in year t , respectively. The index of industrial agglomeration is positively related to the level of industrial agglomeration.

2.2.2. Spatial Autocorrelation Test Model

Testing for the presence of spatial correlation between variables is a prerequisite for the use of spatial econometric models, and the global Moran's I is one of the most common methods [51]. Thus, this study drew on the methods of scholars such as Huang et al. [52], using the global Moran's I to conduct spatial correlation tests. The formula is as follows:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (4)$$

where I is the global Moran's index, and the absolute value of Moran's index is directly proportional to the strength of spatial correlation. When $I > 0$ or $I < 0$, it indicates that similar values tend to cluster in space. When Moran's I is close to 0, it indicates that the space is stochastic. w_{ij} is the element of the spatial weight matrix. x_j and x_i represent the

level of agricultural industrial agglomeration or the level of development of new quality productive forces in regions j and i , respectively. $\bar{x}$ represents the sample mean, and

$S^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n}$ is the sample variance.

2.2.3. Spatial Econometric Model

The spatial econometric models are usually used to analyze the existence of spatial effects between things. Since there may be spatial effects between agricultural industrial agglomeration and agricultural new productive forces, this study used spatial econometric models for analysis. With reference to the methods of Xu et al. [53], a spatial econometric model was constructed, and the LR and Wald tests were used to determine which model to choose. The formula is as follows:

$$NQPF_{it} = \alpha + \rho \sum_{j=1, j \neq i}^n w_{ij} NQPF_{jt} + \beta LQ_{it} + \gamma control_{it} + \theta \sum_{j=1, j \neq i}^n w_{ij} (LQ_{jt} + control_{jt}) + \mu_i + \delta_t + \varepsilon_{it} \quad (5)$$

where α is the constant term; ρ is the spatial autocorrelation coefficient; β and γ are the regression coefficients; θ is the lag term coefficient; i and t represent the regions and years, respectively; μ_i and δ_t denote the spatial and temporal fixed effects, respectively; w_{ij} represents the adjacent spatial weight matrix; ε_{it} is the random error term; LQ is the degree of agricultural industrial agglomeration; $control_{it}$ denotes the various control variables; and $NQPF$ is the development level of agricultural new quality productive forces. If $\rho = 0$ and $\theta = 0$, the above equation is a spatial error model. If $\rho \neq 0$ and $\theta = 0$, it is a spatial lag model.

To analyze the development level of agricultural new quality productive forces more comprehensively, this paper selected five control variables from the literature in addition to the core explanatory variables [54,55], as shown in Table 2.

Table 2. Summary of control variables.

Variant	Description of Variables	Measurement Method
Level of government intervention	Gov	General public budget expenditure/gross regional product
Level of economic development	Eco	GDP per capita
Urbanization level	Urb	Urbanization rate
Industrial structure	Ind	Tertiary sector output/secondary sector output
Population density level	Pop	Total population/land area of the region

3. Empirical Analysis

3.1. Data Sources

In this paper, according to the principles of data availability and operability, the relevant data of 16 prefecture-level cities in Shandong Province, China, from 2010 to 2022 were selected from the Statistical Yearbook and Shandong Province Statistical Yearbook published by the statistical bureaus of each prefecture-level city in Shandong Province. The study area is shown in Figure 2. To supplement some missing values, linear interpolation methods were chosen for processing and improvement [56].

In this paper, descriptive statistics were analyzed for each variable, as shown in Table 3. As can be seen from the table, the average value of agricultural new quality productive forces in Shandong Province is 0.359, and the average value of agricultural industrial agglomeration is 1.097. When the level of agricultural industrial agglomeration is higher than 1, it indicates that the region has formed an industrial agglomeration and has competitive

advantages [57]. Therefore, these data indicate that the level of agricultural industrial agglomeration in Shandong Province is relatively high and has formed competitive advantages, providing a solid foundation for the development of agricultural new quality productive forces. This paper also tested for the presence of multicollinearity among the variables, and the results showed that the VIF value was 3.28. Hence, there was no multicollinearity effect.

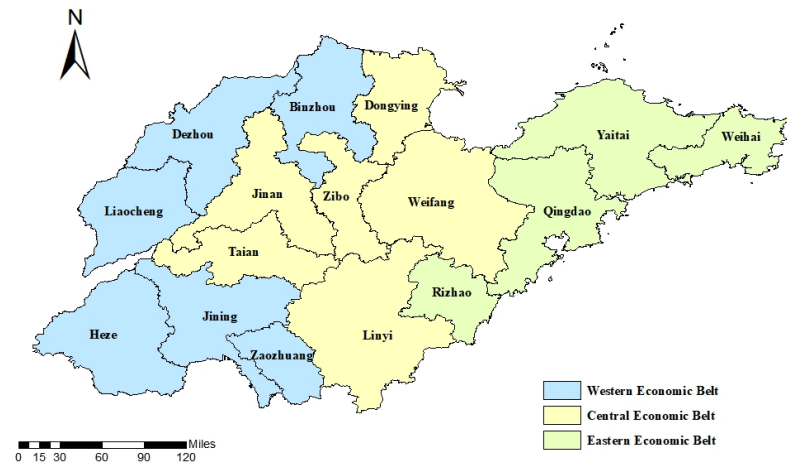


Figure 2. Map of the research area.

Table 3. Variable descriptive statistics.

Variable	Variable Description	Sample Size	Max	Min	Avg.	S.D.
Dependent Variable	NQPF	208	0.551	0.175	0.359	0.084
Explanatory Variable	LQ	208	1.928	0.330	1.097	0.413
Control Variable	Gov	208	0.199	0.079	0.133	0.027
	Eco	208	12.01	9.641	10.93	0.493
	Urb	208	0.763	0.367	0.580	0.096
	Ind	208	1.779	0.404	1.024	0.305
	Pop	208	0.093	0.025	0.063	0.017

3.2. Analysis of Spatiotemporal Evolution Characteristics

3.2.1. Analysis of the Temporal and Spatial Evolution Characteristics of Agricultural Industrial Agglomeration in Shandong Province

This paper used MATLAB R2024a software to create a three-dimensional kernel density estimation map [58], which is shown in Figure 3. According to the position and shape of the distribution, the kernel density curve shows a “left tail” phenomenon, and the distribution center of the development level is slightly tilted to the right, indicating that there are significant differences in the agricultural industrial agglomeration levels among the prefecture-level cities in Shandong Province, with an overall slow upward trend. Secondly, based on the characteristics of the peaks, the peak values experienced two “up–down” fluctuations during the sample period, and the overall performance was a slight downward trend. The peaks gradually narrowed, indicating that the gap in agricultural industrial agglomeration levels in Shandong Province is gradually narrowing. In summary, the agricultural industrial agglomeration level in Shandong Province shows a dynamic evolution trend, with a slight decline in the overall level and a narrowing gap between prefecture-level cities.

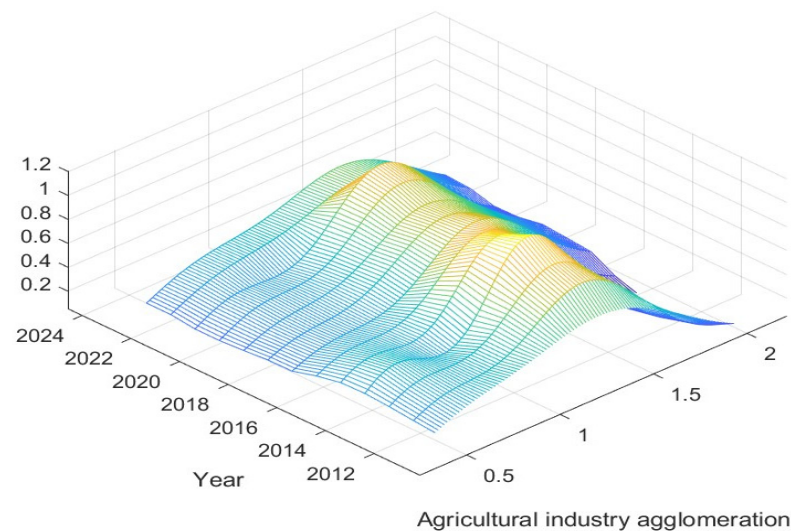


Figure 3. Kernel density estimation map of agricultural industrial agglomeration levels in Shandong Province from 2010 to 2022.

To study the dynamic changes in the levels of agricultural industrial agglomeration in Shandong, China, during the sample period, the spatial and temporal evolution of the agricultural industry agglomeration level of 16 prefecture-level cities in Shandong in the starting and ending years of the sample period (i.e., 2010 and 2022) were mapped using ArcMap 10.8 [59]. The results are shown in Figure 4a,b. In 2010, the cities in Shandong Province with higher agricultural industrial agglomeration levels were Dezhou, Weihai, Jining, and Linyi, with Dezhou being the highest at 1.74. In 2022, the cities with higher agricultural industrial agglomeration levels were Dezhou, Jining, Linyi, and Zaozhuang, with Dezhou still being the highest level at 1.93. In 2022, Zaozhuang reached a higher value level than in 2010, with a value of 1.56. This is mainly due to Zaozhuang being a national pilot area for agricultural green development, which has placed significant emphasis on agricultural development and achieved good results in recent years. In 2022, Weihai reached the median level, possibly due to economic development, with Weihai focusing on non-agricultural industries such as fisheries, food processing, and tourism, and agriculture no longer dominating the economy. Overall, the level of agricultural industrial agglomeration in Shandong Province presents a spatial pattern of “high in the south and low in the north”.

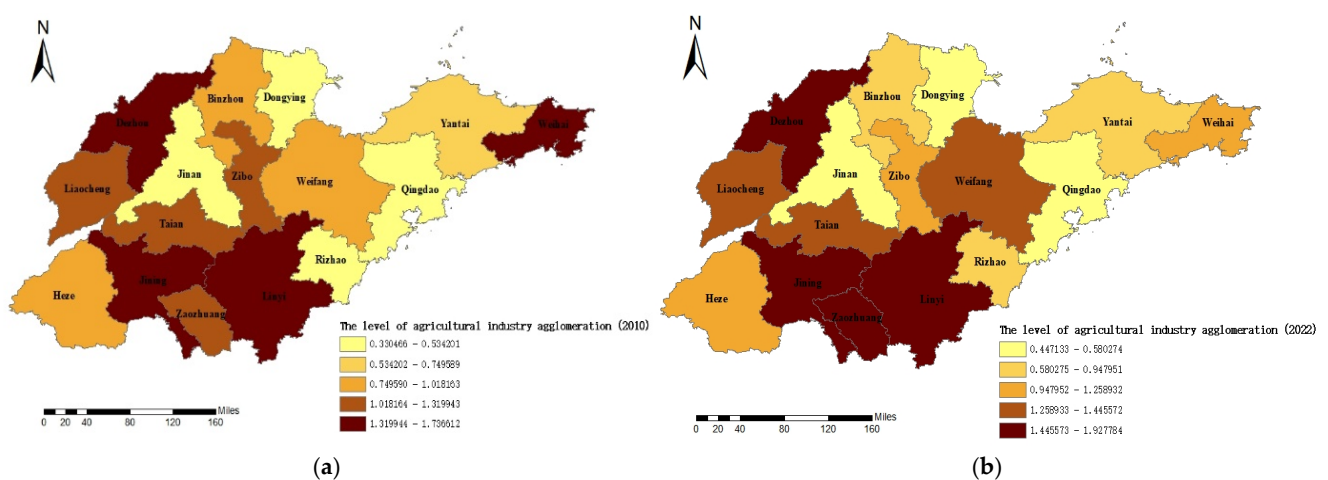


Figure 4. (a) Agricultural industrial agglomeration levels in Shandong Province in 2010. (b) Agricultural industrial agglomeration levels in Shandong Province in 2022.

3.2.2. Analysis of the Spatiotemporal Evolution Characteristics of the New Quality Productive Forces in Shandong Province

Figure 5 shows the kernel density estimation map of the development of agricultural new quality productive forces in 16 prefecture-level cities in Shandong, China, from 2010 to 2022. First, according to the shape and position of the peak distribution, the kernel density curve gradually shifts from a “right tail” to a “left tail” over time, and the distribution center of the development level gradually shifts to the right. This indicates that the development level of agricultural new quality productive forces in Shandong Province was relatively low in the early stages, and then it showed an upward trend as the economy developed. Secondly, based on the characteristics of the peaks, the shape of the peaks changes from wide to narrow, and the peak values show an upward trend over time, indicating that the spatial differences in the development level of agricultural new quality productive forces in Shandong Province show a significant convergence trend. In summary, the development level of agricultural new quality productive forces in Shandong Province shows a dynamic evolution trend in continuous overall improvement while reducing the gaps between prefecture-level cities.

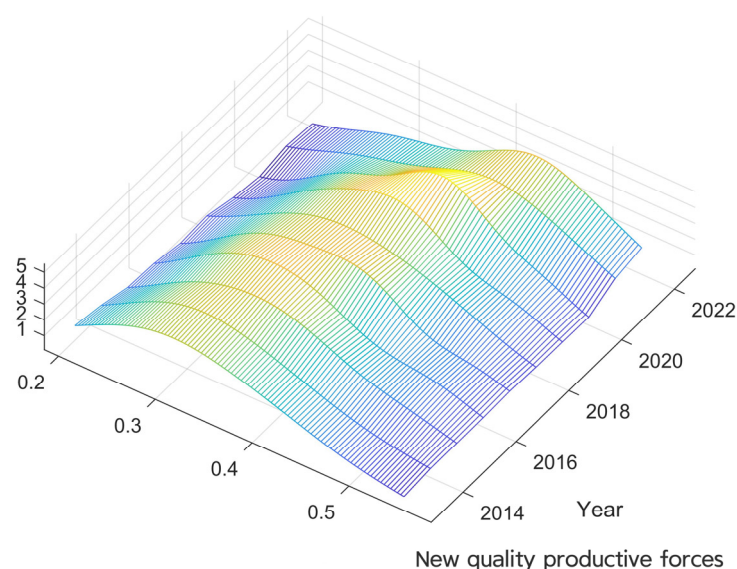


Figure 5. Density estimation map of the levels of agricultural new quality productive forces in Shandong Province from 2010 to 2022.

In Figure 6a,b, the spatial and temporal evolution of the agricultural new quality productive forces in 16 prefecture-level cities in Shandong in the starting and ending years of the sample period (i.e., 2010 and 2022) were mapped using ArcMap 10.8. In 2010, the cities in Shandong Province with high levels of agricultural new quality productive forces were Weifang, Zibo, Weihai, and Yantai, among which Weifang had the highest value of 0.42. In 2022, the cities with high levels of agricultural new quality productive forces were Weihai and Weifang, reaching 0.55 and 0.54, respectively. Due to the strong technological innovation capabilities of these cities, significant improvements in agricultural digitization, networking, intelligence, and total-factor productivity have led to a high level. The development levels in Zibo and Yantai were lower in 2022 than in 2010, possibly due to the slow progress of local agricultural science and technology and the scarcity of talent. Overall, the development level of agricultural new quality productive forces in Shandong Province presents a spatial pattern of “high in the north and low in the south”.

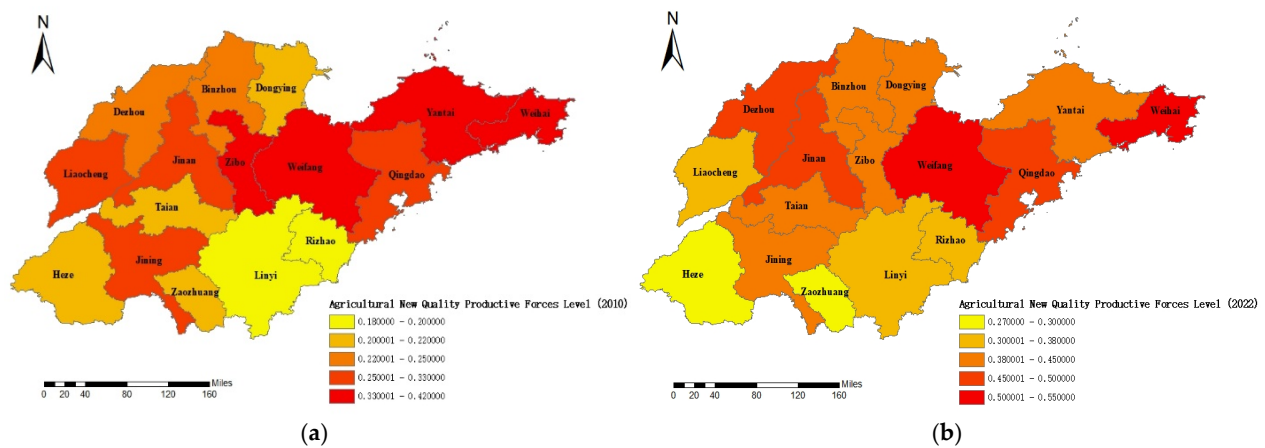


Figure 6. (a) Agricultural new quality productive forces in Shandong Province in 2010. (b) Agricultural new quality productive forces in Shandong Province in 2022.

3.3. Analysis of the Impact of Industrial Agglomeration in the Agricultural Sector of Shandong Province on Agricultural New Quality Productive Forces

3.3.1. Spatial Autocorrelation Test

This paper used the global Moran's index to test spatial correlation between the agricultural industrial agglomeration level and the development level of agricultural new quality productive forces in Shandong Province, based on the economic geographical matrix. Scholars have recommended establishing a spatial weight matrix based on economic geographical location and the level of socioeconomic development to construct a spatial panel econometric model with an organic interconnection between static and dynamic forces, which can correct for biases and compensate for the shortcomings of the economic distance matrix [60]. Table 4 shows the results. According to the data, the global Moran's I value of the explanatory variable failed to pass the test in 2010–2012 and was significantly positive in other years, indicating that, from 2013 to 2022, agricultural industrial agglomeration showed significant spatial correlation in Shandong Province. The global Moran's I value of the explained variable failed to pass the test in all years except for 2010. The coefficients of other years were all positive and passed the verification at the 5% significance level, indicating that the development of agricultural new quality productive forces in Shandong Province had a strong spatial correlation from 2011 to 2022. Thus, Hypothesis 1 is validated. The reason why this was not significant in the early stage is mainly because China is a developing country with a rapidly developing economy. Driven by science and technology, agricultural production methods are gradually being modernized, and production efficiency and economic benefits are being improved accordingly. However, in the early stages of development, the agricultural development level in various regions was low because they lacked new technologies, new factors, and new laborers. The result is that there is no significant spatial correlation between agricultural new quality productive forces and agricultural industrial agglomeration.

In order to understand the spatial agglomeration of agricultural new quality productive forces in Shandong Province more accurately, this paper drew Moran scatter plots based on the local Moran's index to achieve an intuitive description of the local situation. Referring to Yang's approach [61], our representative years (2010, 2014, 2018, and 2022) were selected to draw Moran scatter plots of agricultural new quality productive forces in Shandong Province (as shown in Figure 7). The Moran scatter plots were divided into four quadrants, representing the four types of spatial connection between the observations in the region and those in adjacent regions: low value–low value, high value–low value, high value–high value, and low value–high value [62]. Points falling in the first and third quad-

rants indicate a positive spatial correlation between cities, while those falling in the second and fourth quadrants are the opposite, indicating a negative spatial correlation between cities. As shown in Figure 7, only a few cities do not fall in the first and third quadrants, with most cities located within them. This indicates a significant spatial agglomeration of agricultural new quality productive forces in Shandong Province. Moran's index was significant in all three years, except for 2010, at 0.1305 **, 0.1644 **, and 0.0997 *, respectively. This is consistent with the results of the test above.

Table 4. Spatial autocorrelation test results of agricultural industrial agglomeration and agricultural new quality productive forces in Shandong Province from 2010 to 2022.

Year	Agricultural Industry Clustering		Agricultural New Quality Productive Forces	
	Moran's <i>I</i>	Z	Moran's <i>I</i>	Z
2010	0.167	1.328	0.090	1.554
2011	0.167	1.349	0.137 **	2.046
2012	0.200	1.521	0.136 **	2.063
2013	0.251 *	1.814	0.139 **	2.116
2014	0.268 *	1.920	0.131 **	2.060
2015	0.285 **	2.015	0.147 **	2.168
2016	0.312 **	2.181	0.180 **	2.510
2017	0.306 **	2.151	0.142 **	2.121
2018	0.310 **	2.168	0.164 **	2.324
2019	0.323 **	2.254	0.153 **	2.234
2020	0.315 **	2.196	0.119 **	1.882
2021	0.339 **	2.315	0.159 **	2.270
2022	0.342 **	2.327	0.100 **	1.687

Note: * and ** represent significant at the 10% and 5% levels, respectively.

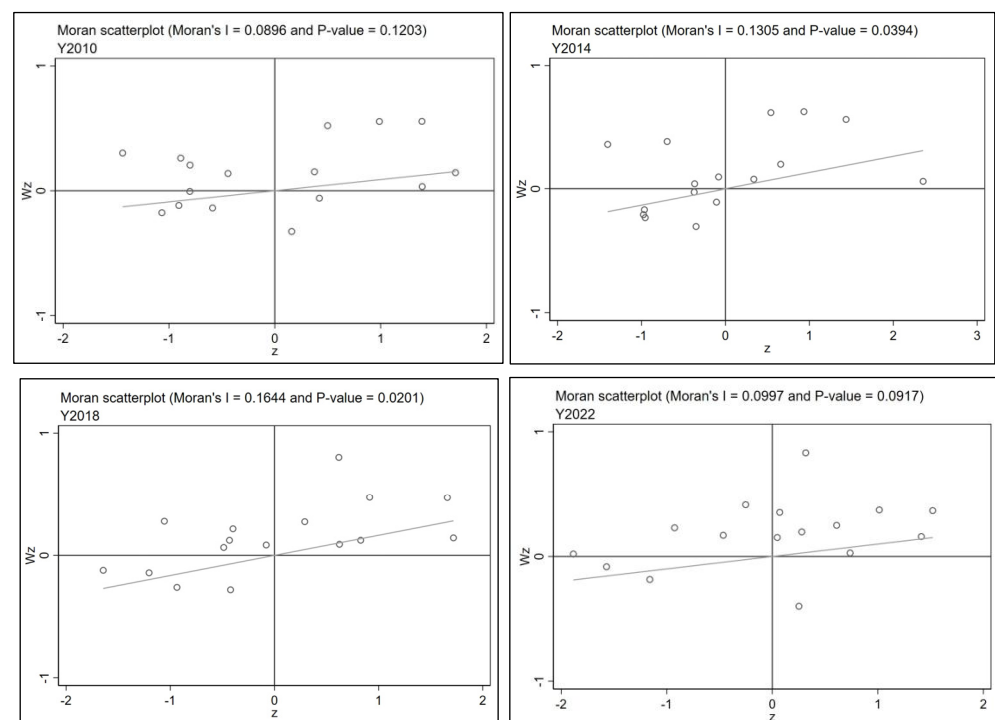


Figure 7. Local Moran's index map of agricultural new quality productive forces in Shandong Province.

3.3.2. Spatial Durbin Model Test

The previous empirical study revealed that the variables to be studied are spatially correlated. Therefore, a spatial econometric model should be used. However, the choice of model between SLM, SEM, and SDM needed to be tested and verified. Table 5 shows the relevant test results of the spatial econometric model. The specific analysis was divided into three steps: (1) According to the LM and robust LM test data, the four results are all significant at a confidence level of 1%, which shows that the constructed model contains lag effects and error effects. Thus, the spatial Durbin model is more suitable for this study. (2) Both the Wald test and the LR test show that the SDM cannot be simplified into the SLM and SEM. (3) In the LR test of time and space, the null hypothesis was significantly rejected, and the test results of the Hausman model also showed a rejection of the null hypothesis, which means that this study should use the SDM with dual fixed effects of time and space.

Table 5. Spatial econometric model test results.

Test Name	Coefficient	Test Name	Coefficient
LM-lag	17.991 ***	LM-error	4.680 ***
Robust LM-lag	36.193 ***	Robust LM-error	22.882 ***
LR_Spatial_lag	34.32 ***	LR_Spatial_error	34.65 ***
Wald_Spatial_lag	37.51 ***	Wald_Spatial_error	39.17 ***
Time LR test	384.93 ***	Hausman	54.87 ***
Spatial LR test	15.97 **		

Note: ** and *** represent significant at the 5% and 1% levels, respectively.

3.3.3. Benchmark Regression Analysis

In this paper, a regression analysis of the SDM was conducted, and the results are shown in Table 6. Among these results, the regression coefficient reaches -0.775^{***} . This indicates that the agricultural new quality productive forces have spatial correlation, and the agricultural industrial agglomeration in adjacent areas will inhibit the development of productivity in the region through spatial spillover effects. This may be due to the fact that there is currently excessive industrial agglomeration in Shandong Province, intensifying the competition for resources, homogenizing production in the region, and affecting the reasonable flow of factors such as land and capital to the field of technological innovation. At the same time, the short industrial chain and weak synergistic effect under the traditional mode of agglomeration inhibit the momentum of sustainable development.

Table 6. Spatial Durbin model regression results.

Variable	Coefficient	Variable	Coefficient
LQ	-0.061^{**}	$W \times LQ$	-0.127^{*}
Gov	0.128	$W \times Gov$	-0.538
Eco	-0.072^{**}	$W \times Eco$	0.168^{**}
Urb	-0.378	$W \times Urb$	-0.803^{**}
Ind	-0.010	$W \times Ind$	-0.265^{**}
Pop	5.046^{**}	$W \times Pop$	12.339^{**}
ρ	-0.775^{***}	R ²	0.001^{***}

Note: *, **, and *** represent significant at the 10%, 5%, and 1% levels, respectively.

3.3.4. Spatial Effect Decomposition

Relevant scholars such as LeSage et al. have argued that if the coefficient ρ in the spatial econometric model is significantly different from 0, spatial lag terms will appear in the explanatory variables, leading to biased results [63]. Based on the above findings, it is certain that the decomposition of direct and indirect effects is measured using partial

differential methods [64]. In this case, the indirect effect refers to the impact of the level of local agricultural industrial agglomeration on the agricultural new quality productive forces in neighboring regions. The direct effect, on the other hand, is the impact on the local area. Table 7 shows the corresponding values after decomposing the total spatial effects of the LQ and the five control variables.

Table 7. Spatial effect decomposition results.

Variable	Direct Effect		Indirect Effect		Total Effect	
	Coefficient	Z Value	Coefficient	Z Value	Coefficient	Z Value
LQ	−0.056 **	−2.28	−0.052 **	−1.08	−0.104 **	−2.11
Gov	0.138	1.05	−0.112	−0.46	0.027	0.10
Eco	−0.091 **	−3.24	0.150 **	2.76	0.059	1.18
Urb	0.033	0.37	−0.509 **	−2.00	−0.477 *	−1.86
Ind	0.014	0.52	−0.170 **	−2.38	−0.155 **	−2.09
Pop	4.284 **	2.58	5.635 *	1.85	9.919 **	2.77

Note: * and ** represent significant at the 10% and 5% levels, respectively.

Based on the decomposition results of agricultural industrial agglomeration (LQ), the coefficient values for direct, indirect, and total effects are −0.056 **, −0.052 **, and −0.104 **, respectively, indicating that agricultural industrial agglomeration in this region and adjacent areas can have a negative effect on the development of agricultural new quality productive forces through spatial spillover effects. The coefficient of the total spatial effect is −0.104 **. The reason for this phenomenon may be that the agricultural development in Shandong Province has not completely abandoned the traditional production mode. Compared to other industries, there are relatively few inputs of intelligent agricultural machinery with high productivity and low consumption. Moreover, the excessive agglomeration of the agricultural industry has caused excessive production pressure. Thus, excessive agricultural industrial agglomeration can constrain the development process of agricultural new quality productive forces.

The decomposition of the five control variables showed that the level of government intervention (Gov) did not show a spatial spillover effect, which may be related to the lack of agricultural financial inputs. The direct and indirect effect coefficients of the level of economic development (Eco) are −0.091 ** and −0.150 **, respectively, indicating a negative inhibition of local agricultural new quality productive forces, but a positive spillover to neighboring regions. Analyzing the reasons, it may be that the region is more economically developed and that the resources are distributed in a biased manner to non-agricultural industries, resulting in insufficient investment in local agricultural innovation, which results in inhibition effects. Neighboring regions can make use of spillover channels such as technology diffusion acceptance, industrial chain synergy, and market radiation to promote the improvement of agricultural new quality productive forces. The indirect effect coefficients of urbanization (Urb) and industrial structure (Ind) are −0.509 ** and −0.170 **, respectively, reflecting the factor of the siphoning effect of neighboring developed regions. The direct effect coefficient for population density (Pop) is 4.284 ** and the indirect effect coefficient is 5.635 *, presenting a double-positive effect of local and neighboring regions, with high-density regions significantly promoting agricultural productivity upgrading through labor abundance, market linkage, and technological synergy.

3.3.5. Robustness Test

The robustness test is an important method to verify that the results are reliable. In this paper, alternative measures of agricultural industry agglomeration and alternative spatial weight matrices are used for the robustness test. The details are shown in Table 8.

Table 8. Robustness test results.

Variable	Replacement of Agricultural Industrial Agglomeration Measurement Method			Replacement of Spatial Weight Matrix		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
LQ	−0.004 **	−0.007 **	−0.011 **	−0.051 **	−0.058 **	−0.109 **
Gov	0.109	−0.121	−0.013	0.125	−0.216	−0.092
Eco	−0.059 **	0.190 **	0.131 **	−0.096 **	0.218 **	0.122 **
Urb	0.018	−0.637 **	−0.619 **	0.003	−0.491 **	−0.488 **
Ind	−0.019	−0.184 **	−0.186 **	0.014	−0.145 **	−0.131 *
Pop	5.308 **	5.534 **	10.84 **	4.176 **	6.465 *	10.64 **

Note: * and ** represent significant at the 10% and 5% levels, respectively.

(1) The measurement method of agricultural industrial agglomeration was changed.

In order to enhance the stability of the empirical results, this paper replaces the measurement method of the explanatory variables and adopts the number of employees in the primary industry to measure the degree of local agricultural industry agglomeration. That is, this paper remeasured the agricultural industrial agglomeration degree of Shandong Province using the ratio of the number of employees in the primary industry of each prefecture-level city to the number of employees in the primary industry of Shandong Province. According to the results, all three effect coefficients are negative, proving that the spatial econometric results are robust.

(2) The type of spatial weight matrix used was changed. The above analysis is based on the economic geography matrix. However, different spatial weight matrices can lead to different results. Therefore, the inverse distance weight matrix was substituted for the previous matrix in the robustness test. According to the results calculated by the inverse distance weight matrix, it can be seen that the total effect, direct effect, and indirect effect of agricultural industrial agglomeration in Shandong Province on the agricultural new quality productive forces are all significantly negative, which also proves that the spatial econometric results are robust.

3.3.6. Regional Heterogeneity Analysis

In order to explore the spatial effects in depth at the regional level, this paper drew on the practice of related scholars [65] and conducts a regional heterogeneity study of the three major economic regions in Shandong Province. The specific results are shown in Table 9.

Table 9. Regional spatial Durbin model estimation.

Variable	Eastern Economic Belt			Central Economic Belt			Western Economic Belt		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
LQ	−0.011 **	−0.173 **	−0.183 **	0.216 ***	0.095 *	0.311 **	−0.111 ***	−0.002	−0.114 **
Gov	0.593 **	−1.960 ***	−1.367 **	0.412 ***	−0.267	0.145	0.402	−1.526 **	−1.123 **
Eco	0.106 **	0.020	0.126	0.293 ***	0.538 ***	0.832 ***	−0.095	−1.148	−0.243 *
Urb	−0.706 **	−0.020	−0.727	−0.216 **	0.912 ***	0.696 **	0.658 ***	0.654 ***	1.311 ***
Ind	0.023	0.083	0.106 **	0.102 **	−0.061	0.041	0.105 **	0.164 **	0.268 **
Pop	9.102 **	−22.84 ***	−13.73 **	12.00 ***	11.69 **	23.69 ***	−5.154	36.95 ***	31.80 ***

Note: *, ** and *** represent significant at the 10%, 5% and 1% levels, respectively.

It was found that the results differed between regions: (1) In the eastern economic belt, the direct effect coefficient of the eastern economic belt is −0.011 ** and the indirect effect coefficient is −0.173 **, indicating that industrial agglomeration produces a double

inhibition of agricultural new quality productivity in the local and neighboring regions. (2) In the central economic belt, the direct effect coefficient is 0.216 *** and the indirect effect coefficient is 0.095 *, indicating that industrial agglomeration promotes the development of new agricultural productivity in local and neighboring regions. (3) In the western economic belt, the indirect effect is not significant and the direct effect coefficient is -0.111 **, indicating that the development of agricultural new quality productive forces in the western economic belt is negatively affected by agricultural industrial agglomeration in the region. One reason for this is that the policy of the eastern economic belt focuses more on the upgrading of industry and service industry, leading to the siphoning of agricultural factors by non-agricultural industries. The lack of a cross-regional synergy policy exacerbates the competition for resources. The central economic belt benefits from the policy tilt of the provincial “agricultural chain leader system”, which forms the spillover of the policy dividend through the strengthening of industrial chain support. The western economic belt is locked into inefficient agglomeration due to weak policy support, insufficient infrastructure investment, and a lagging system for the introduction of talent.

This paper found that the agricultural industrial agglomeration in Shandong Province has both positive and negative impacts on the development of agricultural new quality productive forces, indicating that its influence is nonlinear, thus verifying Hypothesis 2. Moreover, the impacts are regionally heterogeneous within different economic zones, verifying Hypothesis 3.

4. Discussion and Conclusions

After analyzing the theories related to agricultural industrial agglomeration and agricultural new quality productive forces, this paper explores the spatial spillover effect between the two through empirical analysis. The following points can be summarized:

- (1) By plotting the three-dimensional kernel density estimation over the sample period, this paper finds that agricultural industrial agglomeration shows a dynamic evolutionary trend of a slight decline in the overall level and a narrowing of the gap between prefecture-level cities. Agricultural new quality productive forces show a dynamic evolutionary trend of a continuous increase in the overall level and a narrowing of the gap between prefecture-level cities. Subsequently, this paper visually analyzed and studied the levels of agricultural industrial agglomeration and agricultural new quality productive forces in 2010 and 2022. It is found that the level of agricultural industrial agglomeration in Shandong Province showed a spatial pattern of “high in the south and low in the north”. The level of agricultural new quality productive forces showed a spatial pattern of “high in the north and low in the south”.
- (2) The global Moran’s index test showed that the Moran’s index values of agricultural industrial agglomeration and agricultural new quality productive forces were significantly positive from 2013 to 2022 and from 2011 to 2022, respectively, which confirms that the two are spatially correlated. The local Moran’s index further showed that the agricultural industrial agglomeration and agricultural new quality productive forces in 2010, 2014, 2018, and 2022 showed spatial clustering characteristics. Secondly, the regression result of the SDM showed that the regression coefficient of agricultural industrial agglomeration on agricultural new quality productive forces was -0.775 , which indicates that excessive agglomeration will have an inhibitory effect. In addition, after decomposing the model effects, it was found that the direct and indirect effects of agricultural industrial agglomeration were negative. The direct and indirect effects of population density were positive. The indirect effects of industrial structure and urbanization were significantly negative. And government intervention had no

significant effect. Finally, the paper also conducts robustness tests to strengthen the credibility of the conclusions.

- (3) In different economic zones, the impact effects of agricultural industry agglomeration are different. In the eastern economic belt, both the direct and indirect effects are significantly negative, indicating that agricultural industrial agglomeration inhibited the development process of agricultural new quality productive forces in the region and neighboring areas. In the central economic belt, both its direct and indirect effects show significant positive effects. This suggests that agricultural industrial agglomeration in the region promotes the development of agricultural new quality productive forces. However, in the western economic belt, which has the highest degree of agglomeration, the direct effect is significantly negative, suggesting that local agricultural industrial agglomeration can have a negative effect. And the indirect effect is not significant. Thus, it can be seen that agricultural industrial agglomeration can have positive or negative effects in different regions, i.e., its impact is nonlinear.

In summary, the spatial heterogeneity and nonlinear characteristics revealed in this study have important implications for the planning of agricultural industry development in Shandong Province. First, agricultural industrial agglomeration shows a “high in the south and low in the north” pattern, reflecting the fact that traditional agricultural areas in the south, such as Linyi and Heze, still rely on the pattern of resource-consuming large-scale agglomeration models. In contrast, agricultural new quality productive forces present a “north high, south low” pattern, which indicates that northern cities such as Qingdao and Yantai have achieved a leap in low-carbon productivity through green technology innovation. But the lack of technological diffusion has led to an imbalance between the north and the south. Second, spatial econometric modeling confirms the negative spillover effects of over-agglomeration. The agglomeration benefits of the high-density areas in the east and the over-agglomeration areas in the west have ended up inhibiting innovation—the former due to resource overload and the latter due to the single industrial structure and the outflow of labor. Meanwhile, the central moderate agglomeration areas such as Jinan, Zibo, and other cities have made use of industry–university–research synergies to release the scale of the dividend, proving the existence of a sustainable development-oriented “agglomeration threshold”. Third, the positive effect of population density and the negative effect of industrial structure and urbanization highlight the critical importance of the efficiency of green factor allocation. For example, Qingdao Smart Agricultural Park relies on the agglomeration of high-skilled labor to enhance total-factor productivity, but the problems in traditional agricultural areas in western Shandong are exacerbated by the blind expansion of urbanization, which has intensified land fragmentation. Based on this, relevant policy recommendations can be put forward to understand the degree of industrial agglomeration in a scientific manner and promote the development of agricultural new quality productive forces through sustainable spatial governance.

5. Policy Recommendations and Research Outlook

According to the analysis and discussion of our results, Shandong Province can promote agricultural new quality productive forces through the three paths of “zoning capacity constraints—technological compulsion—factor synergy”.

- (1) Optimize the spatial layout of the agricultural industry and build a gradient agglomeration pattern.

Shandong Province can achieve the SDG9 and SDG15 sustainable development goals through this strategy. Prefectural municipal governments can formulate gradualized agglomeration strategies based on regional differences, improve industrial and facility layouts, maintain ecological protection systems in agglomeration areas, and provide inexhaustible

impetus for the sustainable development of new quality productive forces. In the eastern high-density area, industrial density thresholds should be set to limit excessive land transfer and access to high-energy-consuming projects in order to avoid resource overload. In the central potential area, the industry–university–research synergistic network could be expanded to build a regional agricultural science and innovation center and to promote the diffusion of technology and patent transformation. The western over-concentrated area can learn from the successful experience of the integrated management of the fruit and vegetable industry in Italy. It should extend the whole industrial chain and related agricultural enterprises for fruit and vegetables, from picking to sales, to provide a “one-stop” service for production, supply, and marketing. This would realize agricultural production and operation upstream, midstream, and downstream in the industry chain to solve the problems caused by a single industrial structure.

(2) Promote technological paradigm shifts in agriculture and implement green standards and digital empowerment.

Shandong Province can realize the SDG7 and SDG12 sustainable development goals through this strategy, build a green, economic, sustainable, and innovative production system, and upgrade the agricultural industry with green and digital technologies. On the one hand, California’s experience in relying on digital standards to achieve precision agricultural water conservation can play a guiding role in core production areas such as Shouguang (vegetables) and Yantai (apples), among others. Agribusinesses have broken through their own technological bottlenecks, actively promoted the large-scale application of green technologies in agglomeration areas, adopted affordable clean energy, and alleviated the environmental pressures caused by high-energy-consuming and high-polluting production modes. On the other hand, agricultural practitioners can rely on the “Science and Technology Cloud Platform” created by Shandong Province to actively learn and disseminate technical specifications, improve resource allocation efficiency, and market responsiveness to build a sustainable development paradigm.

(3) Improve the factor allocation mechanism and promote the efficient and synergistic utilization of resources.

Shandong Province can achieve the SDG8 sustainable development goal through this strategy, which focuses on promoting full and productive employment by improving the quality of the labor force and strengthening upstream and downstream synergies in the industrial chain. Prefectural and municipal governments, agricultural colleges and universities, and local farmers’ cooperatives have implemented differentiated skills training in response to the needs of agricultural development in different regions. In the traditional agricultural areas of western Shandong, focusing on land consolidation for farmers and training in efficient planting and breeding techniques helps improve the quality and efficiency of traditional agriculture. In Qingdao and other areas at the forefront of the development of smart agriculture, colleges and universities should strengthen the technical training of students in agricultural digitization and intelligence. At the same time, local governments have formulated relevant policies to attract talents in the agricultural field to develop in Shandong and set up a special incentive fund for agricultural talents. These, along with incentives for talents, are contributing to the process of development of agricultural new quality productive forces. In the process of optimizing the industrial structure, efforts have been made to promote the rationalization of the traditional agricultural industrial structure in the western region and respond to the challenge of the imbalance of resources caused by single-grain cultivation. This actively develops the cultivation of specialty cash crops and the processing of agricultural products, and promotes the further development of agricultural new quality productive forces.

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