

Article

A Study on the Correlation Between Urbanization and Agricultural Economy Based on Efficiency Measurement and Quantile Regression: Evidence from China

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Abstract

The impact of urbanization on the agricultural economy has long attracted scholarly attention. Taking China as a case, this study investigates the relationship between urbanization and agricultural development under the dual progress of urbanization and the rural revitalization strategy. Based on panel data from 31 mainland provinces, this paper measures agricultural economic efficiency using the global slack-based measure (SBM) model and employs quantile regression to systematically analyze the influence of various urbanization factors across different levels of agricultural efficiency. A Tobit regression model is further adopted for robustness checks. The results show that representative urbanization factors, such as the proportion of urban population and the prevalence of higher education, exert significant negative impacts on agricultural efficiency, particularly in regions with higher efficiency levels. Freight volume has a significantly negative effect in regions with medium and low efficiency, while freight turnover negatively impacts medium- to high-efficiency areas. In contrast, improvements in healthcare services and digital infrastructure are found to consistently enhance agricultural efficiency. Although the corporatization of agriculture is often regarded as a key outcome of urbanization, its efficiency-improving effect is not statistically significant in most models and is mainly concentrated in high-efficiency regions. Overall, the improvement in China's agricultural economic efficiency relies more on direct support from the rural revitalization strategy, while rapid urbanization has failed to bring substantial benefits and has even led to structural negative effects. These adverse outcomes may stem from the rapid occupation of suburban farmland, increased logistics costs due to the relocation of agricultural activities, and the ineffective absorption of surplus rural labor. This study highlights the need for future urbanization policies in China to pay greater attention to the coordinated development of the agricultural economy. The methods and findings of this research also provide reference value for other developing regions facing similar urbanization-agriculture dynamics.

Keywords: urbanization; agricultural economic; efficiency; DEA; SBM; Tobit model; policy



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1. Introduction

1.1. Urbanization and Modernization

Urbanization has long been considered an objective trend in human societal development, a significant marker of national modernization, and one of the key drivers of modern economic growth, profoundly transforming national socioeconomic structures. As Mumford [1] suggests, the process of urbanization has been a constant throughout human history, representing a more socialized and advanced organizational form compared to villages and rural areas. Rössel et al. [2] argue that modernization encompasses a broader array of processes, including industrialization, urbanization, bureaucratization, expansion of educational opportunities, increased literacy, and even democratization. Marsh [3] also highlights that the core processes of modernization are industrialization and urbanization.

Globally, many countries actively implement urbanization policies to spur economic growth, optimize resource allocation, and enhance the quality of life for residents. Urbanization is not merely the relocation of populations from rural to urban settings but involves a complex array of economic and social transformations.

Firstly, urbanization stimulates economic growth. Cities, as hubs of economic activity, offer abundant job opportunities and an attractive investment environment, drawing significant domestic and international capital. This accelerates industrialization and the growth of the service sector. Urbanization contributes to increased labor productivity and drives national GDP growth through economies of scale and market concentration effects. Tolley [4] explicitly stated that urbanization fosters industrialization and has formed commercialization and services suitable for urban settings, thereby boosting economic development, with an even greater role expected in the future. Zhang et al. [5] explained East Asia's economic miracle from the perspective of urbanization, suggesting that it provides investment opportunities and helps adjust the capital/labor ratio in urban sectors, explaining why East Asian countries were not constrained by diminishing marginal returns during economic development.

Secondly, cities enable more effective resource management and infrastructure investment. Governments can centralize resources through urbanization to enhance the construction of infrastructure such as transport networks and utilities, and the quality and efficiency of education and healthcare services, thereby offering better public services and improving the quality of life for residents. Dr. Phillips [6] noted that despite the rise of infectious and parasitic diseases and the emergence of chronic illnesses in some urban environments, the advent of modern sanitation and healthcare has led to increasingly healthier urban populations compared to rural ones, with higher levels of urbanization equating to better health statuses. Ritchie and Roser [7] found that in almost every country, urban areas have higher rates of electricity coverage than rural areas, more access to improved sanitation facilities, better chances of having clean drinking water, and more usage of clean fuels for cooking and heating, and urban areas exhibit lower rates of child malnutrition. Wang et al. [8] demonstrated that sustainable urbanization policies are a better choice for Pakistan's transport infrastructure and economic growth. Heshmati and Rashidghalam [9] discovered that the level of urbanization and the development of urban infrastructure correlate with different regional economic development levels in China. Chanieabate et al. [10] argued that the level of urbanization plays a significant mediating role in the impact of transportation infrastructure on urban–rural income disparity, highlighting the role of transport infrastructure in enhancing urbanization levels and reducing income gaps.

Urbanization also helps alleviate population and land pressure in rural areas by transferring rural labor to cities, which can release rural land resources and enhance agricultural productivity. Simultaneously, urbanization fosters diversification of social services and enrichment of cultural activities, thus improving the social welfare and quality of life for

urban residents. Satterthwaite et al. [11] suggested that urbanization changes the demand for food and agricultural production systems, releasing land resources while meeting urban residents' demands for high-value foods through commercialized agricultural production, thereby generating better economic benefits. Cali and Menon [12] found in their study on urbanization in India that urbanization has a significant and systematic poverty reduction effect on surrounding rural areas, mainly due to the positive spillover effects of urbanization on the rural economy, including increased demand for local agricultural products, urban–rural remittances, changes in the rural land/population ratio, and non-agricultural employment of rural populations. Urbanization has also fostered the development of scientific and technological innovation, thereby promoting advances in agricultural technologies. For instance, Manni et al. [13] reported the successful application of high-reflective film technology in experimental fields at the University of Perugia, demonstrating that urbanized environments can provide a favorable platform for agricultural innovation. Such advancements not only enhance agricultural productivity but also contribute to the sustainable use of resources. Similarly, the study by Frota de Albuquerque Landi et al. [14] supports the notion that urbanization-driven technological innovation improves agricultural efficiency and strengthens the sustainability of agricultural production.

However, the process of urbanization also comes with a series of challenges, including excessive urban congestion, environmental pollution, housing shortages, social inequality, and urban poverty. It is commonly believed that urbanization directly encroaches on substantial traditional rural land, population, and assets, which may have negative impacts on food systems and agricultural production. Sovani [15] expressed concerns about “over-urbanization,” suggesting that a large number of rural migrants are “pushed” rather than “pulled” into cities, leading to concurrent urban hardship and rural poverty. Chan et al. [16] described previous urbanization in China as “incomplete urbanization.” Akaeze and Nandwani [17] argued that over-urbanization leads to a reduction in farmland around urban centers, adversely affecting urban food production. Rapid disappearance of peri-urban farmland in Asian countries, which once supplied 70% of the vegetables for urban populations, underscores the complexities of urban expansion.

1.2. China's Rapid Urbanization Process

From 1949 to 1980, due to the consistently low economic levels, ideological issues, and strict household registration systems, urbanization in China did not receive due attention, and the rural economy dominated, with the urbanization rate below 20%. Following the economic reforms initiated in the 1980s, China experienced significant economic growth and an unprecedented surge in urbanization as large populations migrated to cities. According to data from the National Bureau of Statistics in 2023, China's urbanization rate reached 65.22% by 2022 [18].

Notably, since 2014, the Chinese government has implemented the “New Urbanization” plan [19], emphasizing its continuity and importance even after the plan's initial phase ended in 2020. This plan represents a comprehensive socio-economic transformation process that focuses not merely on the aggregation of populations in urban areas but, more importantly, on enhancing the quality and efficiency of urbanization. This strategy has played a pivotal role in China's recent development and is characterized by the following aspects:

- **Human-centered Urbanization:**

Hukou System Reform: Addressing the urban–rural dichotomy by gradually relaxing household registration restrictions, allowing migrant workers and other mobile populations to access the same public services and social welfare as local urban residents.

Equalization of Public Services: Enhancing the equality of urban and rural infrastructure and public services, including education, healthcare, and social security.

- Economic Sustainability:

Industrial Upgrading and Transformation: Promoting the transition of industries towards high technology and service sectors, optimizing the industrial structure, and reducing dependence on resources.

Green Development: Emphasizing environmental protection and sustainable growth, promoting green building and low-carbon technologies, and developing public transportation.

- Spatial Balanced Development:

Regional Coordination: Balancing regional development, enhancing the urbanization rate in central and western areas, and creating a multi-centered urban network.

Urban–Rural Integration: Advancing the integration of urban and rural areas, strengthening the urban influence on surrounding rural areas, and sharing resources and markets.

- Social Harmony:

Modernization of Governance: Advancing the modernization of urban management and governance capabilities, enhancing the scientific and detailed level of city administration.

Cultural Heritage: Protecting and utilizing historical and cultural heritage, promoting local cultural characteristics.

China's new urbanization strategy reflects a shift from quantitative expansion to qualitative and efficient development, aiming to address various issues that emerged during the rapid urbanization process in the past and providing a solid foundation for China's sustained development.

China's new urbanization plan and policies have been implemented for a decade. Given the highly centralized and unified governance structure of the Chinese government, urbanization has progressed efficiently. However, due to China's vast land area and significant regional disparities, the long-term effects and future developments of these uniform urbanization policies remain controversial. Yu et al. [20] argue that the dual structure of household management and land property rights is key to urban–rural conflicts in China, with land expropriation, environmental damage by industrial projects, and urban–rural planning as critical risk factors. Lang et al. [21] focus on the evolution of urban villages at the urban–rural interface, noting that although many Chinese cities have attempted to draft new rural plans, these plans have not been effectively implemented. Yuan et al. [22] indicate that local governments often disregard the natural environmental capacity, continuously introducing industrial and real estate projects, leading to ecological degradation and environmental pollution. This results in a lag in population urbanization compared to land urbanization, with the emergence of numerous empty or ghost cities. Ying and Wu [23], while acknowledging urbanization as an inevitable trend in China's development, highlight that the urbanization process has significantly widened the income gap between urban and rural areas and caused a disconnection between urban and rural socio-economic systems, necessitating significant attention.

In the context of China's new urbanization and its impact on rural agriculture, Li et al. [24] argue that the urbanization process could potentially affect the concurrent implementation of the rural revitalization strategy, necessitating mutual adaptation. Urbanization increases pressure on farmers, reducing the economic benefits of traditional agriculture, but also offers opportunities for alternative, high-value agricultural enterprises to utilize urban markets. Ding et al. [25] find that population urbanization has a significant positive impact on agricultural water usage in East Asia, facilitating rural labor transfer and farmland circulation; however, economic urbanization and urban–rural integration have negative

impacts, leading to a widening of absolute income disparities and constraining agricultural development space. Wang et al. [26] note that in China, rural residents have much higher per capita residential land usage compared to urban residents, suggesting that urbanization could release a significant amount of arable land for increased crop production and more efficient large-scale agricultural operations. Zhao et al. [27] show that overall urbanization, land urbanization, and economic urbanization all significantly enhance agricultural technological efficiency in Northeast China. Ge et al. [28] demonstrate that China's rural areas have a surplus of labor and that new urbanization is key to effectively resolving this issue; both household registration-based urbanization and residency-based urbanization significantly promote the efficiency of green agricultural development, although the impact of household registration-based urbanization is less pronounced. The government is easing household registration restrictions and actively guiding surplus agricultural labor to engage in urban service sectors.

Several scholars have expressed concerns about the impact of urbanization on agriculture in China. Liu et al. [29] note that rural hollowing, a widely observed geographic phenomenon in China's rapid urbanization process, leads to the wastage of rural land resources and hinders land use optimization and coordinated urban–rural development. Further research by Liu et al. [30] reveals that excessive out-migration of the rural population has resulted in a scarcity of labor, negatively affecting the intensity of land use. This necessitates compensations through increased inputs of fertilizers and pesticides or changes in crop types, adversely impacting the ecological environment and national food security. Cai et al. [31], using spatial analysis methods, find that China's new urbanization and the agricultural ecological environment are mostly in a state of imbalance and strained coordination. Most provinces lag behind in new urbanization development, and differentiated promotion strategies are required for better outcomes across regions. Jiang et al. [32] argue that while population urbanization can effectively narrow the gap between socioeconomic systems and residents' living systems, industrial urbanization widens the rural–urban divide, and even more so between provinces in the eastern and central-western regions. Ying and Wu [23] similarly highlight that despite the inevitable trend of urbanization in China, the widening income disparities and disconnection between urban and rural socioeconomic systems during the urbanization process necessitate serious consideration. Ge et al. [28] find that while guiding migrant workers into employment can enhance the efficiency of green agricultural development, the employment effects of urbanization in the tertiary sector are more pronounced. However, they estimate that urbanization in 2020 alone resulted in a surplus labor force of 20.64 million, posing significant employment challenges. Su et al. [33] developed new algorithms for analyzing satellite images from Google Earth Engine, which show that the rapid pace of urbanization in Guangdong has significantly increased the rate of farmland abandonment, rising from approximately 500,000 hectares around the year 2000 to 1,898,667 hectares in 2021, as reported by the Guangdong Provincial Government, marking an alarming abandonment rate of 26%.

1.3. Research Objectives and Hypotheses

As previously discussed, urbanization has long been regarded as a more advanced stage of development than rural areas and is key to modernization. The process of urbanization is essentially a transformation of traditional rural areas, where increasing numbers of agricultural laborers become urban enterprise workers and more farmland is converted into urban-specific structures such as buildings, factories, and commercial centers. Whether this process is viewed as the “evolution” of the countryside or a “contest” for resources, it inevitably raises concerns and debates among scholars about the impact of urbanization on food supply and agricultural production.

China, as a country with a non-Western model but rapid economic development, experiences a remarkably fast pace of urbanization. Given that China's agricultural resources are not abundant but its rural population is excessively large, the impact of rapid urbanization on the agricultural economy is of significant interest. Although extensive research has been conducted, it mostly focuses on relatively minor aspects such as the ecological environment, carbon emissions, water, and land resources in rural areas or specific regions like the Northeast or the Yellow River basin.

To establish a sound theoretical foundation, it is essential to articulate the intrinsic link between urbanization pathways and the level of agricultural economic development. Urbanization can generally be categorized into three dimensions: demographic, spatial (land), and economic urbanization, each exerting distinct impacts on agricultural efficiency through mechanisms of labor reallocation, land use transformation, and structural upgrading.

First, demographic urbanization reallocates rural surplus labor to urban areas, potentially enhancing agricultural productivity by reducing labor redundancy. However, in the absence of mechanization or labor substitution, this may lead to labor shortages and reduced agricultural output. Second, spatial urbanization, often characterized by the conversion of farmland into urban land—particularly in peri-urban zones—can constrain high-efficiency agricultural production, exacerbate land fragmentation, and increase logistical distances and costs, thus undermining economic efficiency in agriculture. Third, economic urbanization, through improvements in infrastructure, digital connectivity, and public services, may enhance agricultural performance if such benefits effectively diffuse into rural areas. If not, the result may be widened rural–urban disparities and weakened agricultural competitiveness.

From the perspectives of spatial economics and structural transformation, urbanization is fundamentally a process of spatial reallocation of resources, with labor mobility and land reorganization as two central mechanisms. Labor mobility encompasses the outward migration from rural areas and internal restructuring of the agricultural workforce, while land reorganization involves the transformation of agricultural land-use patterns and spatial layouts. These mechanisms determine whether agricultural sectors can maintain or improve their efficiency amidst urban expansion. Therefore, this study adopts agricultural economic efficiency as a proxy for agricultural performance and investigates how various urbanization pathways affect it through these underlying mechanisms.

This study aims to provide a comprehensive overview of the outcomes following China's implementation of both the new urbanization and rural revitalization policies, using empirical analysis methods to examine the impact of urbanization on China's agricultural economy. The following hypotheses are proposed for this research:

Hypothesis 1. *Overall, China's urbanization process has a positive impact on its agricultural economy.*

Hypothesis 2. *China's population urbanization helps absorb surplus rural labor, thus having a positive impact.*

Hypothesis 3. *Urbanization aids agricultural upgrades through corporatization, enhancing productivity.*

Hypothesis 4. *Improvements in transportation and logistics brought about by urbanization accelerate the circulation of goods in rural areas, thereby improving the agricultural economy.*

Hypothesis 5. *Enhancements in healthcare, information technology, and other infrastructure due to urbanization aid in elevating the agricultural economy.*

2. Materials and Methods

2.1. Research Processes

Based on the foregoing, this study establishes the following research process:

- Collecting, filtering, and analyzing data that can represent the characteristics of China's new urbanization.
- Measuring and evaluating the development level of China's agricultural economy during the same period.
- Analyzing the correlation between the two.
- Discussing and drawing conclusions and recommendations.

The research process is illustrated in Figure 1.

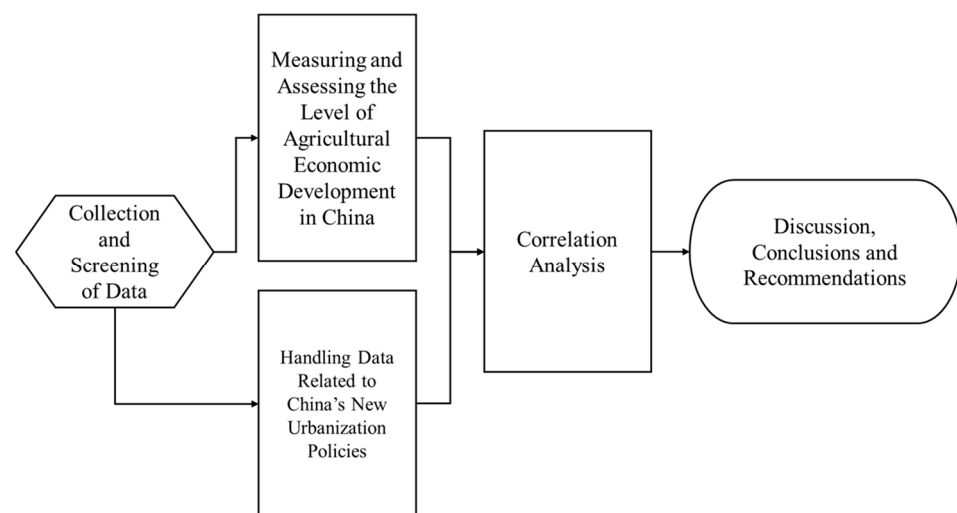


Figure 1. Research flowchart.

2.2. Methods

This study assesses the level of agricultural economic development through efficiency measurement and evaluation. Efficiency analysis in agriculture considers not only the output level but also the utilization of input resources, providing a comprehensive view of agricultural performance, such as the efficiency of resource use (land, labor, capital, and technology). This approach allows for comparative analysis across different regions and types of agricultural economies. Additionally, efficiency analysis can diagnose specific issues in agricultural production, such as over-investment and the rationality of resource allocation, promoting a more efficient and sustainable direction for agricultural economic development.

Efficiency evaluation is widely used in assessing economic levels. Schmookler et al., in 1952, utilized efficiency metrics to evaluate the U.S. economy [34], while Mundaca et al. applied efficiency assessments to studies of the energy economy [35]. Bukarica et al. used efficiency evaluation to investigate energy policies and sustainability levels [36]. In the realm of agricultural economics, Paul et al. conducted studies on U.S. farms and agricultural scale economies using efficiency assessments [37]. Reza et al.'s research on efficiency highlighted changes in global agricultural productivity over five years [38].

This study uses data envelopment analysis (DEA) for efficiency evaluation. The DEA method was first introduced in 1978 [39], where the entities to be evaluated are referred to as decision-making units (DMUs), each having the same input and output variables. After

calculating the input–output efficiency for each DMU, an efficiency frontier is established based on the best efficiency values. DMUs located on the frontier have an efficiency score of 1, while others have efficiency scores less than 1, depending on their distance from the frontier. DEA is a non-parametric method that does not require predefined variable weights, and the results are straightforward and easy to interpret, making it widely applied across various fields and industries.

The foundational model of DEA is the CCR model, named after A. Charnes, W.W. Cooper, and E. Rhodes, which assumes constant returns to scale and is also referred to as technical efficiency (TE). In 1984, the BCC model, named after R.D. Banker, A. Charnes, and W.W. Cooper, was introduced, allowing for variable returns to scale. The relationship between these two models is that the pure technical efficiency (PTE) calculated by the BCC model represents the technical efficiency (TE) of the CCR model adjusted for scale efficiency (SE). The TE score equals the product of PTE and SE, providing substantial explanatory flexibility within the model framework.

The traditional CCR and BCC models focus solely on radial improvements, meaning that if the model is to consider how to improve to reach the efficiency frontier, all input or output variables must be adjusted proportionally, without considering the improvement of individual variables. This is because the frontier formed by these two models is a continuous, smooth, convex polygon. However, in the real world, the optimal efficiency frontier may be more complex, non-convex, or non-smooth. To address these limitations, Tone et al. introduced the slack-based measure (SBM) model in 2001 [40]. This model accounts for the improvement of individual variables by introducing the concept of “slack variables.” By evaluating the “slackness” of each variable for each DMU, the SBM model constructs a more optimized efficiency frontier. This model better reflects real-world issues, significantly improving the fit while maintaining the characteristic that the TE score equals the product of PTE and SE. Furthermore, it provides a slack measure for individual variables, offering a broader potential for interpretation. Consequently, the SBM model has been widely adopted across various industries.

For instance, Ohsato and Takahashi employed the SBM model to assess the managerial efficiency of banks in Japan [41]. Cecchini et al. used an SBM model incorporating undesired outputs to evaluate the green production efficiency of dairy farms in Italy [42]. Su et al. applied the SBM model to assess China’s culture and tourism industries [43], while Shang et al. utilized an SBM model with undesired outputs to evaluate the green efficiency of China’s energy sector [44]. Gao et al. adopted the SBM model to measure tourism efficiency in Chinese provinces [45], and Hsu et al. used the model to assess the agricultural economy in various Chinese regions [46]. Li et al. opted for a super-efficiency SBM model to evaluate the ecological utilization efficiency of arable land [47].

The standard DEA-SBM model evaluates relative efficiency scores based on cross-sectional data from a single period, constructing an envelope surface with DMUs of that period as the reference set. In the case of panel data spanning multiple periods, the reference set and the envelope surface differ across these periods, rendering the efficiency scores of each DMU only relative to others within the same period. Consequently, efficiency scores from different periods for the same DMU are not directly comparable and do not reflect changes over time. Thus, the standard SBM model is not suitable for analyzing trends and changes over time. Especially when many studies use efficiency scores from the standard SBM model of different periods as dependent variables in correlation analyses, conducting regression analysis with other time-series independent variables, the results might not accurately represent the real situation because these dependent variables do not incorporate time effects.

To address these limitations, Golany and Roll introduced the global DEA model in 1989 [48], which considers all DMUs from all periods as a single reference set, treating DMUs from different periods as distinct entities. This model generates efficiency scores that not only reflect comparisons with other DMUs but also track the same DMUs across different periods. Hence, efficiency scores derived from this model are directly comparable across periods, adding no additional complexity to model computations. The global DEA model facilitates the analysis of efficiency trends and evolutions and yields more reasonable results in regression analyses since the efficiency scores include time effects.

Streimikis et al. employed the global DEA model to evaluate energy efficiency in European Union agriculture [49]. Ben Lahouel et al. used the global Malmquist index to study inclusive green growth in OECD countries [50]. Zhao et al. employed the global metafrontier SBM super-efficiency model to analyze the impact of environmental regulations on green economic growth in China [51]. This study constructs a global SBM model, considering all DMUs from all periods as the reference set, treating DMUs from different periods as distinct for model construction, identical in computation to the standard SBM model, not detailed separately here.

In assessing the efficiency of China's agricultural economy, this study employs the global SBM model, which is available in input-oriented, output-oriented, and non-oriented variants. This study opts for the non-oriented SBM model, simultaneously considering slack in both input and output variables. The formula for the non-oriented SBM model is as follows [52]:

Let the set of DMUs be $j = \{1, 2, \dots, n\}$, each DMU having m inputs and s outputs. We denote the vectors of inputs and outputs for DMU_j by $x_j = (x_{1j}, x_{2j}, \dots, x_{mj})^T$ and $y_j = (y_{1j}, y_{2j}, \dots, y_{sj})^T$, respectively. We define input and output matrices X and Y by $X = (x_1, x_2, \dots, x_n) \in R^{m \times n}$ and $Y = (y_1, y_2, \dots, y_n) \in R^{s \times n}$.

We assume that all data are positive, i.e., $X > 0$ and $Y > 0$.

In order to evaluate the relative efficiency of $DMU_o = (x_o, y_o)$, we solve the following linear program. This process is repeated n times for $o = (1, \dots, n)$.

Nonoriented or both-oriented SBM efficiency ρ_{IO}^* is defined by [SBM-C]

$$\rho_{IO}^* = \min_{\lambda, s^-, s^+} \frac{1 - (1/m) \sum_{i=1}^m (s_i^- / x_{io})}{1 + (1/s) \sum_{r=1}^s (s_r^+ / y_{ro})} \quad (1)$$

Subject to

$$x_{io} = \sum_{j=1}^n x_{ij} \lambda_j + s_i^- \quad (i = 1, \dots, m), \quad (2)$$

$$y_{ro} = \sum_{j=1}^n y_{rj} \lambda_j - s_r^+ \quad (r = 1, \dots, s), \quad (3)$$

$$\lambda_j \geq 0 (\forall j), \quad s_j^- \geq 0 (\forall i), \quad s_r^+ \geq 0 (\forall r)$$

After calculating the efficiency of China's agricultural economy, this study further explores the correlation between urbanization and agricultural economy. The most commonly used method for correlation analysis is regression analysis, where the efficiency scores obtained from the SBM model are used as the dependent variable, and the collected data related to China's urbanization process are used as independent variables. It is important to note that the efficiency scores derived from the SBM model, ranging between 0 and 1, represent typical censored data. Therefore, the correlation analysis in this study adopts the Tobit regression model proposed by James Tobin in 1958 [53], which utilizes maximum likelihood estimation (MLE), making it more suitable for handling censored dependent variables.

The core idea of MLE is to estimate model parameters by maximizing the likelihood function (or log-likelihood function), such that the probability of observing the data, given the parameters, is maximized. In other words, MLE seeks to find the parameter values that make the observed data “most likely” to occur. The mathematical expression for MLE is as follows: assuming the data follows a certain probability distribution (such as a normal distribution), the likelihood function is given by:

$$L(\theta) = \prod_{i=1}^n f(x_i|\theta) \quad (4)$$

In this context, $f(x_i|\theta)$ represents the probability density function of the data point x_i under parameter θ . MLE is applicable to any model where a probability distribution can be clearly defined, and it performs particularly well when handling nonlinear models, discrete data, censored data, or complex distributions. Compared to the least squares method used in linear regression models, MLE estimation is more suitable for nonlinear, complex models and non-normal distributions. It is also better equipped to handle censored or truncated data and possesses excellent statistical properties, particularly in large samples. As a result, it has been widely applied in Tobit models, logistic regression, survival analysis, and generalized linear models (GLMs). In this study, the Tobit model is employed to analyze the correlation between urbanization and agricultural economic efficiency.

Furthermore, this study incorporates the quantile regression model to investigate the relationship between urbanization and agricultural economic efficiency. This methodological choice stems from concerns regarding the limitations of the Tobit model when using DEA-derived efficiency scores as the dependent variable. Specifically, the Tobit model emphasizes the censored nature of the dependent variable and typically requires a substantial proportion of observations to be located at the censoring thresholds. When this condition is not met, the model’s goodness of fit may be severely compromised. In contrast, quantile regression offers a more robust, distribution-free estimation approach, particularly suitable when the dependent variable is not heavily concentrated near the boundary values. Given that efficiency scores obtained from the global DEA model tend to be distributed across the interior of the (0, 1) interval, quantile regression is more tolerant of outliers and heteroskedasticity and can effectively uncover the heterogeneous effects of explanatory variables across different segments of the efficiency distribution.

Let y_i denote the efficiency score of the i -th observation, and x_i represent the corresponding vector of explanatory variables. The quantile regression model aims to minimize the following objective function:

$$\hat{\beta}_q = \min_{\beta \in \mathbb{R}^k} \sum_{i=1}^n \rho_q(y_i - x_i^\top \beta) \quad (5)$$

The check function $\rho_q(u)$ is defined as follows:

$$\rho_q(u) = u \cdot (q - \mathbb{I}(u < 0)) \quad (6)$$

This represents a typical robust estimation approach, suitable for dependent variables such as efficiency scores that are bounded within a specific range but do not follow a typical truncation pattern.

This study utilized DEARUN software version 3.2.0.5 Trail for constructing DEA models and SPSSAU online analysis software for constructing the quantile regression model and Tobit models. Both software applications feature user-friendly graphical interfaces, include commonly used models that do not require manual coding by users,

and produce clear, standard outputs. Additionally, they provide basic explanations and analytical suggestions.

2.3. Materials

This study selected panel data from 31 provinces and cities in China for the years 2011–2022 as the research basis. The data sources include the China Statistical Yearbook and the China Rural Statistical Yearbook. China comprises 34 provincial-level administrative units; however, this paper excluded Taiwan, Hong Kong, and Macau from the panel data. Due to historical reasons, these three regions exhibit significant differences from the other 31 provinces and cities in terms of political systems, statistical data collection, and policy implementation, and thus were not included in the study scope.

The period from 2011 to 2022 was chosen for several reasons. First, the implementation of China's new urbanization plan began in 2014, and earlier data would not adequately reflect the impacts of this urbanization process. Retaining data from the years 2011, 2012, and 2013 provides a sufficient baseline for comparison prior to the implementation of the new urbanization initiatives. Furthermore, starting in 2011, the National Bureau of Statistics of China began including detailed data related to urbanization and industrialization in its annual publications. For instance, the number of legal entities in the primary sector by province started to be available from 2011. These additions have facilitated more comprehensive research related to urbanization.

Considering the vast differences in climate, types of agricultural products, and production cycles across China's 31 provinces and cities, this study selected agricultural diesel use, pesticide use, fertilizer use, and rural electricity consumption as variables for resource inputs. These four resources are universally utilized across various agricultural sectors such as crop farming, animal husbandry, and aquaculture and have low interdependence. They also represent a significant portion of variable costs in agricultural production. Other costs, such as seed expenses, plastic mulch consumption, and depreciation of agricultural machinery, which constitute a smaller proportion of costs and are not universally incurred across all types of agricultural production, were excluded from the input variables.

In this study, arable land area—commonly regarded as a critical input variable in agricultural efficiency analysis—was intentionally excluded for several reasons. First, land use costs account for a relatively small proportion of total agricultural production expenses in China. For instance, in Jinzhai County, Anhui Province, a mid-level economy region, the annual land rental cost for crop cultivation was as low as 100 RMB per mu in 2022, equivalent to merely 1500 RMB per hectare per year [54]. Second, there exists considerable regional variation across China's 31 provinces. In northern regions, only one crop cycle per year is typical, whereas southern regions may support up to three cropping cycles annually. Moreover, for provinces where animal husbandry dominates, arable land is less relevant than pasture or feeding land. Third, data availability poses challenges. Official statistics on agricultural land, including arable land, are often incomplete or discontinuous, with changes in statistical definitions over time. For example, the 2012 China Rural Statistical Yearbook reports agricultural land data from as early as 2008 across many regions.

Considering the above—namely the relatively low cost impact of land use, significant regional heterogeneity, the limited availability and consistency of land-use data, and the need to minimize the number of inputs to improve the discriminatory power of DEA models—this study opted to exclude arable land area from the input variables.

Lastly, rural population was included as a proxy for human resource input. This choice was made because data on the number of people engaged in agricultural production in rural China are incomplete. Moreover, it is common for all members of rural families in China, including the elderly and children, to participate in farming activities, provided

they are physically able. Although the rural population data are based on the hukou system registration and include a large number of rural residents working in cities, this situation is uniformly present across all provinces. Since this study measures and evaluates relative efficiencies among provinces, such variations are unlikely to significantly impact the results. Moreover, since 2010, China has vigorously promoted the development of the real estate sector and significantly relaxed the restrictions on converting rural household registration (hukou) to urban hukou. A considerable number of rural migrants working in cities have opted to change their registration status for reasons such as securing better educational opportunities for their children. Additionally, when discussing urbanization, official Chinese government statistics and discourse predominantly rely on the dichotomous ratio between the rural and urban populations. In light of these factors, this study adopts the rural population as the proxy variable for labor input in the assessment of agricultural economic efficiency.

In terms of output variables, this study selected the Total Output Value of Agriculture, Forestry, Animal Husbandry, and Fishery as a representative of the total income from agricultural production, and the Added Value of the Primary Industry as an indicator of the gross profit from agricultural activities. This is because although the agricultural production formats vary significantly across the 31 provinces, the ultimate economic value is reflected in monetary terms. For the DEA analysis, a total of seven input–output variables were used, which is less than one-third of the number of DMUs, aligning with the commonly accepted requirements for DEA analysis. All input–output variables are listed in Table 1, with detailed data provided in Supplementary Table S1. All values denominated in CNY were adjusted to 2021 prices using respective price indices to reflect constant prices.

Table 1. Input and output variables of the global SBM model for China’s agricultural circular economy.

Indicator Categories	Indicators
Input indicators	Rural Population (10,000 Persons)
	Rural Electricity Consumption (Billion kWh)
	Fertilizer Use (Pure Weight, 10,000 Tons)
	Agricultural diesel use (10,000 Tons)
	Pesticide use (Ton)
output indicators	Agriculture, Forestry, Animal Husbandry, and Fishery Total Output Value (Billion Yuan)
	Primary Industry Added Value (Billion Yuan)

This study selected nine independent variables to analyze the impact of new urbanization on agricultural economy, which include:

- Proportion of Urban Population (%), which is commonly considered the best representative of the level of urbanization in a region.
- Proportion of Urban Fixed Asset Investment in Total Social Fixed Assets (%), representing the share of urban fixed asset investment in total fixed asset investments for the year. This variable reflects the degree of urbanization in economic and investment activities across different provinces and cities.
- Proportion of the Population with Junior College Education or Higher (%), which is based on a survey of the population aged six and above across 31 provinces, with typical sampling rates around 1% in different years. This variable represents the influence of urbanization on the educational level of residents, indicating higher proportions of individuals with at least junior college education in more urbanized provinces.

- Number of Broadband Subscribers per 100,000 People (Subscribers), as many studies have shown a higher level of informatization in urban areas compared to rural, with a pervasive “digital divide” existing globally [55,56]. This variable reflects the impact of urbanization in the fields of information and digital economy in China’s 31 provinces.
- Per Capita Freight Volume (Tons), illustrating the enhancement of transportation infrastructure due to urbanization, which influences the total volume of material circulation.
- Per Capita Freight Turnover (Thousand Ton-Kilometers), representing the impact of urbanization on transportation freight volume.
- Number of Agricultural Legal Entities per 10,000 People (Units), depicting how urbanization affects the organizational modes of agricultural production. Traditional agricultural production in Chinese rural areas has been family based, characterized by small scale and outdated methods due to limited resources and high agricultural population. Urbanization transforms these traditional patterns, leading to more centralized and corporate agricultural production.
- Number of Hospital Beds per 10,000 People (Beds), indicating improvements in medical conditions due to urbanization.
- Per Capita Agricultural Fiscal Expenditure (10,000 CNY), calculated as the government’s fiscal expenditure on agriculture per capita. While this variable is not directly related to urbanization, it is generally considered to have a significant impact on the local agricultural economy. This variable is included in the study to contrast the effects of other variables.

For detailed values of the above independent variables, see Supplementary Table S3.

In this study, a total of nine explanatory variables were employed in both the Tobit regression model and the quantile regression models. To ensure the reliability of the regression results, it was necessary to conduct a multicollinearity diagnosis for these independent variables. The Variance Inflation Factor (VIF) values for all variables are presented in Table 2. Most of the variables exhibited VIF values within acceptable limits; however, the VIF for Proportion of Urban Population was 5.28, which approaches the commonly used threshold of 5. Additionally, the VIF for Proportion of the Population with Junior College Education or Higher reached 6.99, indicating a moderate level of multicollinearity.

Table 2. Multicollinearity diagnostics of explanatory variables in the regression models.

	VIF	Tolerance
Number of Agricultural Legal Entities per 10,000 People	2.19	0.457
Per Capita Freight Volume	1.492	0.67
Per Capita Freight Turnover	1.809	0.553
Number of Hospital Beds per 10,000 People	2.294	0.436
Proportion of Urban Fixed Asset Investment in Total Social Fixed Assets	1.696	0.59
Per Capita Agricultural Fiscal Expenditure	3.021	0.331
Proportion of the Population with Junior College Education or Higher	6.983	0.143
Proportion of Urban Population	5.497	0.182
Number of Broadband Subscribers per 10,000 People	2.611	0.383

Given the importance of these two variables in the analysis and the fact that their VIF values do not exceed the commonly accepted severe threshold of 10, this study further conducted Augmented Dickey–Fuller (ADF) tests to examine their stationarity. As shown in Table 3, both variables passed the ADF test in their original forms, with the null hypothesis of a unit root being significantly rejected. This indicates that the series are stationary and do not suffer from unit root problems. Since stationarity is a critical prerequisite for maintaining the validity of parameter estimates in regression analysis—ensuring that

spurious regression issues are avoided—these variables were retained in their original forms in the construction of the regression models.

Table 3. ADF test results of variables.

	The Order of the Difference	t	p	Threshold Value		
				1%	5%	10%
Proportion of Urban Population	0	−5.463	0	−3.449	−2.87	−2.571
Proportion of the Population with Junior College Education or Higher	0	−4.786	0	−3.449	−2.87	−2.571

3. Results

3.1. Constructing a Global SBM Model for China’s Agricultural Economic Efficiency from 2011 to 2022

In this study, the DEARUN software was utilized to construct a global SBM model for the agricultural economic efficiency of 31 provinces in China from 2011 to 2022, adopting a nonoriented approach. The model outcomes include TE under the assumption of constant returns to scale, PTE under variable returns to scale, and SE. The term “Return to scale” (RTS) indicates the scale efficiency status: CRS denotes constant returns to scale, IRS indicates increasing returns to scale, and DRS represents decreasing returns to scale. Table 4 presents the average efficiency scores for the 31 provinces across different periods, along with an analysis of scale returns, showing the number of provinces assessed as CRS, IRS, and DRS for each period. Detailed data of the model results can be found in the Supplementary Table S2.

Table 4. Summary of results from the global SBM model of China’s agricultural economy, 2011–2022.

	Mean Value of TE	Mean Value of PTE	Mean Value of SE	Number of CRS	Number of DRS	Number of IRS
2011	0.373	0.415	0.9174	2	16	13
2012	0.390	0.429	0.915	2	16	13
2013	0.402	0.450	0.906	1	17	13
2014	0.403	0.450	0.907	1	15	15
2015	0.408	0.453	0.906	1	18	12
2016	0.433	0.474	0.909	3	18	10
2017	0.418	0.452	0.924	3	19	9
2018	0.442	0.493	0.903	3	16	12
2019	0.469	0.548	0.886	3	19	9
2020	0.545	0.654	0.861	4	20	7
2021	0.707	0.834	0.861	9	12	10
2022	0.605	0.773	0.808	7	15	9

TE: technical efficiency; PTE: pure technical efficiency; SE: scale efficiency; CRS: constant returns to scale; DRS: decreasing returns to scale; IRS: increasing returns to scale.

3.2. Constructing Tobit Regression Models for New Urbanization and Agricultural Economy in China

To test the robustness of the Tobit model, this study constructed two Tobit models for comparison, differing in their dependent variables. The first model, Tobit Model 1, uses the TE scores under the constant returns to scale assumption from the 2011–2022 global SBM model of agricultural economy across 31 provinces in China as the dependent variable. This model was built using data series of the same nine independent variables from these

provinces during the same period. The dependent variable in Model 1 is censored with lower and upper boundaries set at 0 and 1.001, respectively. The sample size for the model, as shown in Table 5, includes all 372 observations from 12 periods across 31 provinces, which were used in constructing the model.

Table 5. Summary table of Model 1 samples.

	Censor Data Samples			
	Sample Size	Uncensored	Left-Censored	Right-Censored
Number	372	372	0	0
Percentage	100%	100.00%	0.00%	0.00%

The likelihood ratio test results for Model 1 are presented in Table 6. The p -value of the model is less than 0.05, indicating rejection of the null hypothesis, which posits that no independent variables significantly affect the dependent variable; thus, Model 1 is validated as effective. The Akaike information criterion (AIC), named after the Japanese statistician Hirotugu Akaike [57], is employed to compare the fit and complexity of different models, with lower values indicating better model fit. The Bayesian information criterion (BIC), introduced by Schwarz [58], prevents overfitting due to excessive model complexity. In the likelihood ratio test of Model 1, both AIC and BIC values are relatively low, suggesting a good fit of the model.

Table 6. Results of Model 1 likelihood ratio test.

Model	$-2 \times \text{Log-Likelihood}$	Cardinality	df	p	AIC	BIC
Intercept-only	−27.321					
Final model	−240.050	212.729	9	0.000	−220.050	−180.861

The p -value serves as an indicator for assessing whether the influence of independent variables on the dependent variable is statistically significant within a model. It measures the probability of observing the sample results (or more extreme results) under the assumption that the null hypothesis is true (i.e., the coefficient of the independent variable is zero, indicating no effect on the dependent variable). When $p < 0.05$, it is generally considered a standard level of statistical significance, implying a 5% risk of erroneously rejecting the null hypothesis. This means there is a 5% chance that the significant effect of the independent variable is merely by chance. Conversely, when $p < 0.01$, it meets a stricter standard of significance testing, with an error probability of 1%, indicating a lower likelihood of the variable's impact being coincidental and providing stronger statistical evidence.

The final results for Model 1 are shown in Table 7.

Table 7. Results of Model 1.

	Regression Coefficient	Standard Error	t	p	95% CI
Intercept	1.26	0.993	1.268	0.205	−0.687~3.207
Number of Agricultural Legal Entities per 10,000 People	0.003	0.002	1.795	0.073	−0.000~0.006
Per Capita Freight Volume	−0.002	0.001	−3.333	0.001	−0.004~−0.001
Per Capita Freight Turnover (Thousand Ton-Kilometers)	−0.001	0.001	−1.033	0.302	−0.002~0.001

Table 7. Cont.

	Regression Coefficient	Standard Error	t	p	95% CI
Number of Hospital Beds per 10,000 People (Beds)	0.005	0.001	4.252	0	0.003~0.007
Proportion of Urban Fixed Asset Investment in Total Social Fixed Assets (%)	−0.008	0.01	−0.791	0.429	−0.029~−0.012
Per Capita Agricultural Fiscal Expenditure (10,000 CNY)	0	0	7.088	0	0.000~0.000
Proportion of the Population with Junior College Education or Higher (%)	−0.014	0.003	−4.547	0	−0.020~−0.008
Proportion of Urban Population (%)	−0.004	0.002	−2.427	0.015	−0.007~−0.001
Number of Broadband Subscribers per 10,000 People (Subscribers)	0.043	0.013	3.421	0.001	0.018~0.068
log (Sigma)	−1.742	0.037	−47.504	0	−1.813~−1.670

McFadden R^2 = −7.786.

Using the PTE scores from the global SBM model under the constant returns to scale assumption as the dependent variable, Tobit Model 2 was constructed with the aforementioned nine independent variables. The truncation boundaries for the dependent variable in Model 2 were set at 0 and 1.001. The sample conditions for the model are presented in Table 8. A total of 372 samples from 31 provinces across 12 years (2011–2022) were included in the model construction.

Table 8. Summary table of Model 2 samples.

	Censor Data Samples			
	Sample Size	Uncensored	Left-Censored	Right-Censored
Number	372	372	0	0
Percentage	100%	100.00%	0.00%	0.00%

The likelihood ratio test results for Model 2 are shown in Table 9. The p -value of the model is less than 0.05, indicating that the null hypothesis is rejected, meaning that at least one independent variable has a significant effect on the dependent variable, thus validating Model 2. However, based on the AIC and BIC values, Model 2 demonstrates a lower fit compared to Model 1.

Table 9. Results of Model 2 likelihood ratio test.

Model	−2 × Log-Likelihood	Cardinality	df	p	AIC	BIC
Intercept-only	64.106					
Final model	−98.220	162.325	9	0.000	−78.050	−39.031

The final results for Model 2 are shown in Table 10.

Table 10. Results of Model 2.

	Regression Coefficient	Standard Error	t	p	95% CI
Intercept	1.724	1.202	1.435	0.151	−0.631~4.080
Number of Agricultural Legal Entities per 10,000 People (Units)	0.001	0.002	0.28	0.78	−0.003~0.005

Table 10. Cont.

	Regression Coefficient	Standard Error	t	p	95% CI
Per Capita Freight Volume (Tons)	−0.003	0.001	−3.61	0	−0.005~−0.001
Per Capita Freight Turnover (Thousand Ton-Kilometers)	−0.002	0.001	−2.653	0.008	−0.004~−0.001
Number of Hospital Beds per 10,000 People (Beds)	0.003	0.001	2.298	0.022	0.000~0.006
Proportion of Urban Fixed Asset Investment in Total Social Fixed Assets (%)	−0.012	0.013	−0.943	0.346	−0.036~0.013
Per Capita Agricultural Fiscal Expenditure (10,000 CNY)	0	0	5.157	0	0.000~0.000
Proportion of the Population with Junior College Education or Higher (%)	−0.001	0.004	−0.324	0.746	−0.009~0.006
Proportion of Urban Population (%)	−0.006	0.002	−3.138	0.002	−0.010~−0.002
Number of Broadband Subscribers per 10,000 People (Subscribers)	0.077	0.015	5.059	0	0.047~0.107
log (Sigma)	−1.551	0.037	−42.304	0	−1.623~−1.479

McFadden $R^2 = 2.532$.

3.3. Constructing Quantile Regression Models for New Urbanization and Agricultural Economy in China

Taking the TE scores under the assumption of constant returns to scale in the global SBM model as the dependent variable, a quantile regression model was constructed using the nine independent variables described above. The estimation results are presented in Table 11.

Table 11. Results or quantile regression models.

q = 0.25, $R^2 = 0.241$	Regression Coefficient	Standard Error	t	p	95% CI
Constant	−0.854	0.838	−1.019	0.309	−2.501~0.793
Number of Agricultural Legal Entities per 10,000 People	0	0.002	−0.155	0.877	−0.003~0.003
Per Capita Freight Volume (Tons)	−0.001	0.001	−1.286	0.199	−0.002~0.000
Per Capita Freight Turnover (Thousand Ton-Kilometers)	−0.002	0.001	−3.948	0.000 **	−0.004~−0.001
Number of Hospital Beds per 10,000 People (Beds)	0.006	0.001	6.485	0.000 **	0.004~0.008
Proportion of Urban Fixed Asset Investment in Total Social Fixed Assets (%)	0.011	0.009	1.241	0.215	−0.006~0.028
Per Capita Agricultural Fiscal Expenditure (10,000 CNY)	0	0	6.855	0.000 **	0.000~0.000
Proportion of the Population with Junior College Education or Higher (%)	−0.014	0.003	−4.97	0.000 **	−0.020~−0.009
Proportion of Urban Population (%)	−0.001	0.001	−0.704	0.482	−0.004~0.002
Number of Broadband Subscribers per 10,000 People (Subscribers)	0.034	0.102	0.332	0.74	−0.167~0.234

Table 11. Cont.

q = 0.5, R² = 0.241	Regression Coefficient	Standard Error	t	p	95% CI
Constant	−0.897	1.156	−0.776	0.438	−3.171~1.376
Number of Agricultural Legal Entities per 10,000 People (Units)	0.002	0.002	0.807	0.42	−0.002~0.005
Per Capita Freight Volume (Tons)	−0.002	0.001	−1.989	0.047 *	−0.003~−0.000
Per Capita Freight Turnover (Thousand Ton-Kilometers)	−0.002	0.001	−3.321	0.001 **	−0.004~−0.001
Number of Hospital Beds per 10,000 People (Beds)	0.007	0.001	5.471	0.000 **	0.005~0.010
Proportion of Urban Fixed Asset Investment in Total Social Fixed Assets (%)	0.012	0.012	1.016	0.31	−0.011~0.036
Per Capita Agricultural Fiscal Expenditure (10,000 CNY)	0	0	6.296	0.000 **	0.000~0.000
Proportion of the Population with Junior College Education or Higher (%)	−0.014	0.004	−3.885	0.000 **	−0.021~−0.007
Proportion of Urban Population (%)	−0.003	0.002	−1.558	0.12	−0.007~0.001
Number of Broadband Subscribers per 10,000 People (Subscribers)	0.212	0.146	1.447	0.149	−0.076~0.499
q = 0.75, R² = 0.241	Regression Coefficient	Standard Error	t	p	95% CI
Constant	1.576	1.312	1.201	0.231	−1.004~4.156
Number of Agricultural Legal Entities per 10,000 People (Units)	0.008	0.002	3.924	0.000 **	0.004~0.012
Per Capita Freight Volume (Tons)	−0.004	0.001	−3.54	0.000 **	−0.006~−0.002
Per Capita Freight Turnover (Thousand Ton-Kilometers)	0.001	0.001	0.861	0.39	−0.001~0.002
Number of Hospital Beds per 10,000 People (Beds)	0.005	0.001	3.202	0.001 **	0.002~0.008
Proportion of Urban Fixed Asset Investment in Total Social Fixed Assets (%)	−0.009	0.014	−0.628	0.53	−0.036~0.018
Per Capita Agricultural Fiscal Expenditure (10,000 CNY)	0	0	3.951	0.000 **	0.000~0.000
Proportion of the Population with Junior College Education or Higher (%)	−0.003	0.003	−0.753	0.452	−0.009~0.004
Proportion of Urban Population (%)	−0.009	0.002	−4.581	0.000 **	−0.013~−0.005
Number of Broadband Subscribers per 10,000 People (Subscribers)	0.318	0.16	1.981	0.048 *	0.002~0.633

* $p < 0.05$, ** $p < 0.01$.

4. Discussions

4.1. Trends in Agricultural Economic Efficiency in China: An Overall Upward Trajectory

The global SBM model constructed in Section 4.1 of this paper facilitates cross-regional comparisons. Figure 2 illustrates the average TE, PTE, and SE values of the agricultural economies of the 31 provinces in Table 2 along with their linear trends. As shown in Figure 2, from 2011 to 2022, the TE and PTE scores of China's agricultural economy generally exhibit

an upward trend. A notable decline occurred between 2021 and 2020, likely due to the impacts of COVID-19. During 2021–2022, China implemented some of the world’s strictest containment measures, which significantly affected various sectors. These measures were not formally lifted until December 2022.

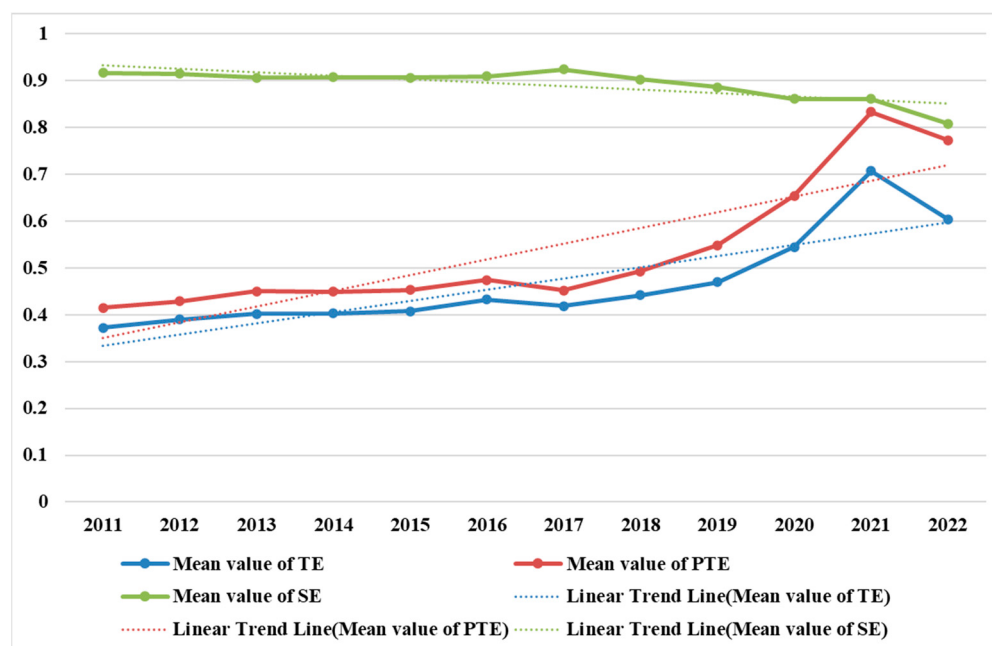


Figure 2. Development trends in China’s agricultural economic efficiency from 2011 to 2022.

Figure 2 also reveals that the SE scores of China’s agricultural economy are relatively high, displaying a gentle declining trend during the study period. SE scores indicate that China’s agricultural production has reached an optimal scale. Analysis of the RTS (returns to scale) shows that provinces in the DRS category outnumber those in IRS and CRS. Merely increasing resource input offers little benefit in enhancing the agricultural economic efficiency of provinces under DRS.

PTE scores, which reflect the efficiency under the assumption of variable returns to scale, demonstrate the impact of factors other than production scale, such as technological and management levels, on agricultural economic efficiency. TE scores are the product of PTE and SE scores. As shown in Figure 2, the consistently low PTE scores are the primary factor depressing TE scores. However, this also suggests significant potential for improvement in PTE. The trend lines for TE and PTE scores in China’s agricultural economy depicted in Figure 2 are very similar, indicating that the upward trend in TE scores is driven by improvements in PTE scores. This further suggests that during the study period, advancements in factors beyond scale, such as technology and management levels, have become the primary forces driving improvements in agricultural economic performance, which is beneficial for long-term development.

4.2. Comparison of Regression Model Results

The purpose of constructing two Tobit models in this study was to test the robustness of the models. Substituting an alternative variable as the dependent variable in regression models is a common method for robustness testing, as demonstrated in studies by Xu et al. on the impact of urbanization on rural land transfers, Su et al. on the digital economy, and Lin et al. on the effects of air pollution on technological innovation [59–61]. In the current study, the comparison of regression coefficients and z-values between Model 1 and the substituted-variable Model 2 is summarized in Table 12.

Table 12. Brief comparison of results from two Tobit models.

	Model 1	Model 2
Number of Agricultural Legal Entities per 10,000 People	0.003 (1.795)	0.001 (0.280)
Per Capita Freight Volume	−0.002 ** (−3.333)	−0.003 ** (−3.610)
Per Capita Freight Turnover	−0.001 (−1.033)	−0.002 ** (−2.653)
Number of Hospital Beds per 10,000 People	0.005 ** (4.252)	0.003 * (2.298)
Proportion of Urban Fixed Asset Investment in Total Social Fixed Assets	−0.008 (−0.791)	−0.012 (−0.943)
Per Capita Agricultural Fiscal Expenditure	0.000 ** (7.088)	0.000 ** (5.157)
Proportion of the Population with Junior College Education or Higher	−0.014 ** (−4.547)	−0.001 (−0.324)
Proportion of Urban Population	−0.004 * (−2.427)	−0.006 ** (−3.138)
Number of Broadband Subscribers per 100,000 People	0.043 ** (3.421)	0.077 ** (5.059)

* $p < 0.05$, ** $p < 0.01$, z-values in parentheses.

From Table 12, it is evident that most of the independent variables remain significant across the two models with different efficiency scores as dependent variables, indicating consistent influence of these variables on efficiency across different efficiency measures. This consistency demonstrates the robustness of the models. The direction of the effects and the relative magnitudes of the regression coefficients also remain consistent across the two models, further supporting the robustness of the models and suggesting that the direction of the variables' impact on efficiency scores is similar, even though the magnitude of the impact may vary by model.

Notable differences between the model results include the Per Capita Freight Turnover, which is not significant in Model 1 but becomes significant in Model 2, and the Proportion of the Population with Junior College Education or Higher, which is significant in Model 1 but not in Model 2. Model 1's dependent variable is the TE score, which assumes constant returns to scale and includes the impact of scale efficiency; Model 2's dependent variable, the PTE score, focuses solely on pure technical efficiency, excluding the impact of scale efficiency. Therefore, the differing significances and changes in estimated coefficients of the independent variables between these two models may indicate different impacts on the scale efficiency of the agricultural economy.

Looking at Tables 6 and 9, Model 1 has lower AIC and BIC values than Model 2. Lower AIC and BIC values suggest that Model 1 may not have excessively increased parameters to fit the data, indicating it might have better statistical efficiency and a lower risk of overfitting, offering a better fit relative to Model 2 and potentially a better balance between complexity and fit quality.

However, as shown in Tables 7 and 10, the McFadden R^2 value of Model 1 is negative, indicating that its fit is worse than that of the null model with only an intercept. This issue arises due to the sparse distribution of TE scores near the truncation boundaries (0 and 1.001). In contrast, the McFadden R^2 value of Model 2 is 2.532, exceeding 1, which suggests overfitting. This overfitting is likely caused by the excessive concentration of PTE scores at

the boundary values. Although both models report statistically significant p -values, these anomalies undermine their reliability in explaining the relationship between dependent and independent variables.

In light of these concerns regarding the Tobit models, this study additionally constructs a quantile regression model using the TE score as the dependent variable, with quantiles set at 0.25, 0.5, and 0.75. The results are presented in Table 11. The pseudo- R^2 values for the quantile regression models are 0.241 ($q = 0.25$), 0.259 ($q = 0.5$), and 0.322 ($q = 0.75$), all falling within the reasonable range of $[0, 1]$, indicating a good model fit. By comparison, the Tobit models exhibit abnormal McFadden R^2 values—negative for Model 1 and greater than 1 for Model 2—suggesting issues with explanatory power and robustness. Therefore, the quantile regression model, particularly the median regression, is deemed more appropriate as the main model in this study. Table 13 compares the results of Model 1 and the quantile regression models, both using TE as the dependent variable.

Table 13. Comparison of Model 1 and quantile regression models using TE score as the dependent variable.

	Model 1	q = 0.25	q = 0.50	q = 0.75
Number of Agricultural Legal Entities per 10,000 People	0.003 (1.795)	−0.000 (−0.155)	0.002 (0.807)	0.008 ** (3.924)
Per Capita Freight Volume	−0.002 ** (−3.333)	−0.001 (−1.286)	−0.002 * (−1.989)	−0.004 ** (−3.540)
Per Capita Freight Turnover	−0.001 (−1.033)	−0.002 ** (−3.948)	−0.002 ** (−3.321)	0.001 (0.861)
Number of Hospital Beds per 10,000 People	0.005 ** (4.252)	0.006 ** (6.485)	0.007 ** (5.471)	0.005 ** (3.202)
Proportion of Urban Fixed Asset Investment in Total Social Fixed Assets	−0.008 (−0.791)	0.011 (1.241)	0.012 (1.016)	−0.009 (−0.628)
Per Capita Agricultural Fiscal Expenditure	0.000 ** (7.088)	0.000 ** (6.855)	0.000 ** (6.296)	0.000 ** (3.951)
Proportion of the Population with Junior College Education or Higher	−0.014 ** (−4.547)	−0.014 ** (−4.970)	−0.014 ** (−3.885)	−0.003 (−0.753)
Proportion of Urban Population	−0.004 * (−2.427)	−0.001 (−0.704)	−0.003 (−1.558)	−0.009 ** (−4.581)
Number of Broadband Subscribers per 10,000 People	0.043 ** (3.421)	0.034 (0.332)	0.212 (1.447)	0.318 * (1.981)

* $p < 0.05$, ** $p < 0.01$. Values in parentheses are z -statistics for Model 1 and t -statistics for quantile regression models.

As shown in Table 13, the regression results of Model 1 (Tobit model) and the quantile regression models ($q = 0.25, 0.50$, and 0.75) are generally consistent. Key variables such as Per Capita Agricultural Fiscal Expenditure, Number of Hospital Beds per 10,000 People, and Proportion of the Population with Junior College Education or Higher are statistically significant across all models, with stable coefficient signs and magnitudes. While the significance levels of other variables vary across models, their directions of influence remain largely consistent, further reinforcing the robustness of the findings. The overall consistency across different model specifications suggests that the empirical conclusions of this study are both stable and reliable and are not driven by model selection or distributional assumptions. These results provide strong empirical support for the robust relationship between new-type urbanization factors and agricultural economic efficiency.

4.3. Analysis of the Impact of Urban Population Growth

Among the variables included in the regression models, Proportion of Urban Population serves as the most direct indicator of the level of population urbanization. As illustrated in Figure 3, this proportion has exhibited a continuously increasing trend throughout the study period. However, as shown in Tables 12 and 13, Proportion of Urban Population demonstrates a statistically significant negative effect in both Tobit models: it reaches the 5% significance level in Model 1 and the 1% level in Model 2, indicating a significant adverse impact on both TE and PTE scores. In the quantile regression models, the variable exhibits a negative influence in the 25th and 50th percentile models, although these effects are not statistically significant. Notably, in the 75th percentile model, Proportion of Urban Population has a significantly negative effect at the 1% level. This suggests that the negative impact of urban population proportion is more pronounced in provinces with higher agricultural efficiency scores, while its influence is not statistically significant in regions with medium or low efficiency.

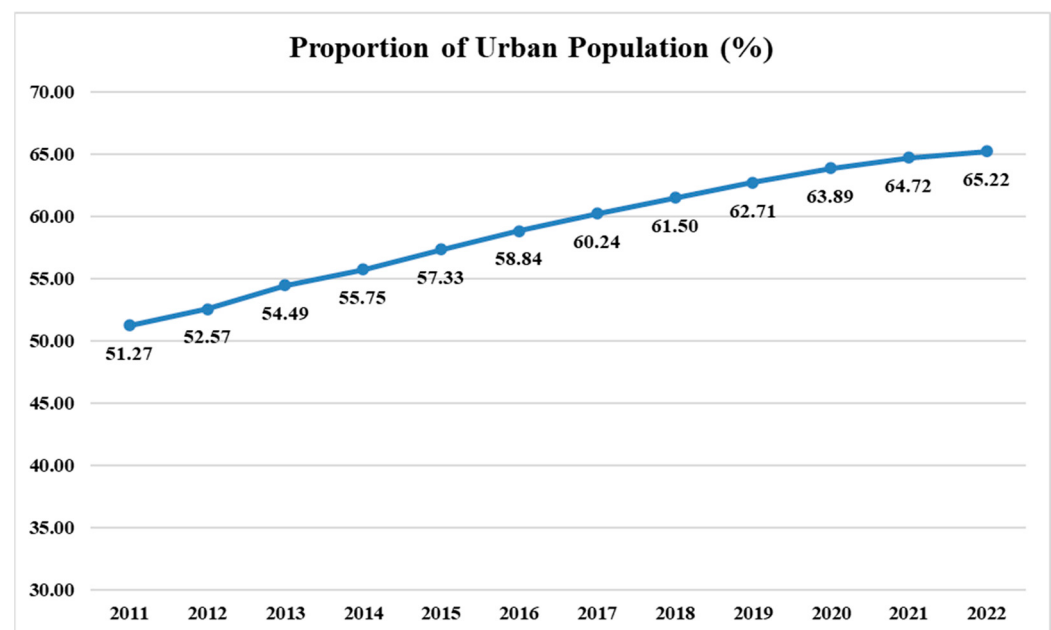


Figure 3. Development trend of the Proportion of Urban Population in China, 2011–2022.

Accordingly, Hypothesis 2 proposed in this study is not supported, and the null hypothesis can be rejected. It is commonly believed that higher levels of urbanization—reflected by a greater Proportion of Urban Population—can facilitate the transfer of surplus rural labor into urban areas, thereby reducing labor inputs in agriculture and enhancing overall agricultural efficiency. However, the results of this study suggest otherwise: population urbanization in China has not led to a significant positive impact on agricultural economic efficiency and, in fact, exhibits a significantly negative effect in more efficient regions.

The observed results may be linked to China's unique household registration system (hukou). For local governments aiming to meet urbanization targets, it is relatively straightforward to reclassify rural residents as urban dwellers via the hukou system. However, this conversion might not grant them the benefits and entitlements of urban citizens while simultaneously stripping them of rural rights, such as land allocations, which is detrimental to agricultural productivity. Research by Hsu and Ma [62] highlighted a trend where China's rural population favored migration to larger cities in 2005, whereas by 2015, the shift was more towards smaller cities, likely reflecting mere administrative changes in

hukou rather than actual relocation. Han et al. [63] found significant semi-urbanization, a direct consequence of the hukou system, where there is a notable discrepancy between the registered urban population and the actual urban dwellers. According to the National Bureau of Statistics, this semi-urban population reached 220 million in 2019 alone [64]. Han et al. further noted that the presence of a large semi-urban population adversely affects energy efficiency. Similarly, Ni [65] observed that Jiangsu's approach to urbanization often involves converting counties into districts, a method that may lead to fragmented governance, necessitating ongoing and reflective research.

The Proportion of Urban Population does not exhibit a significant positive effect on agricultural economic efficiency. One possible explanation is that China's agricultural production has yet to fully adapt to the structural transformations brought about by population urbanization. In a rational evolutionary pathway, agricultural production is expected to undergo a transition towards enterprise-based and large-scale operations in tandem with urbanization. Such a shift would imply moving away from traditional smallholder farming, typically organized at the household level, toward modern agricultural systems dominated by legal entities. This transformation can enhance resource allocation efficiency, reduce labor redundancy, and ultimately contribute to improvements in agricultural productivity.

However, the regression results of this study suggest that this transformation is not yet evident. The variable Number of Agricultural Legal Entities per 10,000 People, which serves as a proxy for the degree of agricultural corporatization, exhibits a positive but statistically insignificant effect in the Tobit models. In the quantile regressions, a significant positive effect on TE scores is only observed in the 75th percentile model. This indicates that agricultural corporatization does contribute to efficiency improvements, but its effects are currently confined to regions with higher baseline efficiency. Overall, the process of new-type urbanization in China has not yet effectively driven the corporatization of agriculture, and the mechanisms through which it might promote agricultural efficiency remain underdeveloped.

Another variable closely associated with the urbanization process is the Proportion of the Population with Junior College Education or Higher, which serves as a proxy for population quality. As shown in Figure 4, this variable has increased steadily over the study period. Numerous studies have confirmed the strong correlation between education and urbanization; for example, Roberts et al. [66] identify education as a key dimension of urban development, while Zhao et al. [67] find that the coordination between urbanization and higher education in China improved from a basic to an intermediate level between 2010 and 2020.

However, our empirical results suggest a counterintuitive relationship in the agricultural context. In Model 1 (Tobit), this variable has a significantly negative impact on TE scores at the 1% level. In the quantile regression models, significant negative effects are also observed at the 25th and 50th percentiles, but not at the 75th percentile. These results imply that the negative influence of education levels is concentrated in low- and mid-efficiency regions, while high-efficiency regions remain unaffected.

This finding may indicate that China's new-type urbanization has unintentionally widened the rural–urban talent gap. The improvement in urban education systems may have been accompanied by a misallocation of educational resources or a mismatch between higher education outputs and agricultural sector needs. As urban areas absorb a growing share of highly educated individuals, rural regions may experience talent outflows, reducing the human capital available for agricultural innovation and management. This could partially explain the observed negative effect of higher education proportions on agricultural efficiency.

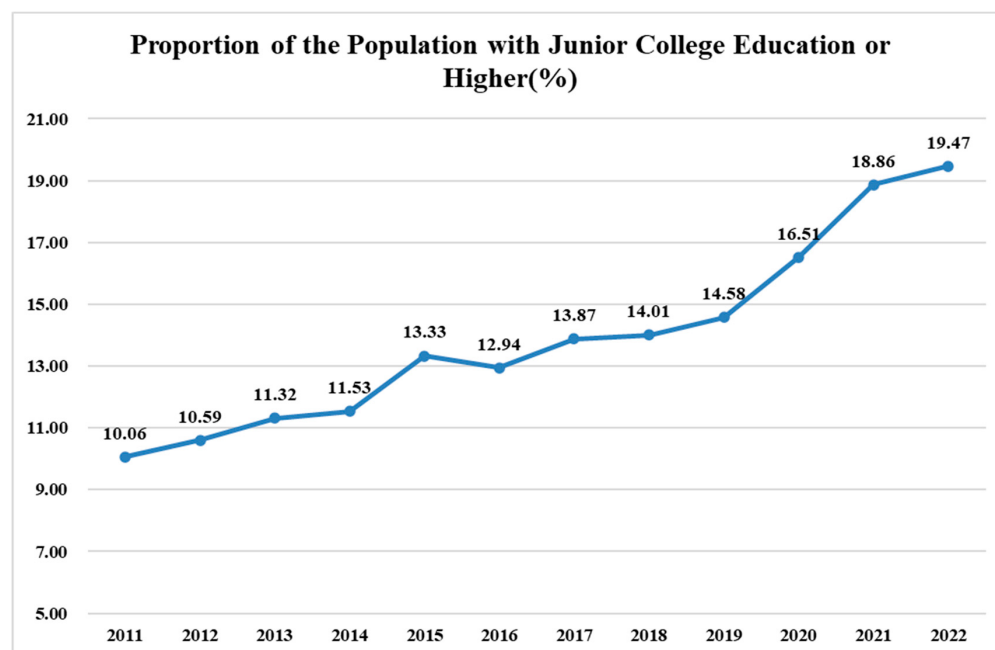


Figure 4. Development trend of the Proportion of the Population with Junior College Education or Higher in China from 2011 to 2022.

Although this study primarily relies on quantile regression as the main empirical strategy, we also refer to the Tobit model for additional insight into the decomposition of agricultural efficiency. Specifically, total efficiency (TE) is the product of pure technical efficiency (PTE) and scale efficiency (SE).

According to the Tobit model results, the proportion of the population with junior college education or higher exhibits a significant negative effect on TE at the 1% level, but its impact on PTE is not statistically significant. This suggests that the negative influence primarily affects scale efficiency rather than technical efficiency. Moreover, the variable Number of Agricultural Legal Entities per 10,000 People does not show a significant positive effect in either model, implying that improvements in educational attainment alone—without concurrent restructuring of the agricultural economy and enhancement of employment absorption—may lead to inefficiencies due to resource misallocation.

Therefore, advancing education must be accompanied by industrial transformation and enterprise-based agricultural production to effectively enhance overall agricultural efficiency.

The variable Proportion of Urban Fixed Asset Investment in Total Social Fixed Assets, which reflects the degree of fixed asset investment concentration in urban areas, fails to exhibit a statistically significant positive effect across all model specifications. This result indicates that urban-oriented industrial and investment patterns have not contributed significantly to improvements in agricultural economic efficiency in China.

Taken together, these findings lead to the rejection of Hypothesis 3. That is, the current form of China's new urbanization strategy has yet to enhance agricultural economic efficiency through enterprise-level transformation or structural upgrading.

4.4. Analysis of the Impact of Transportation Infrastructure

China's urbanization and rural revitalization strategies place a high priority on infrastructure development in rural areas, particularly roads, inland water transport facilities, railways, and navigable airports. It is commonly believed that improvements in these facilities enhance freight volumes and expedite cargo turnover cycles, benefiting the economy in all aspects. Research by Ma et al. on the urbanization and transportation infrastructure of five Central Asian countries demonstrates the significant impact of railway construction

mileage, total volume of goods trade, and actual use of foreign investment on urbanization and economic development [68]. Maparu et al.'s study on the causal relationship between transportation infrastructure and urbanization in India over a 20-year period found a unidirectional long-term causality from Paved Roads to Urbanization, while a bidirectional causality exists between State Highways and Urbanization [69].

This study selects Per Capita Freight Volume and Per Capita Freight Turnover as proxies for improvements in transportation infrastructure, aiming to assess their impact on agricultural economic efficiency. The mean values and trend lines of these two variables during the study period are depicted in Figure 5. As shown in the figure, both indicators exhibit an upward trend over time.

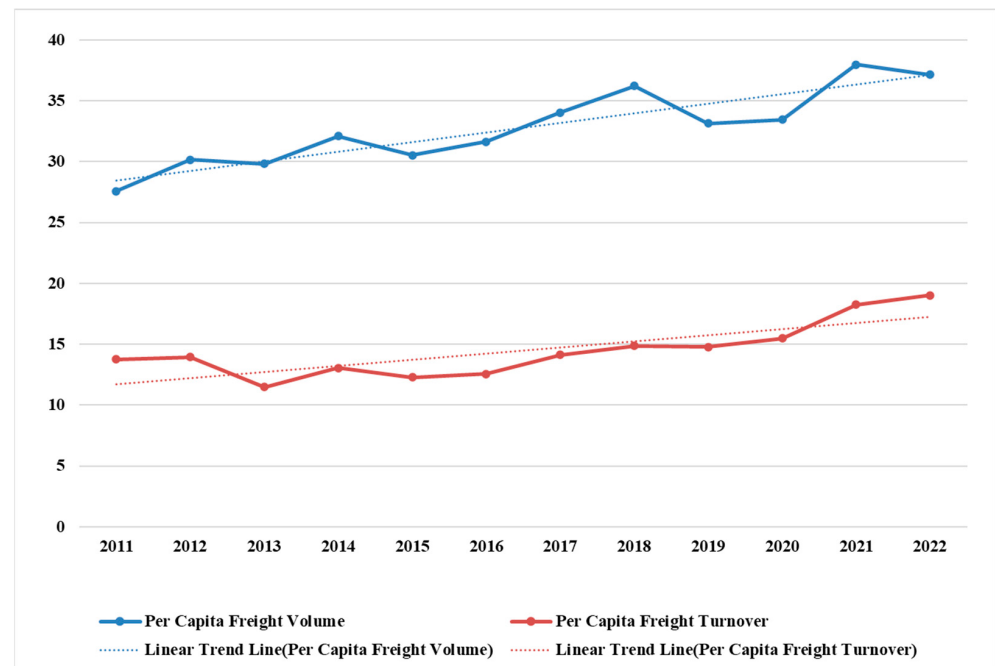


Figure 5. Development trends of Per Capita Freight Volume and Per Capita Freight Turnover, 2011–2022.

However, the regression results reveal a surprising pattern. Per Capita Freight Volume exerts a significantly negative effect in the quantile regression models at the 50th and 75th percentiles, while its effect at the 25th percentile is not statistically significant. In both Tobit models, using TE and PTE scores as dependent variables, the variable demonstrates a statistically significant negative impact at the 1% level. Similarly, Per Capita Freight Turnover has a significantly negative influence in the quantile regression models at the 25th and 50th percentiles, while the effect at the 75th percentile is not significant. In the Tobit models, it shows no significant impact on the TE score but exhibits a statistically significant negative effect on the PTE score at the 1% level. These findings deviate considerably from conventional expectations.

Firstly, in recent years, the fastest development in economic levels has not been characterized by increased goods transportation, and urbanization's boost to economic development does not necessarily concentrate on stimulating the real economy, particularly in economically developed regions where the main drivers of economic growth are no longer high-volume manufacturing industries. Ma et al. [68] analyzed the data of goods transportation volume and GDP from 2003 to 2018 in China, finding a bidirectional Granger causality relationship between goods transportation volume and GDP in the Northeast economic zone. In contrast, a unidirectional relationship was observed in the Bohai Rim, Pearl River, Central, Southwest, and Northwest regions, with no clear Granger causality in the Yangtze River Economic Belt. Notably, the Northeast is one of the less economically developed areas, whereas the Yangtze River Economic Belt and coastal

areas are among the most developed. This research indicates a decoupling between freight volume and economic development levels in China. Wang et al. [70] also indicated that with the advancement of new urbanization processes, China's economic development and freight demand have begun to decouple negatively, showing an inverted U-shaped trend, especially in economically developed areas such as Beijing, Shanghai, and Tianjin.

Secondly, specific to the agricultural economy, the urbanization of land in new urbanization usually expands outward from cities, and suburban lands often used for producing perishable agricultural products, such as vegetables, are pushed further out by urbanization processes, thus increasing distribution costs. Huang and Chiu [71] found that suburbanization in Taiwan caused a low energy value exchange rate for agricultural products, subsequently damaging the regional economy. Mulya et al. [72] argued that suburban agriculture is crucial for the economic development of urban and surrounding areas, and its disruption can lead to increased disasters and food shortages. From this perspective, the disruption of suburban agricultural systems is likely to lead to an increase in the transportation of agricultural products, implying higher costs and thus harming the efficiency of the agricultural economy.

In summary, Hypothesis 4 is rejected: improvements in transportation infrastructure under China's urbanization process have not achieved the intended goal of enhancing agricultural economic performance by accelerating material circulation. Instead, the effects have been largely negative. From the perspective of spatial economics, the underlying mechanisms become clearer. As illustrated in Figure 6, enhanced transportation accessibility facilitates the rapid conversion of suburban agricultural land into non-agricultural uses. This process compresses agricultural production space, pushes farming activities further away from urban centers, and results in longer logistics chains and rising transportation costs—all of which undermine agricultural efficiency.

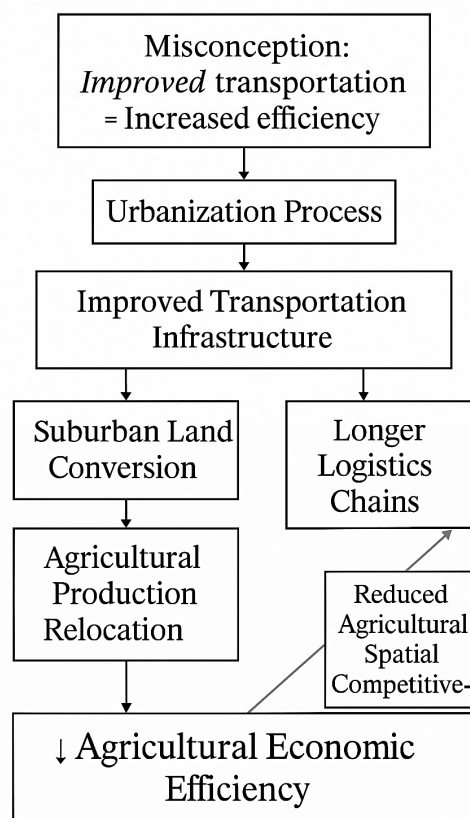


Figure 6. Potential mechanism pathways linking urbanization-driven transportation improvements to agricultural economic efficiency in China.

Moreover, urban capital concentration and land value intensification attract high-return non-agricultural activities, reducing the spatial competitiveness of agriculture. These structural forces indicate that under the current urbanization model in China, improvements in transportation infrastructure have not substantively promoted agricultural efficiency and, in fact, may have introduced systemic and spatial disadvantages.

4.5. Comprehensive Analysis of Impact Factors

Urbanization is commonly believed to ameliorate the backward medical facilities in rural areas and significantly benefit the development of informatization infrastructure. In this study, the variable “Number of Hospital Beds per 10,000 People” was used to represent improvements in medical facilities, while “Number of Broadband Subscribers per 100,000 People” indicated the enhancement of information infrastructure. Nationally, the trends of these variables from 2011 to 2022, as illustrated in Figure 7, show a rapid increase.

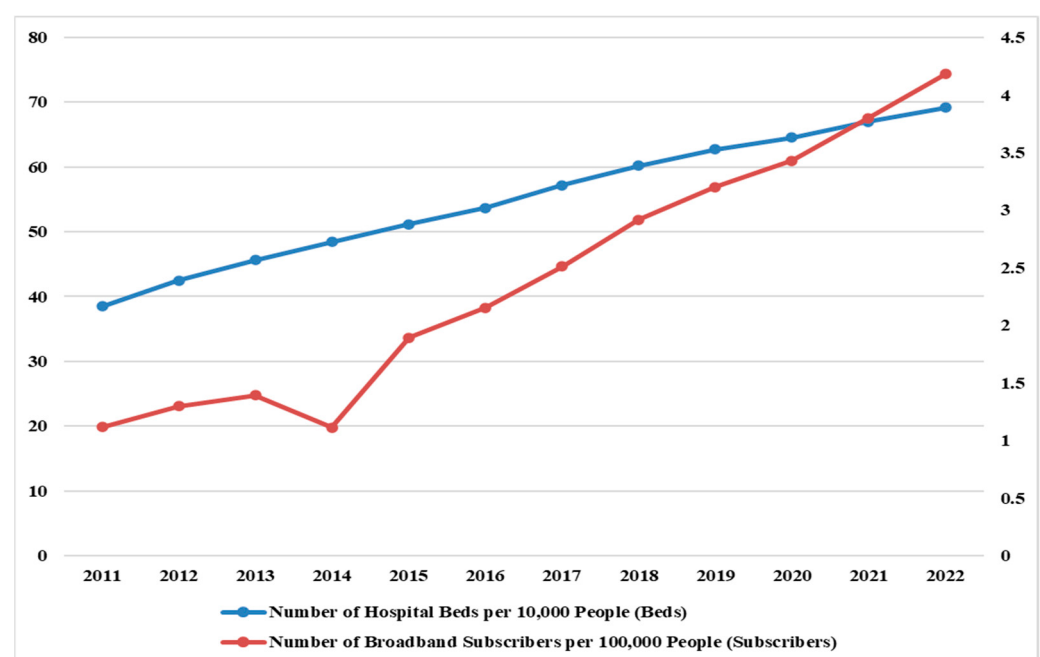


Figure 7. Development trends of Number of Hospital Beds per 10,000 People and Number of Broadband Subscribers per 100,000 People from 2011 to 2022.

The variable Number of Hospital Beds per 10,000 People, which reflects improvements in medical infrastructure, exhibits a consistently significant positive effect on agricultural economic efficiency across all models. This suggests that enhanced healthcare services under the new urbanization strategy have effectively improved rural labor health and stability, thereby supporting higher and more sustainable agricultural productivity.

The variable “Number of Broadband Subscribers per 10,000 People” is used as a proxy for improvements in informatization brought about by new urbanization. The regression results indicate that this variable has a significantly positive impact on agricultural economic efficiency in the 75th percentile quantile regression model, while the effects are not statistically significant in the 25th and 50th percentile models. In addition, both Tobit models—with TE and PTE as dependent variables—also show a significantly positive association with this variable. These findings suggest that broadband-based information infrastructure exerts a positive influence on agricultural economic efficiency, especially in regions with higher efficiency levels. In line with the analysis in Section 4.1, which identifies pure technical efficiency as the primary driver of agricultural efficiency gains, it can be inferred that informatization improvements under new urbanization not only enhance com-

munication capabilities but also facilitate the digitalization, automation, and e-commerce transformation of agriculture, thus contributing to broader gains in production efficiency.

Based on these results, Hypothesis 5 of this study is confirmed, suggesting that the improvements in medical facilities and informatization levels associated with urbanization significantly aid agricultural economic development.

Reviewing the five hypotheses proposed in this study, Hypotheses 2, 3, and 4 were rejected, indicating that aspects such as population dynamics, transportation logistics, and industrial upgrades do not positively influence China's agricultural economy and may even have a negative impact. Only Hypothesis 5 was confirmed, demonstrating significant positive effects from medical and informatization advancements. Considering these results collectively, Hypothesis 1 is also rejected, indicating that the overall process of urbanization does not significantly enhance agricultural economic efficiency.

In this study, Per Capita Agricultural Fiscal Expenditure is introduced as a control variable to reflect the fiscal support provided to agriculture under China's Rural Revitalization Strategy. This variable is not directly related to the process of new-type urbanization but rather represents the intensity of agricultural policy interventions during the study period. The regression results consistently indicate a statistically significant positive effect of this variable across both Tobit models and quantile regression models at various percentiles, suggesting that fiscal expenditure has played a stable and positive role in enhancing agricultural economic efficiency.

Combined with the SBM global efficiency analysis presented in Section 4.1 and considering the centralized governance structure of China's policy implementation, we infer that the observed improvement in agricultural economic efficiency over time is primarily driven by direct agricultural support policies, rather than by positive spillovers from new-type urbanization. On the contrary, the empirical results indicate that several urbanization-related factors—such as population urbanization and improvements in transportation infrastructure—have had negative effects on agricultural economic efficiency. Therefore, this study argues that the rural revitalization strategy has offset the adverse impacts of rapid urbanization on agriculture and has been a key driver in sustaining the improvement in agricultural productivity.

5. Conclusions

This study on the correlation between urbanization and agricultural economics in China has led to the following conclusions:

Overall, during the study period, the trend in agricultural economic production efficiency in China has been improving annually. The main driving forces are policies aimed at rural development and the industrial structural upgrade of agricultural production itself, which did not benefit from the concurrent urbanization processes in China.

China's population urbanization, both in terms of quantity and quality, has had a negative impact on agricultural economic efficiency. The changes in industrial structure brought about by urbanization have not effectively absorbed the surplus rural labor force and may even have drawn away more highly qualified talents, producing negative effects. The impact of agricultural corporatization is also not yet evident.

The enhancement of transportation logistics in China has negatively impacted agricultural economic efficiency. This may be attributed to the rapid urbanization that has increased the volume of logistics and freight, utilizing suburban land that could have been available for agriculture. The incomplete corporatization of agriculture has not sufficiently absorbed the resultant costs, indicating that urbanization has yet to yield beneficial effects on the agricultural economy.

Improvements in medical facilities have had a significantly positive impact on agricultural economic efficiency. Therefore, from a long-term perspective, future efforts should more actively improve the medical and eldercare welfare of rural residents. Information technology construction has significantly improved agricultural economic efficiency, likely primarily reflecting its impact on the construction of smart agriculture.

Considering all analysis results, the current rural revitalization strategy effectively mitigates the adverse effects of rapid urbanization, suggesting that simultaneous advancement of both sets of policies is necessary to avoid making rural areas the cost of urbanization. This study recommends that urbanization should be advanced with special attention to coordinated development with agricultural economics, focusing on how to help rural areas absorb surplus labor, enhance the quality of agricultural talent, and assist in upgrading agricultural industries to eliminate the urban–rural gap and achieve common development goals.

This study employed Tobit and quantile regression models to empirically analyze the factors influencing agricultural economic efficiency in the context of rapid urbanization in China from 2011 to 2022. Based on DEA efficiency scores (TE and PTE), it systematically evaluated how multiple indicators of urbanization—including population urbanization, fixed asset investment, education, transportation, healthcare, and informatization—affect agricultural efficiency. These factors were further compared with the policy support variables from the rural revitalization strategy implemented in parallel.

Despite the methodological rigor and empirical insights, several limitations should be acknowledged.

First, data limitations restrict the inclusion of certain relevant variables, such as agricultural technology diffusion, local policy enforcement intensity, and labor mobility patterns. These unobserved factors may affect the interpretation of the underlying mechanisms. Second, the DEA-based efficiency scores (TE, PTE), while reasonable, remain constrained by the SBM model structure. Future work may incorporate alternative methods, such as stochastic frontier analysis (SFA) or Bootstrap-DEA, to enhance robustness.

Third, although the regression results across models are largely consistent, key variables like the proportion of urban population and higher education attainment display significant heterogeneity across quantiles, indicating differential impacts depending on the region's efficiency level. Exploring such heterogeneity in greater depth presents a promising direction for future research.

Finally, given China's unique institutional structure, centralized fiscal governance, and coordinated rural–urban policy design, the generalizability of our findings to other national contexts requires caution and contextual adaptation.

Nevertheless, this study offers several notable contributions:

Methodological contribution: By incorporating DEA efficiency scores as dependent variables in Tobit and quantile regression models, we provide a robust framework to analyze asymmetric and region-specific drivers of agricultural efficiency.

Empirical insights: The results suggest that key urbanization components (e.g., education and transportation infrastructure) have not significantly improved agricultural efficiency, and in some cases have had negative structural impacts. In contrast, improvements in digital and medical infrastructure, along with fiscal support from the rural revitalization strategy, were positively associated with efficiency gains. These insights offer valuable guidance for policymakers aiming to refine integrated urban–rural development strategies.

Practical applicability: The analytical framework developed here may serve as a methodological reference for evaluating urbanization–agriculture interactions in other emerging economies facing similar transitions.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su17135908/su17135908/s1>, Table S1: Table of Input Industrial Variables for the DEA Model of China's Agricultural Economy, 2011–2022. Table S2: Global Non-oriented SBM Model Results for China's Agricultural Economy, 2011–2022. Table S3: Tobit Model Independent Variables Value Table.

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