agriculture

Article

An Empirical Investigation of the "Mezzogiorno Trap" in China's Agricultural Economy: Insights from Data Envelopment Analysis (2015–2021)

Xiaotuan Li [1], Panfei Yang [2] and Yuntao Zou [3,4,*]

[1] School of Politics and Law, Northeast Normal University, Changchun 130024, China; lixt636@nenu.edu.cn
[2] China Electronic Product Reliability and Environmental Testing Research Institute, Guangzhou 510610, China; yangpanfei@ceprei.com
[3] School of Computer of Science and Technology, Huazhong University of Science and Technology, Wuhan 430074, China
[4] School of Energy and Power Engineering, Huazhong University of Science and Technology, Wuhan 430074, China
* Correspondence: zouyuntao@hust.edu.cn

Abstract: Reducing regional inequality is one of the seventeen Sustainable Development Goals (SDGs) established by the United Nations. However, a persistent regional disparity known as the "Mezzogiorno Trap" presents a significant challenge. The underdeveloped regions that fall into the "Mezzogiorno Trap", even though they can narrow the gap with other regions through substantial support, see the disparity widen again when the level of assistance starts to decline. This paper proposes a methodology for identifying the "Mezzogiorno Trap". By employing this approach and combining panel data on Chinese agriculture from 2015 to 2021, it is discovered that despite the overall development of the Chinese agricultural economy during this period, the "Mezzogiorno Trap" still exists. The paper analyzes the reasons behind the "Mezzogiorno Trap" in the Chinese agricultural economy and presents constructive recommendations based on the research findings. The research process demonstrates that this methodology is better suited for studying regional disparities in specific economic sectors, and the obtained results are more stable and reliable.

Keywords: regional disparity; productivity disparities; agriculture; economy; sustainability; DEA; meta-frontier model

Citation: Li, X.; Yang, P.; Zou, Y. An Empirical Investigation of the "Mezzogiorno Trap" in China's Agricultural Economy: Insights from Data Envelopment Analysis (2015–2021). *Agriculture* **2023**, *13*, 1806. https://doi.org/10.3390/agriculture13091806

Academic Editors: Roberto Henke and Filiberto Altobelli

Received: 14 August 2023
Revised: 7 September 2023
Accepted: 7 September 2023
Published: 13 September 2023

1. Introduction

1.1. The "Mezzogiorno Trap" in Economic Development

"Mezzogiorno" refers to regions in the south of Italy and Sicily, which are often perceived as economically less developed than the cities and regions in the north of the country. This disparity between lagging and developed regions reflects, to some extent, Italy's unbalanced regional development. Since the end of World War II, the economic and social issues in these areas have posed significant challenges to Italy's economic progress. As early as 1970, Watson described the enormous disparity between the north and the south as, "Italy is, in effect, two nations" [1]. Even today, research by Daniele still indicates a productivity gap of up to 30% between southern Italy and the central and northern regions [2]. Additionally, a significant body of research demonstrates that such disparities persist, and they are indeed comprehensive [3–5].

Therefore, the term "Mezzogiorno Trap" is often used by scholars to describe the discrepancy and imbalance in regional economic development. However, its meaning extends beyond mere economic differences between regions. Over the decades, the Italian government has directed substantial aid towards the Mezzogiorno region. When this aid diminishes or disappears, the regional economy experiences significant setbacks, forming a sort of "trap". Research conducted by Iuzzolino et al. also validates this phenomenon.

In the 20 years following World War II, under the impetus of productivity enhancement and structural changes in the south, Italy witnessed the first substantial and sustained convergence between the north and the south. However, this trend abruptly halted in the mid-1970s, resulting in a renewed divergence [6]. Terrasi used the Theil Index to analyze the regional convergence of per capita GDP in Italy from 1953 to 1993 and found that the economic differences between regions in Italy were minimized only during the period from 1960 to 1975 [7]. The characteristics of the "trap" were quite apparent. Research by Torrisi et al. showed that between 1996 and 2008, the transfer payments received by southern Italy from the European Union accounted for 70% to 87% of Italy's total transfer payments. The funds obtained by the south were equivalent to around 11% of total investment and around 40% of public investment, considerably higher than in the central and northern regions [8]. However, in 2006 and 2007, the average income of residents in the richest region (Valle d'Aosta) was 2.6 times that of residents in the poorest region, indicating a significant disparity.

Hence, a succinct definition of the "Mezzogiorno Trap" can be posited: it is a distinct phenomenon of regional economic disparity characterized by the extensive governmental support enjoyed by lagging regions. The peculiarity lies in the fact that once these regions are devoid of such support, the disparities re-emerge and widen.

Economically, the "Mezzogiorno Trap" implies that the region's economic development heavily relies on external aid rather than internal economic activities. This may stem from the region's underdeveloped infrastructure, insufficient industrial development, and lower-quality human resources, which result in a weak economic development capability. Salvati and others conducted an exploratory analysis on 133 indicators across 7 thematic areas (population/housing, labor market, economic structure, quality of life, agriculture/rural development, landscape/water, environmental/soil resources), with results suggesting that latitude, altitude, and urban gradient dictate the complex spatial pattern of socio-economic and environmental variables in Italy [3]. Research by Daniele indicates a significant positive correlation between relative poverty levels and students' mathematics scores [2].

Socially, the "Mezzogiorno Trap" may reflect issues of regional social injustice. For instance, social resources such as education and healthcare might be unevenly distributed across regions, leading to a significantly lower quality of life for residents in certain areas. This social injustice can impact social mobility, thereby further exacerbating economic inequality [4]. In their study of the dynamics of poverty in Italy, Giarda and colleagues conducted a comparative analysis with the UK and Spain. Utilizing econometric methods, they found that the persistence of poverty in Italy exceeds that in the UK and Spain. Research by Bruzzi and others on the performance of healthcare systems across different Italian regions found that despite considerable support, healthcare performance in most southern regions remains poor [9].

From a policy perspective, the "Mezzogiorno Trap" might reflect the shortsightedness and errors of policy makers in their development strategies. For example, if policy makers overly rely on external aid to stimulate regional economic development without adequately considering how to enhance the region's self-sufficiency, issues could arise once external aid decreases. Research by Fazio et al. indicates that during the seven-year implementation of new strategic policy interventions from 1997 to 2003, regional economic disparities remained unchanged [10]. This demonstrates that inappropriate policies cannot effectively alleviate the "Mezzogiorno Trap". In their investigation of disparities among European Union (EU) countries, Geppert et al. discovered that European integration policies facilitated the catch-up process of lagging countries. However, concurrently, the force of economic activity agglomeration often expanded the internal gaps among EU member states [11]. This highlights the significant challenges inherent in policy formulation. In their study examining regional disparities in China before and after the abolition of agricultural tax, Ruan et al. [12] found that improper policy selection can lead to a dramatic widening of regional gaps once support is reduced. Additionally, in their investigation of economic disparities among the 28 European Union countries, López-Villuendas et al. [12,13] observed that since the implementation of the NUTS (Nomenclature of Territorial Units for Statistics) classification, economic disparities have been concentrating at the national level within regions categorized under NUTS2. Simultaneously, in areas delineated by the more granular NUTS3 classification, disparities have been progressively widening.

1.2. Examples of "Mezzogiorno Trap" in Other Areas

The concept of the "Mezzogiorno Trap" is indeed prominent in the southern regions of Italy, but in fact, similar economic disparities and developmental challenges exist in numerous other regions and countries. Here are some examples:

The United States' "Rust Belt": This region was once the industrial hub of the US. However, due to globalization and industrial transformation, many industries in these areas have declined. Lacking sufficient investment and support, these areas may also face analogous developmental predicaments. Research conducted by Harrison et al. found that the community housing vacancy rate in the Rust Belt was significantly higher than in the Sun Belt from 2012 to 2019, persistently remaining elevated [14]. Hegerty demonstrated that Detroit, the most representative city of the "Rust Belt", has fallen into uniformly poor conditions with a certain degree of contagion, in stark contrast to the cities in the southern and western "Sunbelt" [15].

Eastern Germany: Since German reunification, an economic disparity has existed between the East and West. At the time of reunification, the economic development level of the East (former East Germany) was far behind that of the West (former West Germany). Although the West provided substantial fiscal aid to the East, undertook massive infrastructure construction, and implemented various policies to stimulate economic growth, the economic development of the East remains slow. Herrschel found significant regional differences not only between the East and West but also within different states in the East [16]. Berentsen et al. believe that progress has been slow in eliminating regional inequalities in Germany, and these inequalities continue to evolve. However, the research also points out that according to EU standards, the difference between East and West Germany is not large. The East may perform better in certain aspects (such as education and health) than in its economic performance [17]. Dörr et al. still found an increased incidence and mortality rate related to heart failure in East Germany 30 years after reunification, much higher than in West Germany [18].

Rural areas in India: In India, there is a significant economic disparity between rural and urban areas. The economic development of rural areas primarily depends on agriculture and handicrafts, industries often less developed than the modern industries of cities. Therefore, these areas may also face similar developmental dilemmas. Birthal focused on agriculture to study the economic growth of various Indian states, finding absolute differences that require significant improvements in infrastructure and human resources [19]. Jose et al. demonstrated that there is a considerable disparity in socio-economic development between different states in India, evident in basic facilities such as sanitation, banking, road connectivity, clean drinking water, post offices, and telephony, and this disparity continues to increase [20].

1.3. How to Tell If the "Mezzogiorno Trap" Exists

In summary, to determine whether a region has fallen into the "Mezzogiorno Trap", several aspects can be considered:

1. Economic development gap: if a region lags significantly behind other regions or countries in its level of economic development, it may be at risk of the "Mezzogiorno Trap".
2. Dependence on external aid or investment: if a region's economic development heavily relies on external aid or investment, rather than on internal economic activities, then it might be susceptible to the "Mezzogiorno Trap".

3. Internal economic activity level: if a region's internal economic activities, such as industrial production and commercial activities, appear inactive or small-scale compared to the magnitude of external aid or investment, then it could potentially face the risk of the "Mezzogiorno Trap".
4. Changes in external aid or investment: if there is a decrease or disappearance in external aid or investment in a region, and this leads to a significant downturn in the local economy, the region may have already fallen into the "Mezzogiorno Trap".
5. Continuity of policy support: if a region's economic development largely depends on policy support, which may change for various reasons (e.g., regime changes, shifts in economic policy), then it too could be at risk of the "Mezzogiorno Trap".

1.4. Objectives and Contributions of This Paper

China exhibits a typical dualistic economic structure between urban and rural areas. There are significant disparities between cities and villages in terms of economic output, per capita income, social welfare, and other aspects. Despite China's ascent to becoming the world's second-largest economy, driven primarily by rapid urban economic development, agriculture still accounts for a substantial proportion of the population and the economy. Therefore, this paper focuses on the agricultural economy in China to investigate the potential existence of the "Mezzogiorno Trap" and aims to achieve the following objectives and contributions:

1. By studying the research process and findings, a more reasonable approach to assessing the "Mezzogiorno Trap" is summarized, which can be extended to further investigate regional disparities in a wider range of areas and regions.
2. By employing quantitative methods derived from operations research, management science, and economics, an assessment is conducted to determine the presence of the "Mezzogiorno Trap" in China's agricultural economy.
3. Constructive policy proposals and adjustments are put forward to address the "Mezzogiorno Trap". By studying the "Mezzogiorno Trap", the achievements of regional economic disparity research from various countries worldwide can be introduced into the relevant policy research for rural development in China.

2. Literature Review

2.1. The Possible Existence of the "Mezzogiorno Trap" in China

In China, the primary drivers of economic development are located in the eastern and coastal regions, possessing robust industrial bases and international trade networks, whereas the western economy lags significantly. In January 2000, the State Council established the Western Development Leadership Group. On 8 December 2006, the State Council Executive Meeting reviewed and in principle approved the "Eleventh Five-Year Plan for Western Development" [21], aiming to "use the residual economic development capacity of the eastern coastal regions to enhance the economic and social development level of the western regions, and consolidate national defense". A series of supportive policies known as the "Western Development" were subsequently introduced.

Since the implementation of the Western Development policy in 1999, the economic growth rate of the western regions has remained relatively high, with some provinces like Sichuan and Chongqing experiencing particularly rapid economic growth. However, China's eastern coastal regions have very favorable conditions, holding significant advantages over the western regions in terms of geographical location, climate, economy, science and technology, education, and talent. The pace of their development has not slowed, and the economic gap persists, even widening in some instances. This advantage is especially prominent in high-end industries like technology, finance, and services.

When Chen et al. studied the sample data of 815 Chinese listed companies from 1998 to 2004, they found that although China has shifted its development focus from the eastern coast to the inland regions, the difficulty for the government in guiding the economy is increasing. The influence of market mechanisms on the economy far surpasses that of the government, suggesting that reforms need to be further deepened for supportive policies to take effect [22]. Fan et al. also found, through research, that despite the Chinese government's efforts, the gap between the East and West continues to widen [23]. When Zhang et al. studied the factors influencing innovation in China's high-tech industries, they discovered that the central and western regions lag far behind the eastern region in terms of the decisive factor of innovation investment, with considerable gaps in other factors as well. The ultimate result is that the eastern region's technological innovation capability far exceeds that of the West [24].

In summary, there is a possibility that the "Mezzogiorno Trap" indeed exists in the Chinese economy, especially in the western regions. Previous research indicates that despite receiving favorable policies and substantial financial support, the disparities in industrial structure, education, population quality, geographical location, financial environment, and level of marketization in the western regions are challenging to bridge rapidly through simple financial support and preferential policies. Earlier studies demonstrate that in many aspects, the gap between the western regions and the developed areas is still widening.

2.2. A Review of Relevant Studies on China's Agricultural Support Policies and Regional Differences

Since 2000, the Chinese government has implemented a series of agricultural support policies aimed at increasing agricultural productivity, raising farmers' incomes, improving rural infrastructure, and promoting urban–rural economic integration. Below are some significant policy measures:

1. Agricultural subsidy policy: since 2004, the Chinese government has implemented direct agricultural subsidy policies, including grain planting subsidies and agricultural machinery purchase subsidies, aiming to enhance agricultural productivity and safeguard farmers' interests.
2. Abolition of the agricultural tax: the agricultural tax was a levy on farmers' income from planting grains and other agricultural products. In 2006, China completely abolished this tax, significantly reducing farmers' burden, increasing their income, and stimulating the zeal for agricultural production [25].
3. Agricultural insurance system: to mitigate farmers' losses due to natural disasters and other factors, the Chinese government introduced an agricultural insurance system, subsidizing part of the insurance costs for insured farmers.
4. New rural cooperative medical system: this policy, aimed at improving rural medical conditions, provides basic medical security for farmers through government subsidies and social fundraising [26].
5. Rural land system reform: the government relaxed restrictions on the transfer of rural land use rights, allowing farmers to gain income through leasing or transferring land, creating conditions for the modernization and scaling of agriculture.
6. Agricultural technological advancement policy: the government increased support for agricultural scientific research and promotion, to enhance agricultural productivity and yield, including the promotion of quality seeds and agricultural mechanization.
7. Rural infrastructure construction: this involves building rural roads, water supplies, and power supplies to improve rural living conditions and the production environment.
8. Rural poverty alleviation work: this includes offering low-interest loans, vocational training, rural labor transfer, and other poverty alleviation methods to decrease rural poverty.

By 2018, the Chinese government launched a strategy to comprehensively improve the economic, social, and environmental conditions of rural areas. Its core objective is to achieve balanced development between rural and urban areas, enhance the quality of life and work in rural areas, promote agricultural modernization, and strengthen the economic capacity of rural areas. The rural revitalization strategy covers all aspects of rural areas, including industry, talent, culture, ecology, and organization [27].

These intense agricultural support policies have significantly facilitated rapid growth in China's agriculture. However, they have also sparked concern among some scholars and experts. Research by Chan and colleagues indicated that, while rural economies were growing rapidly, disparities among rural regions across different provinces were also widening. The efficiency discrepancy between collective enterprises in the rural areas of the eastern and western provinces was a primary contributor to this divergence [28].

Li and colleagues, through studying the differences reflected by the agriculture, manufacturing, and service sectors from 1995 to 2004, found that the loss of agricultural employment in the central and western regions was not compensated for by growth in other sectors. The speed variance in the transformation from agriculture to secondary and tertiary industries widened the gap between the coastal regions and the rest of the country [29]. Chen and associates analyzed the spatio-temporal changes in arable land use intensity at national and provincial levels and found that developed regions had a lower labor intensity and a higher capital intensity. Less developed regions had a higher labor intensity but a lower capital intensity [30].

Research by Liu and colleagues demonstrated that the overall quality of agricultural development in China was steadily improving, but structural problems were evident. From the perspective of regional differences, a primarily "high in the East, low in the West" pattern was observed, which was mainly caused by interregional differences and showed a gradually declining trend during the selected period [31].

2.3. Possible Problems with the Study of Regional Disparities in the Agricultural Economy

Previous studies have indeed provided a wealth of insight and assistance. However, we believe there are areas for further refinement. In many studies, the regional differences in the overall economy can interfere with the regional differences in a specific field. For example, from an overall perspective, there is a significant difference between eastern and western China, involving multiple aspects such as the economy, society, and policy. The differences are especially profound in high-tech manufacturing and modern financial services. However, agriculture has a long history in all regions of China, and the level of the agricultural economy in a western province may not necessarily be inferior to that of eastern provinces. When many studies target regional differences in the overall economy, they may categorize this western province as less developed due to its geographical location, which could cause bias in the part of the study concerning the agricultural economy.

Moreover, the potential "Mezzogiorno Trap" in regional differences has not received adequate attention. As previously mentioned, the "Mezzogiorno Trap" typically describes a region whose economic development heavily relies on external aid or investment, rather than internal economic activities. When external assistance or investment declines or disappears, the economy of the region may experience a significant downturn. Therefore, examining whether a region has fallen into the "Mezzogiorno Trap" is meaningful for policy adjustment and the self-construction of underdeveloped areas. However, the issue does not receive much attention in studies on China's regional differences. On one hand, the "Mezzogiorno Trap" in regional economic differences may be obscured by inherent disparities between regions. On the other hand, in specific fields such as agriculture, the process of identifying the "Mezzogiorno Trap" can easily be disrupted.

In conclusion, we have decided to prioritize one crucial step in investigating the existence of the "Mezzogiorno Trap" in the Chinese agricultural economy: utilizing quantitative analysis to identify the regions with genuinely low agricultural economic efficiency. We believe that this is an important step for ensuring the credibility and validity of our research findings and will also serve as a significant foundation for future studies on regional economic disparities in specific sectors.

3. Materials and Methods

3.1. Data Sources

This paper uses relevant data from 31 provinces and cities in China from 2015 to 2021 as the research basis. All original data come from the "China Statistical Yearbook" published by the National Bureau of Statistics of China, as well as the "China Rural

Statistical Yearbook" jointly published by the National Bureau of Statistics and the Ministry of Agriculture and Rural Affairs. The period from 2015 to 2021 was chosen for two main reasons. First, the statistical methods used during this period are relatively consistent, and the data are relatively complete. Earlier data contain significant differences due to changes in statistical methods. Second, this period straddles the major "Rural Revitalization Strategy" initiative, enabling effective observation of changes and trends caused by policy.

Data Sources:

- China Statistical Yearbook, 2016–2022 [32]
- China Rural Statistical Yearbook, 2016–2022 [33]

Note: Each annual edition of the China Statistical Yearbook and China Rural Statistical Yearbook publishes statistical data from the preceding year. For instance, the 2016 China Statistical Yearbook provides statistics from the year 2015.

3.2. Research Process

In typical research on regional disparities, subjects are usually categorized into different groups for comparative study. In the context of China, the vast majority of studies directly classify subjects according to geographical variation. This approach is driven by the focus on the disparities between the eastern and western parts of China, where the substantial economic difference is axiomatic from a macroeconomic perspective [23,28,34]. Some research divides Chinese provinces and cities into eastern, central, and western regions, while others compare coastal regions with inland areas in China [29,35].

Our research objective is to determine whether the "Mezzogiorno Trap" exists in China's agricultural economy, considering the possibility that the agricultural economic level of a western province or city might surpass that of an eastern one. Consequently, we argue against the mere reliance on traditional geographical grouping. Instead, we advocate for a quantitative analysis approach to identify regions that lag behind in terms of agricultural economic development for comparison with more advanced regions.

In accordance with the characteristics of the "Mezzogiorno Trap", a simple regional disparity is insufficient for its identification. It is crucial to observe the changes in disparities over a specific period, and to combine this observation with changes in associated aid and investments during the same timeframe, to derive a comprehensive conclusion.

In summary, our research process is as follows, as illustrated in Figure 1.

1. Data collection.
    - Grouping using the super-efficient SBM model.
    - Constructing a meta-frontier SBM model of the agricultural economy in 31 provinces and cities, 2015–2021, calculating intra-group gaps.
    - Calculating financial support for agriculture in China during 2015–2021.
2. Determine if the "Mezzogiorno Trap" exists.
    - Calculating financial support for China's agricultural subgroups during 2015–2021.
    - Constructing an SBM Model of the Agricultural Economy in 31 Provinces and Cities, 2015–2021 We compute the intensity of financial support for agricultural groups in China from 2015 to 2021.
    - Constructing the SBM-Malmquist Model of Agricultural Economy in 31 Provinces and Cities, 2015–2021.
3. Analysis of the factors influencing the "Mezzogiorno Trap".
4. Conclusions and recommendations.

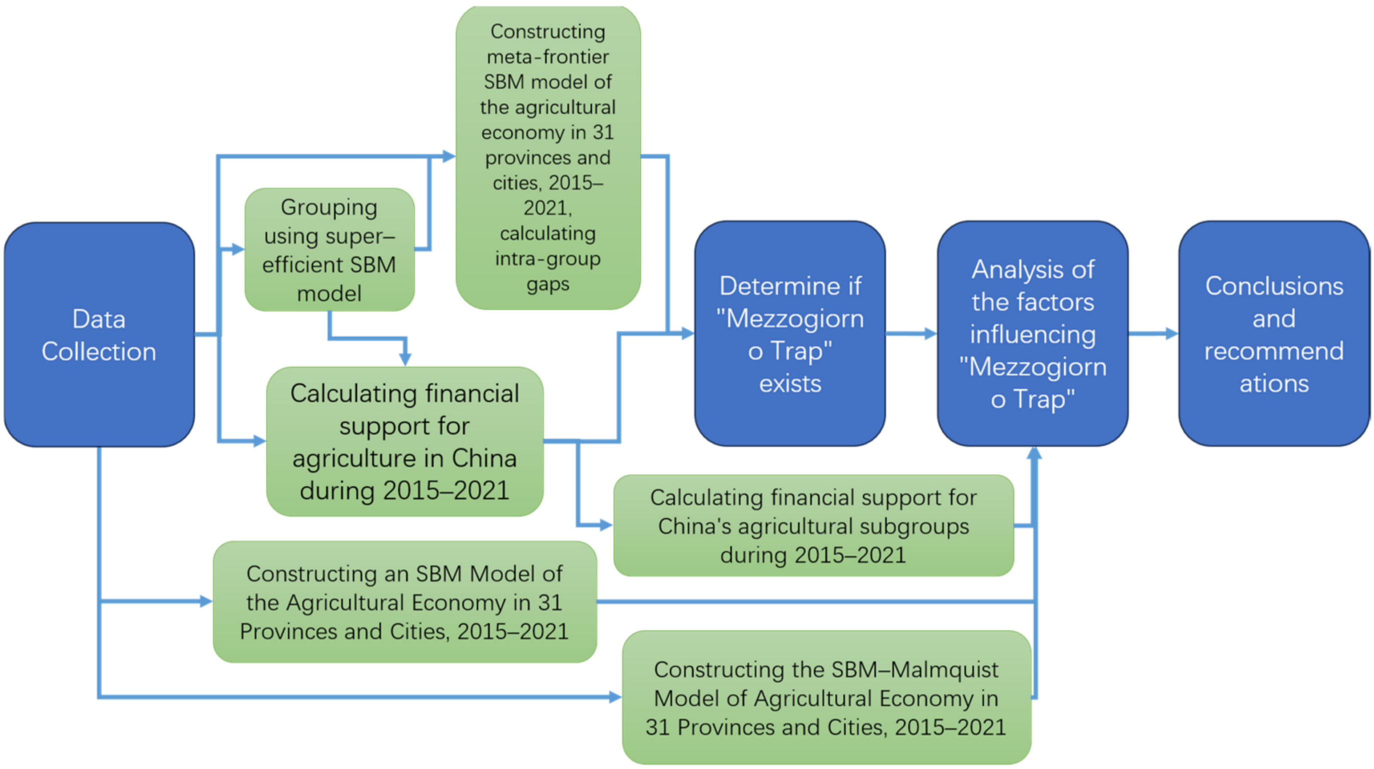

Figure 1. Flowchart of the research process for the "Mezzogiorno Trap" in Chinese agricultural economics.

3.3. Research Methods

The research methodology of this paper is based on efficiency assessment. There is a large heterogeneity in different regions of China, which is very different in terms of the employed population, total agricultural economy, cultivated land area, agricultural production methods, and so on. Efficiency assessments can better eliminate the heterogeneity. Higher production efficiency means more output with less input, and therefore more advanced technology, more efficient management, and less pollution and better sustainability. Efficiency assessment is widely used in the evaluation of economic levels. As early as 1952, Schmookler et al. used efficiency to evaluate the U.S. economy [36]. Bukarica et al. used efficiency evaluation to study energy policy and the level of sustainable development [37]. Bravo-Ureta et al. used efficiency evaluation to study agricultural and resource economics [38]. Paul et al. also used efficiency evaluation in their study of U.S. farm and agricultural economies of scale [39].

The data envelopment analysis (DEA) method, commonly used in efficiency evaluation, is a technique for analyzing relative efficiency through input–output analysis, proposed by Charnes et al. in 1978 [40]. DEA views each evaluated unit as a decision-making unit (DMU), with all DMUs having identical input and output variables. It calculates the production efficiency frontier surface, also known as the envelopment structure, by examining these input and output variables, thereby evaluating the relative efficiency of each DMU. DMUs situated on the frontier surface are considered DEA-efficient, with a comprehensive technical efficiency score of 1. The efficiency scores of other DMUs are determined by their relative position to the frontier surface, specifically ranging between 0 and 1. As a non-parametric method for evaluating relative effectiveness, the advantage of DEA is that it does not require the pre-assignment of weights for input and output, and it can evaluate the relative efficiency of multiple DMUs with multiple inputs and outputs. Hence, it is widely used in operational research, management, econometrics, and other fields.

The basic DEA models include the CCR model (named after its authors A. Charnes, W.W. Cooper, E. Rhodes) [40] and the BCC model (named after its authors Banker, Charnes, and Cooper) [41]. However, as they only consider radial improvement and neglect the slack of input and output variables, their efficiency calculation is not accurate enough and their efficiency improvement suggestions are not scientifically sound. To address this, Tone et al. established the non-radial SBM (slacks-based measure) model based on variable slack measurements by incorporating all slack measurements into the objective function through a scaling method [42]. Compared to traditional DEA models, the SBM model is more reasonable and rigorous. Like traditional DEA models, it decomposes comprehensive technical efficiency into pure technical efficiency and scale efficiency, which is equally convenient when analyzing causes. Chang et al. applied the SBM-DEA model to study the economic and environmental efficiency of 27 global airlines in 2010 [43]. Lin et al. used the SBM-DEA model to study CO2 emissions and the sustainable economy [44].

The methodology of this paper is based on the SBM-DEA model. The equation for SBM can be presented as follows:

In the input-oriented slacks-based measure (SBM) model [45], the objective is to minimize slack variables or equivalently maximize efficiency, subject to constraints on inputs and outputs. To assess the relative efficiency of $DMU_o = (x_o, y_o)$, the following linear programming formulation can be solved. This process is repeated n times for $o = (1, \ldots, n)$.

[SBM-I-C] (Input-oriented SBM under constant returns-to-scale assumption). Formally, the input-oriented SBM model can be articulated as the following linear programming problem:

Objective Function:

$$\rho_I^* = min_{\lambda, s^-, s^+} 1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i^-}{x_{io}}$$

Subject to:

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

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

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

ρ_I^* is called SBM-input-efficiency.

The SBM model has certain limitations under specific conditions. For example, in this paper, we take the 31 provinces of China as DMUs to analyze the relative efficiency of agricultural economics, firstly ranking and grouping them based on their overall technical efficiency. If we directly adopt the SBM model, there might be instances where multiple provinces have an efficiency score of 1, making it impossible to group them. Therefore, when ranking and grouping, we use the super efficiency SBM model.

The super efficiency model was proposed by Andersen and Petersen in 1993 with the aim of solving the issue in the DEA model when multiple DMUs are on the efficiency frontier, hence further comparison cannot be made [46]. When evaluating a particular DMU with the super efficiency model, it is excluded from the reference set, meaning it is not allowed to participate in calculating its own efficiency score. If this DMU still lies on the new efficiency frontier (i.e., the super efficiency score is greater than 1), then it can be deemed not only more efficient than the original set of DMUs but also higher in efficiency than other DMUs that are evaluated as efficient. The construction of the super efficiency model can thus solve the issue of ranking and grouping.

With the 31 provinces of China ranked and grouped based on the super-efficiency SBM model, subsequent research can be conducted. As the super-efficiency model might exhibit unboundedness, i.e., the super-efficiency scores for some DMUs might be infinite, we only use the super-efficiency SBM model for ranking and grouping. The subsequent research will be conducted by constructing the meta-frontier SBM model.

The meta-frontier model was first proposed by O'Donnell et al. to study the efficiency differences among grouped DMUs [47]. The technical principle involves, firstly, determining an efficiency frontier within each DMU group, termed the group frontier; thus, each DMU obtains an internal group efficiency score. Secondly, an efficiency frontier termed the meta-frontier is established by considering all DMUs together, from which each DMU obtains an efficiency score relative to the meta-frontier. The ratio of these two efficiency scores is referred to as the technology gap ratio (TGR).

Characteristic of the meta-frontier model is its ability to eliminate the heterogeneity of DMUs, commonly employed for comparative studies among regions and, with adjustments, can be used for comparisons between industries, policy comparisons, etc. O'Donnell et al. used the meta-frontier model to study enterprise efficiency, and empirical application was made using cross-national agricultural sector data [47]. Li et al. combined the meta-frontier model with the Malmquist index model and the Tobit regression model for regional comparative studies of China's high-tech industries [48]. Yu et al. employed the meta-frontier SBM model to study the energy efficiency of Eastern, Central, Western, Northeastern China, and various provinces from 2006 to 2016 [49]. Chen et al. also used the meta-frontier model when researching the agricultural economy at the county level in China [22].

In the meta-frontier analysis, this study employs efficiency scores under the CRS assumption, given that the efficiency score under CRS represents technical efficiency (TE). This score is a product of pure technical efficiency (PTE, which is also the efficiency score under the VRS assumption) and scale efficiency (SE). Consequently, TE can be considered as an overall efficiency that integrates both PTE and SE. Our research aim is to assess the overall efficiency of DMUs in all aspects (both technical and scale), making TE more pertinent. In contrast, the efficiency score obtained under the VRS assumption signifies pure technical efficiency, which holds relatively lesser significance when evaluating the comprehensive level of DMUs.

This is not to suggest that our study entirely overlooks the efficiency scores under the VRS assumption. We have additionally formulated SBM models under both CRS and VRS assumptions. Discussions encompassing the pure technical efficiency scores and scale efficiency scores under the VRS assumption have been conducted, which greatly aid in the analysis of the underlying reasons for the "Mezzogiorno Trap".

We also constructed a Malmquist SBM model for the agricultural economic efficiency of 31 provinces and cities in China from 2015 to 2021 to examine the development trend of China's agricultural economic efficiency during this period. This is because both the SBM model and the super-efficiency SBM model calculate the relative efficiency of DMUs within a specific period, and efficiency scores from different periods cannot be directly compared. To compare efficiencies across different periods, the Malmquist index model is used. The Malmquist productivity index was first proposed by Swedish economist Sten Malmquist in 1953 [50], and was later introduced into data envelopment analysis (DEA) by Färe et al. in 1984 to measure the change in production efficiency of DMUs over different time periods [51].

The basic construction of the Malmquist index is as follows: suppose that in two time periods, t and t + 1, each DMU has a corresponding production possibility set (PPS), which can be described by their input and output vectors. We can calculate the efficiency scores of DMUs in periods t and t + 1 based on the PPS of these two periods. The Malmquist productivity index is defined as the geometric mean of the ratio of the efficiency score in period t to the efficiency score in period t + 1. If EFF denotes the efficiency score, then the Malmquist index can be expressed as:

$$\mathrm{Tfpch} = \mathrm{Effch} \times \mathrm{Techch} = \frac{\mathrm{D}^{t+1}\left(\mathrm{X}^{t+1}, \mathrm{Y}^{t+1}\right)}{\mathrm{D}^{t}\left(\mathrm{X}^{t}, \mathrm{Y}^{t}\right)} \times \sqrt{\frac{\mathrm{D}^{t}\left(\mathrm{X}^{t+1}, \mathrm{Y}^{t+1}\right)}{\mathrm{D}^{t+1}\left(\mathrm{X}^{t+1}, \mathrm{Y}^{t+1}\right)} \times \frac{\mathrm{D}^{t}\left(\mathrm{X}^{t}, \mathrm{Y}^{t}\right)}{\mathrm{D}^{t+1}\left(\mathrm{X}^{t}, \mathrm{Y}^{t}\right)}}$$

If Tfpch (total factor productivity change) is greater than 1, then the efficiency score has improved. If a large proportion of provinces or cities exhibit this trend, it would suggest an overall improvement in the efficiency of China's agricultural economy. A Tfpch value of 1 indicates no change in efficiency, while a value less than 1 signifies a decline in efficiency. The purpose of constructing a Malmquist index model is to explore the potential relationship between the "Mezzogiorno Trap" phenomenon and the efficiency development trend in China's agricultural economy. This is aimed at studying the elusive nature of the "Mezzogiorno Trap": even if the overall economy is continuously progressing, a "Mezzogiorno Trap" may still exist and be less easily detected.

4. Results

4.1. Constructing a Super-Efficient SBM Model of the Agricultural Economy in 31 Provinces and Cities in 2017 and Grouping Them According to Rankings

To construct a DEA (data envelopment analysis) model, the first step is to select input and output variables. In this study, we chose the "Rural Population" across 31 provinces in China as the input variable representing labor. Although publicly available data from the Chinese government include the number of employed persons in rural areas, these figures are verified to only encompass rural enterprise employees who contribute to social insurance. A significant labor force in many rural areas of China does not participate in social insurance schemes [52]. Furthermore, agriculture is often a family-based endeavor involving both the elderly and children [53]. Hence, rural population size serves as a more accurate input variable for labor.

Utilizing rural population numbers as an input variable introduces certain uncontrollabilities. However, China presents a unique scenario. Firstly, China adopts a state-owned land system, which results in a notably weaker connection between farmers and their land compared to other nations. Additionally, the country enforces a household registration system, ensuring clear population registration and statistics. Over past decades, with the Chinese government's robust push for urbanization, the urban population swelled from 191 million in 1980 to 622 million in 2009. By 2011, urban residents constituted 51% of the total population, marking the first instance of surpassing the rural demographic [54]. Subsequent to the launch of the Rural Revitalization Strategy in 2018, a multitude of policies shifted in favor of rural development, causing certain regions to experience a phenomenon of "reverse urbanization" [55]. As such, China's rural population figures and proportions adjust significantly in response to government policy shifts. Therefore, employing rural population counts as an input variable is indeed salient for crafting rural policies.

For the material input variables, we have selected diesel consumption, pesticide consumption, and fertilizer consumption, which constitute the major consumables in Chinese agricultural production. These are not only used in crop cultivation but also in forestry and animal husbandry. The data sources also provide information on the consumption of seeds and plastic films; however, these represent a small proportion and have limited application scope. In consideration of the relationship between input variables and the number of decision making units (DMUs), this study opted for the most representative consumables to ensure the effectiveness of the DEA model.

We chose the total output value of agriculture, forestry, animal husbandry, and fishery as the output variable. Although data sources provide various specific outputs like crop yields, livestock, and aquatic products, these variables exhibit collinearity with the total output value. Moreover, provinces exhibit considerable heterogeneity in terms of specific types of agricultural products. Therefore, monetizing the end results of various types of agricultural production yields the total output value that is most representative.

It is noteworthy that some agricultural studies employ arable land area as an input variable. However, considering the latitude range of 31 provinces in China (3°30′ N to 53°33′ N), there are substantial climatic differences. In northern regions, crops mature once a year, while in the south, they can mature up to three times a year. Consequently, the same arable land area could yield significantly different levels of productivity. To eliminate this heterogeneity among the 31 provinces, arable land area was not utilized as an input variable.

The input and output variables used for assessing agricultural efficiency in the DEA model across China's 31 provinces are summarized in Table 1. For specific numerical values, please refer to Table S1 in the Supplementary Materials.

Table 1. Input and output variables for the DEA model of agricultural efficiency in China's 31 provinces.

	Variables	**Data Sources**
Input variables	Rural Population	China Statistical Yearbook
	Consumption of Chemical Fertilizers	China Rural Statistical Yearbook
	Consumption of Pesticides	China Rural Statistical Yearbook
	Consumption of Diesel Fuel	China Rural Statistical Yearbook
Output variables	Gross Output Value of Agriculture, Forestry, Animal Husbandry and Fishery	China Rural Statistical Yearbook

To rank and group the 31 provinces and cities in China, we chose the agricultural economic super-efficiency SBM model of 2017 as the basis. In 2017, it was the year before the "Rural Revitalization Strategy" was proposed. We believe that the regional differences in agricultural economy might be large at this time, and grouping at this time point could reflect the gap in agricultural economic levels more realistically. Subsequent calculations also confirmed our thinking: in all the 7-year meta-frontier SBM models, all the meta-frontier comprehensive technological efficiency scores for the 10 provinces and cities representing the relatively advanced Group 1 were 1. This indicates that these 10 provinces have always been at the highest level of agricultural economy. As for the provinces and cities that were grouped into the relatively backward Group 3, their meta-frontier comprehensive technological efficiency scores were almost at the bottom, with only one–two changes, which shows that our grouping method can represent the regional differences in China's agricultural efficiency.

The above variables were imported into the DEARUN software V3.1 edition to calculate the super-efficiency SBM model of agricultural economy for the 31 provinces and cities. According to the efficiency score ranking, the 31 provinces and cities were divided into three groups: Group 1 (rank 1–10), Group 2 (rank 11–20), and Group 3 (rank 21–31). The results are as follows in Table 2.

Additionally, it is worth noting that the choice to categorize the 31 provinces into three groups, rather than two or more than three, is guided by the following considerations: Segmenting the dataset into only two groups would lack a mid-range control group, thereby compromising the robustness of subsequent comparative analyses. On the other hand, dividing into more than three groups would result in each group containing fewer than 10 provinces. Given that the meta-frontier DEA efficiency analysis would then proceed with fewer than 10 DMUs per group and four input–output variables, this scarcity would negatively impact the validity of the DEA model.

Customary guidelines suggest that the number of DMUs should exceed thrice the sum of the input–output variables. In this study, utilizing the meta-frontier SBM model, there are a total of 31 DMUs and five input–output variables. When establishing the common frontier, the DMU count satisfactorily aligns with the general empirical suggestion. However, once segmented into three groups, each group comprises 10–11 DMUs, not meeting the thrice criterion relative to the input–output variable count. Such a shortfall could adversely influence the frontier formation for each group: a limited DMU number might result in more DMUs being adjudged as efficient, subsequently diminishing the discriminative capability among DMUs within a group.

Table 2. Ranking and grouping of agricultural economic efficiency in 31 Provinces in China.

DMU	Efficiency Score	Ranking	Group
Beijing	0.673728	14	2
Tianjin	0.570652	19	2
Hebei	0.443189	27	3
Shanxi	0.320583	31	3
Inner Mongolia	0.80136	11	2
Liaoning	0.915023	9	1
Jilin	0.443526	26	3
Heilongjiang	1.092438	3	1
Shanghai	0.487126	24	3
Jiangsu	1.029901	7	1
Zhejiang	0.606872	17	2
Anhui	0.438897	28	3
Fujian	1.064987	4	1
Jiangxi	0.50359	23	3
Shandong	0.725972	12	2
Henan	0.420875	29	3
Hubei	0.811924	10	1
Hunan	0.548386	20	2
Guangdong	0.522385	22	3
Guangxi	0.611202	16	2
Hainan	1.160764	2	1
Chongqing	0.577371	18	2
Sichuan	0.719591	13	2
Guizhou	1.573564	1	1
Yunnan	0.444038	25	3
Tibet	0.526058	21	3
Shaanxi	1.013779	8	1
Gansu	0.360777	30	3
Qinghai	1.042648	5	1
Ningxia	0.672134	15	2
Xinjiang	1.035293	6	1

Nonetheless, this paper consciously opts for a tripartite division rather than bifurcation for several reasons: Firstly, the negative repercussions predominantly transpire within each group, rendering it "equitable" across groups. Given that the research aim of our meta-frontier SBM model is to discern inter-group disparities, such adverse effects on between-group variations might be mitigated due to this inherent "equity". Secondly, an SBM model without group distinctions has also been formulated in this study to scrutinize variations between DMUs within each subset, serving to counterbalance potential detrimental effects. Moreover, sustaining the triad, inclusive of a median group for comparison, proves pivotal for inter-group comparative analysis. Lastly, while curtailing the number of input–output variables could ostensibly conform to general guidelines, it would profoundly compromise the model's precision, reliability, and robustness, deficits that are challenging to counteract.

The final distribution of the three groups is shown in Table 3.

Table 3. Grouping table of 31 provinces and cities in China.

Group 1	Group 2	Group 3
Liaoning	Beijing	Hebei
Heilongjiang	Tianjin	Shanxi
Jiangsu	Inner Mongolia	Jilin
Fujian	Zhejiang	Shanghai
Hubei	Shandong	Anhui
Hainan	Hunan	Jiangxi
Guizhou	Guangxi	Henan
Shaanxi	Chongqing	Guangdong
Qinghai	Sichuan	Yunnan
Xinjiang	Ningxia	Tibet
		Gansu

4.2. Constructing the Meta-Frontier SBM-DEA Efficiency Model for the Agricultural Economy of 31 Provinces and Cities in China from 2015 to 2021

In constructing the meta-frontier SBM-DEA (slack-based measure—data envelopment analysis) efficiency model for the agricultural economy of 31 provinces in China for the years 2015–2021, the input and output variables employed were identical to those detailed in Table 1. For specific numerical values, please refer to Table S1 in the Supplementary Materials. We incorporated the ranking and group data from Table 2 into the panel data of 31 provinces spanning from 2015 to 2021. The meta-frontier SBM models for each year were formulated using the DEARUN software. Subsequently, we computed the average TGR (technology gap ratio) values for DMUs (decision making units) within each group, which are organized and presented in Table 4.

Table 4. Average TGR values of meta-frontier SBM Model for Chinese agricultural economy efficiency from 2015 to 2021.

	Group 1	Group 2	Group 3
2015	1	0.839242	0.597488
2016	1	0.809165	0.572281
2017	1	0.700432	0.488344
2018	1	0.71545	0.505777
2019	1	0.640931	0.560976
2020	1	0.723399	0.577238
2021	1	0.637693	0.569133

4.3. Constructing the 2015–2021 SBM-Malmquist Index Model for Agricultural Economics across the 31 Provinces in China

When constructing the SBM-Malmquist index model with DEARUN software, the input and output variables selected are as shown in Table 1. The purpose of this analysis is to test the development trend of China's agricultural economic efficiency. The panel data input has not been ranked or grouped to minimize interference. The model calculated is shown in Table 5, after tidying up.

Table 5. Summary table of SBM-Malmquist index model results for Chinese agricultural economy efficiency from 2015 to 2021.

	Number of Provinces with Effch > 1	Number of Provinces with Techch > 1	Number of Provinces with Tfpch > 1
2015–2016	7	27	28
2016–2017	3	29	19
2017–2018	7	31	31
2018–2019	14	31	31
2019–2020	13	31	30
2020–2021	6	31	31

5. Discussion

5.1. Surprising Grouping

In Figure 2, provinces are annotated on the map of China according to their respective groupings as delineated in Table 6. A summary of the gross regional product, per capita gross regional product, and the corresponding rankings among the 31 provinces for the year 2017 is compiled in Table 6. A counterintuitive observation emerges from these graphical and tabular representations: there is a conspicuous lack of a direct correlation between the efficiency of agricultural economics in Chinese regions and their overall economic performance or geographical location. Intriguingly, Group 3, identified as having the lowest agricultural economic efficiency, includes some of China's most economically advanced provinces such as Shanghai and Guangdong. These provinces excel in metrics like gross regional product and per capita gross regional product and are located along the southeastern coast. In various Chinese regional economic studies, including those focusing on agricultural economic disparities, these provinces are frequently classified among the most developed [23,29,31]. Conversely, Group 3 also comprises economically underdeveloped regions like Tibet, Gansu, and Jilin, which lag in economic indicators and are located in western and northeastern China. Moreover, provinces with medium-level economic performance, such as Jiangxi, Anhui, and Henan, are also incorporated in this group and geographically situated in central China.

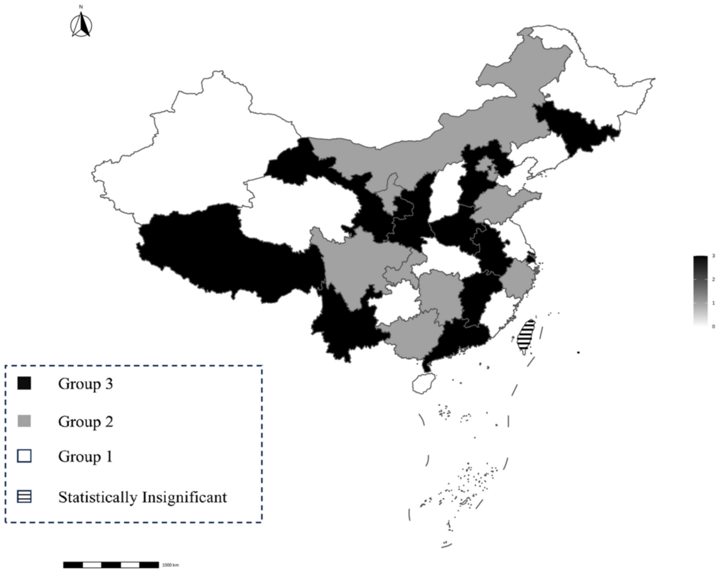

Figure 2. Geographical distribution map of agricultural economic efficiency rankings among China's 31 provinces and municipalities.

Table 6. Summary of gross regional product and ranking, per capita gross regional product and ranking of provinces in Group 3.

	Gross Regional Product (CNY 100 Millions)	Ranking of Gross Regional Product	Per capita Gross Regional Product (CNY)	Ranking of Per Capita Gross Regional Product
Hebei	40,391.27	12	54,231.03	27
Shanxi	22,590.16	20	64,914.26	17
Jilin	13,235.52	26	55,728.49	26
Shanghai	43,214.85	10	173,623.3	2
Anhui	42,959.18	11	70,275.11	13
Jiangxi	29,619.67	15	65,573.77	15
Henan	58,887.41	5	59,584.54	22
Guangdong	124,369.7	1	98,052.41	7
Yunnan	27,146.76	18	57,882.23	23
Tibet	2080.173	31	56,835.32	24
Gansu	10,243.31	27	41,137.77	31

From an agricultural economic perspective, this grouping is justified. Numerous studies have indicated that Shanghai and Guangdong are among the most developed and fastest-growing regions in China [56–58]. However, there may be significant issues regarding agricultural economic efficiency. In economically prosperous areas, there is a prevalent issue of excessively high land-use costs. Research by Gao et al. [59] revealed that urbanization in China is progressing rapidly, leading to over-expropriation of rural land in Shanghai, resulting in land idleness. The ambiguity in China's unique rural land ownership system has made it challenging to utilize this idle land. Studies by Liu et al. [60] show that land rents have heavily impacted areas surrounding Shanghai. After investigating

160 villages in the Qingpu district of Shanghai, Gu et al. [61] found that rural areas on the outskirts of Shanghai are evolving multifunctionally, and solely focusing on agricultural production is no longer the most viable livelihood option in Shanghai's rural areas.

The rural area in Guangdong Province is relatively vast, and the issues therein are more intricate. Rural areas close to the Greater Bay area of the Pearl River delta have been rapidly urbanized over the past few decades. Research by Choy et al. [62] indicates that Shenzhen, situated near Hong Kong, was an agricultural county with an urban built-up area of merely 3 square kilometers in 1980. By 2010, it had transformed into a metropolis with an urban built-up area of 703 square kilometers, with most of its land transitioning from agricultural to industrial use. In contrast, areas far from the Greater Bay Area, due to labor shortages and high transportation costs, exhibit significant land abandonment phenomena. Su et al. developed an algorithm based on phenology and time series and, after analyzing satellite imagery from Google Earth Engine, highlighted that abandoned lands in Guangdong Province have consistently measured around 500,000 hectares. Post-2000, due to the rapid urbanization of Guangdong, the rate of land abandonment has been increasing yearly [63]. In 2021, the Guangdong provincial government announced a cultivated land area of 28,480,000 mu, equivalent to 1,898,667 hectares, with a land abandonment rate reaching 26%. Studies by Hou et al. [64] reveal that land abandonment exists in other areas and that the rate of abandonment is directly proportional to the distance from urban settlements.

Loss of young labor, high land-use costs in areas close to cities, and elevated land abandonment rates in areas distant from cities have profoundly impacted the agricultural economic efficiency of developed provinces and cities like Shanghai and Guangdong. This further substantiates the hypothesis of this paper: when undertaking regional economic research in specific areas, one should not solely rely on empirical judgments. Identifying regions that are advanced and those that are lagging, and distinguishing between them through judicious assessment methods, is a prudent approach.

5.2. China's Agricultural Economy Does Have a "Mezzogiorno Trap" for the Period 2015–2021

Based on the data displayed in Table 4, we take the mean TGR value of Group 1, representing the more advanced agricultural economy, and subtract the mean TGR value of Group 3, representing the less advanced agricultural economy. The resulting difference, which we term "Performance Gap Difference" (PGD), stands for the gap between the advanced and less advanced groups in China's agricultural economy. The larger the PGD value, the larger the gap. The change in the PGD of China's agricultural economic efficiency from 2015 to 2021 is depicted in Figure 3.

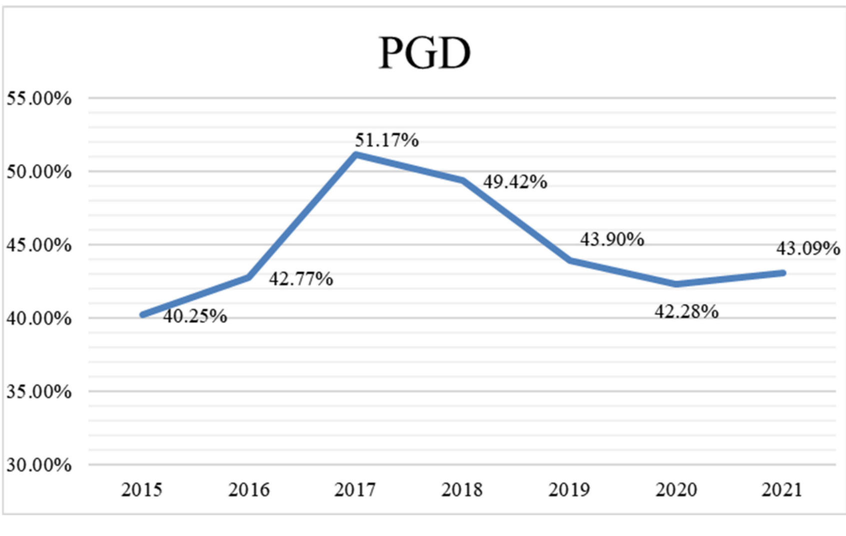

Figure 3. Trend Graph of Chinese Agricultural Economy PGD from 2015 to 2021.

As depicted in Figure 3, the PGD rapidly increased from 2015 to 2017, a period just prior to the introduction of the "Rural Revitalization Strategy". This widening gap was between provinces with high agricultural efficiency and those with lower agricultural efficiency. After the Chinese government proposed the comprehensive "Rural Revitalization Strategy" in 2018, the PGD markedly decreased by 2020. However, by 2021, the PGD started to increase again.

The changes in PGD alone are not sufficient to substantiate the presence of the "Mezzogiorno Trap" in China's agricultural economy. As we previously discussed, the changing circumstances of external aid or investments typically provide compelling evidence for the "Mezzogiorno Trap". We chose to compare the changes in support from the government with the trends in PGD.

For this purpose, we specifically analyzed the government's fiscal support for the agricultural economy from 2015 to 2021. We consider the proportion of expenditure on agriculture, forestry, and water by the governments of each province in their general public budget expenditure during the same period as the degree of agricultural financial support (DAFS). Its expression is:

$$\text{DAFS} = \frac{\text{Expenditure for Agriculture, Forestry and Water Conservancy}}{\text{General Public Budget Expenditure}}$$

The changes in DAFS from 2015 to 2021 are depicted in Figure 4.

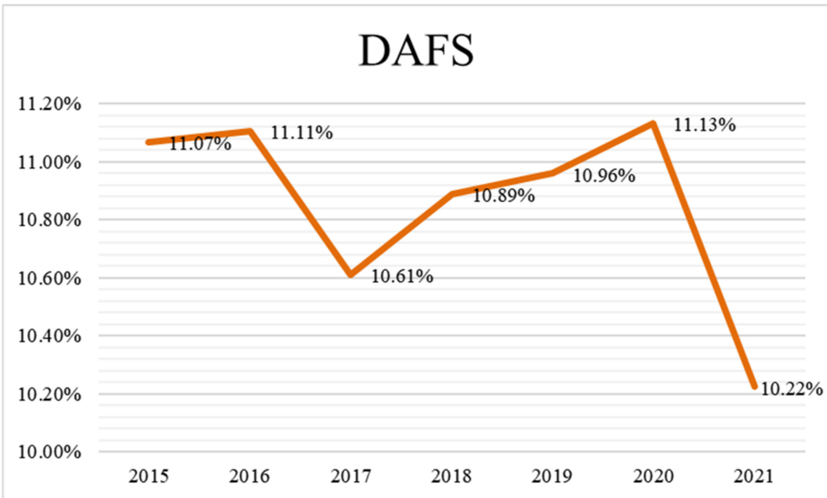

Figure 4. Trend Graph of Chinese Agricultural Economy DAFS from 2015 to 2021.

For easy comparison, we multiplied the DAFS for the years 2015–2021 by 5, and displayed it together with the PGD for the same period in Figure 5. It can be observed that whenever DAFS peaks, the PGD is at a lower level, as evidenced in 2015 and 2020. Conversely, when DAFS dips, PGD rises, as shown in 2017 and 2021. In particular in 2021, we speculate that due to the financial burden brought by COVID-19, DAFS experienced a downturn, leading to an immediate increase in PGD from its continual decline. Such fluctuations reveal a very typical "Mezzogiorno Trap".

In summary, based on our assessment, during the period 2015–2021, the agricultural economic efficiency in China exhibited a clear "Mezzogiorno Trap" for the following reasons:

1. Significant disparities exist between agriculturally lagging regions and agriculturally advanced regions.
2. This disparity remains relatively stable. While the magnitude of the gap may fluctuate, the composition of the lagging and advanced areas remains largely unchanged.
3. This gap correlates with variations in governmental support. When support intensifies, the disparity narrows. Conversely, as support diminishes, the gap widens.

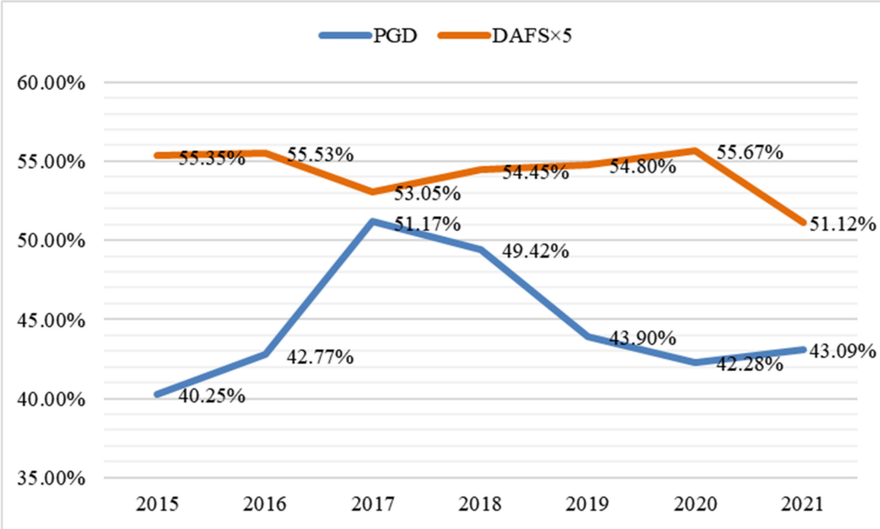

Figure 5. Combined trend graph of PGD and DAFS in Chinese agricultural economy from 2015 to 2021.

This dependence on fiscal support represents the most problematic aspect of the "Mezzogiorno Trap", largely due to the myopic perspective of certain policymakers. These administrators often formulate policies based on simplistic cause-and-effect relationships: subsidies are provided because of poverty, and once these subsidies are dispensed, various metrics immediately improve, leading them to believe that the issue has been resolved. In reality, structural disparities persist, and irrational or excessive subsidies can have severe repercussions, potentially exacerbating the "Mezzogiorno Trap".

McRae's research suggests that subsidies directed towards lagging areas often struggle to be effective due to poor infrastructure [65]. Dvouletý et al. discovered in their study of the Czech food industry that while public subsidies did indeed enhance firms' productivity in the short term, they had a negative impact on total factor productivity (TFP) [66]. Šipikal et al., in their examination of the European Union's regional policies, found that 35% of public subsidies constituted "deadweight" [67]. Research by Tsiouni et al. into Greece's livestock industry revealed that Greek goat farms have developed a significant dependency on government subsidies, with profitability becoming virtually non-existent in the absence of such aid [68].

5.3. Analysis of the Causes of "Mezzogiorno Trap"

As previously analyzed, there is a certain correlation between PGD and DAFS. However, DAFS is not the sole cause of PGD. We grouped the DAFS of the 31 provinces and compiled them into Table 7 and Figure 6. Figure 6 distinctly illustrates that the DAFS of provinces and cities in Group 3 is not the lowest. Throughout all the years, the gray bars representing the mean DAFS for Group 3 are consistently higher than the orange bars for Group 2.

Table 7. Average values table of DAFS groupings in China from 2015 to 2021.

	DAFS of Group 1	DAFS of Group 2	DAFS of Group 3
2015	0.126519343	0.110671251	0.116122018
2016	0.132630976	0.110073457	0.119074741
2017	0.122422637	0.110352681	0.114762524
2018	0.124583928	0.111795782	0.121278352
2019	0.131714679	0.107610036	0.12401321
2020	0.130910846	0.109419802	0.12523234
2021	0.116297515	0.104905896	0.116010143

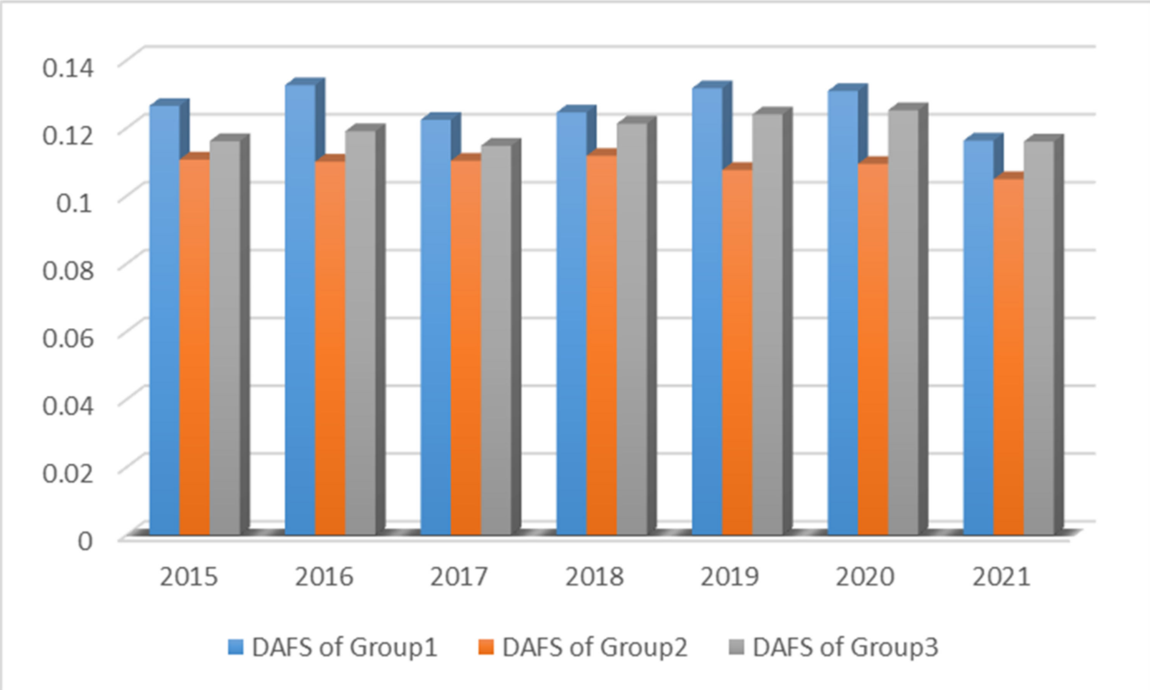

Figure 6. Mean DAFS values by group for the period 2015–2021.

We have reorganized the data from Table 4 into Figure 7. A comparison between Figures 6 and 7 provides a clearer visualization: throughout all years, the mean TGR of Group 3 is consistently lower than that of Group 2, while the DAFS values are consistently higher. This suggests that despite receiving more substantial fiscal support, the agricultural economic efficiency of the provinces and cities in the relatively lagging Group 3 remains inferior to that of Group 2. Fiscal support intensity is not the sole reason for the lower agricultural economic efficiency observed in Group 3.

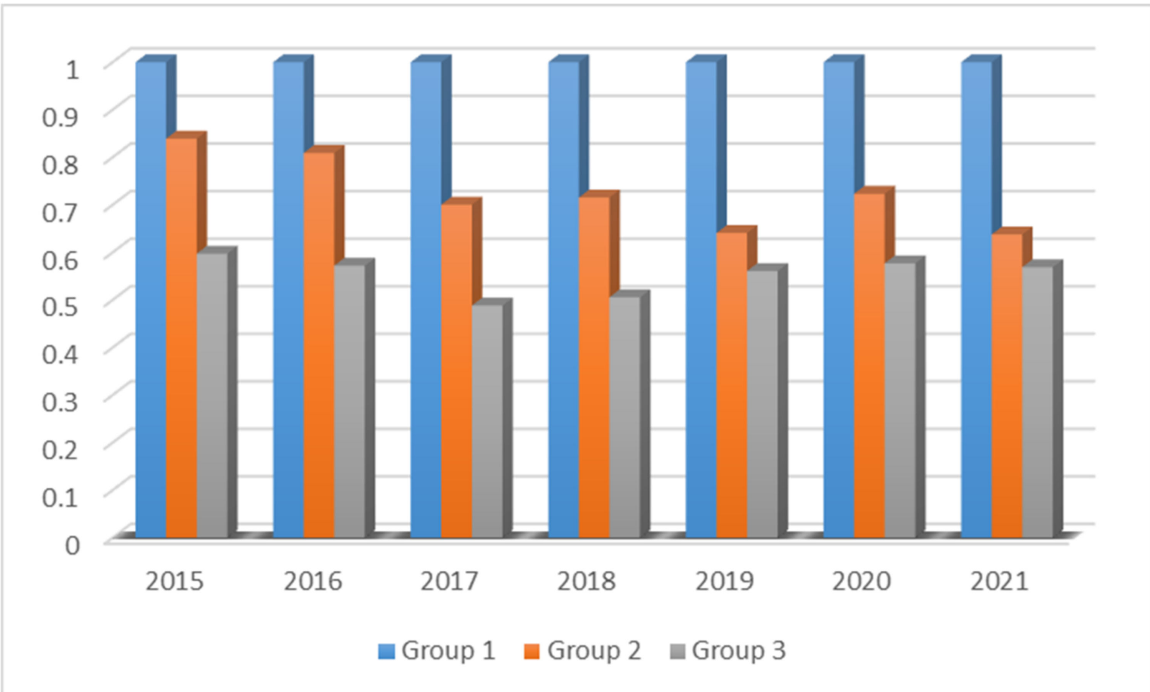

Figure 7. Mean PGD values by group for the period 2015–2021.

Therefore, to further probe into the causes, we continue employing the DEA method. Given that the meta-frontier SBM model cannot be directly decomposed into pure technical efficiency and scale efficiency, we additionally constructed an SBM-DEA model for the agricultural economic efficiency of the 31 provinces from 2015 to 2021 and organized the results as shown in Table 8.

Table 8. Summary table of SBM Model for Chinese agricultural economy from 2015 to 2021.

	Number of Provinces with Crste Values of 1	Number of Provinces with Vrste Values of 1	Number of Provinces with Scale Values of 1	Number of Provinces with DRS	Number of Provinces with IRS
2015	8	17	8	10	13
2016	10	17	10	11	10
2017	8	16	9	12	10
2018	8	16	8	12	10
2019	6	15	6	12	12
2020	8	15	7	14	9
2021	5	14	5	15	11

Table 8 reveals a noticeably larger number of provinces reaching DEA effectiveness in pure technical efficiency than in scale efficiency. This suggests that scale inefficiency is the primary reason behind insufficient agricultural economic efficiency. In light of our grouping of the 31 provinces, we organize the pure technical efficiency and scale efficiency of each group into Table 9. In Group 2, most provinces reach DEA effectiveness in pure technical efficiency. For the more lagging provinces in Group 3, nearly all fail to reach DEA effectiveness in both pure technical efficiency and scale efficiency.

Table 9. Summary table of pure technical efficiency and scale efficiency groupings of SBM Model for Chinese agricultural economy from 2015 to 2021.

	Number of Scale Efficiency Scores of 1 in Group 1	Number of Scale Efficiency Scores of 1 in Group 2	Number of Scale Efficiency Scores of 1 in Group 3	Number of Pure Technical Efficiency Scores of 1 in Group 1	Number of Pure Technical Efficiency Scores of 1 in Group 2	Number of Integrated Technical Efficiency Scores of 1 in Group 3
2015	6	2	0	9	7	1
2016	8	2	0	9	7	1
2017	8	0	0	9	6	1
2018	7	1	0	9	6	1
2019	6	0	0	9	5	1
2020	7	1	0	8	6	1
2021	5	0	0	8	8	1

From Table 9, it can be inferred that the primary reason for the "Mezzogiorno Trap" in China's agricultural economy is the lower scale efficiency, a common issue for provinces and cities in both Group 2 and Group 3. A defining characteristic of China's agricultural production is the fragmentation of farmlands and the dominance of small-scale subsistence farms. This emerged as a consequence of transitioning from the People's Communes to the Household Responsibility System, leading to significant structural issues in agricultural production, as substantiated by several studies [69,70]. Additionally, as previously analyzed, provinces and cities in Group 3, such as Shanghai and Guangdong, are burdened with challenges including labor shortages, high labor costs, elevated land use costs, serious land fallow issues, and high capital costs [71,72]. On the other hand, provinces with generally lagging economies like Tibet and Gansu are confronted with harsh natural environments, outdated infrastructure, and significant labor outflows [73,74]. Hence, for these provinces, enhancing efficiency through scaling proves to be a significant challenge.

Based on the SBM model from 2015 to 2021, provinces and cities in Group 3 with increasing returns to scale [20] and decreasing returns to scale (DRS) are compiled into Table 10. From Table 10, it is evident that the returns to scale status of most provinces and cities remain relatively stable. Shanxi, Shanghai, Tibet, and Gansu consistently exhibit decreasing returns to scale, whereas Hebei, Anhui, Henan, Guangdong, and Yunnan consistently demonstrate increasing returns to scale. Only Jilin and Jiangxi have shown some fluctuations over the period. This indicates that the deficiencies in scale efficiency for provinces and cities in Group 3 are persistent and relatively consistent.

Table 10. Summary table of scale returns groupings of SBM model for Chinese agricultural economy from 2015 to 2021.

	2015	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
Hebei	DRS	DRS	DRS	DRS	DRS	DRS	DRS
Shanxi	IRS	IRS	IRS	IRS	IRS	IRS	IRS
Jilin	IRS	IRS	IRS	IRS	IRS	DRS	DRS
Shanghai	IRS	IRS	IRS	IRS	IRS	IRS	IRS
Anhui	DRS	DRS	DRS	DRS	DRS	DRS	DRS
Jiangxi	DRS	DRS	CRS	CRS	IRS	IRS	IRS
Henan	DRS	DRS	DRS	DRS	DRS	DRS	DRS
Guangdong	DRS	DRS	DRS	DRS	DRS	DRS	DRS
Yunnan	DRS	DRS	DRS	DRS	DRS	DRS	DRS
Tibet	IRS	IRS	IRS	IRS	IRS	IRS	IRS
Gansu	IRS	IRS	IRS	IRS	IRS	IRS	IRS

Furthermore, Table 9 also indicates a significant deficiency in pure technical efficiency among the provinces and cities in Group 3, with only Tibet achieving DEA efficiency. The lack of pure technical efficiency is the primary reason for the gap between Group 3 and Group 2. Pure technical efficiency reflects factors in agricultural production beyond scale, including management expertise, agricultural science and technology, capital efficiency, sales, deep processing of agricultural products, and so on. Only by achieving a high level in these areas can inputs be efficiently transformed into outputs. The discrepancy in pure technical efficiency also elucidates why Group 2 provinces and cities have lower DAFS than Group 3; however, their overall agricultural economic efficiency is higher than Group 3.

In conclusion, the "Mezzogiorno Trap" in China's agricultural economy has multi-faceted causes. In the short term, improvements in areas such as agricultural science and technology and management levels might yield noticeable results, narrowing the gap with Group 2. However, a fundamental resolution to the issue will likely necessitate challenging adjustments in scale.

5.4. Trend of Overall Agricultural Economic Efficiency Development in China from 2015 to 2021

In our prior analysis on the existence of the "Mezzogiorno Trap" in Chinese agriculture, we constructed SBM models for 31 provinces over multiple years and performed a thorough evaluation. From Table 7, it appears that the overall technical efficiency of Chinese agricultural economics is declining, as the number of provinces achieving DEA efficiency decreases each year. However, SBM models provide a relative description of the agricultural economic efficiency of 31 provinces at a certain time, and models from different periods cannot be directly compared. Utilizing the same data and input–output variables, we constructed an SBM Malmquist index model for 31 provinces from 2015 to 2021, adopting an adjacent benchmarking pattern. We obtained results for six periods, which are consolidated and presented in Table 11.

Table 11. Summary table of SBM-Malmquist index model for China's agricultural economy from 2015 to 2021.

	Number of Provinces with Effch > 1	Number of Provinces with Techch > 1	Number of Provinces with Tfpch > 1
2015–2016	7	27	28
2016–2017	3	29	19
2017–2018	7	31	31
2018–2019	14	31	31
2019–2020	13	31	30
2020–2021	6	31	31

A Tfpch (total factor productivity change index) greater than 1 indicates an enhancement in economic efficiency for the given period. Based on Table 11, when Tfpch values are summarized in Figure 8, it becomes evident that, during various time intervals, the number of provinces and cities with a Tfpch greater than 1 only reached its lowest in 2016–2017 with a figure of 19. This suggests that during that year, only 19 provinces and cities achieved progress in total factor productivity. In other periods, the number of provinces and cities with a Tfpch greater than 1 ranged from 28 to 31. Notably, in 2019 and 2021, the agricultural economy of China might have been severely impacted by the COVID-19 pandemic. The SBM static model, as depicted in Table 7, shows that only six and five provinces and cities, respectively, achieved DEA efficiency during these years. However, Figure 8 demonstrates that 30–31 provinces and cities had a Tfpch exceeding 1 during these intervals.

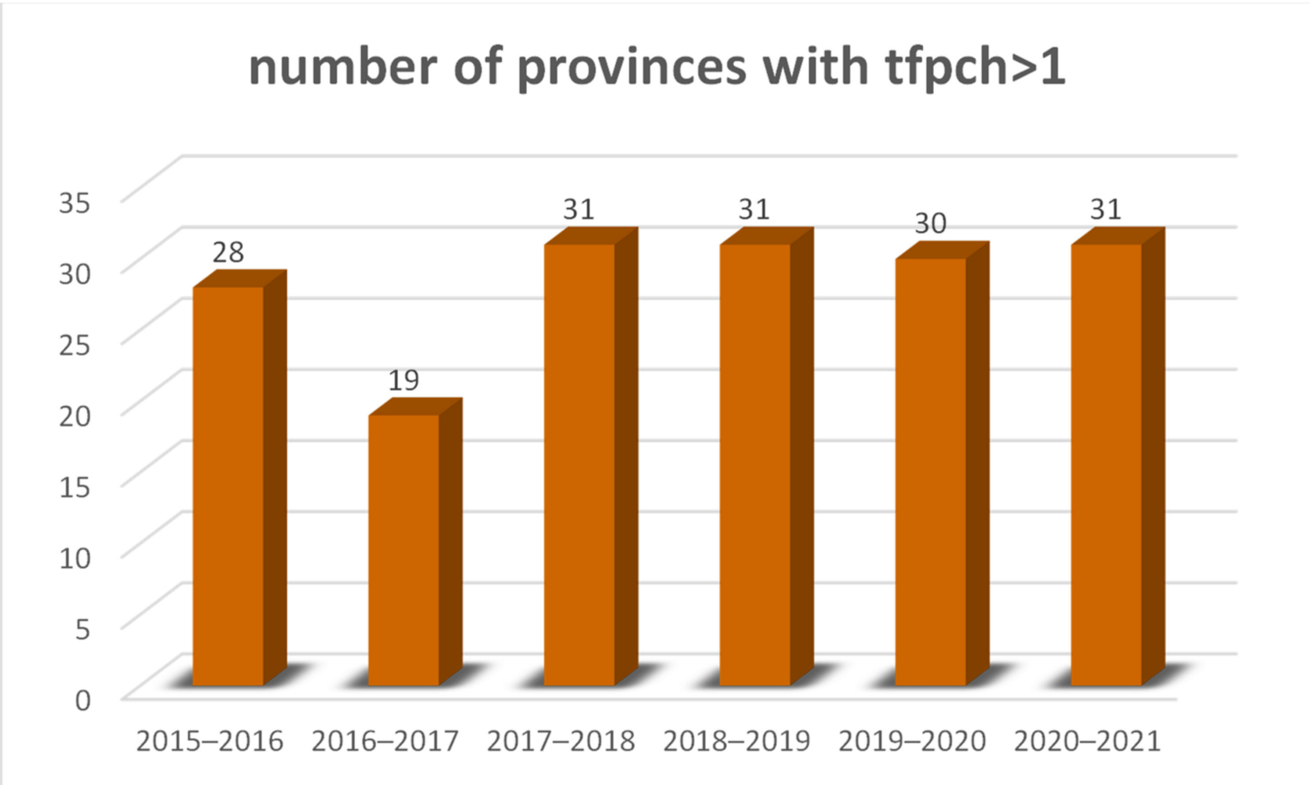

Figure 8. Number of provinces in China with an agricultural Tfpch > 1 from 2015 to 2021.

In fact, the SBM model and the SBM-Malmquist model are not contradictory; they have different reference sets. The SBM model calculates the relative efficiency for a specific year using cross-sectional data from that year as its reference set. In contrast, the Malmquist index model computes the productivity index based on panel data from various periods.

When assessing the trend of production efficiency, the SBM-Malmquist index model should be used as the benchmark.

From the perspective of the SBM-Malmquist index model, the overall development trend of China's agricultural economic efficiency is consistently improving. This trend does not contradict the existence of the "Mezzogiorno Trap": even if the agricultural economic efficiency of less developed provinces is improving, if the rate of improvement lags behind that of more advanced provinces, the gap will continue to widen. This scenario further underscores the subtle nature of the "Mezzogiorno Trap". Even if the overall level of the agricultural economy is on the rise, the trap can still persist or even expand in a concealed manner. Managers and policymakers might overlook the existence of the "Mezzogiorno Trap" due to the overall improvement in agricultural economic efficiency.

Tfpch is the product of Effch and Techch. Summarizing the Effch and Techch from Table 11 into Figure 9, it is evident that most provinces, including those from Group 2 and Group 3, exhibit a significant shortfall in Effch (represented by the green bars). This is a primary factor contributing to the lower values of Tfpch. This aligns with the findings from the SBM model decomposition: the less developed provinces in China's agricultural economy generally suffer from structural issues and require profound industrial structural reforms to enhance scale efficiency.

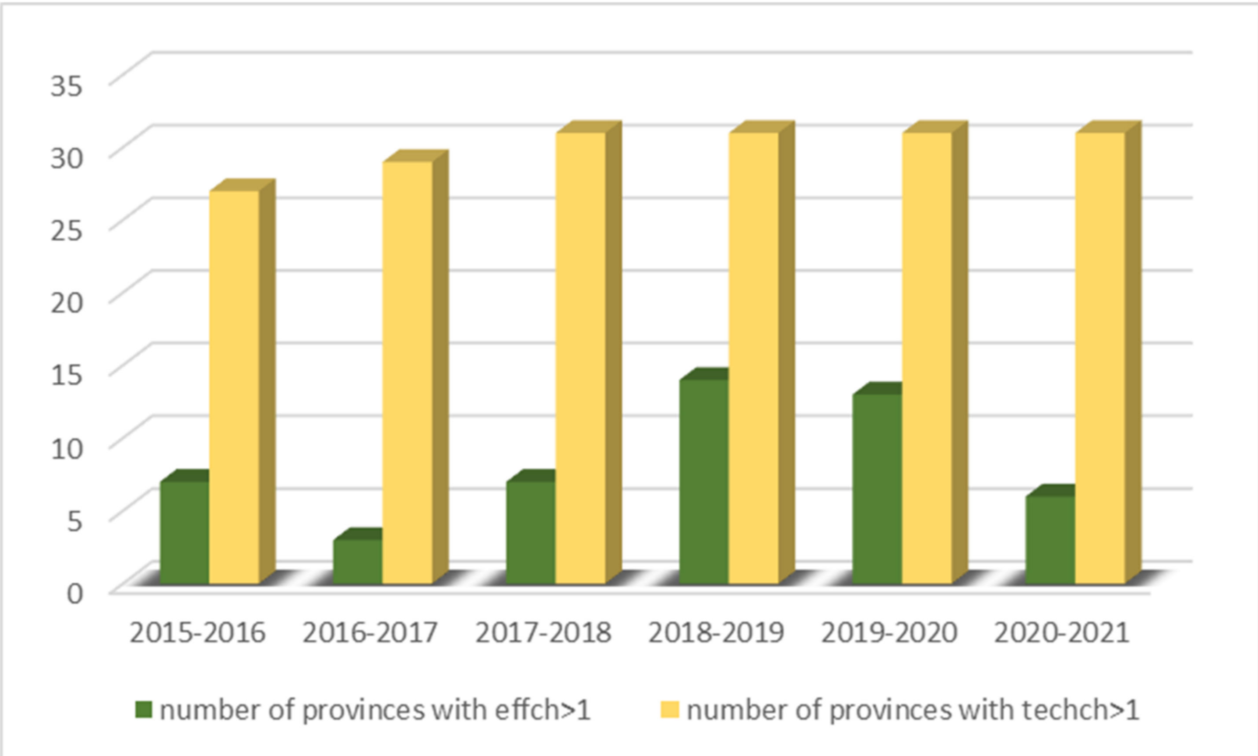

Figure 9. Number of Chinese provinces with agricultural Effch > 1 and Techch > 1 from 2015 to 2021.

The continuous improvement in China's agricultural economic efficiency may render the "Mezzogiorno Trap" more concealed. Some policymakers might be contented with the present achievements, overlooking the structural adjustments with less evident short-term results, thereby failing to address the core of the "Mezzogiorno Trap". However, from an optimistic perspective, the ever-increasing agricultural economic efficiency will eventually aid in ameliorating the "Mezzogiorno Trap": if challenges are identified in a timely manner, the upward development trend provides a broader array of solutions to address the issue.

6. Conclusions, Recommendations, and Shortcomings

6.1. Conclusions

The primary objective of this study is to investigate the existence of the "Mezzogiorno Trap" in China, focusing specifically on the agricultural sector. Based on the results and discussions presented in the preceding sections, we have formulated several conclusions:

1. This paper introduces a methodology tailored for investigating the "Mezzogiorno Trap", particularly within specific industries. Initially, a quantitative analysis is employed to identify underperforming regions. As an example, the super-efficiency SBM model is adopted in this paper to rank and categorize the subjects under study. Subsequently, the disparity between lagging and advanced regions is examined, exemplified in this research by the deployment of a meta-frontier SBM model to compute PGD values. Factors influencing these disparities are then scrutinized to ascertain the presence of the "Mezzogiorno Trap". In this context, a comparative analysis between PGD and DAFS values is utilized to discern additional characteristics of the trap.

Compared to other methodologies, this approach offers an enhanced lens to study the "Mezzogiorno Trap" within specific sectors. Such sectors' regional variations can often be overshadowed by overarching economic differences, thereby inducing biases for researchers. Take, for instance, the agricultural economy focused on in this paper. There exists a pronounced discrepancy between agricultural efficiency and the overall economic standing across Chinese provinces and cities. Some of the economically flourishing provinces paradoxically rank low in terms of agricultural efficiency. Sole reliance on regional economic performance or geographical location for classifying regions as advanced or lagging can lead to substantial inaccuracies, which in turn can significantly impact policy formulation.

Common pitfalls may include excessive enhancement of support levels, engendering a dependency in regions ensnared by the "Mezzogiorno Trap", which is manifestly counterproductive for fully addressing the underlying issues of the trap. Research by Tsiouni et al. [68] illustrates this phenomenon, demonstrating that goat farms in Greece become unsustainable in the absence of governmental subsidies. Furthermore, this dependency is not limited to a single sector but is pervasive across various fields. For instance, Wang et al. investigated China's new energy vehicle industry [75] and discovered a significant negative impact of subsidies on firms' financial performance during the period 2009–2018, requiring structural adjustments for mitigation.

2. Utilizing this approach, we identified the presence of the "Mezzogiorno Trap" in China's agricultural economy from 2015 to 2021. Even during periods characterized by consistently rising overall economic levels, this methodology effectively detected the existence of the "Mezzogiorno Trap". Integrating findings from the SBM-Malmquist index model for the same years, we further corroborated the covert nature of the "Mezzogiorno Trap": even when the overall economic efficiency is on an uptrend, the trap persists and is easily overlooked.
3. Through the decomposable DEA-SBM model, integrated with the unique characteristics of agricultural production, we posit that the primary reason for the "Mezzogiorno Trap" in China's agricultural economy is the insufficiency in scale efficiency. This lack of scale efficiency is not only evident in provinces and cities with relatively lagging agricultural economic efficiency but is also prevalent among those with a moderate performance. Additionally, provinces and cities with a lagging agricultural economic efficiency exhibit deficiencies in pure technical efficiency, marking a significant difference from other regions. The issue of low scale efficiency is a common challenge faced by developing countries, often attributable to an imbalanced industrial structure, as demonstrated by the research conducted by Karimov et al. [76].
4. Fundamentally, regions mired in the "Mezzogiorno Trap" suffer from outdated industrial structures, inferior infrastructure, subpar technological standards, inefficiencies

in capital utilization, and talent deficiencies, among others. The gaps present in these areas cannot be fully bridged solely through basic support policies such as financial subsidies. When such support wanes, the disparities swiftly widen once more.

6.2. Recommendations

1. Maintaining support strength, including fiscal support, is crucial for resolving the "Mezzogiorno Trap". Data analysis reveals a certain correlation between strong support and the "Mezzogiorno Trap", and prematurely weakening support could widen the gap. Several studies have likewise highlighted the significance of government support, including Mutlu's study on Japan's regional economic differentiation [77], Das et al.'s research on the Indian regional economy [78], and Chen et al.'s studies on regional differences in China and Henan Province's agricultural economy [22,79]. These studies show that government support is a material basis and necessary condition for resolving regional differences.
2. However, the essence of addressing the "Mezzogiorno Trap" hinges on structural adjustments tailored to the realities of underdeveloped regions. Fiscal subsidies from the government must be dispensed judiciously; sheer direct capital allocations may inadvertently yield adverse consequences. Integrating the findings from this paper, the primary strategy for China to rectify its agricultural economic "Mezzogiorno Trap" centers on enhancing scale efficiency. Predicated on the characteristics of agricultural production, the emphasis on boosting scale efficiency necessitates a prudent reshaping of the industrial structure, specifically in Group 3 and Group 2 provinces and cities, representing immediate challenges to address.

For provinces evidently mired in the "Mezzogiorno Trap", a rational approach would involve conducting research and analyses tailored to the specific circumstances of these underdeveloped regions, thereby formulating long-term, detailed, and targeted policies.

For Group 3 provinces in the western region where educational levels are low, it is advisable to allocate a portion of financial subsidies towards the attraction and cultivation of agricultural talent, as demonstrated in studies by Démurger et al. [80] and Hitka and Ližbetinová [81]. For provinces with insufficient infrastructure, a portion of the funding could be allocated towards less immediately impactful infrastructure projects, as illustrated by Bhatia [82].

For rural areas surrounding Shanghai, enhancing the role of value-added agricultural processing industries through clustering could be more effective. In Guangdong, the initial focus might be on how to efficiently utilize the currently fallow land.

In the long run, these targeted interventions are likely to yield better outcomes than simply disbursing subsidies, serving to fundamentally address the "Mezzogiorno Trap".

In summation, while sustaining supportive measures, a gradual transition of some direct monetary subsidies to funds dedicated to industrial structural adjustments can act as a catalyst for the industrial evolution in lagging regions. Policymakers need not be overly apprehensive about diminishing subsidies' impact on economic efficiency. As found in the study by Yang et al. examining Jilin province's corn procurement policy shift [83], post-2016, the government annulled the protective purchasing subsidies for corn, ushering in a marked escalation in its marketization level. The agricultural economy exhibited robust performance, manifesting commendable adaptive resilience within the new policy milieu.

3. Our preceding analysis indicates that enhancing pure technical efficiency is crucial for provinces entrapped in the "Mezzogiorno Trap". Pure technical efficiency can be understood as the exclusion of scale-related factors, capturing elements such as technological advancement, managerial improvement, and increased capital efficiency. These distinctions underscore the fundamental differences between modern and traditional agriculture, further highlighting the urgency for industrialization within China's agricultural sector.

It is noteworthy that, compared to Group 2 provinces which have higher TGR averages, the financial support towards agriculture is more pronounced in Group 3 provinces. This suggests that elevating the pure technical efficiency of agriculture in Group 3 provinces to a DEA-efficient level would significantly alleviate the fiscal pressure engendered by agricultural support measures. Such an approach would be highly beneficial in addressing the "Mezzogiorno Trap" faced by these provinces.

4. Advanced provinces should take measures to assist less-developed provinces. Provinces in Group 3 should look to their counterparts in Group 1 for the adoption of advanced agricultural technologies and more efficient policies for agricultural industrialization. This would substantially contribute to the improvement of both pure technical efficiency and scale efficiency. In fact, enhancements in pure technical efficiency and scale efficiency are not mutually exclusive. Due to constraints such as land, climate, and water resources, agricultural production cannot simply optimize through arbitrary expansion or contraction of its scale. Advanced provinces often operate within more efficient production cycles, characterized by robust technological innovation, comprehensive policy formulation, and timely evaluation systems. These best practices offer valuable lessons for provinces that are lagging behind.
5. Provinces in Group 3 should pay particular attention to the heterogeneity of agricultural economies across different regions when formulating localized policies. This notion of diversification has been emphasized in earlier sections. For economically advanced regions like Shanghai and Guangdong, the focus should be on precision agriculture and the corporatization of agriculture. In contrast, less developed regions such as Gansu and Tibet should explore additional revenue streams. For instance, Gansu, which is predominantly characterized by desert and barren landscapes, has made notable strides in the development of solar and wind energy as well as agro-photovoltaic complementation. Recent studies indicate that these initiatives offer opportunities for ameliorating regional disparities [84,85].

6.3. Shortcomings and Improvements

The "Mezzogiorno Trap" reflects an unbridgeable disparity between advanced and less developed regions. However, the data envelopment analysis (DEA) approach assesses relative efficiency, implying perpetual disparities in the DEA model, which can potentially hinder the judgement of the "Mezzogiorno Trap". When determining the "Mezzogiorno Trap" based on the DEA method, we introduced additional supporting evidence, making the assessment process somewhat complex.

There are certainly simpler alternatives. For instance, ranking the overall efficiency of the agricultural economy across different years and comparing the ranking results. If the rankings vary greatly across different years, it suggests that the relative efficiency of each region is constantly changing, with no clear distinction between advanced and backward regions. This could suggest an apparent absence of the "Mezzogiorno Trap".

However, this method is only suitable for eliminating the possibility of the "Mezzogiorno Trap", but insufficient to affirm its existence. Additionally, it is not conducive to subsequent quantitative analyses and examinations of influencing factors. Nevertheless, as part of other agricultural economic research, it appears more succinct.

In terms of studying the influencing factors of the "Mezzogiorno Trap", this paper primarily conducted a comparative analysis with the disparities in fiscal support. We are seeking better ways to establish a more comprehensive "Mezzogiorno Trap" model and introducing more extensive correlation analyses, thereby proposing a broader range of feasible recommendations.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agriculture13091806/s1, Table S1: Data Source: Panel Data on Agricultural Economy across 31 Provinces in China, 2015–2021.

Author Contributions: Conceptualization, X.L. and Y.Z.; methodology, P.Y. and Y.Z.; software, P.Y.; validation, X.L. and Y.Z.; formal analysis, X.L.; investigation, P.Y.; resources, P.Y.; data curation, P.Y.; writing—original draft preparation, X.L.; writing—review and editing, Y.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the major project under the National Social Science Fund of China (No. 21AFX001).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used in this paper are from the China National Bureau of Statistics, the China Statistical Yearbook and the China Ministry of Agriculture and Rural Affairs, the China Rural Statistical Yearbook.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Watson, M.M. *Regional Development Policy and Administration in Italy*; Longman Group Ltd.: London, UK, 1970.
2. Daniele, V. Territorial disparities in labour productivity, wages and prices in Italy: What does the data show? *Eur. Urban Reg. Stud.* **2021**, *28*, 431–449. [CrossRef]
3. Salvati, L.; Zitti, M.; Carlucci, M. In-between regional disparities and spatial heterogeneity: A multivariate analysis of territorial divides in Italy. *J. Environ. Plan. Manag.* **2017**, *60*, 997–1015. [CrossRef]
4. Giarda, E.; Moroni, G. The Degree of Poverty Persistence and the Role of Regional Disparities in Italy in Comparison with France, Spain and the UK. *Soc. Indic. Res.* **2018**, *136*, 163–202. [CrossRef]
5. Castelnovo, P.; Morretta, V.; Vecchi, M. Regional disparities and industrial structure: Territorial capital and productivity in Italian firms. *Reg. Stud.* **2020**, *54*, 1709–1723. [CrossRef]
6. Iuzzolino, G.; Pellegrini, G.; Viesti, G. Convergence among Italian regions, 1861–2011. In *Bank of Italy Economic History Working Paper*; Bank of Italy Economic Research Department: Rome, Italy, 2011.
7. Terrasi, M. Convergence and divergence across Italian regions. *Ann. Reg. Sci.* **1999**, *33*, 491–510. [CrossRef]
8. Torrisi, G.; Pike, A.; Tomaney, J.; Tselios, V. (Re-)exploring the link between decentralization and regional disparities in Italy. *Reg. Stud. Reg. Sci.* **2015**, *2*, 123–140. [CrossRef]
9. Bruzzi, S.; Ivaldi, E.; Santagata, M. Measuring Regional Performance in the Italian NHS: Are Disparities Decreasing? *Soc. Indic. Res.* **2022**, *159*, 1057–1084. [CrossRef]
10. Fazio, G.; Piacentino, D.; Vassallo, E. Regional Disparities and Public Policies in Italy: Some considerations in light of a performance analysis. In Proceedings of the ERSA 2006—46th Congress of the European Regional Science Association, Volos, Greece, 30 August–3 September 2006.
11. Geppert, K.; Stephan, A. Regional disparities in the European Union: Convergence and agglomeration. *Pap. Reg. Sci.* **2008**, *87*, 193–217. [CrossRef]
12. Ruan, M.; Zhao, X. Fiscal pressure, policy choices and regional economic disparity: Evidence from a natural experiment in China. *Sustainability* **2022**, *14*, 12402. [CrossRef]
13. López-Villuendas, A.M.; del Campo, C. Regional Economic Disparities in Europe: Time-Series Clustering of NUTS 3 Regions. *Int. Reg. Sci. Rev.* **2023**, *46*, 265–298. [CrossRef]
14. Harrison, A.; Immergluck, D. *The Battle of the Belts: Comparing Housing Vacancy in Larger Metros in the Sun Belt and the Rust Belt since the Mortgage Crisis, 2012 to 2019*; Andrew Young School of Policy Studies, Georgia State University: Atlanta, GA, USA, 2020.
15. Hegerty, S.W. The rust belt, the sunbelt, and the concentration of poverty within large US cities. *Rev. Reg. Stud.* **2019**, *49*, 474–494.
16. Herrschel, T. Economic transformation, locality and policy in eastern Germany: A comparison of two Länder. *Appl. Geogr.* **1997**, *17*, 267–281. [CrossRef]
17. Berentsen, W.H. Changing Regional Inequalities in United Germany. *Eurasian Geogr. Econ.* **2006**, *47*, 462–477. [CrossRef]
18. Dörr, M.; Riemer, U.; Christ, M.; Bauersachs, J.; Bosch, R.; Laufs, U.; Neumann, A.; Scherer, M.; Störk, S.; Wachter, R. Hospitalizations for heart failure: Still major differences between East and West Germany 30 years after reunification. *Wiley Online Libr.* **2021**, *8*, 2546–2555. [CrossRef]
19. Birthal, P.S.; Singh, H.; Kumar, S. Agriculture, economic growth and regional disparities in India. *J. Int. Dev.* **2011**, *23*, 119–131. [CrossRef]
20. Jose, A. India's regional disparity and its policy responses. *J. Public Aff.* **2019**, *19*, e1933. [CrossRef]
21. State Council of China. The Eleventh Five-Year Plan for National Economic and Social Development of the People's Republic of China. Available online: https://www.gov.cn/gongbao/content/2006/content_268766.htm (accessed on 15 July 2023).
22. Chen, Z.; Song, S. Efficiency and technology gap in China's agriculture: A regional meta-frontier analysis. *China Econ. Rev.* **2008**, *19*, 287–296. [CrossRef]

23. Fan, S.; Kanbur, R.; Zhang, X. China's regional disparities: Experience and policy. *Rev. Dev. Financ.* **2011**, *1*, 47–56. [CrossRef]
24. Zhang, Y. The regional disparity of influencing factors of technological innovation in China: Evidence from high-tech industry. *Technol. Econ. Dev. Econ.* **2021**, *27*, 811–832. [CrossRef]
25. State Council of China. Circular of the State Council on Deepening the Pilot Reform of Rural Taxes and Fees in 2005. Available online: https://www.gov.cn/gongbao/content/2005/content_64331.htm (accessed on 1 August 2023).
26. State Council of China. Approval Reply of the State Council on Agreeing to Establish the New Rural Cooperative Medical Treatment Approval of the Inter-Ministerial Joint Conference System. Available online: https://www.gov.cn/gongbao/content/2003/content_62401.htm (accessed on 1 August 2023).
27. The Central Committee of the Communist Party of China and the State Council. The Central Committee of the Communist Party of China and the State Council Opinions on Implementing the Rural Revitalization Strategy. Available online: https://www.gov.cn/gongbao/content/2018/content_5266232.htm (accessed on 1 September 2023).
28. Chan, H.L.; Chan, K.T. The analysis of rural regional disparity in China. *Asian Econ. J.* **2000**, *14*, 23–38. [CrossRef]
29. Li, H.; Haynes, K.E. Economic structure and regional disparity in China: Beyond the Kuznets transition. *Int. Reg. Sci. Rev.* **2011**, *34*, 157–190. [CrossRef]
30. Chen, Y.; Li, X.; Tian, Y.; Tan, M. Structural change of agricultural land use intensity and its regional disparity in China. *J. Geogr. Sci.* **2009**, *19*, 545–556. [CrossRef]
31. Liu, X.; Wang, X.; Xin, X. Did agricultural technological changes affect China's regional disparity? *China Agric. Econ. Rev.* **2012**, *4*, 440–449. [CrossRef]
32. National Bureau of Statistics of China. China Statistical Yearbook. Available online: http://www.stats.gov.cn/english/Statisticaldata/yearbook/ (accessed on 1 August 2023).
33. Ministry of Agriculture and Rural Development of China. China Rural Statistical Yearbook. Available online: https://navi.cnki.net/knavi/yearbooks/YMCTJ/detail?uniplatform=NZKPT&language=chs (accessed on 1 August 2023).
34. Chen, F.; Yang, K.; Wang, L.; Zhang, Y.; Liu, H. Comprehensive evaluation of power transmission and transformation project based on electric power big data. *Energy Rep.* **2022**, *8*, 733–741. [CrossRef]
35. Chen, M.; Zheng, Y. China's regional disparity and its policy responses. *China World Econ.* **2008**, *16*, 16–32. [CrossRef]
36. Schmookler, J. The changing efficiency of the American economy, 1869–1938. *Rev. Econ. Stat.* **1952**, *34*, 214–231. [CrossRef]
37. Bukarica, V.; Tomšić, Ž. Energy efficiency policy evaluation by moving from techno-economic towards whole society perspective on energy efficiency market. *Renew. Sustain. Energy Rev.* **2017**, *70*, 968–975. [CrossRef]
38. Bravo-Ureta, B.E.; Pinheiro, A.E. Efficiency analysis of developing country agriculture: A review of the frontier function literature. *Agric. Resour. Econ. Rev.* **1993**, *22*, 88–101. [CrossRef]
39. Paul, C.; Nehring, R.; Banker, D.; Somwaru, A. Scale economies and efficiency in US agriculture: Are traditional farms history? *J. Product. Anal.* **2004**, *22*, 185–205. [CrossRef]
40. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
41. Banker, R.D.; Charnes, A.; Cooper, W.W. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manag. Sci.* **1984**, *30*, 1078–1092. [CrossRef]
42. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
43. Chang, Y.-T.; Park, H.-s.; Jeong, J.-b.; Lee, J.-w. Evaluating economic and environmental efficiency of global airlines: A SBM-DEA approach. *Transp. Res. Part D Transp. Environ.* **2014**, *27*, 46–50. [CrossRef]
44. Lin, X.; Zhu, X.; Han, Y.; Geng, Z.; Liu, L. Economy and carbon dioxide emissions effects of energy structures in the world: Evidence based on SBM-DEA model. *Sci. Total Environ.* **2020**, *729*, 138947. [CrossRef] [PubMed]
45. Tone, K. Slacks-based measure of efficiency. In *Handbook on Data Envelopment Analysis*; Springer: Boston, MA, USA, 2011; pp. 195–209.
46. Andersen, P.; Petersen, N.C. A procedure for ranking efficient units in data envelopment analysis. *Manag. Sci.* **1993**, *39*, 1261–1264. [CrossRef]
47. O'Donnell, C.J.; Rao, D.P.; Battese, G.E.J.E.E. Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empir. Econ.* **2008**, *34*, 231–255. [CrossRef]
48. Li, L.-B.; Liu, B.-L.; Liu, W.-L.; Chiu, Y.-H.J.S.-E.P.S. Efficiency evaluation of the regional high-tech industry in China: A new framework based on meta-frontier dynamic DEA analysis. *Econ. Plan. Sci.* **2017**, *60*, 24–33. [CrossRef]
49. Yu, Y.; Huang, J.; Zhang, N. Industrial eco-efficiency, regional disparity, and spatial convergence of China's regions. *J. Clean. Prod.* **2018**, *204*, 872–887. [CrossRef]
50. Malmquist, S. Index numbers and indifference surfaces. *Trab. Estadística* **1953**, *4*, 209–242. [CrossRef]
51. Färe, R.; Grosskopf, S.; Lindgren, B.; Roos, P.J.J.o.p.A. Productivity changes in Swedish pharamacies 1980–1989: A non-parametric Malmquist approach. *J. Product. Anal.* **1992**, *3*, 85–101. [CrossRef]
52. National Bureau of Statistics of China. Statistical Bulletin of the People's Republic of China on National Economic and Social Development. 2022. Available online: https://www.gov.cn/xinwen/2023-02/28/content_5743623.htm (accessed on 1 August 2023).
53. Tang, C.; Zhao, L.; Zhao, Z. Child labor in China. *China Econ. Rev.* **2018**, *51*, 149–166. [CrossRef]

54. Gong, P.; Liang, S.; Carlton, E.J.; Jiang, Q.; Wu, J.; Wang, L.; Remais, J.V. Urbanisation and health in China. *Lancet* **2012**, *379*, 843–852. [CrossRef] [PubMed]
55. Zhao, L. Massive return migration emerging in China. *East Asian Policy* **2018**, *10*, 75–86. [CrossRef]
56. Fan, C.C. Economic opportunities and internal migration: A case study of Guangdong Province, China. *Prof. Geogr.* **1996**, *48*, 28–45. [CrossRef]
57. Zhang, L.-Y. Economic development in Shanghai and the role of the state. *Urban Stud.* **2003**, *40*, 1549–1572. [CrossRef]
58. Lo, C.W.-H.; Tang, S.-Y. Institutional reform, economic changes, and local environmental management in China: The case of Guangdong province. In *Environmental Governance in China*; Routledge: Abingdon, UK, 2013; pp. 42–62.
59. Gao, Y.; Ma, Y. What is absent from the current monitoring: Idleness of rural industrial land in suburban Shanghai. *Habitat Int.* **2015**, *49*, 138–147. [CrossRef]
60. Liu, Z.; Liu, L. Characteristics and driving factors of rural livelihood transition in the east coastal region of China: A case study of suburban Shanghai. *J. Rural. Stud.* **2016**, *43*, 145–158. [CrossRef]
61. Gu, X.; Xie, B.; Zhang, Z.; Guo, H. Rural multifunction in Shanghai suburbs: Evaluation and spatial characteristics based on villages. *Habitat Int.* **2019**, *92*, 102041. [CrossRef]
62. Choy, L.H.T.; Lai, Y.; Lok, W. Economic performance of industrial development on collective land in the urbanization process in China: Empirical evidence from Shenzhen. *Habitat Int.* **2013**, *40*, 184–193. [CrossRef]
63. Su, Y.; Wu, S.; Kang, S.; Xu, H.; Liu, G.; Qiao, Z.; Liu, L. Monitoring Cropland Abandonment in Southern China from 1992 to 2020 Based on the Combination of Phenological and Time-Series Algorithm Using Landsat Imagery and Google Earth Engine. *Remote Sens.* **2023**, *15*, 669. [CrossRef]
64. Hou, D.; Meng, F.; Prishchepov, A.V. How is urbanization shaping agricultural land-use? Unraveling the nexus between farmland abandonment and urbanization in China. *Landsc. Urban Plan.* **2021**, *214*, 104170. [CrossRef]
65. McRae, S. Infrastructure quality and the subsidy trap. *Am. Econ. Rev.* **2015**, *105*, 35–66. [CrossRef]
66. Dvouletý, O.; Blažková, I. The impact of public grants on firm-level productivity: Findings from the Czech food industry. *Sustainability* **2019**, *11*, 552. [CrossRef]
67. Šipikal, M.; Pisár, P.; Labudová, V. Are subsidies reall y needed? The case of eu regional policy in the czech and slovak republics. In *E+ M Ekonomie a Management/E+ M Economics Management Science*; EBSCO Industries, Inc.: Alpharetta, GA, USA, 2013; ,
68. Tsiouni, M.; Aggelopoulos, S.; Pavloudi, A.; Siggia, D. Economic and financial sustainability dependency on subsidies: The case of goat farms in greece. *Sustainability* **2021**, *13*, 7441. [CrossRef]
69. Wang, H.; Tong, J.; Su, F.; Wei, G.; Tao, R. To reallocate or not: Reconsidering the dilemma in China's agricultural land tenure policy. *Land Use Policy* **2011**, *28*, 805–814. [CrossRef]
70. Kendall, H.; Clark, B.; Li, W.; Jin, S.; Jones, G.D.; Chen, J.; Taylor, J.; Li, Z.; Frewer, L.J. Precision agriculture technology adoption: A qualitative study of small-scale commercial "family farms" located in the North China Plain. *Precis. Agric.* **2022**, *23*, 319–351. [CrossRef]
71. Liu, H.; Li, G.; Wang, K. Homestead reduction, economic agglomeration and rural economic development: Evidence from Shanghai, China. *China Agric. Econ. Rev.* **2022**, *14*, 274–293. [CrossRef]
72. Shi, Y.; Yang, Q.; Zhou, L.; Shi, S. Can Moderate Agricultural Scale Operations Be Developed against the Background of Plot Fragmentation and Land Dispersion? Evidence from the Suburbs of Shanghai. *Sustainability* **2022**, *14*, 8697.
73. Li, S.; Yao, Z.; Liu, Z.; Wang, R.; Liu, M.; Adam, J.C. The spatio-temporal characteristics of drought across Tibet, China: Derived from meteorological and agricultural drought indexes. *Theor. Appl. Climatol.* **2019**, *137*, 2409–2424. [CrossRef]
74. Ma, L.; Chen, M.; Fang, F.; Che, X. Research on the spatiotemporal variation of rural-urban transformation and its driving mechanisms in underdeveloped regions: Gansu Province in western China as an example. *Sustain. Cities Soc.* **2019**, *50*, 101675. [CrossRef]
75. Wang, X.; Li, Z.; Shaikh, R.; Ranjha, A.R.; Batala, L.K. Do government subsidies promote financial performance? Fresh evidence from China's new energy vehicle industry. *Sustain. Prod. Consum.* **2021**, *28*, 142–153. [CrossRef]
76. Karimov, A.; Amoke Awotide, B.; Timothy Amos, T. Production and scale efficiency of maize farming households in South-Western Nigeria. *Int. J. Soc. Econ.* **2014**, *41*, 1087–1100. [CrossRef]
77. Mutlu, S. Regional disparities, industry and government policy in Japan. *Dev. Change* **1991**, *22*, 547–586. [CrossRef]
78. Das, K. Regional disparity in India. *ACADEMICIA Int. Multidiscip. Res. J.* **2017**, *7*, 53–69. [CrossRef]
79. Chen, S.; Yang, J.; Kang, X. Effect of Fiscal Expenditure for Supporting Agriculture on Agricultural Economic Efficiency in Central China—A Case Study of Henan Province. *Agriculture* **2023**, *13*, 822. [CrossRef]
80. Démurger, S. Infrastructure Development and Economic Growth: An Explanation for Regional Disparities in China? *J. Comp. Econ.* **2001**, *29*, 95–117. [CrossRef]
81. Hitka, M.; Ližbetinová, L. Human potential of talents in agriculture and forestry in context of Agriculture 4. *0. Agric. Econ.* **2023**, *69*, 223–233. [CrossRef]
82. Bhatia, M. Rural infrastructure and growth in agriculture. *Econ. Political Wkly.* **1999**, *34*, A43–A48.
83. Yang, Q.; Zhang, P.; Li, Y.; Ning, J.; Chu, N. Does the Policy of Decoupled Subsidies Improve the Agricultural Economic Resilience?—Evidence from China's Main Corn Producing Regions. *Sustainability* **2023**, *15*, 10164.

84. Zhang, Y.; Ren, J.; Pu, Y.; Wang, P. Solar energy potential assessment: A framework to integrate geographic, technological, and economic indices for a potential analysis. *Renew. Energy* **2020**, *149*, 577–586. [CrossRef]
85. Sun, Y.; Li, Y.; Wang, R.; Ma, R. Measuring dynamics of solar energy resource quality: Methodology and policy implications for reducing regional energy inequality. *Renew. Energy* **2022**, *197*, 138–150. [CrossRef]