Evaluation of Capital Utilization Efficiency in Agricultural Listed Firms Based on a Three-Stage Data Envelopment Analysis

Abstract: Rural revitalization is intricately tied to national prosperity, with listed companies in agriculture, forestry, animal husbandry, and fisheries playing pivotal roles in driving this transformative agenda. However, these sectors face critical challenges, notably resource constraints and environmental pressures, which underscore the necessity of evaluating capital utilization efficiency. This study employs a combined three-stage DEA model and Malmquist index to analyze capital utilization efficiency across 85 listed companies within China ' s agriculture, forestry, animal husbandry, and fishery industries over the period 2018 – 2022. The primary objectives are to quantify capital utilization efficiency, identify pathways for industry optimization, advance ecological agricultural sustainability, and offer valuable insights to investors and policymakers. Key findings include: (1) When grouped by sub-sector and adjusted to account for external environmental factors and random disturbances, the initial comprehensive capital utilization efficiency in agricultural companies was found to be significantly overestimated. Subsequent third-stage adjustments revealed decreases in average comprehensive efficiency, technical efficiency, and scale efficiency by 29.79%, 3.03%, and 27.37%, respectively, largely driven by a marked decline in scale efficiency, ultimately diminishing overall efficiency. (2) The capital utilization efficiency in agricultural trading firms remains suboptimal, with scale efficiency posing a critical limitation. High dependency on government subsidies and excess specialized personnel further constrain efficiency improvements. (3) Dynamic analysis using the DEA-Malmquist model indicates low total factor productivity in the agricultural sub-sector, primarily due to inefficiencies in capital management and suboptimal scale allocation. These findings underscore the need for targeted strategies to enhance resource allocation and management, bolster talent development and financial management frameworks, and drive technological research and development, innovation, and efficient capital allocation across the agriculture, forestry, animal husbandry, and fishery sectors.

Keywords: Agriculture, forestry, animal husbandry, and fishery; Capital utilization efficiency; Rural revitalization; Three-stage DEA-Malmquist index model

1. Introduction

Rural revitalization represents a critical pathway toward achieving common prosperity and fulfilling China ' s second centenary goal. Driven by the strategic implementation of rural revitalization policies, supported by targeted government initiatives, the agricultural, forestry, animal husbandry, and fishery sectors in China have made notable advancements, with the number of listed companies in these fields experiencing considerable growth. However, as these sectors expand, they also encounter persistent challenges, including capital shortages, low utilization efficiency, and financing constraints. With limited internal funds, enhancing capital utilization efficiency has emerged as a crucial avenue for modern enterprises to improve operational performance. High capital utilization efficiency enables enterprises to achieve greater output with reduced input, representing a superior input-output ratio that directly bolsters their market competitiveness.

This paper integrates a three-stage Data Envelopment Analysis (DEA) model with the Malmquist index to assess the capital utilization efficiency of listed companies in the agricultural, forestry, animal husbandry, and fishery sectors, offering both practical and theoretical insights. A comprehensive review of domestic and international literature highlights a dearth of in-depth studies on capital utilization efficiency within these sectors. Addressing this gap, the study employs the DEA-Malmquist model to systematically evaluate capital holdings and utilization efficiency among listed companies in these industries. Through empirical research and rigorous analysis, the paper seeks to quantify capital utilization efficiency, providing a foundation for industry optimization, promoting sustainable development in ecological agriculture, and delivering valuable guidance for investors and policymakers. The findings offer significant theoretical and practical implications for future assessments of rural revitalization initiatives and provide a valuable framework for understanding capital utilization efficiency across other industries

The application of Data Envelopment Analysis (DEA) for efficiency measurement across various industries has been well-established over time. Initially introduced by(Charnes, 1978). the DEA model was subsequently extended by(H. O. FRIED, 2002), who developed the three-stage DEA model to overcome limitations in the traditional DEA framework. This three-stage DEA model has since been widely employed by international scholars for efficiency evaluation across diverse sectors. For example, (Shyu et al., 2015)utilized the model to examine efficiency in the banking industry across Taiwan, Hong Kong, and mainland China, providing insights into input allocation adjustments to reduce resource wastage. (Lee, 2018)applied the three-stage DEA model to assess operational efficiency within accounting firms, emphasizing contributions from total revenue and case volume. (Liu, 2018)used this model to evaluate the performance of foreign banks in Taiwan, underscoring the accuracy and specificity of efficiency scores. (Zhou et al., 2019)employed the model to analyze operational efficiency within China’s provincial power grid companies, demonstrating significant impacts from external environmental factors on efficiency levels. (Song et al., 2020)similarly utilized the three-stage DEA model to evaluate operational efficiency in China’s aviation industry, incorporating regional environmental factors and statistical noise in the assessment of regional performance. In addition to these examples, studies(Aghakarimi et al., 2023; Chen et al., 2021; Maddah & Roghanian, 2021; Segbenya & Yeboah, 2022; Song et al., 2020; Tan & Li, 2020; Wang et al., 2024; Zhou et al., 2019) have applied the three-stage DEA model to various sectors, such as education, healthcare, performance reform, and technological innovation, to examine capital utilization efficiency. This study applies the three-stage DEA model and Malmquist index model to listed companies in the agriculture, forestry, animal husbandry, and fishery sectors, treating them as open systems. By obtaining initial efficiency values and subsequently removing external environmental factors and random disturbances, this methodology provides a more accurate representation of the technological and managerial efficiency levels of listed companies in these industries.

2. Research Methodology

A comprehensive review of the existing literature shows that Data Envelopment Analysis (DEA) is widely adopted by scholars as a fundamental approach for studying capital utilization efficiency, often supplemented by advanced econometric models to examine efficiency from multifaceted perspectives. However, capital utilization efficiency is significantly influenced by environmental regulations and random disturbances, indicating that traditional DEA models alone may not fully capture its true efficiency. To address these limitations, this study employs a three-stage DEA model to effectively isolate the impact of external environmental factors on capital utilization efficiency. While the three-stage DEA model demonstrates clear advantages in mitigating external interference, it has inherent limitations. Primarily, the DEA model is geared toward static efficiency analysis, making it inadequate for capturing changes in efficiency over time. Consequently, DEA alone falls short in addressing the dynamic characteristics of capital utilization efficiency. To bridge this gap, the Malmquist index model is introduced, effectively complementing the DEA model by enabling a dynamic analysis of efficiency over time.

In this study, 85 listed companies in China's agriculture, animal husbandry, forestry, and fishery sectors were segmented into four distinct sub-industries. The DEA-Malmquist index model was then employed to conduct an in-depth assessment of capital utilization efficiency within each sector. It is noteworthy that, while the Malmquist index provides valuable insights into temporal efficiency changes, its analysis depends significantly on the initial results derived from the DEA model. Thus, the robustness of this approach is contingent on the model ’ s precision and the comprehensiveness of the underlying data. Furthermore, in decomposing technological progress and efficiency shifts, the Malmquist index may be affected by model assumptions and parameter selection, which can impose certain limitations on the reliability of its findings. In conclusion, although the three-stage DEA-Malmquist index model utilized in this research partly mitigates the limitations of traditional DEA models, caution is warranted in interpreting the results. Future studies should consider adopting more dynamic and complex modeling approaches to more fully capture the multi-dimensional aspects of capital utilization efficiency.

2.1 Three-Stage DEA

2.1.1 First Stage

The traditional DEA model, pioneered by Charnes et al., was initially developed to evaluate the operational efficiency of government departments and to establish benchmarks for service performance. It has since become a widely used tool for assessing the relative efficiency of multiple decision-making units, predicting decision outcomes, and conducting policy evaluations. Over time, its application has expanded into a variety of fields. Recognizing that the traditional DEA model is limited to static efficiency analysis, Fried et al. introduced the three-stage DEA model, which incorporates adjustments for external environmental factors and random disturbances. DEA methodology includes several variations, most notably the CCR and BCC models, differentiated by their approach to returns to scale. Considering that capital utilization efficiency often demonstrates variable returns to scale, this study employs the BCC model as the most appropriate framework for measuring relative efficiency. Given that output variables are generally uncontrollable while input variables can be regulated, this research utilizes an output-oriented DEA-BCC model to evaluate the capital utilization efficiency of 85 listed companies in China's agriculture, forestry, animal husbandry, and fishery sectors. The corresponding formula is provided as follows:

$$BCC-S.t.\quad \begin{cases} \min[\varphi-\varepsilon(\sum_{i=1}^{m}s^{-}{}_{i}+\sum_{i=1}^{n}s^{+}{}_{i})], \\ \sum_{i=1}^{n}x_i\lambda_i+S^{-}=\varphi X_0, \\ \sum_{i=1}^{n}y_i\lambda_i-S^{+}=y_0, \\ \lambda_i\geq 0, i=1,2,....,n, \\ S^{+}\geq 0, S^{-}\geq 0, \end{cases} \tag{1}$$

In Equation (1), the input variables are denoted by x, while the output variables are represented by y,the weights assigned to these input and output variables are u and v
respectively.The terms s− and s+ denote the slack variables,and ϵ represents the non-Archimedean infinitesimal.The parameter φ indicates the comprehensive efficiency of the decision-making unit (DMU).A value of φ=1with all slack variables equal to zero signifies that the DMU has achieved optimal input-output efficiency.If φ＝1 but some slack variables are non-zero, the DMU is considered relatively efficient yet still has room for improvement. Conversely,when φ<1, it implies that the DMU exhibits a suboptimal input-output efficiency ratio, indicating considerable potential for enhancement.

The Malmquist index serves as a valuable tool for assessing changes in production efficiency across firms or industries over time. Its fundamental principle is to compare production efficiency at two distinct time points, thereby evaluating both technological advancements and shifts in efficiency. Essentially, the Malmquist index quantifies the variation in production efficiency between periods t and t+1. The detailed formula for this calculation is as follows:

$$M_0=M_I=EC*TC=(X_{t+1}, Y_{t+1}, X_t, Y_t)=[\frac{d_0^t(X_{t+1}, Y_{t+1})}{d_0^t(X_t, Y_t)}*\frac{d_0^{t+1}(X_{t+1}, Y_{t+1})}{d_0^{t+1}(X_t, Y_t)}]^{\frac{1}{2}} \tag{2}$$

In Equation (2), two fundamental components—technological change (TC) and efficiency change (EC)—play a crucial role in determining the Malmquist Index (MI). This formula essentially evaluates the variations in inputs and outputs between two periods. When $MI=1$, it signifies that capital utilization efficiency has remained stable throughout the specified timeframe, with no notable fluctuations.If $MI>1$, it indicates an enhancement in capital utilization efficiency from one period to the next, highlighting an upward trend. In contrast, a value of $MI<1$ suggests a decline in capital utilization efficiency over the observed period.

2.1.2 Second Stage

During the second stage, a Stochastic Frontier Analysis (SFA) regression model is developed to analyze the slack variables identified in the first stage. This method incorporates environmental factors and random disturbances to mitigate inefficiencies in input slacks arising from inadequate control. By doing so, it aims to refine the assessment of resource utilization. The associated formula is as follows:

$$S_{ni}=f(Z_i,\beta^n)+(V_{ni}+U_{ni})\qquad i=1,2,....,I\quad n=1,2,....,N \tag{3}$$

In Equation (3), the composite error term, represented by V_{ni}+U_{ni},comprises two elements: V_{ni} which accounts for random noise, and U_{ni},which captures managerial inefficiency and follows a truncated normal distribution. To ensure unbiased and precise results, all decision-making units (DMUs) are evaluated under standardized external conditions. The modified equation is as follows:

$$X_{ni}^{B} = X_{ni} + [\max(f(Z_i;\beta_n)) - f(Z_i;\beta_n) + [\max(V_{ni} - U_{ni})] \quad (4)$$

The adjustment accounts for external environmental factors, ensuring that all decision-making units (DMUs) are evaluated under uniform external conditions for a more consistent and accurate comparison.

2.1.3 Third Stage

Following the adjustment of input slack variables in the second stage, the revised input and output values are integrated into the traditional one-stage DEA model. This integration enables a recalculation of each decision-making unit's (DMU) relative efficiency, offering a more precise evaluation of their actual utilization efficiency.

2.2 Selection of Evaluation Indicators and Data Sources

This study establishes a framework for evaluating capital utilization efficiency by selecting highly relevant indicators from the input-output perspective, as well as considering external environmental factors. The goal is to assess technical efficiency, scale efficiency, and overall efficiency. To ensure the scientific rigor and validity of the analysis, this paper draws upon the work of numerous previous scholars. It identifies operating cash flow per share and operating costs as input variables. The output variables, reflecting the company's operational performance, financial health, and cash flow over a given period, include net profit, cash flow from operating activities, and operating cash outflows. In addition, environmental factors, such as government subsidies and the number of technical personnel, are treated as external variables influencing the efficiency outcomes. Given the DEA model requirement that the number of DMUs (Decision-Making Units) must be at least twice the number of input-output indicators, companies with significant data gaps were excluded. Ultimately, the study evaluates the capital utilization efficiency of 85 listed companies in the agriculture, forestry, animal husbandry, and fishery sectors in China.

To eliminate the influence of different units of measurement and ensure the comparability of environmental variables, the data were standardized. All data used in this analysis are reliable and sourced from reputable platforms such as Sina Finance, the Shanghai Stock Exchange, and annual reports of listed companies. Table 1 provides a detailed overview of the selected indicators.

Table 1. Evaluation Index System for Capital Utilization Efficiency of Enterprises

Indicator Type	Indicator Name	Unit
Output Indicators	Net Profit	Ten million CNY
	Cash Inflows from Operating Activities	One hundred million CNY
Input Indicators	Cash Outflows from Operating Activities	Ten million CNY
	Operating Cash Flow per Share	One hundred million CNY
	Operating Costs	One hundred million CNY
Environmental Variables	Government Subsidies	One million CNY
	Number of Technical Professionals	Number of people

A Pearson correlation analysis was conducted to examine the relationship between the capital input and output variables of the listed companies. The findings revealed that net profit and cash inflows from operating activities exhibited positive correlation coefficients with the output variables, all of which were statistically significant at the 1% level. These results align with the principle of "positive directionality" [20], indicating a consistent association between these financial metrics.

3. Empirical Analysis

3.1 First-Stage DEA Results Analysis

Based on the core business activities of the listed companies, the 85 publicly traded firms in the agriculture, forestry, animal husbandry, and fishery sectors from 2018 to 2022 were categorized into four sub-industries: agriculture, forestry, animal husbandry, and fishery. To assess their capital input-output efficiency, a two-step approach was adopted. In the first stage, the DEAP2.1 software was employed to calculate the capital utilization efficiency of these 85 companies for the period 2018 – 2022, using the DEA-BCC model. The efficiency derived from the BCC model satisfies the relationship: overall efficiency = pure technical efficiency *scale efficiency. Here, overall efficiency refers to the capital utilization efficiency of each DMU. Without accounting for external environmental variables, a longitudinal analysis of the four sub-industries reveals that the mean values of overall efficiency, pure technical efficiency, and scale efficiency in the forestry and fishery sectors have reached the efficiency frontier, indicating a relatively high level of overall efficiency across these two sectors.

Within the agricultural subsector, comprising 37 companies, the average overall technical efficiency is 0.94, with an average pure technical efficiency of 0.99 and a scale efficiency of 0.95. Notably, 10 companies, including RJNS, KNZY, GNGF, BWKJ, and HNXJ, have fully reached the efficiency frontier (1.00). Additionally, 19 companies, such as QLZY, TYGF, YSJT, JJMY, and HZSY, have achieved strong DEA efficiency (above 0.90). Meanwhile, 8 companies, including LSGF, MHGF, and YSGF, exhibit weak DEA efficiency (below 0.90).In the livestock subsector, comprising a total of 37 companies, the average overall technical efficiency stands at 0.91, with an average pure technical efficiency of 0.97 and scale efficiency at 0.94. Among these, 11 companies, including SWGF, BDH, ZLTY, and HLSW, have fully reached the efficiency frontier (1.00). Additionally, 8 companies, such as ZMGF, FCGF, JXNM, and PLK, have achieved strong DEA efficiency (above 0.90). However, 18 companies, including XWF, ANSW, TMKJ, and ZHKJ, demonstrate weak DEA efficiency (below 0.90). In the forestry subsector, all companies have successfully attained the efficiency frontier, while in the fishery subsector, all but KCGJ have reached the DEA efficiency frontier. Consequently, the ranking of capital utilization efficiency is as follows: forestry companies outperform fishery companies, which in turn exceed agricultural companies, with livestock companies trailing behind. Across all four subsectors, a consistent pattern emerges where pure technical efficiency surpasses scale efficiency. This observation indicates that the enhancement of capital utilization efficiency is predominantly driven by improvements in pure technical efficiency, suggesting that the contributions of technical efficiency are more significant than those stemming from scale advancements. Furthermore, the majority of companies exhibit decreasing returns to scale, implying that excessive scale hampers the efficiency of capital utilization among listed companies. To address this issue, it is imperative to optimize the allocation of capital resources, foster appropriately scaled operations, and ultimately enhance the capital utilization efficiency of these companies.

From a horizontal analysis perspective, the average Malmquist index (MI) of 85 listed companies in the agricultural, forestry, animal husbandry, and fishery sectors exhibited minor fluctuations around the value of 1.00 during the period from 2018 to 2022. Specifically, the MI values for agricultural companies were recorded at 0.90, 1.03, 0.97, and 1.00; for animal husbandry companies, the values were 1.01, 1.02, 0.97, and 1.01; for forestry companies, the values stood at 0.92, 1.18, 0.98, and 1.05; while for fishery companies, the values were 0.99, 1.11, 0.92, and 1.07. These findings indicate that the dynamic changes in funding utilization efficiency across the various sub-industries exhibit distinct characteristics, providing valuable insights for further research.Among the agricultural companies, ZLKJ and among the fishery companies, HDJ exhibited similar trends, as both demonstrated the highest fluctuations in their Malmquist index (MI) efficiency values. During the period from 2019 to 2020, ZLKJ recorded a peak MI efficiency value of 2.48, while HDJ reached a maximum of 1.43, positioning both ahead of their respective industry peers. However, in the subsequent period from 2020 to 2021, ZLKJ's MI efficiency value plummeted to its lowest point at 0.45, and HDJ's MI efficiency also declined to 0.72. These dynamics highlight the volatility of funding utilization efficiency within these sectors, emphasizing the need for targeted strategies to enhance stability and performance.Among the agricultural companies, ZLKJ and among the fishery companies, HDJ exhibited similar trends, as both demonstrated the highest fluctuations in their Malmquist index (MI) efficiency values. During the period from 2019 to 2020, ZLKJ recorded a peak MI efficiency value of 2.48, while HDJ reached a maximum of 1.43, positioning both ahead of their respective industry peers. However, in the subsequent period from 2020 to 2021, ZLKJ's MI efficiency value plummeted to its lowest point at 0.45, and HDJ's MI efficiency also declined to 0.72. These dynamics highlight the volatility of funding utilization efficiency within these sectors, emphasizing the need for targeted strategies to enhance stability and performance.

Table 2. Overall Efficiency Changes of Four Sub-Sectors in the First Stage (2018–2022)

NO.	Stock code	Sub-sector/DMU	TE1	PTE1	SE1	Returns to scale	EC				TC				MI			
		Agricultural					18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22
1	bj830964	RNJS	1.00	1.00	1.00	-	0.93	1.07	0.96	0.99	0.95	1.03	1.01	0.99	0.89	1.10	0.97	0.98
2	bj831087	QLZY	0.92	1.00	0.92	drs	1.01	0.99	1.09	0.97	0.98	1.01	1.01	0.97	0.99	1.00	1.10	0.94
3	bj832023	TYGF	0.90	1.00	0.90	drs	1.06	0.93	1.12	0.95	0.97	1.01	1.01	0.99	1.03	0.93	1.13	0.94
4	bj832419	LSGF	0.85	1.00	0.85	drs	1.03	1.01	0.99	1.02	0.96	0.99	1.02	0.99	0.99	1.00	1.01	1.00
5	bj837403	KNZY	1.00	1.00	1.00	-	0.95	1.05	0.97	1.02	0.93	0.97	0.90	0.98	0.89	1.03	0.87	1.00
6	sh600108	YSJT	0.97	0.99	0.99	drs	0.95	1.02	1.00	1.03	1.02	1.00	1.02	0.97	0.97	1.02	1.02	1.00
7	sh600127	JJMY	0.97	0.98	0.99	drs	0.97	1.03	1.00	0.98	1.02	0.99	1.00	1.01	0.98	1.02	0.99	0.99
8	sh600191	HZSY	0.98	0.99	0.99	drs	1.01	1.01	1.00	1.00	0.98	1.05	1.10	0.85	0.99	1.06	1.10	0.85
9	sh600251	GNGF	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	0.98	1.85	0.68	1.05	0.98	1.85	0.68	1.05
10	sh600313	NFZY	0.97	0.98	0.99	drs	0.97	1.03	0.99	1.04	1.03	1.00	1.01	1.02	1.00	1.04	1.00	1.05
11	sh600354	DHZY	0.93	0.98	0.95	drs	1.00	1.00	1.00	1.07	1.00	1.00	1.00	0.97	1.00	1.00	1.01	1.04
12	sh600371	WXDN	0.92	1.00	0.92	drs	1.03	1.04	1.01	1.00	0.97	1.00	1.04	0.95	0.99	1.05	1.06	0.95
13	sh600540	XSGF	0.96	0.99	0.97	drs	0.98	1.07	1.00	0.94	0.98	1.01	1.12	0.81	0.96	1.08	1.12	0.76
14	sh600883	BWKJ	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	1.10	1.09	0.92	1.22	1.10	1.09	0.92	1.22
15	sh600962	GTZL	0.98	0.99	0.98	drs	1.03	1.00	0.87	1.14	1.05	0.99	1.00	0.97	1.08	0.99	0.87	1.10
16	sh601118	HNXJ	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	1.06	1.04	0.98	1.04	1.06	1.04	0.98	1.04
17	sh603336	HHGS	1.00	1.00	1.00	-	0.94	1.01	1.00	1.02	0.98	1.00	1.01	0.98	0.91	1.01	1.01	1.00
18	sz000639	XWSP	1.00	1.00	1.00	-	0.97	1.01	0.96	0.99	1.03	1.01	1.00	1.00	1.00	1.02	0.96	1.00
19	sz000713	FLZY	0.96	0.98	0.98	drs	0.96	0.98	1.00	1.04	1.02	1.02	1.02	0.96	0.98	0.99	1.02	0.99
20	sz000911	GNTY	0.89	0.90	0.99	drs	1.00	1.14	0.91	1.04	1.01	0.93	1.00	0.97	1.01	1.05	0.90	1.01
21	bj830964	ZLKJ	1.00	1.00	1.00	-	0.77	1.30	0.84	1.19	0.85	1.92	0.54	1.07	0.66	2.48	0.45	1.28
22	sz000972	ZJJK	0.93	0.97	0.96	drs	1.07	1.00	1.00	1.00	1.08	0.84	0.90	1.04	1.16	0.84	0.89	1.04
23	sz000998	LPGK	0.96	1.00	0.96	drs	0.98	1.06	1.00	1.00	1.02	1.05	0.98	0.93	0.99	1.12	0.98	0.93
24	sz002041	DHZY	0.92	0.98	0.94	drs	1.07	1.02	1.00	1.00	0.98	1.02	0.99	0.97	1.04	1.04	0.99	0.97
25	sz002234	MHGF	0.85	1.00	0.85	drs	1.02	1.08	0.99	1.09	1.12	0.74	1.03	0.96	1.15	0.79	1.01	1.05
26	sz002458	YSGF	0.85	1.00	0.85	drs	1.18	0.94	0.97	1.03	1.16	0.74	1.03	0.96	1.37	0.70	0.99	0.99
27	sz002548	JXN	0.97	0.98	1.00	drs	0.95	1.03	0.97	1.03	1.00	1.01	1.01	0.98	0.95	1.04	0.98	1.01
28	sz002746	XTGF	0.87	1.00	0.87	drs	1.06	1.03	0.97	1.04	1.05	0.91	1.02	0.98	1.11	0.94	0.99	1.02
29	sz002772	ZXJY	0.88	0.99	0.89	drs	1.01	1.03	1.07	0.97	0.96	0.97	1.05	0.89	0.98	1.01	1.12	0.86
30	sz300021	DYJS	1.00	1.00	1.00	-	1.00	0.95	0.98	1.04	0.99	0.99	1.03	0.96	0.99	0.94	1.01	1.00
31	sz300119	RPSW	0.91	0.99	0.91	drs	1.00	1.06	0.95	1.03	0.98	0.95	1.03	0.94	0.98	1.01	0.98	0.97
32	sz300138	CGSW	0.98	0.99	0.99	drs	1.02	0.97	1.00	1.03	1.00	0.99	1.01	0.99	1.02	0.96	1.01	1.02
33	sz300175	LYGF	0.96	1.00	0.96	drs	1.00	1.02	0.99	1.01	0.98	1.01	1.01	1.00	0.98	1.02	1.00	1.00
34	sz300189	SNKJ	1.00	1.00	1.00	-	0.97	1.03	0.98	0.99	0.89	1.01	0.98	1.00	0.87	1.03	0.96	0.99
35	sz300511	XRSW	0.90	0.99	0.91	drs	1.01	0.98	0.99	1.04	1.00	1.01	0.99	0.96	1.00	0.99	0.98	1.00
36	sz300673	PDGF	0.78	1.00	0.78	drs	1.28	0.87	1.09	1.01	0.98	0.97	1.03	0.97	1.25	0.84	1.12	0.98
37	sz300972	WCJT	0.78	1.00	0.78	drs	0.94	1.35	0.89	1.02	0.96	0.73	0.99	0.99	0.90	0.99	0.88	1.01
		Mean	0.94	0.99	0.95		1.00	1.03	0.99	1.02	1.00	1.01	0.98	0.98	0.90	1.03	0.97	1.00
		Animal Husbandry					18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22
38	sh600195	ZMGF	0.91	0.98	0.93	drs	1.11	0.78	1.17	1.10	1.00	1.11	0.88	0.97	1.11	0.86	1.03	1.06
39	sh600201	SWGF	1.00	1.00	1.00	-	0.80	1.23	1.00	0.97	1.05	0.96	0.92	1.00	0.84	1.18	0.91	0.97
40	sh600598	BDH	1.00	1.00	1.00	-	1.00	0.92	1.09	1.00	0.99	1.15	0.90	0.95	0.99	1.06	0.98	0.95
41	sh600737	ZLTY	1.00	1.00	1.00	-	0.98	0.89	1.14	1.00	1.06	1.15	0.89	1.06	1.04	1.03	1.02	1.06
42	sh600965	FCGF	0.92	0.97	0.95	drs	1.09	0.89	1.09	1.02	1.25	0.82	0.94	0.97	1.36	0.73	1.02	0.99
43	sh600975	XWF	0.83	0.97	0.86	drs	1.12	0.88	1.21	0.92	0.91	1.07	0.95	0.95	1.02	0.95	1.16	0.88

44	sh603363	ANSW	0.84	0.86	0.98	drs	0.97	0.96	1.08	1.01	1.03	1.14	0.89	1.00	1.00	1.10	0.95	1.01
45	sh603477	JXNM	0.96	1.00	0.96	drs	0.93	0.94	1.08	0.94	1.02	0.98	0.91	0.99	0.95	0.92	0.99	0.93
46	sh603566	PLK	0.95	1.00	0.95	drs	0.91	0.98	1.04	1.00	1.05	1.00	0.94	1.00	0.95	0.98	0.97	1.00
47	sh603609	HFGF	0.93	0.95	0.98	drs	0.96	0.93	1.13	1.02	1.06	1.12	0.92	1.02	1.02	1.04	1.04	1.04
48	sh603668	TMKJ	0.82	0.97	0.85	drs	0.90	0.98	1.20	1.05	1.14	0.95	0.89	1.00	1.03	0.93	1.07	1.05
49	sh603718	HLSW	1.00	1.00	1.00	-	0.95	1.06	0.96	1.04	1.06	0.97	0.97	1.17	1.00	1.03	0.93	1.21
50	sz000702	ZHKJ	0.87	0.97	0.90	drs	0.97	1.18	1.00	1.00	0.98	1.04	0.98	0.97	0.96	1.23	0.98	0.97
51	sz000735	LNS	0.86	0.98	0.88	drs	1.10	0.98	1.09	0.98	0.91	1.04	0.93	0.84	0.99	1.02	1.01	0.83
52	sz000876	XXW	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	1.07	1.12	1.21	0.82	1.07	1.12	1.21	0.82
53	sz002100	TKSW	1.00	1.00	1.00	-	0.90	1.11	0.87	1.05	0.84	1.09	0.85	1.00	0.76	1.21	0.74	1.05
54	sz002124	TBSP	0.89	0.93	0.96	drs	0.99	1.11	0.85	1.13	1.02	1.11	0.89	1.00	1.01	1.23	0.76	1.13
55	sz002286	BLB	0.84	0.96	0.87	drs	1.03	0.88	1.17	1.09	0.98	1.05	0.91	0.99	1.00	0.92	1.06	1.07
56	sz002299	SNFZ	1.00	1.00	1.00	drs	0.98	0.82	1.12	1.00	1.16	1.08	0.81	0.99	1.14	0.89	0.90	0.99
57	sz002321	HYNY	0.89	0.95	0.93	drs	1.00	1.06	0.86	1.21	1.10	1.11	0.97	0.98	1.10	1.18	0.84	1.18
58	sz002385	BDN	0.93	0.94	0.99	drs	0.97	1.02	1.03	1.00	1.07	1.04	0.94	1.02	1.03	1.06	0.96	1.02
59	sz002481	STSP	0.87	0.97	0.90	drs	1.15	0.89	1.13	0.92	0.97	1.19	0.89	0.94	1.12	1.06	1.00	0.87
60	sz002505	PDNM	0.88	0.90	0.98	drs	0.97	1.01	1.08	1.00	1.03	1.00	0.94	0.99	1.00	1.01	1.02	0.99
61	sz002556	HLGF	0.82	0.92	0.90	drs	0.93	1.05	1.06	1.03	1.13	1.04	0.95	1.00	1.05	1.09	1.00	1.02
62	sz002679	FJJS	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	0.89	0.94	1.05	0.90	0.89	0.94	1.05	0.90
63	sz002688	JHSW	0.87	0.97	0.90	drs	0.99	0.98	1.07	1.01	0.99	1.00	0.94	0.99	0.98	0.99	1.01	1.01
64	sz002696	BYGF	0.88	0.97	0.91	drs	0.88	1.08	1.09	0.95	0.99	1.06	0.94	0.99	0.87	1.14	1.03	0.94
65	sz002714	MYGF	0.94	0.95	0.99	drs	1.06	1.00	1.00	1.00	1.26	1.19	0.77	1.02	1.34	1.19	0.77	1.02
66	sz002852	DDQ	0.85	0.96	0.88	drs	1.18	0.82	1.19	0.91	0.99	1.04	0.90	0.98	1.17	0.86	1.07	0.89
67	sz002868	LKSH	0.90	0.99	0.90	drs	1.09	1.03	0.99	1.01	0.92	1.04	0.97	1.04	1.00	1.07	0.96	1.05
68	sz002891	ZCGF	0.85	0.97	0.88	drs	0.99	1.00	0.98	1.07	0.97	1.10	0.91	1.00	0.96	1.10	0.89	1.07
69	sz300094	GLSC	0.86	0.97	0.89	drs	1.07	0.99	0.99	1.03	1.00	1.03	0.95	1.00	1.07	1.02	0.94	1.03
70	sz300268	*STJW	1.00	1.00	1.00	-	0.74	1.00	1.05	1.08	0.77	1.10	0.87	0.94	0.57	1.10	0.91	1.01
71	sz300313	*STTS	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	0.97	1.10	1.02	1.21	0.97	1.10	1.02	1.21
72	sz300498	WSGF	1.00	1.00	1.00	-	1.00	1.00	0.94	1.07	1.10	0.99	0.97	1.04	1.10	0.99	0.91	1.11
73	sz300761	LHGF	0.87	1.00	0.87	drs	1.04	0.88	1.07	1.03	1.03	1.12	0.82	0.95	1.07	0.98	0.88	0.99
74	sz300967	XMGF	0.81	0.99	0.81	drs	1.18	0.87	1.04	1.07	0.95	0.99	0.95	1.00	1.12	0.87	0.98	1.07
		Mean	0.91	0.97	0.94		0.99	0.97	1.05	1.02	1.02	1.05	0.92	0.99	1.01	1.02	0.97	1.01
		Forestry					18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22
75	sh600265	*STJG	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	0.69	1.71	0.74	1.08	0.69	1.71	0.74	1.08
76	sz000592	PTFZ	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	1.09	1.11	0.83	0.93	1.09	1.11	0.83	0.93
77	sz000663	YALY	1.00	1.00	1.00	-	0.91	1.10	1.00	1.00	1.04	0.92	1.16	1.23	0.95	1.01	1.16	1.23
78	sz002567	TRS	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	1.00	1.01	1.31	0.99	1.00	1.01	1.31	0.99
		Mean	1.00	1.00	1.00		0.98	1.02	1.00	1.00	0.94	1.15	0.98	1.05	0.92	1.18	0.98	1.05
		Fishery					18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22
79	sh600097	KCGJ	0.99	1.00	0.99	drs	1.01	1.00	0.91	1.04	0.96	1.04	1.05	1.00	0.97	1.04	0.95	1.03
80	sh600257	THGF	1.00	1.00	1.00	-	0.98	1.00	1.02	1.00	0.96	1.07	0.94	1.00	0.94	1.07	0.96	1.00
81	sh600359	XNKF	1.00	1.00	1.00	irs	1.00	1.00	1.00	1.00	1.04	1.16	0.92	1.05	1.04	1.16	0.92	1.05
82	sh600467	HDJ	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	1.05	1.43	0.72	0.96	1.05	1.43	0.72	0.96
83	sz000798	ZSYY	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	1.02	1.04	1.02	1.28	1.02	1.04	1.02	1.28
84	sz002069	ZZD	1.00	1.00	1.00	-	1.00	1.00	1.01	1.00	0.98	1.02	0.98	1.01	0.98	1.01	0.99	1.01
85	sz300087	QYGK	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	0.94	1.09	0.95	1.21	0.94	1.09	0.95	1.21
		Mean	1.00	1.00	1.00		1.00	1.00	0.99	1.01	0.99	1.11	0.93	1.07	0.99	1.11	0.92	1.07

Note:bj refers to the Beijing Stock Exchange，sh refers to the Shanghai Stock Exchangesz refers to the Shenzhen Stock Exchange.TE1 represents the overall efficiency score in the initial phase.PTE1 denotes the pure technical efficiency in the first stage, while SE1 reflects the scale efficiency at this stage.irs signifies increasing returns to scale, dre denotes decreasing returns to scale, and "-" indicates constant returns to scale.

3.2 Second-Stage SFA Regression Analysis

To ensure accuracy and reliability in the results, slack variables for input factors were calculated by subtracting the original input values from the target input values derived in the first stage. These slack variables were then utilized as dependent variables, while government subsidies and the number of technical professionals were incorporated as independent variables representing external environmental factors. To address dimensional effects, the environmental variables were standardized, and data estimation was performed using Frontier 4.1 software. The regression outcomes are detailed in Table 3. The LR test statistics for all three models were significant at the 1% level, underscoring the necessity of accounting for external environmental influences and random disturbances in this analysis. With the exception of the slack value of operating cash flow per share, the γ values for the other variables were 532.27 and met the 1% significance threshold, indicating that both managerial inefficiency and random noise significantly impact the capital utilization efficiency of listed firms in the agriculture, forestry, animal husbandry, and fishery sectors. A negative regression coefficient reveals that an increase in the environmental variable reduces input redundancy, thereby enhancing capital utilization efficiency. Conversely, a positive regression coefficient implies that the environmental variable hinders progress in capital utilization efficiency.

Government subsidies are found to have a significant positive correlation with the slack values of cash outflows from operating activities and operating costs, yet they exert no meaningful impact on the slack value of operating cash flow per share. Although government subsidies can bolster capital inputs for companies in the agriculture, forestry, animal husbandry, and fishery sectors by leveraging resource allocation mechanisms, they may simultaneously diminish these firms' motivation to enhance capital utilization efficiency, despite providing some relief from financial constraints. Likewise, the number of technical professionals is positively correlated with the slack values of cash outflows and operating costs, without significantly influencing the slack value of operating cash flow per share. While technical professionals undoubtedly add substantial value to companies and drive subsequent rounds of research and development, their contributions can also lead to elevated expectations and an expansion of business operations, resulting in increased capital and labor investments. However, if not managed properly, this unchecked growth may lead to inefficient use of production resources, thereby raising input slack. Moreover, inadequate management practices can further impede the overall efficiency of capital utilization.

Table 3. Second-Stage SFA Regression Results

Project	Slack Value of Cash Outflows from Operating Activities		Slack Value of Operating Cash Flow per Share		Slack Value of Operating Costs	
	Result	t-value	Result	t-value	Result	t-value
Constant	-28.36***	-3.292	0.28	36.59	-28.36***	-3.29
Government Subsidies	37.54 ***	9.98	0.02	3.92	37.54***	9.98
Technical Professionals	10.14 ***	3.28	0.01	1.37	10.14 ***	3.28
σ^2	39051.57***	37767.99	0.01	8.54	39051.57***	37767.99
γ	0.93***	168.17	0.48	7.66	0.93***	168.17
LR Value	532.27		68.92		532.27	

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

3.3 Third Stage Adjusted DEA Results Analysis

After excluding external environmental factors and random disturbances, the input and output variables of China's agricultural, forestry, animal husbandry, and fishery listed companies over the past five years were readjusted and recalculated using the DEAP 2.1 software. A comparison of the longitudinal data in Tables 1 and 4 reveals that, after removing the impact of external factors on efficiency, the average comprehensive efficiency of agricultural companies decreased from 0.94 to 0.66, while the average scale efficiency dropped from 0.95 to 0.69. This represents significant declines of 29.79% and 27.37%, respectively. These findings underscore the substantial impact of external variables on the efficiency metrics within the agricultural sector, indicating a pressing need for companies to adapt their operational strategies accordingly.

Following the adjustments, the average comprehensive technical efficiency, technical efficiency, and scale efficiency did not reach the efficiency frontier. Among the four sub-industries, the capital utilization efficiency of agricultural companies was found to be significantly overestimated. During the study period, after adjusting the inputs, 46 agricultural, forestry, animal husbandry, and fishery listed companies experienced a decline in efficiency, with most companies having their capital utilization efficiency overestimated prior to adjustments. Notably, RJNS and HNXJ showed the most significant declines, dropping from an adjusted efficiency of 1.00 to 0.56. In contrast, after adjusting the inputs, 24 companies, including ZMGF and FCGF, demonstrated improved capital utilization efficiency, indicating that external environmental factors negatively affected their capital utilization activities. The most pronounced improvement was observed in XMGF, which increased from an adjusted efficiency of 0.81 to 0.96. After excluding the influence of external factors, only the agricultural sub-industry exhibited significant variability in capital utilization efficiency, with ZLKJ emerging as the sole company in this sector to achieve efficiency frontier status. These results highlight the critical need for accurate assessments of capital efficiency, particularly in the agricultural sector, where external influences can markedly distort efficiency evaluations.

In terms of pure technical efficiency, after adjusting the inputs, four companies in the agricultural, forestry, animal husbandry, and fishery sectors, namely XSGF, LNS, BDN, and MYGF, exhibited improvements in efficiency. However, the majority of companies had their pure technical efficiency overestimated prior to adjustments. Notably, 30 companies, including ZLKJ, SWGF, and HLSW, maintained their status at the efficiency frontier, with no changes in pure technical efficiency before and after the input adjustments. After accounting for external environmental factors, it was found that, except for the agricultural sector, the differences in pure technical efficiency among the remaining three sub-industries were minimal. This suggests that, while some companies have room for improvement, others have effectively optimized their operations to remain at the efficiency frontier. Overall, these findings underline the importance of precise input adjustments to accurately assess and enhance technical efficiency across these sectors.

In terms of scale efficiency, the adjustment of inputs led to a decline in efficiency for 42 companies in the agricultural, forestry, animal husbandry, and fishery sectors, including PDNM, YALY, and ZSYY. This trend suggests that the decrease in capital utilization efficiency is primarily driven by a reduction in scale efficiency. Among these companies, HNXJ exhibited the most pronounced decline in scale efficiency, plummeting from 0.98 before the adjustments to 0.57 afterward. Conversely, 24 companies, including XWF, ANSW, and TMKJ, improved their scale efficiency following the input adjustments. After excluding the influence of external environmental factors, the disparities in scale efficiency among the three sub-sectors, aside from agriculture, were minimal.

From a horizontal analysis perspective, following adjustments during the period from 2018 to

2022, the mean Malmquist Index (MI) for 85 listed companies in the agriculture, forestry, animal husbandry, and fishery sectors stands at 1.00. The average technical progress efficiency is 0.86, while the average scale efficiency is 1.15. The scale efficiency exceeding 1 indicates an improvement, whereas the technical efficiency below 1 signals a regression in the utilization of technology among these companies.Specifically, the MI averages for agricultural companies are recorded at 1.05, 0.96, 1.00, and 0.98; for animal husbandry companies, the figures are 1.02, 1.04, 0.96, and 1.01; for forestry companies, the MI averages are 1.00, 1.02, 1.05, and 1.02; and for fishery companies, they stand at 1.00, 1.05, 0.96, and 1.07. Notably, both agricultural and animal husbandry companies show slight improvements in total factor productivity compared to pre-adjustment figures. In contrast, forestry and fishery companies experience minor declines in their total factor productivity relative to the previous period.

Among the agricultural companies, ZLKJ exhibits significant fluctuations in its Malmquist Index (MI) after adjustments. During the period from 2018 to 2019, its MI increased dramatically from 0.66 to 4.68, while the Technical Change (TC) index rose from 0.85 to 4.68. However, in the subsequent period of 2019 to 2020, the MI plummeted from 2.48 to 0.19, with the TC index also declining from 1.98 to 0.19. Several factors contribute to these fluctuations within the context of the prevailing economic landscape. First, macroeconomic volatility, shifts in industry demand, raw material prices, and imbalances in market supply and demand can directly impact operational costs and revenues, leading to variations in capital utilization efficiency. Second, significant technological advancements or regressions within the company may also cause considerable volatility in the MI. Third, unexpected external factors such as global economic conditions, geopolitical risks, natural disasters, and public health emergencies (such as pandemics) can destabilize company operations, resulting in short-term fluctuations in capital utilization efficiency. These elements collectively influence the efficiency of capital utilization in different years, causing the MI to exhibit substantial variations in certain periods.

Overall, as shown in Table 5, the Malmquist Index (MI) for the 85 agricultural, forestry, animal husbandry, and fishery listed companies exhibited a gradual annual increase from 2018 to 2020. This trend may be attributed to the post-pandemic recovery, during which government support policies enabled these companies to promptly adjust their strategic planning, capital utilization strategies, and management measures in alignment with their current development status.

Table 4. Overall Efficiency Changes of Four Sub-Sectors in the Third Stage (2018–2022)

NO.	Stock code	Sub-sector	TE3	PTE3	SE3	Returns to scale	EC				TC				MI			
		Agricultural					18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22
1	bj830964	RNJS	0.56	0.96	0.58	drs	0.12	8.79	0.80	1.01	7.93	0.11	1.21	0.98	0.98	0.98	0.97	0.99
2	bj831087	QLZY	0.67	0.96	0.70	drs	1.18	1.09	0.75	1.17	0.84	0.91	1.23	0.88	0.99	1.00	0.92	1.02
3	bj832023	TYGF	0.67	0.96	0.70	drs	1.20	1.08	0.86	1.06	0.85	0.91	1.19	0.94	1.01	0.98	1.03	0.99
4	bj832419	LSGF	0.67	0.96	0.69	drs	1.13	1.13	0.83	1.11	0.88	0.89	1.21	0.91	0.99	1.01	1.00	1.00
5	bj837403	KNZY	0.67	0.96	0.70	drs	1.08	1.14	0.83	1.19	0.98	0.84	1.25	0.92	1.06	0.96	1.04	1.09
6	sh600108	YSJT	0.63	0.96	0.66	drs	1.33	1.02	0.87	1.02	0.75	0.98	1.13	0.97	1.01	1.00	0.98	0.99
7	sh600127	JJMY	0.62	0.95	0.65	drs	1.34	1.00	0.95	0.90	0.73	1.04	1.01	1.05	0.97	1.04	0.96	0.95
8	sh600191	HZSY	0.66	0.95	0.69	drs	1.26	1.05	0.87	1.13	0.79	0.95	1.16	0.95	1.00	0.99	1.01	1.08
9	sh600251	GNGF	0.62	0.96	0.64	drs	1.01	1.61	0.76	0.98	0.84	1.21	0.87	0.95	0.85	1.94	0.66	0.92
10	sh600313	NFZY	0.62	0.96	0.65	drs	1.36	0.99	0.92	1.03	0.72	1.00	1.11	1.01	0.98	0.99	1.02	1.03
11	sh600354	DHZY	0.65	0.94	0.69	drs	1.27	1.06	0.84	1.04	0.77	0.94	1.18	0.91	0.98	0.99	1.00	0.95
12	sh600371	WXDN	0.67	0.96	0.70	drs	1.20	1.11	0.81	1.10	0.83	0.94	1.18	0.92	1.00	1.04	0.95	1.01
13	sh600540	XSGF	0.64	0.96	0.67	drs	1.24	1.14	1.12	0.72	0.79	0.98	1.01	0.86	0.98	1.11	1.13	0.62
14	sh600883	BWKJ	0.66	0.96	0.69	drs	1.26	1.06	0.86	1.06	0.79	0.95	1.16	0.95	0.99	1.01	1.00	1.01
15	sh600962	GTZL	0.64	0.96	0.67	drs	1.56	0.88	0.78	1.05	0.71	1.06	1.15	0.90	1.11	0.93	0.89	0.94
16	sh601118	HNXJ	0.56	0.98	0.57	drs	1.71	0.88	1.19	0.74	0.57	1.17	0.84	1.37	0.97	1.03	1.00	1.02
17	sh603336	HHGS	0.65	0.96	0.68	drs	1.25	1.07	0.88	1.04	0.76	0.95	1.15	0.97	0.95	1.01	1.01	1.00
18	sz000639	XWSP	0.59	0.99	0.60	drs	1.26	1.07	1.03	0.89	0.82	0.96	1.06	1.02	1.03	1.03	1.10	0.91
19	sz000713	FLZY	0.65	0.96	0.68	drs	1.20	1.05	0.90	1.00	0.77	0.93	1.16	0.94	0.93	0.98	1.05	0.93
20	sz000911	GNTY	0.65	0.89	0.73	drs	1.19	1.12	0.92	1.03	1.64	0.44	1.20	0.95	1.95	0.49	1.11	0.98
21	bj830964	ZLKJ	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	4.68	0.19	0.66	1.65	4.68	0.19	0.66	1.65
22	sz000972	ZJJK	0.64	0.93	0.68	drs	1.25	1.09	0.91	0.99	0.86	0.93	1.14	0.95	1.08	1.02	1.04	0.94
23	sz000998	LPGK	0.68	1.00	0.68	drs	1.22	1.03	0.76	1.19	0.77	0.90	1.26	0.88	0.94	0.92	0.95	1.04
24	sz002041	DHZY	0.66	0.95	0.70	drs	1.21	1.09	0.83	1.13	0.81	0.90	1.21	0.93	0.98	0.98	1.01	1.05
25	sz002234	MHGF	0.66	0.98	0.67	drs	0.60	2.07	0.91	1.29	1.34	0.65	1.19	0.93	0.80	1.35	1.09	1.20
26	sz002458	YSGF	0.66	0.97	0.68	drs	0.76	1.69	0.86	1.02	1.19	0.76	1.14	0.96	0.91	1.29	0.99	0.98
27	sz002548	JXN	0.60	0.94	0.64	drs	1.26	1.12	0.84	1.06	0.80	0.90	1.15	1.00	1.02	1.01	0.96	1.06
28	sz002746	XTGF	0.65	0.98	0.66	drs	0.93	1.31	0.96	0.93	1.25	0.71	1.16	0.99	1.16	0.93	1.11	0.91
29	sz002772	ZXJY	0.67	0.96	0.69	drs	1.03	1.21	1.15	0.77	0.93	0.84	1.13	0.89	0.96	1.01	1.29	0.69
30	sz300021	DYJS	0.65	0.96	0.68	drs	1.36	1.02	0.80	1.02	0.84	1.01	1.13	0.95	1.14	1.03	0.90	0.97
31	sz300119	RPSW	0.68	0.97	0.70	drs	1.04	1.19	0.82	1.12	0.92	0.85	1.26	0.88	0.95	1.00	1.03	0.99
32	sz300138	CGSW	0.76	0.97	0.79	drs	1.26	1.04	1.00	1.00	0.80	0.86	1.26	0.97	1.01	0.89	1.26	0.97
33	sz300175	LYGF	0.66	0.96	0.69	drs	1.25	1.03	0.87	1.07	0.79	0.95	1.17	0.94	0.99	0.98	1.01	1.00
34	sz300189	SNKJ	0.67	0.96	0.70	drs	1.25	1.05	0.86	1.06	0.83	0.95	1.17	0.95	1.04	0.99	1.01	1.01
35	sz300511	XRSW	0.71	0.97	0.74	drs	0.91	1.25	0.83	1.07	1.01	0.81	1.23	0.91	0.93	1.02	1.02	0.97
36	sz300673	PDGF	0.66	0.96	0.69	drs	1.37	0.90	0.94	0.94	0.84	0.94	1.18	0.93	1.15	0.84	1.12	0.87
37	sz300972	WCJT	0.67	0.96	0.69	drs	0.93	1.29	0.86	1.14	1.01	0.80	1.24	0.89	0.95	1.03	1.06	1.02
		Mean	0.66	0.96	0.69		1.10	1.18	0.89	1.02	0.96	0.81	1.13	0.96	1.05	0.96	1.00	0.98
		AnimalHusban					18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22
38	sh600195	ZMGF	0.95	0.97	0.98	drs	0.99	0.81	1.24	1.05	1.02	1.16	0.83	1.00	1.01	0.94	1.03	1.05
39	sh600201	SWGF	1.00	1.00	1.00	-	0.97	0.81	1.26	1.00	0.99	1.23	0.81	1.02	0.96	1.00	1.02	1.02
40	sh600598	BDH	1.00	1.00	1.00	-	0.98	0.82	1.21	0.98	1.01	1.24	0.79	1.02	0.99	1.01	0.96	1.01
41	sh600737	ZLTY	0.95	0.95	1.00	drs	0.94	0.88	1.28	1.00	1.12	1.14	0.86	1.04	1.06	1.00	1.10	1.04
42	sh600965	FCGF	0.94	0.97	0.98	drs	1.04	0.83	1.21	0.98	1.00	1.15	0.85	1.01	1.03	0.96	1.03	0.99
43	sh600975	XWF	0.96	0.97	0.99	drs	1.01	0.86	1.21	0.95	0.99	1.13	0.89	0.98	1.00	0.96	1.08	0.93

44	sh603363	ANSW	0.85	0.86	0.99	drs	1.09	0.79	1.13	1.02	1.03	1.22	0.82	0.99	1.12	0.97	0.94	1.01
45	sh603477	JXNM	0.97	0.97	0.99	drs	1.00	0.77	1.30	0.93	1.00	1.23	0.82	1.02	1.00	0.94	1.06	0.94
46	sh603566	PLK	1.00	1.00	1.00	irs	1.00	0.77	1.30	0.94	1.01	1.29	0.77	1.02	1.01	1.00	1.00	0.96
47	sh603609	HFGF	0.92	0.94	0.98	drs	0.92	0.87	1.23	1.02	1.10	1.18	0.85	1.03	1.02	1.02	1.04	1.06
48	sh603668	TMKJ	0.94	0.96	0.98	drs	1.01	0.73	1.34	1.02	1.01	1.39	0.79	1.01	1.02	1.01	1.06	1.03
49	sh603718	HLSW	0.98	1.00	0.98	irs	1.00	0.84	1.21	1.01	1.00	1.17	0.85	1.02	0.99	0.98	1.03	1.03
50	sz000702	ZHKJ	0.94	0.97	0.97	drs	1.00	1.00	1.02	1.05	0.99	1.13	0.87	1.01	0.99	1.12	0.88	1.06
51	sz000735	LNS	1.00	1.00	1.00	-	1.00	0.92	1.08	1.00	1.00	1.12	0.79	1.02	1.00	1.03	0.86	1.02
52	sz000876	XXW	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	1.11	1.17	1.12	0.84	1.11	1.17	1.12	0.84
53	sz002100	TKSW	1.00	1.00	1.00	-	0.92	1.08	0.81	1.15	0.91	1.12	0.82	0.99	0.84	1.22	0.66	1.14
54	sz002124	TBSP	0.91	0.92	0.99	drs	1.01	0.69	1.24	1.24	1.03	1.37	0.72	1.00	1.04	0.95	0.89	1.24
55	sz002286	BLB	0.95	0.96	0.99	drs	0.99	0.75	1.35	1.02	1.00	1.26	0.79	1.02	0.99	0.94	1.06	1.04
56	sz002299	SNFZ	1.00	1.00	1.00	-	1.00	0.61	1.51	0.97	1.10	1.56	0.67	1.00	1.10	0.96	1.01	0.97
57	sz002321	HYNY	0.94	0.95	0.99	drs	0.95	1.02	0.93	1.16	1.04	1.19	0.90	0.99	0.99	1.22	0.83	1.15
58	sz002385	BDN	1.00	1.00	1.00	-	0.96	0.96	1.00	1.00	1.09	1.16	0.85	1.03	1.05	1.10	0.84	1.03
59	sz002481	STSP	0.94	0.96	0.97	drs	1.02	0.85	1.22	0.96	1.00	1.17	0.83	1.01	1.02	0.99	1.01	0.97
60	sz002505	PDNM	0.86	0.9	0.96	drs	1.00	0.92	1.19	0.96	1.03	1.09	0.87	0.99	1.04	1.01	1.03	0.96
61	sz002556	HLGF	0.85	0.91	0.93	drs	0.91	0.95	1.18	0.97	1.12	1.19	0.84	1.00	1.02	1.13	1.00	0.97
62	sz002679	FJJS	1.00	1.00	1.00	irs	1.00	0.87	1.16	1.00	1.00	1.15	0.84	1.02	1.00	1.00	0.97	1.02
63	sz002688	JHSW	0.97	0.97	0.99	drs	0.98	0.84	1.22	0.99	1.00	1.19	0.84	1.01	0.98	1.01	1.02	1.00
64	sz002696	BYGF	0.94	0.96	0.97	drs	0.96	0.93	1.18	0.95	1.01	1.20	0.87	1.01	0.97	1.12	1.03	0.96
65	sz002714	MYGF	0.97	0.98	1.00	drs	1.03	1.00	1.00	1.00	1.16	1.97	0.66	1.02	1.19	1.97	0.66	1.02
66	sz002852	DDQ	0.95	0.96	0.98	drs	1.06	0.82	1.19	0.88	1.00	1.09	0.87	0.99	1.06	0.89	1.03	0.88
67	sz002868	LKSH	0.97	0.97	1.00	-	1.03	0.77	1.27	1.02	1.01	1.27	0.83	1.01	1.04	0.98	1.05	1.03
68	sz002891	ZCGF	0.94	0.96	0.97	drs	1.00	0.90	1.09	1.00	0.99	1.17	0.83	1.02	1.00	1.06	0.91	1.02
69	sz300094	GLSC	0.95	0.97	0.98	drs	0.96	0.97	1.08	1.00	1.01	1.09	0.87	1.01	0.98	1.06	0.94	1.01
70	sz300268	*STJW	1.00	1.00	1.00	-	0.87	0.83	1.20	0.93	0.89	1.29	0.77	1.01	0.78	1.07	0.92	0.95
71	sz300313	*STTS	0.88	0.88	1.00	-	1.13	0.86	1.17	0.98	1.00	1.13	0.87	1.01	1.13	0.98	1.02	0.99
72	sz300498	WSGF	1.00	1.00	1.00	-	1.00	1.00	0.83	1.20	1.20	1.09	0.93	1.07	1.20	1.09	0.78	1.28
73	sz300761	LHGF	0.97	1.00	0.97	drs	0.97	0.81	1.13	1.02	1.07	1.36	0.76	1.00	1.04	1.11	0.86	1.02
74	sz300967	XMGF	0.96	0.96	1.00	drs	1.00	0.80	1.25	0.98	1.01	1.33	0.79	1.02	1.01	1.06	0.98	1.00
		Mean	0.96	0.97	0.99		0.99	0.86	1.16	1.01	1.03	1.22	0.83	1.01	1.02	1.04	0.96	1.01
		Forestry					18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22
75	sh600265	*STJG	1.00	1.00	1.00	-	1.00	0.96	1.04	1.00	1.01	0.99	1.03	1.00	1.01	0.95	1.07	1.00
76	sz000592	PTFZ	1.00	1.00	1.00	-	1.00	1.00	0.99	1.02	0.98	1.01	0.98	1.01	0.98	1.01	0.97	1.02
77	sz000663	YALY	0.96	1.00	0.96	irs	1.03	1.01	1.00	1.00	0.98	1.03	0.96	1.02	1.01	1.04	0.96	1.02
78	sz002567	TRS	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	1.00	1.07	1.23	1.05	1.00	1.07	1.23	1.05
		Mean	0.99	1.00	0.99		1.01	0.99	1.01	1.00	0.99	1.02	1.04	1.02	1.00	1.02	1.05	1.02
		Fishery					18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22	18-19	19-20	20-21	21-22
79	sh600097	KCGJ	0.97	1.00	0.97	drs	1.02	0.97	0.98	1.00	1.00	1.04	1.02	0.99	1.01	1.01	1.00	0.99
80	sh600257	THGF	1.00	1.00	1.00	-	0.98	1.00	1.00	0.99	0.98	1.03	0.97	0.99	0.96	1.03	0.98	0.99
81	sh600359	XNKF	0.99	1.00	0.99	irs	1.01	1.00	0.98	0.99	1.01	0.99	1.02	1.01	1.03	0.99	1.00	1.00
82	sh600467	HDJ	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	1.03	1.16	0.84	1.01	1.03	1.16	0.84	1.01
83	sz000798	ZSYY	0.99	1.00	0.99	drs	1.00	0.98	0.97	1.05	1.00	1.04	0.97	1.27	1.00	1.02	0.95	1.34
84	sz002069	ZZD	1.00	1.00	1.00	-	1.00	1.00	1.00	1.00	0.95	1.06	1.02	0.98	0.95	1.06	1.02	0.98
85	sz300087	QYGK	1.00	1.00	1.00	drs	1.00	1.00	1.00	1.00	1.02	1.06	0.95	1.24	1.02	1.06	0.95	1.24
		Mean	0.99	1.00	0.99		1.00	0.99	0.99	1.01	1.00	1.05	0.97	1.06	1.00	1.05	0.96	1.07

Note:TE3 represents the comprehensive efficiency score in the third stage.PTE3 denotes the pure technical efficiency in the third stage, while SE3 represents the scale efficiency at the third stage.

Table 5. Malmquist Index of 85 Listed Companies in the Agriculture, Forestry, Animal Husbandry, and Fishery Sectors (2018–2022)

Year	Comprehensive Efficiency	Technological Progress Efficiency	Pure Technical Efficiency	Scale Efficiency	Malmquist 指数
2018-2019	1.38	0.71	1.01	1.38	0.99
2019-2020	1.15	0.86	1.00	1.15	0.99
2020-2021	0.95	1.07	0.90	1.05	1.01
2021-2022	1.19	0.84	1.13	1.05	1.00
Mean	1.16	0.86	1.01	1.15	1.00

4. Conclusion

This study employs the three-stage DEA model to analyze the capital utilization efficiency of 85 listed companies in China's agriculture, forestry, animal husbandry, and fishery sectors, complemented by the Malmquist index to assess the dynamic changes in adjusted capital utilization efficiency over time. The findings yield valuable insights that may assist these listed companies in enhancing their capital utilization efficiency, while also providing strategic guidance for similar enterprises in these sectors aiming for public listing. Over the period from 2018 to 2022, capital utilization efficiency across these 85 listed companies remained relatively low, influenced not only by internal organizational factors but also by the global pandemic and related policies and regulations. Based on the comprehensive and objective analysis conducted in this study, the following conclusions are presented:

The findings reveal that: First, the comprehensive efficiency of China's 85 listed companies in the agricultural, forestry, animal husbandry, and fishery sectors was significantly overestimated in the initial analysis. Government support and the availability of technical personnel have posed constraints on enhancing capital utilization efficiency, suggesting that external environmental factors play a substantial role in shaping efficiency levels in these industries. Second, after excluding the impact of external environmental factors and random disturbances, the study observed that the average comprehensive efficiency of agricultural companies declined from 0.94 to 0.66, while the average scale efficiency decreased from 0.95 to 0.69, marking reductions of 29.79% and 27.37%, respectively. This indicates that scale efficiency is a crucial factor limiting the improvement of capital utilization efficiency among agricultural firms. The observed decreasing returns to scale are attributed to excessive expansion, hindering these companies from achieving optimal scale efficiency. To address this, agricultural firms should focus on strengthening management capabilities, streamlining organizational structures, consolidating internal resources, accelerating structural adjustments, reducing ineffective investments, and enhancing output levels. Third, dynamic analysis using the DEA-Malmquist model over the period 2018 to 2022 reveals a steady improvement in the Malmquist Index across the 85 listed companies. However, total factor productivity efficiency in the agricultural sub-sector remains relatively low, with the company ZLKJ exhibiting the most pronounced fluctuations in the Malmquist Index. This variability may be due to low capital management efficiency, suboptimal scale allocation, unexpected external risks, and the impact of relevant policies and regulations.

Agriculture: Upon removing external environmental factors, the capital utilization efficiency within the agricultural sub-industry exhibited a substantial decline, indicating a high dependency on external support. Although agricultural firms generally display relatively high technical efficiency, utilizing existing technology effectively at a given scale, the lack of sufficient scale efficiency remains a pivotal constraint on further capital utilization improvement. Findings indicate a tendency for over-investment in capital during expansion, leading not only to redundant capital usage but also to reduced resource allocation efficiency. In this context, agricultural firms should carefully assess their capital expansion strategies to mitigate the risks of resource waste associated with unchecked growth.

Animal Husbandry: While animal husbandry firms achieve strong technical efficiency, their scale efficiency is comparatively lower. Analysis indicates that capital utilization efficiency within this sub-industry is less influenced by external environmental factors, likely due to the stability of its production processes. With mature operational structures and stable input-output relationships, these firms maintain high technical efficiency even without external factors. However, enhancing scale efficiency necessitates further optimization of production processes and refined management practices. To increase capital utilization efficiency, firms in animal husbandry should prioritize internal process optimization and cost control, ensuring maximum resource efficiency at every stage of production. Furthermore, reducing dependence on unregulated expansion and avoiding the administrative burdens of excessive scaling can support more effective resource allocation.

Forestry: The forestry sub-industry demonstrates relatively high capital utilization efficiency, with most forestry firms sustaining near-frontier efficiency even after excluding external factors. High levels of both scale and technical efficiencies suggest that forestry firms have achieved a balanced approach to resource utilization and scale management. Effective control over scale expansion in this sub-industry reflects a prudent approach to capital growth, ensuring rational resource allocation and fostering efficiency stability over time. To further improve capital utilization efficiency, forestry firms may consider increasing investments in technological innovation to maintain their leadership in the sector. Such ongoing technological investments can help forestry firms maintain a competitive edge and support continuous optimization of efficiency levels.

Fishery: The fishery sub-industry shows generally high capital utilization efficiency, albeit with significant variability across firms. This variability is mainly attributed to fluctuations in market demand and uncertainties in resource supply. While most fishery companies operate near the efficiency frontier, some firms display marked efficiency fluctuations after removing external environmental factors. These fluctuations are likely driven by the dynamic nature of market demand and the seasonal instability of resource supply, necessitating flexible responses to external environmental changes. To improve capital utilization efficiency, fishery firms should adopt more adaptable capital allocation strategies to accommodate shifts in market demand. Furthermore, establishing a resilient supply chain system to address resource supply uncertainties may enhance capital efficiency and strengthen these firms' competitiveness in volatile markets.

Based on the preceding findings, the following recommendations are outlined:

Firstly, enhancing the allocation and management of capital while reducing the extent of government support funding is crucial. In China's listed agricultural, forestry, animal husbandry, and fishery sectors, low scale efficiency remains a primary obstacle to capital utilization improvements. This inefficiency largely stems from the substantial government support funding allocated to these companies, with over 90% operating under diminishing returns to scale. It is recommended that these companies tailor government support funding in accordance with their specific operational capacities. Such adjustments would facilitate optimal scale efficiency, reduce dependency on government support, and ultimately elevate capital utilization efficiency across these industries. Secondly, strengthening talent development and financial management systems within these sectors is essential. Professional technical talent plays a pivotal role in the commercialization of products, yet recent expansions in R&D investment have resulted in an oversupply of skilled personnel. Companies should, therefore, enhance performance management strategies to retain core technical talent, minimize labor costs, and establish structured training and career advancement pathways. Moreover, improved financial planning and forecasting are vital to maintain fiscal stability, enabling companies to devise and implement judicious capital utilization plans that enhance overall financial and operational efficiency.Thirdly, enhancing investment in technological innovation and fostering high-level scientific and technical expertise are critical. The adjusted results reveal that the average pure technical efficiency value remains below the efficiency frontier, underscoring substantial potential for technological progress. It is recommended that companies develop specialized agricultural technology talent and focus on research into practical applications, which are crucial for advancing agricultural technology and driving sector-wide innovation. Furthermore, recent research(Segbenya & Yeboah, 2022)highlights that improved employee health and safety management can mitigate accidents and losses in production processes, thereby contributing to greater capital utilization efficiency. Fourthly, while capital utilization rates are currently low among agricultural companies, the adoption of green supply chain management strategies(Khokhar et al., 2020), along with rigorous supplier selection and circular supply chain management(Hou et al., 2023; Khokhar & Zia et al., 2022; Sahabuddin et al., 2023), can significantly reduce waste and promote sustainable capital utilization. Approaches such as the Triple Bottom Line (TBL) and Circular Sustainable Chain Management (CSCM) frameworks also provide effective pathways for enhancing sustainable capital usage within agricultural enterprises.Fifth, enhancing capital structure management is essential. Listed companies in agriculture, forestry, animal husbandry, and fishery sectors should strategically design their capital structure to maintain an optimal asset-to-liability ratio, thereby mitigating the financial pressures associated with over-reliance on external financing. Through the optimization of financing approaches and the selection of appropriate capital instruments—such as bonds and equity—companies can effectively reduce capital costs and enhance the efficiency of capital utilization. Sixth, advancing green finance and sustainable development strategies is critical. In alignment with national goals such as carbon peaking and carbon neutrality (Ospanova et al., 2022)listed companies in these sectors are encouraged to leverage green financial instruments and refine their use of environmental technologies, reducing reliance on government subsidies and maximizing autonomous capital efficiency. Investment in sustainable development projects, including renewable energy and environmental technology, enhances capital utilization while attracting policy incentives and fostering social recognition, ultimately boosting market competitiveness. Furthermore, strategies to enhance employee welfare and improve working conditions(Khokhar & Devi et al., 2022) can bolster corporate performance and capital utilization efficiency. Insights from cross-cultural research on CSR practices in the cosmetics industry may also provide Chinese agricultural enterprises with valuable international perspectives on social responsibility practices.

While this study offers valuable insights for assessing the effectiveness of rural revitalization strategies and analyzing capital utilization efficiency across industries, it also presents certain limitations. Compared to recent studies in leading journals, this research, despite its emphasis on social responsibility, promotion of sustainable development, and improvement of resource utilization and capital management efficiency, lacks a thorough exploration of the mechanisms by which external factors influence efficiency. Additionally, the study does not sufficiently address the unique characteristics and specific challenges inherent to different industries. Furthermore, the relatively short time span of the data limits the ability to capture long-term trends and to thoroughly investigate relationships between efficiency factors, indicating avenues for further research.

Future research could prioritize the following key directions:

Advancement of the Three-Stage DEA Model: Integrating more dynamic efficiency analysis approaches, such as dynamic DEA models or multi-period panel data analysis, could enable future research to capture the evolving characteristics of capital utilization efficiency with greater precision. This enhancement would refine the accuracy of efficiency assessment, elucidate variations in capital utilization efficiency over time, and inform the design of forward-looking strategic frameworks.

Broadening the Scope of External Environmental Factors: Current findings indicate that external elements, such as government subsidies and technical personnel levels, significantly affect capital utilization efficiency. Building on this insight, future research could comprehensively examine the influence of additional factors, such as market demand volatility, regulatory shifts, and macroeconomic trends. Developing a more nuanced model of capital efficiency evaluation would allow for deeper insights, equipping corporate management with more robust strategic guidance.

Exploring the Role of Technological Innovation in Efficiency Enhancement: Future research could delve into the role of technological innovation and advancements in improving capital utilization efficiency. By analyzing the pathways for industry technology upgrades and the impact of innovation on resource optimization, studies could reveal how technological progress drives overall efficiency gains within the industry. Such research would provide firms with strategic guidance on technology investment priorities and optimal areas for development. Sector-Specific Efficiency Analysis: The present study underscores significant disparities in capital utilization efficiency across different sub-sectors. Future research could further investigate the distinctive characteristics of each sub-sector, performing in-depth analyses of unique operational conditions and efficiency constraints. Such targeted examination would aid in identifying sub-sector-specific challenges and inform companies and policymakers in crafting tailored strategies for improvement.

Through these focused areas of inquiry, future research could advance the theoretical framework for capital utilization efficiency and offer practical, actionable insights for governments, corporate leaders, and other stakeholders in optimizing resource allocation, policy formation, and management practices.

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