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Behavior and Effectiveness Evaluation of Financial Subsidies for Agricultural Insurance in China

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Abstract

Based on the special characteristics of agricultural risks, traditional commercial insurance companies find it difficult to carry out pure agricultural insurance business due to technological lag and institutional constraints. Since the implementation of the central financial premium subsidy policy in 2007, it has significantly expanded the coverage of agricultural risk protection and pushed China to become the largest country in the world in terms of the scale of agricultural insurance by 2021. This study measures the efficiency of the current policy concerning the single form of agricultural insurance subsidies, lack of regional differentiation, and misalignment of product supply and demand based on provincial panel data from 2018-2021 using a three-stage DEA approach. The results show that the efficiency of agricultural insurance subsidies fluctuates significantly, the overall level is low, inter-provincial differences are apparent, the efficiency is higher in economically developed regions and main grain-producing areas, and the efficiency is poor in the west and less developed regions.

Keywords

Agricultural Insurance, Financial Subsidy Efficiency, Three-Stage DEA Methodology, Regional Differences

1. Introduction

Agriculture, as the foundation of the national economy, possesses both natural and economic reproduction characteristics. Its production process involves multiple stages and is susceptible to unforeseeable risks, resulting in high uncertainty and vulnerability. Agricultural insurance plays a crucial role in mitigating the risks of major agricultural disasters, ensuring food security, maintaining ecological balance, promoting urban-rural integration, safeguarding social stability, and achieving common prosperity in national strategic initiatives. National policy-based agricultural insurance premium subsidies are an important measure to safeguard national food security, advance China's agricultural and rural modernization, and achieve rural revitalization and common prosperity.

In 2007, China implemented an agricultural insurance premium subsidy policy, which reduced the operational costs of insurance companies through fiscal subsidies, significantly enhancing the risk protection capacity of agricultural insurance. Subsequently, China's agricultural insurance market experienced rapid growth, surpassing the trillion-yuan threshold, and by 2021, China had become the world's largest market in terms of agricultural insurance premium volume.

However, the development of agricultural insurance still faces multiple challenges: some insurance companies are reluctant to pay claims, their business philosophy is overly focused on economic benefits, they have a weak sense of social responsibility, and they lack understanding of the role of commercial insurance in national strategy, failing to actively integrate insurance services into agricultural risk management and the rural revitalization strategy. Government financial resources are tight, limiting the actual amount of subsidies, and there is a strong desire for administrative promotion, but there is a certain gap between financial support and policy objectives; Farmers and new agricultural operators have a high willingness to participate in insurance, generally recognizing the role and value of insurance in agricultural risk management. However, due to economic constraints, their actual purchasing power is weak, leading to difficulties in improving insurance coverage rates.

This study adopts a central government fiscal perspective, using central agricultural insurance premium subsidy amounts as input variables, and selects key output indicators such as policy effectiveness and agricultural risk protection levels to empirically calculate the efficiency of agricultural insurance subsidy policies across provincial-level administrative units. On one hand, this study systematically analyzes the operational efficiency of each province under the current subsidy policy through efficiency measurement and indicator decomposition, deepens understanding of the current implementation status of the agricultural insurance subsidy system, identifies shortcomings in the current policy, and derives methods to optimize efficiency. On the other hand, the research findings contribute to the improvement and innovation of the subsidy policy system and, based on methods to enhance efficiency, assist the agricultural insurance system in promoting agricultural and rural development and strengthening its risk transfer and loss compensation functions. In terms of methodology, this study innovatively introduces the random frontier analysis model to effectively analyze the impact of different environmental variables on subsidy efficiency, providing comprehensive data support and theoretical references for improving the efficiency of fiscal subsidy funds.

2. Literature Review

2.1. Agricultural Insurance and Finance

In the early 20th century, flood insurance in the United States marked the beginning of market-oriented agricultural insurance research (Ahsan et al., 1982; Kramer, 1983). Agricultural insurance supported by strong government backing can effectively promote agricultural technological progress, increase agricultural output, reduce residents' reliance on public resources, and enhance farmers' demand for agricultural insurance (Bigman, 1996). Government subsidies facilitate the development of agricultural insurance. Government relief measures have a significant "watering effect" on agricultural insurance premium income, and even social insurance programs can exert a significant crowding-out effect on commercial insurance (Brown & Schulte, 2011). Based on the standards of Pigouvian welfare economics, fiscal subsidies, as a form of redistribution, can enhance the overall welfare of farmers and society as a whole (Goodwin & Smith, 1995).

From international practice, the design of agricultural insurance systems in major countries is typically government-led, with governments directly or indirectly operating all-risk and multi-risk agricultural insurance, while private sector attempts to assume multi-risk agricultural insurance have not formed sustainable models (Wright & Hewitt, 1994). Government subsidies can compensate farmers for losses and also bring welfare benefits to non-agricultural sectors, stimulating effective demand in the agricultural insurance market (Mishra, 1996). Agricultural insurance subsidies can enhance farm specialization levels and promote agricultural production efficiency (O'Donoghue et al., 2009). Additionally, agricultural insurance subsidies can increase agricultural market participants' production expectations, guide crop planting structures toward high-yield varieties, and typically involve increased input of production factors, thereby promoting agricultural mechanization (Yang & Leatham, 1997). Low farmer incomes and high insurance premiums can lead to insufficient effective demand for agricultural insurance. Government subsidies can alleviate farmers' premium burden and increase participation rates (Nadolnyak et al., 2008; Xu & Liao, 2014).

The social benefits of agricultural insurance under government-market collaboration outweigh its economic benefits. The public good attributes of agricultural insurance objectively require necessary government fiscal subsidies. Otherwise, market imbalances or failures, operational challenges caused by information asymmetry, and agricultural risks that fail to meet the law of large numbers under market-driven operations could lead to market collapse (Jiang & Zhang, 2018; Shao & Guo, 2020; Ding & Sun, 2021). China's agricultural insurance failed to develop well in its early stages due to the lack of government financial support. The optimal subsidy method should involve the government directly allocating funds to insurance companies based on regulations and insurance enrollment status (Wang & Ouyang, 2008). The design of China's agricultural insurance premium subsidies should be tailored to local conditions, with the government leading diverse premium subsidy models, clarifying the policy-oriented positioning, encouraging diversified operations to achieve effective transfer of fiscal funds, promoting the redistribution of national income, and advancing the sustainable development of agricultural production while enhancing farmers' welfare (Fang, 2008).

2.2. Evolution of the Agricultural Insurance System and Fiscal Subsidy Policies

Since China's accession to the World Trade Organization, the importance placed on agriculture has gradually increased, and with the strengthening of national fiscal capabilities, the scope and intensity of agricultural insurance subsidies have also expanded. Since 2004, the Central Document No. 1 has focused on "agriculture, rural areas, and farmers" issues for 22 consecutive years, gradually establishing a multi-tiered subsidy system covering comprehensive cost insurance for the three major grain crops and local specialty agricultural product insurance through important policy platforms such as the Central Economic Work Conference. As shown in **Figure 1**, by the end of 2024, agricultural insurance premium income reached over 150 billion yuan for the first time, with an average annual compound growth rate of 16.2% over the past five years (2020-2024). Central government subsidies exceeded 30 billion yuan, with an average annual growth rate of 15%, and the comprehensive claims ratio reached 81.5%. However, despite this progress, structural imbalances between supply and demand in agricultural insurance remain prominent. Currently, the main issues with China's agricultural insurance system include: first, low coverage levels, which fail to effectively stimulate farmers' demand, leading to low enthusiasm for purchasing agricultural insurance; second, insufficient product differentiation, as current insurance products have limited coverage scope and diversification, unable to adequately address the risks faced by different types of agricultural operators, and so on. In this context, analyzing and measuring the efficiency of subsidy mechanisms using a three-stage DEA model holds significant policy value: on one hand, by decomposing subsidy efficiency, it is possible to accurately identify areas for improvement in fiscal subsidies across provinces; on the other hand, it provides data and theoretical support for designing differentiated subsidy policies, thereby fully leveraging the leverage effect of fiscal subsidy funds.

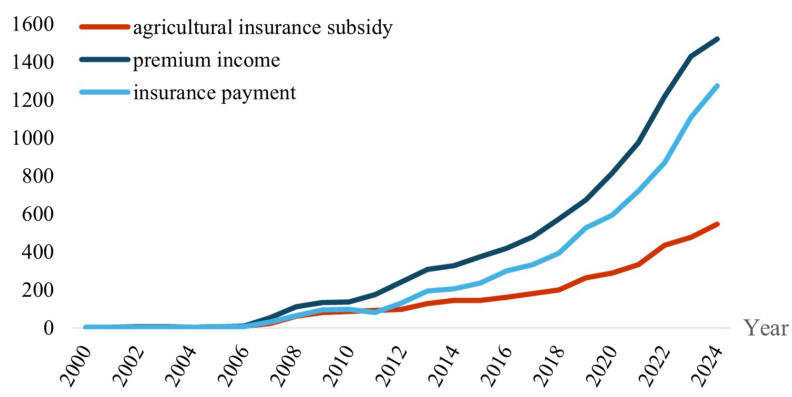

Figure 1. Comparison of trends in agricultural insurance subsidies, premium income, and insurance claims. (2000-2024, Unit: 100 million yuan).

Since its implementation in 2007, the central government's policy-based agricultural insurance premium subsidy program has seen its subsidy mechanism increasingly refined and management standards steadily improved. Both the 2008 and 2009 Central Document No. 1 called for expanding the scope of subsidy pilot programs and increasing the intensity of premium subsidies. The 2009 Central Document No. 1 proposed "exploring the establishment of a bank-insurance interaction mechanism combining rural credit with agricultural insurance." In 2012, it was proposed to steadily expand the types and coverage of agricultural insurance. Since 2013, each annual Central Document No. 1 has placed high priority on agricultural insurance. In 2014, it was proposed to adjust the subsidy ratios for main grain crop insurance across all levels of government. In 2015, it was first proposed to pilot price insurance for agricultural products. In 2016, it was pointed out that agricultural insurance should be designated as an important means of supporting agricultural development. In 2018, agricultural insurance was listed as part of the "agricultural support and protection system," elevating its importance to the national strategic level of assisting rural revitalization, thereby raising its significance to a new height. In 2019, it was proposed to explore pilot programs for incentive-based subsidies for locally advantageous agricultural products. In early 2022, the Ministry of Finance proposed improving the method for determining subsidy ratios, particularly for certain major agricultural products, emphasizing the need to formulate regionally differentiated policies based on the characteristics of agricultural production, risk distribution, and economic development levels in each region to enhance the precision and effectiveness of policy implementation. In 2023, policies encouraged insurance institutions to strengthen the "technology empowerment" of agricultural insurance, widely applying scientific and technological innovations such as satellite remote sensing and drones across all operational phases of agricultural insurance. In 2024, the scope of insurance coverage was further expanded to achieve nationwide coverage for the three major grains, promoting precise underwriting and claims processing, and optimizing subsidy management. China's policy-based agricultural insurance premium subsidy system has continuously adapted to the needs of agricultural development through its evolution, gradually establishing a more scientific and efficient protection system through differentiated adjustments and technology-driven approaches. The 2025 Central Document No. 1 focuses its support for agricultural insurance on reducing the county-level premium subsidy ratio for major grain-producing counties, improving the multi-tiered agricultural insurance system, and supporting the development of insurance for specialty agricultural products.

Additionally, China has gradually explored various "agricultural credit + agricultural guarantee + agricultural insurance" models to promote agricultural investment, guiding financial institutions to continuously increase credit allocation to the "three rural areas." Agricultural credit allocation has continued to grow rapidly, with the annual growth rate of agricultural loans reaching 14.94% from 2007 to 2024. By 2024, the balance of agricultural loans reached 61.53 trillion yuan, providing strong financial support for achieving high-quality agricultural development and promoting rural revitalization.

2.3. Measuring the Efficiency of Fiscal Subsidies for Agricultural Insurance

Assessing the efficiency of agricultural insurance premium subsidies involves evaluating the behavior and outcomes of farmers, insurance companies, and the government, specifically including the impact of agricultural insurance premium subsidies on increasing farmers' income, improving agricultural production efficiency, and enhancing the efficiency of fiscal fund allocation. Data Envelopment Analysis (DEA) uses non-parametric methods to construct a production possibility frontier, maps the efficiency values of decision-making units onto the frontier, and then quantifies their deviation from the frontier to calculate the relative efficiency levels of each decision-making unit (Charnes et al., 1978). This method has been optimized and developed over the years (Wei, 1986) and has become an important tool in the fields of decision-making effectiveness analysis and policy evaluation. In terms of specific efficiency assessment methods, scholars have proposed various innovative models. The efficiency of the fiscal subsidy structure and resource allocation policies for policy-based agricultural insurance can be scientifically assessed using a three-stage DEA model (Qian et al., 2014), and improved DEA models and three-stage DEA-Tobit models can be applied to test and evaluate the efficiency levels of agricultural insurance premium subsidies (Wang & Pang, 2020; Wang et al., 2022).

3. Theoretical Analysis and Research Hypotheses

3.1. Theoretical Analysis

Current research on the efficiency assessment of agricultural insurance primarily relies on single-stage Data Envelopment Analysis (DEA) models. However, this method has certain limitations. Especially for panel data, environmental heterogeneity and random errors can significantly impact the evaluation of decision-making unit efficiency, leading to assessment conclusions that may not align with actual efficiency levels. To address this, this study constructs a three-stage DEA model: first, the initial efficiency values are calculated using the traditional DEA model; next, the Stochastic Frontier Analysis (SFA) model is introduced to remove environmental factors and random disturbances from the input slack variables obtained in the first stage; finally, the adjusted input variables are subjected to another efficiency assessment to obtain more accurate measurement results.

In terms of indicator system design, this study simultaneously considers the direct protective effects and indirect developmental effects of fiscal subsidies on agricultural insurance coverage. The following indicators were selected: Agricultural insurance penetration (premium income/total output value of agriculture, forestry, animal husbandry, and fisheries) to represent risk protection levels; agricultural insurance density (premium income/rural population) to reflect the degree of insurance inclusiveness; agricultural insurance claims payments to measure the realization of insurance compensation functions; and grain production to reflect the stability of agricultural production. By using total output value of agriculture, forestry, animal husbandry, and fisheries and rural population as the denominator, the dynamic impact of fiscal subsidies on risk coverage and market expansion can be precisely captured.

Additionally, input variables focus on the amount of central government fiscal subsidies for agricultural insurance, primarily based on policy-driven considerations. Although the policy introduced in 2014 to "reduce or eliminate county-level fiscal premium subsidies for the three major grain crops in major grain-producing counties" explicitly required reducing the fiscal burden on counties, local governments' differentiated subsidy strategies still play an indispensable regulatory role in the development of agricultural insurance. Due to data availability and research objectives, this study has not yet included local fiscal subsidies in the efficiency analysis framework, which is a direction for future improvements in this research.

3.2. Research Hypothesis

Regions with developed economies have well-established agricultural insurance systems and higher local government budgets, enabling them to better utilize agricultural insurance premium subsidy policies to enhance agricultural production efficiency. However, in underdeveloped western regions, diminishing returns to scale and low pure technical efficiency result in lower overall efficiency of agricultural insurance premium subsidies (Wang et al., 2022). Additionally, in western regions prone to natural disasters, farmers have a high demand for agricultural insurance, but due to economic constraints, farmers often struggle to afford higher premiums. Furthermore, the fiscal strength of underdeveloped regions in the west is weak, and local governments have limited fiscal expenditure capacity, making it difficult to bear high agricultural insurance subsidies. This further illustrates that environmental factors such as natural disaster losses and income levels may have a greater negative impact on subsidy efficiency in western regions. Therefore, after controlling for environmental variables, the differences in subsidy efficiency across regions can be more clearly identified (Luo et al., 2011; Huang & Wang, 2019). Based on this, the following hypothesis is proposed:

Hypothesis 1: When environmental variables (such as natural disaster losses, planting area, and income levels) are introduced into the assessment of agricultural insurance subsidy efficiency to eliminate interference, economically developed regions and major grain-producing provinces exhibit a significant advantage in subsidy efficiency, while underdeveloped western regions demonstrate a clear efficiency disadvantage.

Theoretically, agricultural insurance can stabilize farmers' income expectations, improve access to credit, promote specialization, and optimize crop structures, thereby enhancing the scale efficiency of agriculture. Research indicates that agricultural insurance encourages farmers to expand their planting scale or cultivate high-yield crops through risk transfer and income effects, thereby improving agricultural scale efficiency and pure technical efficiency (Wen et al., 2023). This suggests that theoretically, expanding agricultural insurance subsidies may have a positive impact on scale efficiency. Based on this, we propose:

Hypothesis 2: Reasonably expanding the scale of agricultural insurance subsidies can enhance scale efficiency in most provinces.

Under the current agricultural insurance premium subsidy policy, as the scale of agricultural insurance expands, fiscal pressures at the provincial, municipal, and county levels have significantly increased, leading to a slowdown in the growth rate of agricultural insurance (Niu et al., 2020). The central government's subsidies to provinces are insufficiently differentiated, resulting in excessive fiscal pressure on major agricultural provinces and a mismatch between county-level fiscal capacity and expenditure responsibilities. Additionally, uniform premium rates lead to low-risk farmers reducing their willingness to insure due to insufficient subsidies, while high-risk regions experience waste due to excessive subsidies (Zhang et al., 2016). Based on this, we propose:

Hypothesis 3: Differentiated agricultural insurance subsidy mechanisms can improve subsidy efficiency.

4. Model and Variables

4.1. Model Construction

Fried pointed out that traditional Data Envelopment Analysis (DEA) does not account for the interference of environmental factors and random noise on the evaluation of decision-making unit efficiency. Therefore, he proposed a three-stage DEA model based on the BCC model. In the second stage, the Stochastic Frontier Analysis (SFA) model is utilized to analyze the relationship between environmental variables and slack variables, thereby separating and eliminating the effects of managerial inefficiency, environmental factors, and statistical noise. In the third stage, after decision-making units are adjusted and placed under the same environmental conditions, efficiency values are recalculated based on the adjusted input-output data, yielding assessment results closer to true technical efficiency (Fried et al., 2002). This study establishes the following core assumptions to construct the subsequent model:

1) Under constant output levels, the focus is on examining the input efficiency optimization path of policy-based agricultural insurance premium subsidies.

2) Given that agricultural insurance possesses public goods characteristics and externalities, and the market is currently underdeveloped, it is assumed that the production frontier exhibits a variable returns to scale (VRS) structure, and there is a nonlinear relationship between input scale and efficiency changes.

3) To align with the input-oriented characteristics of the DEA model, the stochastic frontier regression adopts a cost function form to analyze the marginal impact of environmental variables on input redundancy.

4) Assuming that efficiency losses are jointly caused by environmental factors and random noise, a second-stage SFA model is required to separate and eliminate

the interference.

5) The inefficiency term is assumed to follow a half-normal distribution, and the random error term follows a normal distribution. Within this theoretical framework, this study will use a three-stage DEA model to conduct a comparative evaluation of the efficiency of agricultural insurance subsidies for 31 provincial-level administrative units in China from 2018 to 2021.

In the first stage of the study, an input-oriented data envelopment analysis model is more suitable for studying subsidy inputs. This study assumes variable returns to scale and calculates the initial technical efficiency of each province using raw input-output data. The specific model formula is:

$$\begin{cases} min\theta \\ \sum_{i=1}^{n} X_i \lambda_i + S^- = \theta X_0 \\ \sum_{i=1}^{n} Y_i \lambda_i + S^+ = Y_0 \\ \sum_{i=1}^{n} \lambda_i = 1 \\ \lambda_j \geq 0, i = 1, \ldots, n \\ S^-, S^+ \geq 0 \end{cases} \tag{1}$$

Among them, ***i*** represents the decision-making unit of the study, and *X*, *Y* represents the selected input and output vector.

The efficiency values obtained from the model can be divided into three parts: total technical efficiency (TE), scale efficiency (SE), and pure technical efficiency (PTE). The relationship between the three can be expressed as: TE = SE * PTE.

Based on the input-oriented model, the input relaxation variables obtained in the first stage are used for SFA regression with the environmental variables used in this study. The SFA-like regression function constructed is as follows:

$$S_{nj} = f\left(Z_j; \beta_n\right) + v_{nj} + \mu_{nj}; j = 1, 2, \cdots, I; n = 1, 2, \cdots, N \tag{2}$$

Among them, S_{nj} represents the relaxation variable value of the nth input of the jth decision unit; Z_j represents the environmental variables involved in the regression; β_n is the regression coefficient corresponding to the explanatory variable; $v_{nj} + \mu_{nj}$ as a mixed error term, where v_{nj} is random interference and μ_{nj} is management inefficiency.

In order to ensure a relatively fair environment for all decision-making units, environmental factors and random disturbances must be adjusted using the following formula:

$$\begin{gathered} X_{nj}^{A} = X_{nj} + \left[\max\left(f\left(Z_j; \hat{\beta}_n\right)\right) - f\left(Z_j; \hat{\beta}_n\right)\right] + \left[\max\left(v_{nj}\right) - v_{nj}\right] \\ j = 1, 2, \cdots, I; n = 1, 2, \cdots, N \end{gathered} \tag{3}$$

Among them, X_{nj}^{A} is the adjusted input variable value; X_{nj} is the value before adjustment; $\left[\max\left(f\left(Z_j; \hat{\beta}_n\right)\right) - f\left(Z_j; \hat{\beta}_n\right)\right]$ is used to adjust external environmental factors; $\left[\max\left(v_{nj}\right) - v_{nj}\right]$ can unify the luck level of the decision-making unit.

Based on the ideas of Jondrow et al. (1981) and Luo (2012), this study adopts the following separation form for managing inefficient items:

$$E(\mu \mid \varepsilon) = \sigma_* \left[\frac{\phi\left(\lambda \frac{\varepsilon}{\sigma}\right)}{\Phi\left(\frac{\lambda\varepsilon}{\sigma}\right)} + \frac{\lambda\varepsilon}{\sigma} \right] \tag{4}$$

Among them, $\sigma_* = \frac{\sigma_\mu \sigma_v}{\sigma}, \sigma = \sqrt{\sigma_\mu^2 + \sigma_v^2}, \lambda = \sigma_\mu / \sigma_v$.

Calculate the random error term μ using the following formula:

$$E\left[v_{nj} \middle| v_{nj} + \mu_{nj}\right] = s_{nj} - f\left(z_j; \beta_n\right) - E[\left[u_{nj} \middle| v_{nj} + \mu_{nj}\right] \tag{5}$$

After adjustment, the output variable remains unchanged. The new input variable is re-substituted into the one-stage model to calculate the efficiency of agricultural insurance premium subsidies after excluding environmental factors and random errors.

4.2. Variable Selection

Building on the work of previous researchers in **Table 1** and grounded in this study, this research uses agricultural insurance premium subsidies as an input indicator, representing the intensity of premium subsidies. When selecting output variables, both the direct effects of agricultural insurance subsidies (i.e., the extent to which subsidies cover claims losses, insurance penetration, and coverage) and indirect effects (i.e., improvements in agricultural output as subsidy policies are implemented) are considered. The final output indicators selected are agricultural insurance claims and payouts, agricultural insurance density, agricultural insurance penetration, and grain production.

Table 1. Selection of previous indicators.

Author	Input variables	Output variables	Environmental variables
Hou Qianqian (2021)	Central government subsidies Local government subsidies Crop planting area	Agricultural insurance premium income Agricultural insurance claims expenditure Agricultural insurance density	Per capita disposable income of farmers Disaster rate Educational attainment of farmers
Qian Zhenwei, Zhang Yan, & Gao Dongxue (2014)	Central government subsidies Provincial government subsidies Municipal government subsidies Farmers' contributions	Number of insured Number of participating farmers Claims payments	Per capita net income of households Area affected by disasters Illiteracy rate
Li Yongbin & Wang Xuanqing (2018)	Central government subsidy amount Provincial government subsidy amount Municipal and county government subsidy amount Farmers' own contributions	Agricultural insurance density Claims paid	Per capita net income of farmers Agricultural production disaster rate Educational attainment of farmers

Continued

Du Weian, Yang Tianqi, & Lu Chenhui (2016)	Premium subsidy Subsidy ratio	Agricultural insurance density Grain production Agricultural insurance claims and payments Total agricultural output value Agricultural insurance premium income	Per capita net income of farmers Affected area
Wang Guodong & Pang Kai (2020)	Total subsidy amount Subsidy availability rate Ratio of subsidy to premium income	Agricultural insurance premium income Level of protection Insurance density Insurance penetration	Local fiscal revenue Area of crops affected by disasters Average level of education Proportion of agricultural income
Wang Qing & Wang Miao (2022)	Fiscal agricultural expenditure	Total output value of agriculture, forestry, animal husbandry, and fishery Grain production Irrigated arable land area Area of soil and water conservation Per capita disposable income Per capita consumption expenditure	Per capita regional gross domestic product Per capita agricultural machinery power
Ning Wei, Li Yancheun, & Zhou Jingxian (2021)	Central subsidy amount Provincial subsidy amount	Agricultural insurance penetration Agricultural insurance density Subsidy burden rate Risk protection level	Per capita disposable income in rural areas Total grain production Area affected by disasters
Wang Ren & Mo Tingcheng (2016)	Central government subsidy amount Provincial government subsidy amount Municipal and county government subsidy amount Total number of agricultural insurance workers	Number of insured farmers Agricultural insurance claims	Area affected by disaster Per capita net income of farmers Educational attainment of farmers
Zhang Ying & Zhang Ruiyu (2021)	Total premium subsidy Proportion of subsidy to total premium	Total agricultural insurance premium income Agricultural insurance density Agricultural insurance penetration	
Wu Qiang & Xie Xiaorong (2020)	Agricultural insurance premium subsidies Agricultural insurance premium subsidy rate Crop planting area	Agricultural insurance premium expenditure Per capita disposable income Agricultural output value Agricultural insurance density	

The premium subsidy policy has played a significant role in promoting the development of agricultural insurance in China. Since the pilot implementation of the subsidy policy in 2007, the total central subsidy funds have exceeded 300 billion yuan, with an annual compound growth rate of 22%. In 2024, the allocated funds reached 54.7 billion yuan, enabling China's agricultural insurance premium scale to remain among the top globally, providing robust risk protection for farmers and agricultural production. Therefore, this study selects the amount of agricultural insurance premium subsidies as the input variable.

"Agricultural insurance claims and payouts" reflect the risk coverage role of agricultural insurance in compensating for losses. "Agricultural insurance density and penetration" can comprehensively reflect the development level and status of agricultural insurance across China's provinces. Considering that this study focuses solely on the efficiency of agricultural insurance subsidies, when calculating agricultural insurance penetration and density, the total output value of agriculture, forestry, animal husbandry, and fisheries is used as the denominator, and the number of rural residents in each province is used as the denominator, while agricultural insurance premium income is used as the numerator, ensuring a targeted reflection of agricultural insurance development. "Grain production" can reflect the actual effects of agricultural production brought about by the implementation of subsidy policies.

Table 2. Input-output variable table.

Variable type	Indicator	Unit
Input variable	Agricultural insurance premium	Million
Output variables	Agricultural insurance penetration	
	Agricultural insurance density	Yuan/person
	Agricultural insurance claims and payments	Million Yuan
	Grain production	Ten thousand tons
Environment variables	Direct economic losses	Hundred million Yuan
	Per capita disposable income	Yuan
	Total crop planting area	Thousand hectares

The input variable, output variables, and environmental variables of this study are shown in Table 2. The data used in this study comes from the Wind database, China Statistical Yearbook, official websites of provincial statistical yearbooks in China, China Insurance Yearbook, etc. Missing or unpublished data was predicted using the GRWOTH function.

5. Empirical Results and Analysis

5.1. Interprovincial Premium Subsidy Efficiency

Based on input-output data from 2018 to 2021, using the 31 provinces, municipalities, and autonomous regions across China as decision-making units, the

DEAP 2.1 software was employed to analyze their subsidy efficiency annually. Adopting an input-oriented approach, a DEA model with variable returns to scale was utilized. The results from the first stage and the adjusted third stage are presented as follows.

Based on the data in **Table 3**, the following can be observed:

1) After the second-stage adjustment, some regions that did not achieve efficiency reached the frontier (e.g., Xinjiang, Beijing) after removing the effects of environmental factors and random errors, demonstrating that the second-stage adjustment of input variables was necessary.

2) The efficiency of agricultural insurance premium subsidies in most provinces and municipalities nationwide is in the inefficient range (efficiency values < 0.9), with only a few provinces exceeding 0.9. Among them, Beijing, Heilongjiang, and other provinces and municipalities have relatively high technical efficiency, and after the second-stage adjustment, they are basically at the efficient level with an efficiency value of 1.

3) There are significant regional and inter-provincial differences in the efficiency of agricultural insurance subsidies. Specifically, the efficiency of premium subsidies in eastern regions is generally higher than that in western regions, and the efficiency of developed cities is higher than that of underdeveloped cities. This may be due to the fact that eastern regions and developed cities have more well-developed policies and implementation strategies for subsidies, as well as higher levels of subsidy utilization.

4) As indicated by the results, the efficiency of agricultural insurance subsidies in most regions of China was unstable from 2018 to 2021, with some showing a declining trend. Except for Beijing, Heilongjiang, Shanghai, and Henan, where technical efficiency remained stable and was basically at an effective level, the efficiency values of subsidies in other provinces all showed varying degrees of decline or were at suboptimal levels with significant fluctuations.

Table 3. Efficiency values for stages one and three.

	Stage 1 efficiency value				Stage 3 efficiency value			
	2021	2020	2019	2018	2021	2020	2019	2018
Anhui	0.495	0.519	0.559	0.561	0.756	0.845	0.675	0.825
Beijing	0.767	0.548	0.857	1	1	1	0.962	1
Fujian	0.584	0.397	0.382	0.403	0.207	0.18	0.181	0.214
Gansu	0.71	0.614	0.434	0.45	0.59	0.577	0.459	0.478
Guangdong	0.29	0.344	0.221	0.221	0.553	0.44	0.319	0.446
Guangxi	0.275	0.209	0.276	0.257	0.55	0.419	0.43	0.404
Guizhou	0.619	0.409	0.357	0.398	0.38	0.346	0.301	0.333
Hainan	0.239	0.203	0.142	0.186	0.766	0.792	0.812	0.81
Hebei	0.375	0.313	0.378	0.378	0.72	0.675	0.646	0.697
Henan	0.661	0.541	0.527	0.431	0.982	0.928	0.918	0.981
Heilongjiang	1	1	1	1	1	1	1	1
Hubei	0.512	0.606	0.726	0.8	0.556	0.492	0.474	0.461
Hunan	0.329	0.284	0.299	0.361	0.706	0.722	0.572	0.78

Continued

Jilin	0.563	0.551	0.603	0.47	0.87	0.753	0.757	0.739
Jiangsu	0.849	0.526	0.227	0.23	0.841	0.722	0.501	0.556
Jiangxi	0.417	0.456	0.348	0.265	0.498	0.469	0.446	0.432
Liaoning	0.479	0.312	0.32	0.244	0.668	0.678	0.629	0.568
Inner Mongolia	0.354	0.356	0.287	0.266	0.783	0.927	0.983	0.854
Ningxia	0.559	0.234	0.577	0.666	0.788	0.898	0.969	0.925
Qinghai	0.193	0.138	0.125	0.135	0.97	0.963	0.946	0.685
Shandong	0.579	0.515	0.555	0.571	0.808	0.799	0.786	0.993
Shanxi	0.68	0.468	0.455	0.395	0.543	0.558	0.424	0.433
Shaanxi	0.515	0.554	0.39	0.308	0.501	0.443	0.358	0.31
Shanghai	1	1	1	1	0.903	0.881	1	0.984
Sichuan	0.624	0.719	0.349	0.355	0.833	0.73	0.606	0.945
Tianjin	0.624	0.409	0.289	0.335	0.666	0.807	0.65	0.711
Xizang	0.241	0.202	0.205	0.318	0.854	0.977	0.993	1
Xinjiang	0.499	0.213	0.243	0.275	1	1	1	1
Yunnan	0.799	0.481	0.518	0.517	0.497	0.444	0.385	0.501
Zhejiang	0.536	0.328	0.288	0.282	0.391	0.339	0.289	0.326
Chongqing	1	0.726	0.66	0.524	0.332	0.255	0.261	0.261

5.2. Analysis of the Results of the Second Stage

After obtaining the target values of the input variables in the first stage, the slack variables were calculated based on the differences between the target values and the actual values. Then, using the total crop planting area, per capita disposable income, and direct economic losses caused by natural disasters in each province as environmental variables, the panel data from 2018 to 2021 was entered into the FRONTIER 4.1 software, and regression analysis was performed using the cost function. The results are shown in Table 4 below:

Table 4. Environmental variable SFA regression results.

	Coefficient	Standard error	t-value
Constant term	249.8378	170.6321	1.4642
Direct economic loss	(0.2571)	0.1405	(2.8306)
Per capita disposable income	0.0056	0.0088	0.6403
Total crop planting area	0.0651	0.0134	4.8381
σ^2	189669.9300	1.2660	149819.2300
γ	0.7787	0.0322	24.1855
One-sided generalized likelihood ratio test LR: 44.612415			

Based on the one-sided generalized likelihood ratio test, at the 0.01 significance level, we can reject H0: there is no inefficiency term, i.e., it is reasonable to adopt the stochastic frontier model. The reason for the small coefficient may be due to the influence of dimensionality, which causes the original values to be too large. The GAMMA value is 0.7787, indicating that there is interference from both environmental variables and random errors. Therefore, the SFA model adjusts the input variables from both aspects.

Direct economic losses have a negative impact on the slack variable of agricultural insurance premium subsidies, indicating that the higher the extent of crop losses, the greater the need for increased agricultural insurance premium subsidies. On one hand, higher risks of losses increase farmers' demand for insurance, necessitating fiscal subsidies to achieve efficiency maximization; on the other hand, insurance companies face increased pressure from claims payments and also require corresponding subsidy policies for support.

The impact of per capita disposable income is positive but not statistically significant, indicating that the level of per capita disposable income has little effect on the level of premium subsidies. The total crop planting area has a positive impact on the slack variable, indicating that in regions with a higher total crop planting area, agricultural development is more advanced, and agricultural welfare and safeguards are more comprehensive. Agricultural insurance premium subsidies contribute limited value to local agricultural production, potentially leading to redundant subsidy amounts.

5.3. Analysis of Premium Subsidy Efficiency by Province in 2021

Based on the BCC model used in this study, the technical efficiency of agricultural insurance premium subsidies consists of two parts: pure technical efficiency and scale efficiency. Pure technical efficiency reflects the ability of each province to achieve policy objectives by optimizing the allocation of fiscal resources within a given framework. Scale efficiency measures the appropriateness of the scale of fiscal subsidy input under a given agricultural insurance subsidy system. Scale returns play a significant role in the analysis of agricultural insurance subsidy efficiency, and are categorized into three types: increasing returns to scale (IRS), constant returns to scale (CRS), and decreasing returns to scale (DRS). These represent three scenarios: expanding the subsidy scale can enhance the efficiency of fund utilization, production is within the optimal scale range, and the subsidy scale is redundant. Here, cross-sectional data from 2021 is used to analyze the pure technical efficiency, scale efficiency, and scale returns of 31 provincial-level administrative regions.

Table 5. 2021 efficiency values by province and city.

	crste	vrste	scale	
Anhui	0.756	0.967	0.782	irs
Beijing	1	1	1	-
Fujian	0.207	0.994	0.208	irs
Gansu	0.59	0.998	0.591	irs
Guangdong	0.553	0.95	0.582	irs
Guangxi	0.55	0.942	0.583	irs
Guizhou	0.38	0.998	0.381	irs
Hainan	0.766	0.976	0.784	irs
Hebei	0.72	0.884	0.815	irs

Continued

Henan	0.982	0.987	0.995	irs
Heilongjiang	1	1	1	-
Hubei	0.556	0.985	0.564	irs
Hunan	0.706	0.889	0.794	irs
Jilin	0.87	0.97	0.897	irs
Jiangsu	0.841	1	0.841	irs
Jiangxi	0.498	0.966	0.515	irs
Liaoning	0.668	0.963	0.694	irs
Inner Mongolia	0.783	1	0.783	drs
Ningxia	0.788	0.989	0.796	irs
Qinghai	0.97	0.972	0.997	irs
Shandong	0.808	0.981	0.824	irs
Shanxi	0.543	0.991	0.548	irs
Shaanxi	0.501	0.985	0.509	irs
Shanghai	0.903	1	0.903	irs
Sichuan	0.833	0.995	0.837	irs
Tianjin	0.666	0.994	0.67	irs
Xizang	0.854	0.972	0.879	irs
Xinjiang	1	1	1	-
Yunnan	0.497	1	0.497	irs
Zhejiang	0.391	0.996	0.393	irs
Chongqing	0.332	1	0.332	irs

As shown in **Table 5**, provinces and cities such as Beijing, Heilongjiang, Xinjiang, and Shanghai had effective pure technical efficiency in 2021, while most other provinces were ineffective. However, the number of effective provinces has improved compared to previous years, with a total of eight provincial-level administrative regions having pure technical efficiency within the effective range. Overall, provinces with better economies or those that are major grain-producing provinces have higher pure technical efficiency, while other regions generally have lower efficiency.

From the perspective of scale efficiency, the number of provinces with effective scale efficiency is fewer than those with effective pure technical efficiency, with only three provinces meeting the criteria. This indicates that the subsidy scale in most regions is not yet optimal. Among these, Inner Mongolia exhibits diminishing returns to scale, while other regions consistently show increasing returns to scale. This suggests that there is further room for increasing agricultural insurance subsidies in most provinces in China, and additional investments can be made in the future.

6. Research Conclusions and Policy Recommendations

Since the launch of the policy-based agricultural insurance program in 2007, subsidies have played a significant role in promoting the development of agricultural insurance, providing a certain level of protection against risks faced by China's agricultural production. However, issues such as low efficiency in the use of subsidy funds, inadequate protection levels, and significant interprovincial disparities remain. This study employs a three-stage DEA model, utilizing provincial agricultural insurance premium subsidy data from 2018 to 2021 in China. After adjusting for environmental variables and random errors, the study analyzes the efficiency of fiscal subsidies, with metrics including technical efficiency, pure technical efficiency, and scale efficiency. Based on the empirical results and conclusions, this study offers the following recommendations for the development of China's agricultural insurance subsidy policy:

1) The overall efficiency of fiscal subsidies for agricultural insurance is poor, and the intensity of subsidies needs to be increased. Based on the efficiency analysis results, most regions are in a state of inefficiency with increasing returns to scale. Therefore, the implementation and intensity of fiscal subsidy policies should be maintained to leverage the promotional role of insurance in agricultural development, while also focusing on improving the subsidy mechanism. Additionally, efficiency values fluctuate significantly across different years, and their stability and risk-resistance capabilities need to be enhanced.

2) Implement differentiated subsidy policies tailored to the specific conditions of different regions; based on the analysis in the second phase, the efficiency of agricultural insurance premium subsidies is significantly influenced by the specific environmental conditions of each province. Therefore, the allocation of subsidy funds and the implementation of specific subsidy policies in each region should fully consider local economic conditions, agricultural development status, natural environment, and differences in risk levels to formulate reasonable policies suited to local conditions. For example, appropriately increase subsidy intensity for major grain crops and grain-producing counties, and include agricultural machinery, fertilizers, and other resources and equipment within the scope of subsidy coverage to achieve differentiated resource allocation nationwide.

3) Improving the mechanism for determining subsidy scales is key to enhancing subsidy efficiency. Based on the decomposition results of technical efficiency, the scale efficiency levels of provinces generally lag behind pure technical efficiency levels, indicating that the mechanism for determining fiscal subsidy amounts constrains improvements in technical efficiency. Therefore, efforts should be made to standardize and accurately assess the scale of these agricultural support funds to ensure that every dollar is used effectively. Conduct regional surveys to understand farmers' needs and strive to mitigate issues such as subsidy misallocation, ensuring subsidies are distributed reasonably. Simultaneously, strengthen the promotion of agricultural insurance, enhance risk management awareness, and promptly disclose information to enable farmers to access relevant policies and product information. Ensure proper insurance claims processing and identify local demand for agricultural insurance.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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