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Financial Support Efficiency of Rural Revitalization: Based on Three-Stage DEA Model and Malmquist Index Model

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Abstract: Financial resources play a crucial role in rural revitalization. Understanding the efficiency of financial support is essential for the scientific and rational allocation of these resources. Therefore, we conducted an assessment over the period 2011–2020 utilizing the three-stage DEA model and the Malmquist index model to measure the efficiency of financial support for rural revitalization across 30 Chinese provinces (excluding Hong Kong, Macao, Taiwan, and Tibet) from both static and dynamic perspectives. The results indicate the following: (1) Despite an overall downward trend, efficiency increased during specific intervals, namely 2012–2013, 2015–2016, and 2018–2019. (2) Regionally, the decline in the efficiency of financial support for rural revitalization is particularly notable in the northeast region. The eastern and central regions also experienced this trend to a lesser extent, whereas the western region experienced a more moderate decrease. However, a detailed analysis revealed that 10 provinces experienced efficiency gains. (3) Stochastic Frontier Analysis (SFA) regression results suggest that environmental variables have a measurable impact on the efficiency of financial support for rural revitalization.

Keywords: rural revitalization; three-stage DEA model; Malmquist index model; financial support; efficiency evaluation

1. Introduction

Since its inception, China's rural revitalization strategy has emerged as a pivotal national development priority. As a crucial pillar of the modern economic landscape, finance holds significant importance in fostering rural economic growth, enhancing farmers' living standards, and driving agricultural modernization [1–3]. High-quality and effective financial resource allocation is a prerequisite and foundation for giving full play to the effectiveness of financial support for rural revitalization. A full understanding of the effectiveness of financial support for rural revitalization is the only way to allocate financial resources in a scientific and reasonable manner, better assist rural revitalization, and achieve sustainable development in villages. However, owing to the unique characteristics of rural areas, including their remote geographical locations, diverse economic development levels, and underdeveloped financial service systems, notable regional disparities exist in the efficiency of financial resource allocation [4]. Thus, developing effective means to gauge the effectiveness of financial support for rural revitalization and ensuring the optimal allocation and efficient utilization of financial resources remain key challenges.

Rural revitalization has rich connotations, covering five aspects: industrial prosperity, ecological livability, rural civilization, effective governance, and life affluence [5]. Since the concept of rural revitalization was put forward, academics have explored its multiple

Academic Editor: Francesco Tajani

Received: 5 December 2024
Revised: 9 January 2025
Accepted: 22 January 2025
Published: 24 January 2025

Citation: Liu, X.; Zhuang, Y.; Qiu, X. Financial Support Efficiency of Rural Revitalization: Based on Three-Stage DEA Model and Malmquist Index Model. *Sustainability* **2025**, *17*, 946. https://doi.org/10.3390/su17030946

dimensions of rural revitalization in depth, including the construction of an evaluation system and the analysis of influencing factors [6–8]. However, many scholars have pointed out that despite the significance of the rural revitalization strategy, it still faces many challenges in its implementation. These challenges include the monolithic nature of the rural industrial structure, lack of capital, backwardness of technology, and lack of human resources [9,10].

Finance is an essential factor in driving rural revitalization. As the lifeblood of real economic development, it plays a crucial role in fostering rural resilience and promoting environmental sustainability [11–13]. Improving the efficiency of financial support is key to promoting sustainable rural development. Enhanced financial efficiency ensures that financial resources flow more precisely and efficiently into the key areas of rural development. Wang et al. [14] discovered that the expansion of bank branches resulted in increased financial penetration, which consequently raised the income of rural households and decreased the likelihood of them falling back into poverty. Qian et al. [2] noted that, in comparison to traditional financial services, emerging financial services exhibit a notably more favorable impact on the income and consumption patterns of rural residents. Lin and Peng's [15] findings showed that digital finance can significantly contribute to rural development.

Data envelopment analysis (DEA), a non-parametric approach for efficiency evaluation, has been extensively utilized to assess the efficiency of public sectors, enterprises, and specific policies or projects [16–19]. Its advantage is that it does not require knowledge of a specific production function while efficiently managing multiple inputs and outputs. In recent years, this approach has received much attention in studies on the efficiency of rural poverty alleviation as well as the efficiency of financial support. Yang et al. [20] evaluated the effectiveness of anti-poverty policies in China using a two-stage data envelopment analysis model. Chen et al. [21] employed a type-2 fuzzy data envelopment analysis (DEA) model to quantify the relative efficiency of rural poverty reduction initiatives in Hainan Province. Wang et al. [22] utilized the Super-SBM model to evaluate the effectiveness of tourism-based poverty alleviation programs in 40 districts and counties in the Liupan Mountain region of Gansu Province, China, over a period of 10 years from 2009 to 2018. Xiao et al. [23] conducted a dynamic evaluation of poverty reduction efforts in China based on the non-convex global two-stage Data Envelopment Analysis (DEA) and the Malmquist index model. Wang et al. [24] used a two-stage dynamic DEA model to measure and analyze the spatio-temporal evolution of agricultural production efficiency and poverty reduction in China. Xue and Li [25] applied the DEA-Malmquist index to evaluate the efficiency of financial support for agricultural industrialization. Lu and Zhang [26] evaluated the efficiency of financial support for high-tech industries using the DEA model and the DEA-Malmquist index.

Recently, several scholars have employed DEA models to assess the effectiveness of financial assistance in reducing poverty. For instance, Jing and Li [27] employed the DEA-Malmquist index model utilizing provincial panel data spanning 2014 to 2020 to evaluate the synergistic impact of fiscal spending and digital inclusive finance on reducing relative poverty in China's central and western provinces. Similarly, Liu [28] utilized an output-oriented DEA model to assess the efficiency of financial poverty alleviation in 18 cities in Henan Province, China. However, DEA models have rarely been used to analyze the effectiveness of financial support for rural revitalization, which is currently a central topic in academic discourse. For example, Liu et al. [29] investigated the positive impact of digital inclusive finance on rural revitalization using data from 52 counties and cities in Hubei Province. Wei et al. [30] empirically found that financial support plays a positive and long-term role in improving environmental quality and promoting rural revitalization and sustainable development, applying a VAR model with data from Shaanxi Province, China, over the period 2004–2019. Xiong et al. [31] analyzed the impact of digital inclusive finance on rural revitalization using multiple linear regression, a mediation effect model, and a threshold effect model with data from a sample of 30 provinces in China from 2011 to 2020. Xia and Kong [32] examined the impact of digital finance on rural revitalization using a fixed effect model and differential GMM model with data from 30 provinces in China from 2012 to 2019.

In summary, the current research lacks an in-depth analysis of the efficiency of financial support for rural revitalization. Compared to poverty alleviation, measuring the efficiency of rural revitalization proves more challenging because of its multifaceted nature, which encompasses dimensions such as industrial prosperity, ecological livability, rural civilization, effective governance, and life affluence [33]. Therefore, to gain insights into the efficiency of financial support for rural revitalization, this study selected 30 provinces in China as measurement units, based on the 'Rural Revitalization Strategy Planning (2018–2022)'. In taking the period from 2011 to 2020 as the evaluation period, this study employed the entropy method to measure the comprehensive level of rural revitalization in these 30 provinces. Subsequently, the three-stage Data Envelopment Analysis (DEA) and Malmquist index models were applied to evaluate the efficiency of China's financial support for rural revitalization from both static and dynamic perspectives. This study further enriches the theory and methodology for evaluating the effectiveness of financial support for rural revitalization. The results of this study provide a decision-making basis for China's financial support for the sustainable development of rural areas.

2. Methods

2.1. Three-Stage DEA Model

Stage 1: To calculate the initial efficiency using the BCC-DEA model, consider n decision-making units (DMUs), each characterized by p inputs and q outputs. For the i^{th} DMU, its input–output vectors are denoted as X_i and Y_i, where $X_i = (x_{1i}, x_{2i}, \ldots, x_{pi})^T$ and $Y_i = (y_{1i}, y_{2i}, \ldots, y_{qi})^T$. By incorporating the non-Archimedean infinitesimal ε, weight variable λ_j, efficiency value θ of the DMU under evaluation, slack variable S^-, and surplus variable S^+, the BCC-DEA model can be formulated as follows:

$$Min\left[\theta - \varepsilon\left(e_I^T S^- + e_O^T S^+\right)\right]$$
$$s.t.\begin{cases} \sum_{j=1}^{n} X_j\lambda_j + S^- = \theta X_0, \\ \sum_{j=1}^{n} Y_j\lambda_j - S^+ = Y_0, \\ \sum_{j=1}^{n} \lambda_j = 1, \\ S^- \geq 0, S^+ \geq 0, \lambda_j \geq 0 \end{cases} \tag{1}$$

Stage 2: The construction of a similar SFA model. Factors such as the external environment, inefficient management, and stochastic disturbances can affect the slack variables and efficiency values observed in the first stage. To minimize the deviation in efficiency values, this study drew on the work of Fried et al. [34] to develop an SFA regression model tailored to the input slack variable.

$$S_{ij}^- = f^i(Z_j; \beta_i) + v_{ij} + u_{ij} \tag{2}$$

In (2), S_{ij}^{-} represents the slack variable associated with the j^{th} input for the i^{th} decision-making unit (DMU). Vector $Z_j = \left(z_{1j}, z_{2j}, \ldots, z_{lj}\right)$ denotes the environmental variable, with β_i representing the estimated parameter vector of the environmental variable. $v_{ij} + u_{ij}$ constitutes a combinatorial error term, where $v_{ij} \sim N\left(0, \sigma_{vj}^2\right)$ signifies stochastic disturbance, and $u_{ij} \sim N\left(0, \sigma_{uj}^2\right)$ denotes management noise. These two error components are assumed to be statistically independent.

Stage 3: Using the BCC-DEA model, we recalculate the final efficiency with adjusted input variables according to (1). This process enabled us to determine the adjusted efficiency value of financial support for rural revitalization in each province.

2.2. DEA-Malmquist Index

The three-stage DEA model can only measure the efficiency of financial support for rural revitalization in a static dimension, while the DEA-Malmquist index model [35] can capture dynamic changes in such efficiency. DEA-Malmquist is a dynamic efficiency analysis method that measures the Malmquist total factor productivity index through the change in productivity from one period to the next. The Malmquist index can be decomposed into three components: the pure technical efficiency index (PECH), technical progress index (TECH), and scale efficiency index (SECH). The formula is as follows:

$$TFPCH = PECH \times TECH \times SECH \tag{3}$$

Here, the total factor productivity index $TFPCH > 1$ indicates an increase in total factor productivity; $TFPCH = 1$ signifies no change in total factor productivity; and $TFPCH < 1$ suggests a decrease in total factor productivity. The pure technical efficiency index (PECH) represents the change in the ability of decision-making units to utilize existing technology more efficiently without changing the scale of production. $PECH > 1$ signifies an improvement in the ability to use existing technology more effectively. The technical progress index (TECH) primarily refers to the impact of technical progress on decision-making units. $TECH > 1$ signifies the occurrence of technical progress or innovation, indicating a shift in the production frontier toward increased efficiency. The scale efficiency index (SECH) denotes the change in the ability of decision-making units to operate at the most productive scale, given the technology. $SECH > 1$ indicates an improvement in scale efficiency, suggesting that the unit is operating closer to the most efficient scale size under conditions of variable returns to scale.

In addition, the technical efficiency index (EFFCH) can be calculated by multiplying the pure technical efficiency index (PECH) and the scale efficiency index (SECH), which is expressed as $EFFCH = PECH \times SECH$. It is primarily concerned with the use of existing technology by the decision-making unit. $EFFCH > 1$ indicates that the decision-making unit is closer to the production frontier, implying an improvement in technical efficiency. Conversely, $EFFCH < 1$ indicates that the decision-making unit's use of existing technology is suboptimal.

3. Variables

3.1. Input Variables

Financial institutions, including rural commercial banks, policy banks, and insurance companies, play a key role in rural revitalization. They provide credit support to rural areas and offer a variety of financial services such as agricultural insurance, investment, financing, and advisory services. Together, these services form the financial backbone that supports rural development. Within the strategic framework of the 'Rural Revitalization Strategic Plan (2018–2022)', agricultural insurance is recognized as a significant component of the 'agricultural support and protection system'. It plays a pivotal role in rural revitalization by adeptly managing risks and providing a safety net for farmers' livelihoods [36,37]. Hence, this study incorporates agricultural insurance as a key variable in the analysis of financial inputs. Agricultural credit is crucial for rural revitalization, providing financial support to farmers and agribusinesses [36,38]. Consequently, we select agricultural credit as a key input variable, with the per capita balance serving as a primary indicator for measuring its level. Financial institutions and their staff are the most basic financial inputs that influence the availability of funds to rural populations [11,14]. In this study, we define the population coverage of branches and staff within rural financial institutions as measures of financial services coverage and human capital (Table 1).

Table 1. Input variables.

Variable	Measure
Agricultural insurance	Agricultural insurance density
Agricultural credit	Per capita balance of agricultural credit
Financial service coverage	Population coverage of branches within rural financial institutions
Human capital	Population coverage of staff within rural financial institutions

3.2. Output Variables

In this study, we chose to focus on the level of rural revitalization as the sole output variable, considering the applicability of the three-stage DEA model. Considering that rural revitalization aims at comprehensive and harmonious development, we identified five key dimensions: industrial prosperity, ecological livability, rural civilization, effective governance, and life affluence. Drawing on existing research [11,39,40], we selected 23 indicators and used the entropy method to assess the level of rural revitalization in 30 provinces in China. Details are shown in Table 2.

Table 2. Output variables.

Variable	Definition	Measure	Attribute
Level of rural revitalization	Industrial prosperity	Land productivity	+
		The total power of agricultural machinery/total sown area of crops	+
		Labor productivity	+
		Electricity consumption/village total population	+
		Production building area/Village total population	+
	Ecological livability	Road paving area/total road area	+
		The number of pesticide applications/total sown area of crops	-
		The number of agricultural fertilizer applications/total sown area of crops	-
		Forestry area/total area of land	+
		Number of households with a sanitary latrine/total number of households	+
	Rural civilization	Number of rural residents with a high school diploma or higher/village total population	+
		Number of full-time primary school teachers with a bachelor's degree or higher/number of full-time teachers in the village	+
		The average number of health workers per thousand rural residents	+
		Number of cultural stations owned per 100,00 rural residents	+
		Per capita consumption expenditure on culture, education, and entertainment/per capita consumption expenditure of rural residents	+
	Effective governance	Number of villages with overall planning/total number of villages	+
		Number of rural residents receiving subsistence allowance/village total population	-
		Per capita subsistence allowance of rural residents	+
	Life affluence	Disposable income per rural inhabitant	+
		Per capita consumption expenditure of rural residents	+
		Engel coefficient	-
		The average number of computers per hundred rural residents	+
		Total residential area/village total population	+

+ denotes a positive indicator, - denotes a negative indicator.

3.3. Environmental Variables

When selecting environmental variables, our primary focus was to identify factors that have a significant impact on rural revitalization and are beyond the control of decision-making units. Based on existing research, we believe that local fiscal support, natural disasters, and the regional economy are key environmental variables to consider.

Local fiscal support: As a crucial driver of rural revitalization, local fiscal support has an undeniable impact on rural development [27,41]. In light of this, this study includes it in the environmental variables for in-depth analysis, using the expenditure on agriculture, forestry, and water in the local general public budget as a specific measurement indicator.

Natural disasters: The development of agriculture is intimately linked to the dynamic and complex natural environment, and various natural disasters significantly hamper the progress of the agricultural economy. It is clear that these disasters have a significant impact on rural revitalization but are beyond the control of decision-making units [42–44]. Therefore, it is imperative to include them in environmental variables. Based on existing research, the impact of natural disasters can be quantified by evaluating affected crop areas.

Regional economy: Compared to areas with a poor regional economy, areas with a good regional economy can provide better technological support, more market expansion opportunities, and so on. These elements work synergistically to promote agricultural modernization, increase farm incomes, and improve social services. In addition, areas with a robust regional economy tend to attract talent back to the countryside, thereby catalyzing the innovative capacity of rural regions and strengthening their intrinsic development drive. Therefore, it is essential to include the regional economy as an integral part of the analysis in a three-stage DEA model [33,45]. To achieve this objective, the present study chose a precise quantitative indicator—regional Gross Domestic Product (GDP) per capita, including both urban and rural areas—to quantify and represent this environmental variable (Table 3).

Table 3. Environmental variables.

Variable	Measure
Local fiscal support	The expenditure on agriculture, forestry and water in the local general public budget
Natural disasters	The affected crop areas
Regional economy	Regional Gross Domestic Product (GDP) per capita

4. Results

4.1. Data Source and Processing

The research data were mainly obtained from various sources, including the China Statistical Yearbook, China Rural Statistical Yearbook, China Insurance Statistical Yearbook, China Environmental Statistical Yearbook, China Urban and Rural Construction Statistical Yearbook, China Civil Affairs Statistical Yearbook, China Social Statistical Yearbook, China Education Statistical Yearbook, China Population and Employment Statistical Yearbook, China Rural Finance Yearbook, China Finance Yearbook, and local statistical yearbooks of the 30 provinces. In addition, data were obtained from the China Economic Database and the China Stock Market & Accounting Research Database.

Due to significant data gaps in Tibet and notable differences in data collection methods and statistical standards among Hong Kong, Macau, and Taiwan compared to other provinces, data comparability could potentially be undermined. Therefore, this study chose to use only data from the remaining 30 provinces, excluding the above four regions, for the years 2011 to 2020 as the primary analytical basis for our investigation. In addition, interpolation methods were used for data processing to address missing data in individual years.

According to the classification of the National Bureau of Statistics of China, this study divided China's economic regions into four major areas: the eastern, central, western, and northeastern regions. The eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. Finally, the northeast region consists of Liaoning, Jilin, and Heilongjiang.

4.2. Three-Stage DEA Results

Before performing an efficiency analysis, it was crucial to verify that the input and output variables satisfy the 'homogeneity' assumption. To this end, a Pearson correlation coefficient analysis was conducted for both the input and output variables. The results revealed a significant positive correlation between the output and input variables at the 0.01 level of significance.

(1) The evaluation results of stage 1

In this part, we employed the BCC-DEA model in conjunction with DEAP2.1 to compute the overall technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) concerning financial support for rural revitalization across 30 Chinese provinces during stage 1, which encompasses the years from 2011 to 2020. The results are presented in Table 4.

Table 4. The evaluation results of stage 1.

Area	2011				2020				MEAN		
	TE	PTE	SE		TE	PTE	SE		TE	PTE	SE
Beijing	0.685	0.996	0.688	drs	0.615	0.615	1	-	0.713	0.796	0.908
Fujian	1	1	1	-	1	1	1	-	1	1	1
Guangdong	1	1	1	-	1	1	1	-	1	1	1
Hainan	0.88	0.962	0.914	irs	0.878	1	0.878	irs	0.857	0.945	0.908
Hebei	0.826	0.828	0.998	drs	0.714	0.796	0.897	irs	0.803	0.824	0.974
Jiangsu	1	1	1	-	0.546	0.629	0.868	drs	0.889	0.913	0.965
Shanghai	1	1	1	-	1	1	1	-	1	1	1
Shandong	1	1	1	-	0.723	0.734	0.985	irs	0.861	0.87	0.988
Tianjian	0.582	0.677	0.86	drs	0.55	0.552	0.995	irs	0.584	0.644	0.909
Mhejiang	0.965	1	0.965	drs	0.95	1	0.95	drs	0.961	1	0.961
Eastern mean	0.894	0.946	0.943		0.798	0.833	0.957		0.867	0.899	0.961
Anhui	0.768	0.937	0.819	irs	0.707	0.759	0.932	irs	0.755	0.877	0.864
Henan	0.953	0.971	0.982	irs	0.732	0.914	0.801	irs	0.808	0.924	0.874
Hubei	1	1	1	-	1	1	1	-	1	1	1
Hunan	1	1	1	-	0.761	0.885	0.86	irs	0.942	0.978	0.961
Jiangxi	1	1	1	-	0.711	0.711	1	-	0.904	0.913	0.989
Shanxi	0.542	0.543	0.998	irs	0.479	0.625	0.766	irs	0.543	0.645	0.857
Central mean	0.877	0.909	0.967		0.732	0.816	0.893		0.825	0.890	0.924
Inner Mongolia	0.357	0.411	0.868	irs	0.311	0.398	0.782	irs	0.355	0.406	0.875
Ningxia	0.52	0.669	0.778	irs	0.361	0.5	0.722	irs	0.431	0.595	0.727
Qinghai	0.739	0.893	0.827	irs	0.502	0.608	0.826	irs	0.596	0.697	0.852
Shaanxi	1	1	1	-	0.755	0.831	0.909	irs	0.888	0.913	0.971
Gansu	0.661	0.921	0.717	irs	0.632	0.779	0.812	irs	0.632	0.787	0.808
Sichuan	0.655	0.749	0.875	irs	0.772	0.879	0.878	irs	0.705	0.791	0.892
Xinjiang	0.56	0.849	0.659	irs	0.479	0.672	0.713	irs	0.567	0.869	0.654
Yunnan	0.838	1	0.838	irs	1	1	-	0.957	1	0.957	
Chongqing	0.717	0.725	0.988	irs	0.885	0.988	0.896	irs	0.824	0.891	0.93
Guangxi	1	1	1	-	0.891	1	0.891	irs	0.98	1	0.98
Guizhou	1	1	1	-	0.644	0.775	0.83	irs	0.781	0.91	0.854
Western Mean	0.732	0.838	0.868		0.657	0.766	0.842		0.701	0.805	0.864

Table 4. *Cont.*

Area	2011				2020				MEAN		
	TE	PTE	SE		TE	PTE	SE		TE	PTE	SE
Liaoning	0.614	0.615	0.998	drs	0.463	0.587	0.789	irs	0.6	0.635	0.943
Heilongjiang	0.59	0.676	0.873	irs	0.433	0.6	0.721	irs	0.559	0.688	0.811
Jilin	0.654	0.718	0.912	irs	0.484	0.716	0.676	irs	0.565	0.695	0.813
Northeastern mean	0.619	0.670	0.928		0.460	0.634	0.729		0.575	0.673	0.856
National average	0.804	0.871	0.919		0.699	0.785	0.879		0.769	0.84	0.908

Table 4 presents a clear regional distribution of overall technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) in the first stage, with the trend in the east, central, west, and northeast in descending order. In 2011, 11 provinces were on the efficiency frontier, but this number dropped to five by 2020. Fujian, Guangdong, Shanghai, and Hubei maintained their positions on the efficiency frontier for a decade. However, Inner Mongolia, Ningxia, Shanxi, Tianjin, and Xinjiang consistently had lower levels of both overall technical efficiency (TE) and pure technical efficiency (PTE) throughout the ten years.

(2) SFA regression

In the second stage, we conducted a regression analysis analogous to Stochastic Frontier Analysis (SFA) using Frontier 4.1. In this analysis, we selected the slack variables of four input indicators as dependent variables, which encompass agricultural insurance density, population coverage of branches within rural financial institutions, population coverage of staff within rural financial institutions, and per capita balance of agricultural credit. We introduced three environmental variables as independent variables: local fiscal support, natural disasters, and regional economy. To ensure the accuracy of the data analysis, these environmental variables were standardized to eliminate the potential impact of inconsistent units. The detailed regression analysis results are shown in Table 5.

Table 5. SFA regression results.

	Agricultural Insurance Density	Population Coverage of Branches Within Rural Financial Institutions	Population Coverage of Staff Within Rural Financial Institutions	Per Capita Balance of Agricultural Credit
Constant term	−40.728 **	0.064	−0.874	278.698
Local fiscal support	98.853 ***	0.034	3.493 **	−4896.892 ***
Natural disasters	−18.771 *	−0.168 ***	−2.107 ***	−5806.298 ***
Regional economy	−155.233 ***	−0.383 ***	−5.840 ***	3377.087 ***
Sigma-squared	14,022.395 ***	0.353 ***	86.748 ***	255,882,420.000 ***
Gamma	0.885 ***	0.930 ***	0.929 ***	0.741 ***
Log-likelihood function	−1584.312	75.774	−751.910	−3162.450
LR test of the one-sided error	323.799 ***	397.493 ***	395.528 ***	150.582 ***

*, **, and *** indicate significance levels at 0.1, 0.05, and 0.01, respectively.

As indicated in Table 5, the log-likelihood (LR) values for all models are significant at the 0.01 level, thereby robustly endorsing the appropriateness of employing the Stochastic Frontier Analysis (SFA) model. The gamma values, as presented in the regression equations, are 0.885, 0.93, 0.929, and 0.741, respectively, each significant at the 0.01 level. These findings suggest that environmental variables substantially influence the efficiency of rural financial inputs, corroborating the necessity of using SFA regression analysis.

Local fiscal support: The impact coefficient of local fiscal support on the input variable of agricultural credit is −4896.892, which is significant at the 0.01 level of significance. This result indicates that as local fiscal support increases, the slack of agricultural credit inputs decreases significantly. However, for the two input variables of agricultural insurance density and population coverage of staff in rural financial institutions, local fiscal support showed a positive and significant coefficient relationship. This means that an increase in fiscal support leads to an increase in the slack of these two inputs, which may reduce resource utilization efficiency.

Natural disasters: Natural disasters have a negative and significant correlation with all input variables, suggesting that their occurrence significantly reduces the slack of the input factors.

Regional economy: The impact coefficient of the regional economy on agricultural credit, among the environmental variables, is positive and significant at the 0.01 level, indicating that an improvement in the regional economy leads to an increase in agricultural credit slack. Conversely, the impact coefficient of the regional economy on variables such as agricultural insurance and financial infrastructure investment is negative and significant, indicating that as the regional economy develops, the slack of these two investments decreases.

(3) The evaluation results of stage 3

In this stage, we recalculated the efficiency of financial support for rural revitalization in China with adjusted inputs using the BCC-DEA model. Table 6 reveals that upon mitigating the impacts of external factors and random errors, notable changes are evident in efficiency across the period from 2011 to 2020.

Table 6. The evaluation results of stage 3.

Area	2011				2020				MEAN		
	TE	**PTE**	**SE**		**TE**	**PTE**	**SE**		**TE**	**PTE**	**SE**
Beijing	0.788	0.964	0.818	drs	0.683	0.685	0.997	irs	0.831	0.871	0.956
Fujian	1	1	1	-	1	1	1	-	1	1	1
Guangdong	1	1	1	-	1	1	1	-	1	1	1
Hainan	0.847	1	0.847	irs	0.812	1	0.812	irs	0.824	0.997	0.827
Hebei	0.919	0.938	0.98	irs	0.807	0.866	0.932	irs	0.897	0.939	0.955
Jiangsu	1	1	1	-	0.777	0.806	0.964	drs	0.95	0.956	0.993
Shandong	1	1	1	-	0.826	0.919	0.899	irs	0.952	0.982	0.969
Shanghai	1	1	1	-	1	1	1	-	1	1	1
Tianjin	0.666	0.709	0.94	drs	0.645	0.65	0.992	irs	0.692	0.708	0.979
Zhejiang	1	1	1	-	1	1	1	-	1	1	1
Eastern mean	0.922	0.961	0.959		0.855	0.893	0.960		0.915	0.945	0.968
Anhui	0.733	1	0.733	irs	0.778	0.834	0.934	irs	0.767	0.951	0.809
Heinan	0.923	1	0.923	irs	0.778	0.947	0.821	irs	0.832	0.976	0.852
Hubei	0.853	1	0.853	irs	1	1	1	-	0.938	0.999	0.939
Hunan	0.867	1	0.867	irs	0.801	0.924	0.867	irs	0.887	0.989	0.897
Jiangxi	1	1	1	-	0.807	0.876	0.921	irs	0.947	0.974	0.972
Shanxi	0.712	0.84	0.848	irs	0.597	0.845	0.707	irs	0.722	0.878	0.824
Central mean	0.848	0.973	0.871		0.794	0.904	0.875		0.849	0.961	0.882
Gansu	0.636	0.998	0.637	irs	0.716	0.849	0.844	irs	0.698	0.93	0.753
Guangxi	0.833	1	0.833	irs	0.847	1	0.847	irs	0.896	1	0.896
Guizhou	0.511	1	0.511	irs	0.736	0.995	0.74	irs	0.707	0.99	0.715
Inner Mongolia	0.559	0.744	0.752	irs	0.35	0.448	0.782	irs	0.464	0.616	0.755
Ningxia	0.594	0.816	0.728	irs	0.436	0.572	0.762	irs	0.524	0.741	0.709
Qinghai	0.72	0.907	0.793	irs	0.55	0.684	0.804	irs	0.647	0.809	0.8
Shaanxi	0.947	1	0.947	irs	0.79	0.876	0.901	irs	0.894	0.958	0.933
Sichuan	0.833	0.943	0.884	irs	0.843	0.975	0.865	irs	0.845	0.955	0.885
Xinjiang	0.584	0.946	0.618	irs	0.539	0.747	0.721	irs	0.578	0.928	0.626
Yunnan	0.746	1	0.746	irs	0.938	1	0.938	irs	0.867	1	0.867
Chongqing	0.769	0.926	0.83	irs	0.845	0.884	0.955	irs	0.818	0.892	0.917
Western Mean	0.703	0.935	0.753		0.69	0.821	0.833		0.722	0.893	0.805

Table 6. *Cont.*

Area	2011				2020				MEAN		
	TE	PTE	SE		TE	PTE	SE		TE	PTE	SE
Liaoning	0.832	0.863	0.964	irs	0.532	0.641	0.829	irs	0.742	0.812	0.911
Heilongjiang	0.663	0.864	0.767	irs	0.465	0.648	0.718	irs	0.607	0.809	0.75
Jilin	0.775	0.95	0.815	irs	0.489	0.752	0.649	irs	0.644	0.867	0.74
Northeastern mean	0.757	0.892	0.849		0.495	0.680	0.732		0.664	0.829	0.800
National average	0.81	0.947	0.854		0.746	0.847	0.873		0.806	0.918	0.874

Compared to Tables 4 and 6, the efficiency of financial support for rural revitalization during the third stage mirrors that of the first stage, continuing to exhibit regional disparities characterized by the trend 'East > Central > West > Northeast'. Nevertheless, the number of provinces positioned on the efficiency frontier in the third stage decreased relative to the first stage.

The disparities in overall technical efficiency (TE) between various provinces at stages 1 and 3 are evident. These variations indicate that the chosen environmental variables significantly influence the TE associated with financial support for rural revitalization. Specifically, from 2011 to 2020, most provinces demonstrated substantial enhancement in their TE. Nevertheless, there were several conspicuous exceptions: Hainan, Hunan, Guangxi, Guizhou, Yunnan, and Chongqing experienced a decline in TE. Particularly noteworthy is the case of Hubei Province, which had a TE value of 1 in stage 1, signifying its position on the efficiency frontier. However, its average TE decreased to 0.938 at stage 3.

Overall technical efficiency (TE) can be decomposed into two components: pure technical efficiency (PTE) and scale efficiency (SE). A comparison between the first and third stages reveals that almost all provinces achieved some degree of improvement in their pure technical efficiency. This indicates that the elimination of environmental variables and random noise has a substantial impact on pure technical efficiency. Furthermore, most provinces exhibited a decline in scale efficiency in the third stage compared to the first. This suggests that PTE is the primary driver of the TE increase.

4.3. Analysis of Dynamics

In this section, we evaluate the efficiency of financial support for rural revitalization over different periods using the Malmquist index model. Our analysis is based on provincial panel data from 2011 to 2020 and employs DEAP 2.1. The results are presented in Tables 7 and 8.

Table 7. Change trend in Malmquist index and its decomposition in China from 2011 to 2020.

Year	EFFCH	TECH	PECH	SECH	TFPCH
2011–2012	1.011	0.968	0.985	1.027	0.979
2012–2013	0.97	1.034	0.99	0.98	1.003
2013–2014	1.039	0.92	0.996	1.043	0.956
2014–2015	1.004	0.991	0.997	1.007	0.995
2015–2016	0.954	1.054	1.001	0.953	1.006
2016–2017	0.99	1.005	1.003	0.987	0.995
2017–2018	1.114	0.884	0.998	1.117	0.985
2018–2019	0.877	1.164	0.993	0.883	1.02
2019–2020	0.959	1.02	0.916	1.047	0.978

Table 7 illustrates the trend in the Malmquist index and its decomposition, which measures the efficiency of China's financial support for rural revitalization from 2011 to 2020. The technical progress index (TECH) exhibits an average annual growth rate of 0.2%.

This is in contrast to the technical efficiency index (EFFCH), which experienced an average annual decline of 1.1%. A closer examination reveals that the pure technical efficiency index (PECH) contributes to this decline, with an average annual decrease of 1.4%, while the scale efficiency index (SECH) shows a more positive trend, with an upswing of 4.7% per year.

Additionally, Table 7 illustrates that the evolutionary trends in total factor productivity (TFPCH) and the technical progress index (TECH) are fundamentally similar. However, total factor productivity (TFPCH) exhibits less fluctuation compared to the technical progress index (TECH), which is attributed to the impact of the technical efficiency index (EFFCH). The overall trajectory of the TFPCH index was downward, with a mean value of 0.991, indicating an average rate of decline of 0.9%.

The findings from the analysis mentioned above indicate that despite the gradual increase in financial support for rural development across various regions, there has been a noticeable decline in the efficiency of resource utilization. Therefore, as certain provinces increase their overall allocation of financial resources, there is an urgent need to examine the distribution of financial resources and improve the efficiency of resource utilization.

Table 8. Malmquist index and its decomposition for the 30 provinces (2012–2020).

Area	EFFCH	TECH	PECH	SECH	TFPCH
Beijing	0.984	1.007	0.963	1.022	0.992
Fujian	1	1.005	1	1	1.005
Guangdong	1	0.981	1	1	0.981
Hainan	0.995	1.024	1	0.995	1.019
Hebei	0.986	0.989	0.991	0.994	0.974
Jiangsu	0.972	1.005	0.976	0.996	0.977
Shandong	0.979	0.993	0.991	0.988	0.972
Shanghai	1	1.035	1	1	1.035
Tianjin	0.996	0.992	0.99	1.006	0.989
Zhejiang	1	0.986	1	1	0.986
Eastern Mean	0.991	1.002	0.991	1.000	0.993
Anhui	1.007	0.996	0.98	1.027	1.003
Henan	0.981	0.992	0.994	0.987	0.973
Hubei	1.018	1.068	1	1.018	1.087
Hunan	0.991	0.991	0.991	1	0.982
Jiangxi	0.976	0.989	0.985	0.991	0.965
Shanxi	0.981	0.981	1.001	0.98	0.962
Central mean	0.992	1.003	0.992	1.001	0.995
Gansu	1.013	0.991	0.982	1.032	1.005
Guangxi	1.002	0.99	1	1.002	0.992
Guizhou	1.041	0.99	0.999	1.042	1.031
Inner Mongolia	0.949	1.005	0.945	1.004	0.954
Ningxia	0.966	1.011	0.961	1.005	0.977
Qinghai	0.971	1.031	0.969	1.002	1.001
Shaanxi	0.98	0.983	0.985	0.994	0.963
Sichuan	1.001	0.986	1.004	0.998	0.987
Xinjiang	0.991	1.041	0.974	1.017	1.032
Yunnan	1.026	1.006	1	1.026	1.032
Chongqing	1.01	0.982	0.995	1.016	0.993
Western Mean	0.995	1.001	0.983	1.013	0.997
Liaoning	0.951	0.992	0.967	0.983	0.944
Heilongjiang	0.961	1.009	0.968	0.993	0.97
Jilin	0.95	0.999	0.974	0.975	0.949
Northeastern mean	0.954	1.000	0.970	0.984	0.954
National mean	0.989	1.002	0.986	1.003	0.991

According to Table 8, the efficiency of financial support for rural revitalization improved in 10 provinces, as indicated by a total factor productivity (TFPCH) score greater than 1. These provinces include Fujian, Hainan, and Shanghai in the eastern region; Anhui and Hubei in the central region; and Gansu, Guizhou, Qinghai, Xinjiang, and Yunnan in the western region. This indicates an upward trend in the efficiency of financial support for rural revitalization in these areas. Among them, Fujian, Shanghai, Hubei, and Yunnan have both EFFCH and TECH scores not less than 1, indicating that the improvement in their total factor productivity is due to the combined contribution of EFFCH and TECH. For Hainan, Qinghai, and Xinjiang, the EFFCH is less than 1 while the TECH is greater than 1, indicating that the improvement in their TFPCH is mainly due to the contribution of TECH. For the remaining provinces, the EFFCH is greater than 1, but the TECH is less than 1, indicating that the improvement in their TFPCH is mainly due to the contribution of EFFCH.

Total factor productivity (TFPCH) varies across regions in China. Specifically, the eastern, central, western, and northeastern regions had average TFPCHs of 0.993, 0.995, 0.997, and 0.954, respectively. This indicates a performance ranking from highest to lowest as follows: western > central > eastern > northeastern. In addition, the total factor productivity is less than 1 in most areas of China. The effectiveness of financial support for rural revitalization is declining. A significant discrepancy between rural financial demand and supply has led to the problem of superfluous financial input.

5. Conclusions

Financial resources are crucial for rural development and constitute a significant factor in rural revitalization. A thorough understanding of the efficiency of financial support is essential for the scientific and rational allocation of financial resources, which in turn improves the utilization rate of these resources during rural revitalization. Based on this, we chose the years 2011–2020 as the assessment period, employing the entropy method to quantitatively evaluate the level of rural revitalization across 30 Chinese provinces (excluding Hong Kong, Macao, Taiwan, and Tibet). Subsequently, we utilized the three-stage DEA and Malmquist index models from both static and dynamic perspectives to measure the efficiency of financial support for rural revitalization. The results of this study are as follows:

First, although there is an overall downward trend, the efficiency of financial support for rural revitalization has increased during specific intervals, namely the periods 2012–2013, 2015–2016, and 2018–2019.

Second, from a regional perspective, the decline in the efficiency of financial support for rural revitalization is particularly notable in the northeastern region. The eastern and central regions have also experienced this trend to a lesser extent, whereas the western region has seen a more moderate decrease. However, upon closer examination of the specific situations in individual provinces, it becomes evident that the decline in the efficiency of financial support is not universal. Specifically, ten provinces experienced efficiency gains: Fujian, Hainan, and Shanghai in the east; Anhui and Hubei in the central region; and Gansu, Guizhou, Qinghai, Xinjiang, and Yunnan in the west.

Third, the regression results from the Stochastic Frontier Analysis (SFA) suggest that environmental variables exert a measurable impact on the efficiency of financial support for rural revitalization.

Based on the results analyzed in this paper, the following policy recommendations are made. First, tailor financial products to meet the risk tolerance of groups vulnerable to returning to poverty in remote rural areas with low levels of education, low incomes, and weak risk tolerance. Second, create a service model that integrates online and offline services to empower rural residents in remote areas to access financial services through online channels. Finally, utilize digital financial instruments to integrate agriculture-related data, encompassing rural construction projects, rural land rights, land transfers, agricultural insurance, agricultural subsidies, farmers' deposits, and farmers' borrowing and lending activities. Efforts should be made to accelerate the construction of national agriculture-related public data and information-sharing platforms, aiming to establish a unified national public data platform and enhance the convenience and efficiency of data utilization.

This study has certain limitations. It primarily focused on analyzing the change in the efficiency of financial support for rural revitalization, but the specific reasons behind this change have not yet been analyzed in depth. In view of this, we intend to further deepen our research not only to explore the specific reasons for the change in financial support efficiency for rural revitalization but also to investigate whether this change is correlated with changes in government efficiency.

Author Contributions: Conceptualization, X.L.; methodology, X.L.; formal analysis, X.L.; writing—original draft preparation, X.L.; writing—review and editing, X.L. and X.Q.; supervision, Y.Z.; funding acquisition, Y.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Humanities and Social Science Fund of the Ministry of Education of China under Grant 21YJA630128 and the Emergency Management Project of the National Natural Science Foundation of China under Grant 72141019.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data in this study are mainly from the China Statistical Yearbook, China Rural Statistical Yearbook, Yearbook of China's Insurance, China Statistical Yearbook on Environment, China Urban-Rural Construction Statistical Yearbook, China Civil Affairs' Statistical Yearbook, China Social Statistical Yearbook, Educational Statistics Yearbook of China, China Population & Employment Statistical Yearbook, and local statistical yearbook in China. In addition, data were obtained from the China Economic Database and the China Stock Market & Accounting Research Database (CSMAR).

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

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