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Effect of Fiscal Expenditure for Supporting Agriculture on Agricultural Economic Efficiency in Central China—A Case Study of Henan Province

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Abstract: The policy guidance and financial support for industrial development from public finance provide an important guarantee for practicing green and circular development of agriculture. By sorting out the development context of fiscal support for agriculture in Henan province in different historical stages, this paper analyzes the development status of fiscal support for agriculture and the agricultural circular economy in the province. Relying on data envelopment analysis (DEA), it measures the efficiency of the agricultural circular economy in Henan province in 2013–2019 using the Charnes, Cooper, and Rhodes (CCR) model, the Banker, Charnes, and Cooper (BCC) model, and super-efficiency DEA models and empirically analyzes the effect of the fiscal expenditure for supporting agriculture on the efficiency of the agricultural circular economy using the fixed effect model. According to the results, (1) the expenditure on comprehensive agricultural development of Henan Province was mainly supported by the government's fiscal funds to such a degree that the proportion of fiscal funds from the central government exceeded 40% throughout the year. Particular stress was laid on the land governance projects of comprehensive agricultural development in the province. (2) The overall development level of the agricultural circular economy in Henan Province was low, and there were considerable gaps between cities (counties). Under the super-efficiency DEA model, only Hebi City, which ranked first in terms of average efficiency, achieved relative efficiency. (3) The fiscal expenditure for supporting agriculture had a positive incentive effect on the efficiency of the agricultural circular economy in Henan province, and the incentive effect became more significant after the time effect was controlled. Accordingly, this paper puts forward some targeted policy suggestions, which enrich the existing research on fiscal support for agriculture and agricultural circular economy at both theoretical and practical levels.

Keywords: fiscal support for agriculture; efficiency of agricultural circular economy; super-efficiency DEA; panel data model

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1. Introduction

China first launched the mechanism of supporting rural and agricultural development with public finance as early as the 1950s, and the related projects covered multiple links of production and circulation, including agriculture, forestry, animal husbandry, and fishery. Besides covering the expenditure on rural education, health, and culture with fiscal funds, the state also actively invests in rural infrastructure construction to meet the basic living needs of farmers. To improve agricultural production conditions, the state continuously expands the scope of fiscal support for agriculture to subsidize the purchase of improved varieties and agricultural machinery and constantly improves the subsidy system [1]. In studies on the scale of the fiscal expenditure for supporting agriculture, most scholars suggest that because of the importance of agriculture in the national economy, the current scale of the fiscal expenditure for supporting agriculture still needs to be enlarged.

However, some scholars argue that a larger expenditure scale is not always better, as there is an optimal expenditure scale. As the state attaches increasing importance to "agriculture, rural areas, and farmers", China's agricultural system reform has continuously deepened, and fiscal and financial support for agricultural development has significantly increased [2]. However, the asynchrony between the fund demands of agriculture and the supply rate of market funds inevitably affects the stable development of agriculture.

1.1. Related Research on Fiscal Expenditure for Supporting Agriculture

Due to the public goods attribute and weakness of agriculture, the sustainable, high-quality development of modern agriculture requires financial support and policy guarantee from public finance. Most related studies at home and abroad have also confirmed this point. Specifically, the economic benefits of fiscal support for agriculture have been studied, suggesting that the fund investment made by national finance plays a certain role in increasing farmers' income while maintaining the stable development of the rural economy and increasing the output value of agriculture [3]. To explore the effect of macro policies on agricultural output efficiency, an empirical analysis is performed using data from Pakistan covering 1972–2010, and it was found that financial support from the three channels of energy, finance, and currency have positive incentive effects on agricultural output efficiency [4]. Agricultural output efficiency is also focused, a C-D production function is built, and the government can significantly improve agricultural productivity by investing in agricultural infrastructure construction and increasing fiscal support for agricultural scientific research [5].

With the deepening of research on the policy of fiscal support for agriculture, more and more scholars have proposed that the scale of the fiscal expenditure for supporting agriculture should not be expanded infinitely. Although public finance can serve as an effective supplement to private capital and improve the long-term growth rate of the economy, a fiscal expenditure level that is significantly higher or lower than the equilibrium level will still affect the development of the macro-economy and related industries to varying degrees [6]. Many scholars believe that a larger scale of fiscal expenditure for supporting agriculture is not always better, as there is an optimal expenditure scale. To validate this, the viewpoint is modeled that there is an optimal scale for the fiscal expenditure for supporting agriculture [7], which provides references for further research by other scholars. Based on empirical measurements, the performance of fiscal support for agriculture can be maximized in China only when the proportion of the fiscal expenditure for supporting agriculture in the total output value of agriculture reaches 8.26% [8]. There is an optimal scale; however, unlike our previous study, the optimal scale is calculated to be 47.2% of the total output value of agriculture, pointing out that there is still a certain gap between the real and optimal scale [9]. The optimal scale calculated by Islard (1965) is 76% of the total output value of agriculture [10], which is far higher than the results calculated by Anersen and Petersen (1993) [11] and Donner et al. (2021) [12]. The above results suggest that the optimal scale for the fiscal expenditure for supporting agriculture presents an upward trend with economic development [13].

Regarding the structure of the fiscal expenditure for supporting agriculture, it should be configured by public finance with a view to the specific development stages of the agricultural economy. The belief that the output efficiency of an industry is affected by the production capacity of the industry is shared, which is affected by the relative scale of the fiscal expenditure (i.e., the proportion of the fiscal expenditure of the total expenditure) [14]. Domestic studies generally believe that there is a problem of structural mismatch with existing fiscal expenditure for supporting agriculture, and the expenditure structure should be adjusted. The changes in the scale and structure of China's fiscal expenditure for supporting agriculture from 1978 to 2008 were analyzed, and the absolute scale had a steady growth in the study period, while the relative scale was generally low [15]. The expenditure structure was also irrational, which limited its utility in promoting agricultural development and increasing farmers' income [16]. After analyzing the distribution of

China's fiscal expenditure for supporting agriculture in 1978–2008, they concluded that the expenditure structure in China needs to be optimized, and the proportion of the expenditure on agricultural capital construction and the "three expenses" (i.e., expenses for new product trial production, pilot tests, and research subsidies) of agricultural science and technology is low in the total expenditure. At a moment when the scale of the fiscal expenditure for supporting agriculture cannot be expected to expand on a large scale, agricultural development can be effectively promoted only by adjusting the structure of the fiscal expenditure for supporting agriculture [17].

1.2. Related Research on the Efficiency of Agricultural Circular Economy

The earliest researcher on the agricultural circular economy in China expounded on the connotations of an agricultural circular economy and pointed out the significance and importance of promoting the sustainable and circular development of agriculture [18]. Influenced by Abramovitz [19], many domestic scholars have joined in the discussion and research on agricultural circular economy and explored the connotations of circular agriculture in different times and economic development stages [20]. The theory of circular economy and the idea of the sustainable development of agriculture into agricultural economic activities are introduced, proposing that the goal of developing an agricultural circular economy is to reduce pollution, protect the environment, and save resources [21]. Domestic studies on the agricultural circular economy are not limited to theoretical research but have always paid attention to its practical significance. Agriculture is regarded as a major force driving China's economic development, arguing that the extensive agricultural production mode has posed a series of environmental problems in the current stage, including eco-environmental deterioration and low resource utilization efficiency [22]. They suggested that such environmental problems can be alleviated by developing an agricultural circular economy, and it is necessary to transform the concept of agricultural development as soon as possible and place greater emphasis on resources and environmental benefits [23]. Based on field research on the circular agriculture base of Jiangsu Academy of Agricultural Sciences (JAAS), the industrial integration mode of "planting, breeding, and processing" has truly achieved the optimal allocation of agricultural resources by realizing the effective flow of biological production capacity within the system [24]. In a new era, promoting ecological civilization construction has become a national priority that concerns the well-being of the people. Accordingly, the agricultural circular economy has been imprinted with the brand of the new era [25]. The promotion of ecological civilization construction in the new era must adhere to the concept of green development, and increasing importance must be attached to the circular economy as the way to transform the economic development mode and promote high-quality green development [26].

1.3. Effect of Fiscal Expenditure for Supporting Agriculture on the Efficiency of Agricultural Circular Economy

Compared with the efficiency of an agricultural circular economy, traditional agricultural productivity only focuses on the economic benefits of agricultural production, i.e., the total output value of agriculture. However, the concept of "economism" in discussions about the values of agricultural production has neglected the resources and environmental problems in agricultural production. It only considers the expected output (economic benefits) of agricultural production but has left out its unexpected output (ecological deterioration) [27]. Any examination of the total utility brought by the agricultural circular economy to society should also consider its impacts on the economic society and the ecological environment. Traditional agricultural productivity is limited, as it only considers the economic utility of agricultural development but fails to consider the ecological environment [28]. With the continuous spread of the concept of circular economy, more and more scholars are trying to incorporate production factors that may affect the ecological environment into the evaluation system of agricultural productivity [29,30]. After measuring the efficiency level of the agricultural circular economy, the measurement results were used to analyze the development status of the regional agricultural circular economy [31]. In addition to the efficiency of an agricultural circular economy, other concepts of agricultural productivity that also consider the resources and environmental problems in agricultural production have also been embraced by domestic and foreign studies [32,33]. Notwithstanding their different names, all these efficiency evaluation methods consider the eco-environment when evaluating agricultural productivity [34]. For example, some scholars [35,36] have incorporated environmental factors into the measurement and analysis framework of agricultural total factor productivity, thus coining the term "agricultural green productivity".

Domestic scholars have used a variety of methods to measure production efficiency, including the Solow residual value method, the stochastic frontier approach, the Malmquist index method, and the data envelopment analysis (DEA) [37]. China's green total factor productivity (GTFP) change index in 1992–2010 has been measured using the stochastic frontier approach and has been compared with the total factor productivity measured with the Malmquist TFP index method and a decomposition analysis [38]. The representative research results [39] of agricultural green productivity have been measured using the parametric method. Because of the incorporation of environmental constraints into the TFP framework, resources, the environment, and agricultural growth have been incorporated into the same framework to measure China's agricultural green productivity in 1978–2008 [40]. In addition, many scholars have measured input–output efficiency using the DEA method [41,42]. The development level of the low-carbon economy in Hubei Province in 2011–2016 was evaluated using CCR and BCC models, and Hubei's low-carbon economy presents a promising development trend [43]. The efficiency of the fiscal expenditure for supporting agriculture was measured using the BCC model. The measurement results revealed that the average comprehensive technical efficiency of the fiscal expenditure for supporting agriculture in Hunan Province in 2008–2013 remained above 0.8, and the maximum difference in comprehensive technical efficiency between cities (prefectures) was 0.637. The overall performance level of fiscal support for agriculture in Hunan Province in the study period was high, but there were considerable differences between regions [44]. Some scholars [45,46] have used the super-efficiency DEA model to rank multiple relatively efficient decision-making units (DMUs) in the order of efficiency value. Wen (2009) measured the efficiency of the agricultural circular economy in Shandong Province in 2007 using the super-efficiency DEA. The measurement results indicated that the efficiency of the agricultural circular economy achieved relative efficiency in ten cities (counties) in 2007. Among them, Laiwu ranked first, with an efficiency value of 3.17, while Rizhao ranked last among relatively efficient cities (counties), with an efficiency value of 1.01 [47]. The efficiency of China's regional green economy was measured under the super-efficiency DEA model. They found that there is regional heterogeneity in the efficiency of China's green economy, and the efficiency of the green economy in western China is low [48]. Regarding the applications of the efficiency of agricultural circular economy, many scholars [49] have reached preliminary conclusions. However, the rich connotations of the agricultural circular economy still need to be further mined, and the factors affecting the efficiency of the agricultural circular economy are changing constantly. As suggested by Taslima and Salina (2019) [50], in terms of theory, the existing theories related to the development of the agricultural circular economy in China are insufficient, and constant improvement, innovation, and summary are needed. In terms of practice, continuous efforts should be made to develop new modes for the agricultural circular economy; encourage scientific and technological innovation for empowering the long-term development of the agricultural circular economy; and establish a sound, scientific, and rational mechanism for the performance evaluation of the agricultural circular economy, thereby serving the construction of a new socialist countryside. To realize the sustainable development of the agricultural economy and advocate its growth mode based on resource recycling, the state should actively bring into play the role of public finance and promote the circular and sustainable transformation of agricultural production activities through fiscal support for agriculture.

Scholars at home and abroad have different perspectives and research depths when it comes to the correlation between fiscal support for agriculture and the sustainable development of modern agriculture, whether in terms of qualitative or quantitative analysis. It is generally believed that the policy of fiscal support for agriculture has a positive promoting effect on the economic benefits of agricultural output. The implementation effect of China's agricultural subsidy policy was evaluated from the perspective of agricultural production and consumption. The conclusion is that fiscal subsidies affect farmers' consumption behaviors, on the one hand, as a subsidy income and influence agricultural output, on the other hand, by adjusting agricultural factor inputs [51]. However, some scholars argue that the implementation of the policy of fiscal support for agriculture does not necessarily produce a positive incentive for agriculture. The effect of the agricultural subsidy policy was analyzed based on the data from a field survey conducted in Jiangxi Province and found that the agricultural subsidy mode of Jiangxi Province is yet to be rationalized, and agricultural subsidies have failed to significantly increase food crop yield [52]. Naiwei et al. (2018) pointed out that in the process of economic development, resource misuse and environmental deterioration are mainly affected by market failure and the distortion of the market mechanism by policies [8]. Moderate agricultural production and fiscal subsidies help to promote agricultural production and increase farmers' income [53]. However, the neglect of the importance of ecological protection in agricultural production has led to resource misuse and environmental pollution. The agricultural subsidy policy achieves its objectives by affecting farmers' production behaviors [54]. After recognizing the importance of fiscal support for agriculture and the role played by the concept of the agricultural circular economy in promoting the green development of agriculture, domestic scholars have gradually incorporated the two factors into a unified evaluation system. China's rural areas currently have a low development level, and most of them still have weak economic strength [55]. The development of an agricultural circular economy requires sufficient financial support and technical strength, so the government's fiscal support for agriculture and rural areas is particularly important. When analyzing the measures taken to develop the agricultural circular economy in China, the importance of fiscal expenditure for the development of the agricultural circular economy was confirmed, which reflects the sustainable growth of the economy and the green and circular development of agriculture [56].

1.4. Aim of This Study

Domestic and foreign studies on fiscal support for agriculture mostly focus on the scale and structure of the fiscal funds for supporting agriculture and the development process and performance evaluation of the policy of fiscal support for agriculture. Regarding the agricultural circular economy, more scholars are turning their attention to the environmental impact of agricultural development and are building various models to evaluate the efficiency level of the agricultural circular economy. On this basis, domestic and foreign scholars have made some achievements regarding the relationship between fiscal support for agriculture and the agricultural circular economy. This paper finds that as far as research on the relationship between fiscal support for agriculture and the agricultural circular economy is concerned, further efforts are needed to deepen our discussions in certain directions. For example, new considerations can be given to the factors that affect the efficiency of the agricultural circular economy, and further attempts can be made to develop new methods for efficiency measurement. In addition, analysis of the relationship between fiscal support for agriculture and the agricultural circular economy can also be extended from individual regions to larger spaces. Therefore, this paper attempts to further discuss the correlation between the fiscal expenditure for supporting agriculture and the efficiency of the agricultural circular economy based on existing research results. Taking Henan Province, a typical major agricultural province in China, as the research object, this paper measures the efficiency of the agricultural circular economy using the super-efficiency DEA model. Discarding the fuzzy concept of fiscal support for agriculture, it takes the path of fiscal expenditure for supporting agriculture, agricultural production inputs, and agricultural circular economy efficiency to discuss the effect of fiscal support for agriculture on the agricultural circular economy and gives policy suggestions.

In the process of efficiency calculation and empirical research, it is difficult to obtain the data on part of the variables; therefore, it is not comprehensive enough to collect the data. For example, when discussing the effect of fiscal expenditure for supporting agriculture on the agricultural circular economy, in order to ensure the comparability of data, the paper only selects the relevant data of Henan Province from 2013 to 2019, of which the time span is not long enough, because the data of fiscal expenditure for supporting agriculture have different measures in different times. In the selection of the impact path of fiscal expenditure for supporting agriculture on the agricultural circular economy, the paper analyzes the fiscal expenditure for supporting agriculture on the scale and structure of the agricultural production input. The path is still not fruitful; therefore, the analysis framework is not comprehensive enough.

2. Methods and Data

2.1. Measurement of the Efficiency of the Agricultural Circular Economy in Henan Province

At present, the application of the DEA-based performance evaluation has been relatively mature at home and abroad, and multiple DEA models have been developed based on different premises and assumptions. Among them, the CCR and BCC models are the most traditional and widely used. The main difference between them lies in the premises and assumptions. The CCR model assumes constant returns to scale, whereas the BCC model is based on the premise of variable returns to scale. It can be assumed that there are n decision-making units (DMUs) to be evaluated, each with the same *m* input and *s* output factors. After denoting the jth DMU as DMU_j, the numbers of the ith input factors and the rth output factors of DMU_j can be denoted as X_{ij} and Y_{rj} ($1 \leq i \leq m$, $1 \leq r \leq s$, j = 1,2,...,n), respectively. Thus, constrained by the efficiency indices of all DMUs, a CCR model can be constructed by adding an Archimedes infinite decimal as follows:

$$\min\left[\theta - \varepsilon\left(\sum_{j=1}^{m} s^{-} + \sum_{j=1}^{r} s^{+}\right)\right]$$
$$s.t.\begin{cases} \sum\limits_{j=1}^{n} x_j\lambda_j + s^{-} = \theta x_0 \\ \sum\limits_{j=1}^{n} y_j\lambda_j - s^{+} = y_0 \\ \lambda_j \geq 0 \\ s^{+} \geq 0,\ s^{-} \geq 0 \end{cases} \tag{1}$$

where θ is the technical efficiency index of a DMU, and λ is the combined weight. A BCC model with variable scale efficiency can be constructed by adding constraints on this basis:

$$\min\left[\theta - \varepsilon\left(\sum_{j=1}^{m} s^{-} + \sum_{j=1}^{r} s^{+}\right)\right]$$
$$s.t.\begin{cases} \sum\limits_{j=1}^{n} x_j\lambda_j + s^{-} = \theta x_0 \\ \sum\limits_{j=1}^{n} y_j\lambda_j - s^{+} = y_0 \\ \lambda_j \geq 0 \\ s^{+} \geq 0,\ s^{-} \geq 0 \\ \sum\limits_{i=1}^{n} \lambda_i = 1 \end{cases} \tag{2}$$

Notwithstanding their different premises and assumptions, CCR and BCC models follow roughly the same measurement principles. When θ = 1, S^- = S^+ = 0, in which case the DMU is regarded as relatively DEA-efficient; when $\theta \neq 1$, S^- = 0, or S^+ = 0, in which case the DMU is regarded as DEA-efficient; and when θ < 1, the DMU is inefficient. Traditional DEA models can basically realize the evaluation of the relative efficiency of a DMU with multiple inputs and outputs, but it is difficult to implement traditional DEA rules for the further evaluation of multiple relatively efficient DMUs. The super-efficiency DEA model proposed by Anersen et al. (1993) [11] excludes the DMU that is also at the production frontier from the set of DMUs and replaces it with the linear combination of the inputs and outputs of all the other DMUs. In this way, the DMU with increased inputs still retains a relatively efficient maximum input–output ratio, i.e., super-efficiency value, which may be greater than 1. This makes it possible to re-rank relatively efficient DMUs in the order of efficiency value, thereby evaluating their efficiency. Therefore, the efficiency calculation of the kth DMU can be converted into:

$$\min[\ \theta-\varepsilon\left(\sum_{i=1}^{m}s_i{}^{-}+\sum_{r=1}^{s}s_r{}^{+}\right)]$$
$$s.t.\begin{cases}\sum\limits_{j=1,j\neq j_0}^{n}x_{ij}\lambda_j+s_i^-=\theta x_{ij_0},i=1,2,\ldots,m\\ \sum\limits_{j=1,j\neq j_0}^{n}y_{rj}\lambda_j-s_r^+=y_{rj_0},r=1,2,\ldots,s\\ \lambda_j\geq 0,s_i^-\geq 0,s_r^+\geq 0\\ j=1,2,\ldots,n\end{cases} \tag{3}$$

The symbols used in the super-efficiency DEA model are basically consistent with those used in traditional DEA models. However, as the efficiency value of a DMU may be greater than 1 under the super-efficiency DEA model, θ, the efficiency value of the evaluated DMU is unconstrained in the model. $0 \leq \theta \leq 1$ indicates that the region is relatively inefficient in the set of DMUs, and $\theta \geq 1$ indicates that the region is relatively efficient.

2.2. Indices, Data Sources, and Descriptions

The selection of measurement indices is crucial for efficiency evaluation. For an accurate evaluation of the efficiency of the agricultural circular economy, the indices selected must comprehensively reflect their basic characteristics and connotations. Therefore, the selection of measurement indices in this section has given comprehensive consideration to the index factors that affect the economic and ecological fields during agricultural production in China, thereby trying to reflect the concept of the agricultural circular economy in a more precise manner. This paper refers to the existing literature on the selection of input and output variables. In terms of input variables, five indices that affect both the agricultural economy and the eco-environment, which are pesticides, fertilizers, agricultural machinery, labor force, and land use, are selected. In terms of output variables, total output value, farmers' income, and food crop yield are selected to represent the economic and social benefits of agricultural development. Table 1 describes, in detail, a total of eight measurement indices of inputs and outputs.

2.3. Measurement Results and Evaluation Analysis

The efficiency of the agricultural circular economy in 28 cities (counties) of Henan Province in 2013–2019 is measured using Matlab software. The evaluation results of two traditional DEA models (CCR and BCC) are compared with those of the super-efficiency DEA model to analyze the development status of the agricultural circular economy in Henan Province. Table 2 provides the measurement results of the CCR model. The overall efficiency of the agricultural circular economy tended to be relatively efficient in various cities (counties) of Henan Province in 2013–2019, but none of them reached a fully DEA-efficient level in the observation period. Among these cities (counties), Hebi, Xinyang, Jiaozuo, and Luyi ranked in the top four in succession in terms of average efficiency and surpassed all the cities (counties) following them, whether measured by the number of relatively efficient years or the efficiency level and stability of previous years. The nine cities (counties) ranked from 5th to 13th, including Gushi, Yongcheng, Zhumadian, Huaxian, and Changyuan, had a smaller number of relatively efficient years, but their efficiency values were relatively stable. In contrast, 15 cities (counties) that ranked from 14th to 28th, including Luohe, Zhoukou, Kaifeng, Xinxiang, and Xincai, rarely achieved relative efficiency in the observation period, and their efficiency values changed greatly. The efficiency and ranking indicate that the city with the highest average efficiency was not the one with the largest number of relatively efficient years. Hebi and Yongcheng, which ranked first and sixth, respectively, can be cited for illustration. Yongcheng had a larger number of relatively efficient years than Hebi, but the efficiency value of Hebi in the observation period tended to stay relatively more efficient than that of Yongcheng. On the whole, the efficiency level of the agricultural circular economy in Henan Province was low. There were considerable gaps between cities (counties), and most of them failed to achieve relative efficiency.

Table 1. Index system for evaluating the efficiency of the agricultural circular economy in Henan Province.

Classification of Indices	Index	Unit	Description
Input variables	Pesticide application amount	t	Amount of pesticides applied in agricultural production in the current year
	Number of persons employed in agriculture, forestry, animal husbandry, and fishery	10,000 persons	Number of people engaged in the industries of agriculture, forestry, animal husbandry, and fishery in the current year
	Converted pure amount of agricultural fertilizers applied	t	Amount of fertilizers applied in agricultural production in the current year
	Total power of agricultural machinery	kWh	Power consumption of machinery used in agricultural production in the current year
	Sown area of crops	1000 ha.	Area of land invested in agricultural production in the current year
Output variables	Total output value of agriculture, forestry, animal husbandry, and fishery	100 million yuan	Economic value of total agricultural output in the current year
	Per capita net income of rural residents	Yuan	Per capita disposable income of rural households in the current year
	Food crop yield	10,000 t	Total food crop yield in the current year

Note: Data on the above measurement indices are mainly derived from the Henan Statistical Yearbook, China Statistical Yearbook, and statistical yearbooks of some cities and counties. They cover the data on the related indices of 28 cities and counties of Henan Province in 2013–2019.

Table 3 provides the efficiency result under the BCC model, which differs slightly from that under the CCR model. The ranking of various cities (counties) in terms of the average efficiency differs from one year to another. Overall, the efficiency level of the agricultural circular economy in various cities (counties) of Henan Province was significantly higher under the BCC model. Specifically, Gongyi achieved relative efficiency in five of the seven years of observation and ranked first in terms of average efficiency. This suggests that Gongyi had the highest input–output efficiency of agricultural development and the highest overall development level of the agricultural circular economy. By contrast, Dengzhou, which ranked last, failed to achieve relative efficiency in any of the seven years and had a low input–output efficiency. Its efficiency (which is far lower than that of other cities (counties)) indicates that Dengzhou still has a lot of work to do to achieve relative efficiency in the development of the agricultural circular economy. In addition, by examining the efficiency values of various cities (counties) of Henan Province in the observation period, it is found that the top two cities (counties) (Gongyi and Xinyang) achieved relative efficiency in five years; the 17 cities (counties) that ranked from 3rd to 19th (including Jiaozuo, Changyuan, Hebi, Jiyuan, Zhumadian, and Luyi) achieved relative efficiency in at least three years; and the 9 cities (counties) that ranked from 20th to 28th (including Xincai, Anyang, Luohe, and Luoyang) failed to achieve relative efficiency in any year of the observation period. Clearly, notwithstanding their differences in the efficiency values obtained, both the CCR and BCC models indicate that the efficiency level of the agricultural circular economy in Henan Province was low on the whole, and there were considerable gaps between cities (counties).

Table 2. Efficiency of the agricultural circular economy in various cities (counties) of Henan Province in 2013–2019 under the CCR model.

Region	2013	2014	2015	2016	2017	2018	2019	Mean	Ranking
Zhengzhou	0.6609	0.6837	0.7302	0.757	0.706	0.738	0.7517	0.7182	26
Kaifeng	0.7978	0.8154	0.8474	0.916	0.907	0.9202	1	0.8863	16
Luoyang	0.8377	0.8375	0.868	0.8335	0.817	0.8974	0.9576	0.8641	19
Pingdingshan	0.6772	0.6886	0.7294	0.7591	0.7503	0.7577	0.8055	0.7383	25
Anyang	0.7916	0.8054	0.8271	0.8264	0.8466	0.8855	0.9022	0.8407	23
Hebi	0.9712	0.9906	1	0.9975	0.9799	0.984	1	0.9890	1
Xinxiang	0.837	0.8483	0.8707	0.8591	0.9316	0.8899	0.9101	0.8781	17
Jiaozuo	0.9492	0.962	0.9737	1	0.9864	0.9934	1	0.9807	3
Puyang	0.8664	0.871	0.8907	0.8963	1	0.967	1	0.9273	10
Xuchang	0.8704	0.8635	0.893	0.9196	0.9367	0.9858	1	0.9241	11
Luohe	0.8466	0.8477	0.8731	0.8862	0.8854	0.9125	0.9693	0.8887	14
Sanmenxia	0.731	0.8676	0.8908	0.9366	0.9034	0.9221	1	0.8931	13
Nanyang	0.5946	0.5981	0.6187	0.6136	0.6594	0.6644	0.721	0.6385	28
Shangqiu	0.7699	0.7875	0.8316	0.863	0.9021	0.8847	0.9181	0.8510	22
Xinyang	0.9869	0.9868	0.9653	1	0.9468	0.9966	1	0.9832	2
Zhoukou	0.8463	0.8386	0.8576	0.8755	0.9463	0.9169	0.9347	0.8880	15
Zhumadian	0.929	0.9248	0.9553	0.9667	1	0.9016	0.9342	0.9445	7
Jiyuan	0.8283	0.8611	0.87	0.9215	0.9052	0.9922	1	0.9112	12
Gongyi	0.7376	0.7328	0.8558	0.8481	0.8865	0.972	1	0.8618	20
Lankao	0.7369	0.7612	0.8045	0.8676	0.8931	0.9523	1	0.8594	21
Ruzhou	0.771	0.7782	0.815	0.827	0.8007	0.8294	0.89	0.8159	24
Huaxia	0.8808	0.9013	0.9217	0.9046	0.966	1	1	0.9392	8
Changyuan	0.8565	0.8845	0.9211	0.9145	0.9671	1	1	0.9348	9
Dengzhou	0.6501	0.6625	0.7004	0.7253	0.723	0.6945	0.7506	0.7009	27
Yongcheng	0.8884	0.9104	0.9539	1	1	0.9874	1	0.9629	6
Gushi	1	0.9966	0.9988	0.9775	0.8906	0.9534	0.9415	0.9655	5
Luyi	0.9443	0.9319	0.95	1	0.9812	1	1	0.9725	4
Xincai	0.7396	0.8117	0.8396	0.9084	0.9508	0.8841	0.9303	0.8664	18

Table 3. Efficiency of the agricultural circular economy in various cities (counties) of Henan Province in 2013–2019 under the BCC model.

Region	2013	2014	2015	2016	2017	2018	2019	Mean	Ranking
Zhengzhou	0.6612	0.687	0.7385	0.7772	0.7386	0.7851	1	0.7697	25
Kaifeng	0.8148	0.837	0.8667	1	0.9665	0.925	1	0.9157	18
Luoyang	0.8637	0.8637	0.9013	0.8608	0.848	0.9283	0.9817	0.8925	23
Pingdingshan	0.6851	0.6985	0.7392	0.7736	0.7595	0.7714	0.8454	0.7532	26
Anyang	0.8405	0.8623	0.8933	0.8702	0.9009	0.9387	0.9694	0.8965	21
Hebi	0.974	0.9933	1	0.9981	0.9802	0.9883	1	0.9906	5
Xinxiang	0.9107	0.9273	0.9491	0.9286	1	0.9723	1	0.9554	13
Jiaozuo	0.9818	0.9862	1	1	0.9882	0.9934	1	0.9928	3
Puyang	0.908	0.9163	0.9396	0.9258	1	0.9821	1	0.9531	14
Xuchang	0.8855	0.8764	0.9066	0.9488	0.9672	0.9979	1	0.9403	16
Luohe	0.8474	0.8483	0.8746	0.8867	0.8863	0.9138	0.9988	0.8937	22
Sanmenxia	0.7382	0.873	0.895	0.9515	0.9274	0.9336	1	0.9027	19
Nanyang	0.6603	0.6712	0.7122	0.6878	0.7463	0.7934	1	0.7530	27
Shangqiu	0.8803	0.9132	0.9695	0.9539	0.9993	0.9827	1	0.9570	12
Xinyang	1	1	0.9914	1	0.9587	1	1	0.9929	2

Table 3. *Cont.*

Region	2013	2014	2015	2016	2017	2018	2019	Mean	Ranking
Zhoukou	0.9479	0.9276	0.9529	0.9401	1	1	1	0.9669	11
Zhumadian	0.9734	0.9819	0.9997	1	1	0.9704	1	0.9893	7
Jiyuan	1	0.9898	0.9656	0.9781	1	1	1	0.9905	6
Gongyi	1	0.9996	1	1	0.9971	1	1	0.9995	1
Lankao	0.8139	0.8258	0.8584	0.9938	1	1	1	0.9274	17
Ruzhou	0.7955	0.7958	0.8288	0.8362	0.8117	0.8403	0.8994	0.8297	24
Huaxia	0.8811	0.9013	0.9292	0.9137	0.9981	1	1	0.9462	15
Changyuan	0.9964	1	0.9883	0.9687	0.9834	1	1	0.9910	4
Dengzhou	0.659	0.6701	0.7051	0.7282	0.7249	0.695	0.751	0.7048	28
Yongcheng	0.8888	0.9363	0.9696	1	1	0.9918	1	0.9695	9
Gushi	1	0.9979	1	0.9787	0.8923	0.9539	0.9504	0.9676	10
Luyi	0.9454	0.9326	0.9513	1	0.9844	1	1	0.9734	8
Xincai	0.8037	0.8513	0.8732	0.9529	0.9818	0.887	0.931	0.8973	20

To identify valid efficiency values, the super-efficiency DEA model is used for efficiency measurement. The following conclusions can be drawn from the efficiency and average efficiency of the agricultural circular economy in 28 cities (counties) of Henan Province in 2013–2019 in Table 4.

Table 4. Efficiency of the agricultural circular economy in various cities (counties) of Henan Province in 2013–2019 under the super-efficiency DEA model.

Region	2013	2014	2015	2016	2017	2018	2019	Mean	Ranking
Zhengzhou	0.6609	0.6837	0.7302	0.757	0.706	0.738	0.7517	0.7182	26
Kaifeng	0.7978	0.8154	0.8474	0.916	0.907	0.9202	1.0656	0.8956	16
Luoyang	0.8377	0.8375	0.868	0.8335	0.817	0.8974	0.9576	0.8641	21
Pingdingshan	0.6772	0.6886	0.7294	0.7591	0.7503	0.7577	0.8055	0.7383	25
Anyang	0.7916	0.8054	0.8271	0.8264	0.8466	0.8855	0.9022	0.8407	23
Hebi	0.9712	0.9906	1.0186	0.9975	0.9799	0.984	1.1986	1.0201	1
Xinxiang	0.837	0.8483	0.8707	0.8591	0.9316	0.8899	0.9101	0.8781	19
Jiaozuo	0.9492	0.962	0.9737	1.0114	0.9864	0.9934	1.0767	0.9933	5
Puyang	0.8664	0.871	0.8907	0.8963	1.0014	0.967	1.0338	0.9324	12
Xuchang	0.8704	0.8635	0.893	0.9196	0.9367	0.9858	1.0761	0.9350	11
Luohe	0.8466	0.8477	0.8731	0.8862	0.8854	0.9125	0.9693	0.8887	17
Sanmenxia	0.731	0.8676	0.8908	0.9366	0.9034	0.9221	1.2731	0.9321	13
Nanyang	0.5946	0.5981	0.6187	0.6136	0.6594	0.6644	0.721	0.6385	28
Shangqiu	0.7699	0.7875	0.8316	0.863	0.9021	0.8847	0.9181	0.8510	22
Xinyang	0.9869	0.9868	0.9653	1.007	0.9468	0.9966	1.0863	0.9965	2
Zhoukou	0.8463	0.8386	0.8576	0.8755	0.9463	0.9169	0.9347	0.8880	18
Zhumadian	0.929	0.9248	0.9553	0.9667	1.0069	0.9016	0.9342	0.9455	9
Jiyuan	0.8283	0.8611	0.87	0.9215	0.9052	0.9922	1.1387	0.9310	14
Gongyi	0.7376	0.7328	0.8558	0.8481	0.8865	0.972	1.9377	0.9958	3
Lankao	0.7369	0.7612	0.8045	0.8676	0.8931	0.9523	1.3194	0.9050	15
Ruzhou	0.771	0.7782	0.815	0.827	0.8007	0.8294	0.89	0.8159	24
Huaxia	0.8808	0.9013	0.9217	0.9046	0.966	1.0149	1.0088	0.9426	10
Changyuan	0.8565	0.8845	0.9211	0.9145	0.9671	1.1282	1.1241	0.9709	8
Dengzhou	0.6501	0.6625	0.7004	0.7253	0.723	0.6945	0.7506	0.7009	27
Yongcheng	0.8884	0.9104	0.9539	1.0479	1.0143	0.9874	1.0821	0.9835	6
Gushi	1.0796	0.9966	0.9988	0.9775	0.8906	0.9534	0.9415	0.9769	7
Luyi	0.9443	0.9319	0.95	1.0163	0.9812	1.0062	1.1335	0.9948	4
Xincai	0.7396	0.8117	0.8396	0.9084	0.9508	0.8841	0.9303	0.8664	20

(1) The average super-efficiency in 2013–2019 indicates that only Hebi, which ranked first, had an average super-efficiency of above 1 and achieved relative efficiency, and its ranking result was consistent with that under the CCR model. Each of the four cities (counties) that ranked from second to fifth (i.e., Xinyang, Gongyi, Luyi, and Jiaozuo) had

an average super-efficiency of above 0.99 in the seven-year observation period and were relatively efficient, accounting for 14.29% of the province. The 11 cities (counties) that ranked from 6th to 16th (including Yongcheng, Gushi, Changyuan, Zhumadian, Huaxian, and Xuchang) had an average efficiency of 0.90–0.98, accounting for 39.29% of the province. This means that these 11 cities (counties) had a relatively stable average efficiency, which presented a striking contrast with the average efficiency of the 12 cities (counties) ranked from 17th to 28th place (including Luohe, Zhoukou, Luoyang, and Zhengzhou, accounting for 42.86% of the province). The above results suggested that the cities (counties) ranked at the bottom had a low overall efficiency of the agricultural circular economy, and there were considerable gaps between them.

(2) The development of the agricultural circular economy in Henan Province was remarkable in seven years. From 2013 to 2015, a few of the 28 cities (counties) of Henan Province achieved relative efficiency, and they had an efficiency of 0–1 in this period. From 2016 on, the number of cities (counties) that achieved relatively efficient development of the agricultural circular economy made a breakthrough and peaked (14) in 2019. The efficiency value of Gongyi reached a historical high of 1.9377, which means that Gongyi would still maintain relative efficiency even if the input were to be increased by an equal proportion of 93.77%.

To analyze the effects of different input–output indices on efficiency in greater depth, this paper divides various cities (counties) of Henan Province into two groups (i.e., relatively efficient group and relatively inefficient group) based on the average efficiency measured by the super-efficiency DEA model, as presented in Tables 5 and 6. Because a few of the 28 cities (counties) of Henan Province achieved relative efficiency in 2013–2015 and none of them achieved relative efficiency in 2014, only the average values of the input–output indices of these cities (counties) in 2016–2019 are compared. The following conclusions are drawn:

Table 5. Average values of the input–output indices of relatively DEA-efficient cities (counties).

Classification of Indices	Index	Average Value of Relatively Efficient Group			
		2016	**2017**	**2018**	**2019**
Input variables	Pesticide application amount	4399.245	4087.657	1266.333	2520.786
	Number of persons employed in agriculture, forestry, animal husbandry, and fisheries	86.025	123.161	18.85	57.362
	Converted pure amount of agricultural fertilizers applied	235,232.525	406,425.440	124,340.333	162,869.571
	Total power of agricultural machinery	264.002	608.518	139	243.323
	Sown area of crops	505.559	818.700	196.073	358.145
Output variables	Total output value of agriculture, forestry, animal husbandry, and fisheries	320.563	382.073	290.883	249.550
	Per capita net income of rural residents	12,128.000	11,905.667	14865	16,685.052
	Food crop yield	251.004	399.690	109.10	172.967

(1) Vertically, the input–output variables of various cities (counties) in 2016–2019 indicate that the input variables of the relatively efficient group presented a downward trend year by year. However, the input variables of the relatively inefficient group presented a significantly increasing trend year by year. This suggests that the differences in efficiency values between the two groups were largely related to the differences in input factors. In terms of output variables, the per capita net income of farmers in the relatively efficient group rose faster than that in the relatively inefficient group. In other aspects (i.e., total output value of agriculture, forestry, animal husbandry, and fisheries and food crop yield), the two groups experienced opposite change directions, which reflects the causality between agricultural production inputs and outputs to a certain extent.

Table 6. Average values of the input–output indices of relatively DEA-inefficient cities (counties).

Classification of Indices	Index	Average Value of Relatively Inefficient Group			
		2016	**2017**	**2018**	**2019**
Input variables	Pesticide application amount	5217.652	4930.847	5084.12	6287.143
	Number of persons employed in agriculture, forestry, animal husbandry, and fisheries	103.732	99.571	108.024	122.704
	Converted pure amount of agricultural fertilizers applied	303,443.262	278,802.114	306,742.680	391,415.786
	Total power of agricultural machinery	421.273	382.581	443.72	591.375
	Sown area of crops	590.370	553.953	641.782	823.610
Output variables	Total output value of agriculture, forestry, animal husbandry, and fisheries	311.976	293.836	333.691	438.685
	Per capita net income of rural residents	12,570.083	13,855.840	14,877.36	15,653.234
	Food crop yield	254.285	248.288	289.17	370.914

(2) Horizontally, the five input indices (i.e., pesticide application amount; the number of persons employed in agriculture, forestry, animal husbandry, and fisheries; the converted pure amount of agricultural fertilizers applied; the total power of agricultural machinery; and sown area of crops) of the relatively efficient group were smaller than those of the relatively inefficient group in 2016–2019 (excluding 2017). In terms of output indices, in 2016–2019, the two groups had different change directions in the total output value of agriculture, forestry, animal husbandry, and the per capita net income of farmers, which, however, did not produce any considerable gaps on the whole. The relatively efficient group had fewer inputs in indices harmful to the ecological benefits of agriculture (such as pesticides and fertilizers), which, to some extent, explains why the efficiency level of the agricultural circular economy in the relatively efficient group was higher than that of the relatively inefficient group. Moreover, the higher growth rate of farmers' income in the relatively efficient group also suggests that the driving effect of the development of the agricultural circular economy on farmers' income was cumulative.

3. Results and Discussion

To further empirically study the effect of fiscal support for agriculture on the efficiency of the agricultural circular economy, this paper takes 28 cities (counties) of Henan Province as the research sample and selects the evaluation results of the efficiency of the agricultural circular economy under the super-efficiency DEA model as the explained variable. By comprehensively considering the economy, society, agricultural production, and other relevant factors, it explores the mechanism through which fiscal support for agriculture affects the efficiency of the agricultural circular economy.

3.1. Model Selection

A model is built using the panel data of 28 cities (counties) of Henan Province in 2013–2019. The panel data, which have integrated time series data and cross-section data, can avoid the effect of the possible multiple collinearities between data and reflect individual heterogeneity. Panel data models include three basic models—the fixed effect model, random effect model, and mixed effect model. Among them, the fixed effect model allows for correlation between explanatory variables and variables that do not change over time, so the endogenous problem between them does not affect the consistency in estimation results. By contrast, the random effect model assumes that explanatory variables are completely exogenous. In terms of model selection, generally, the results of the Hausman test are used to judge whether to select the fixed effect model or the random effect model, while the results of the BP test are used to determine whether to select the mixed effect model or the random effect model. The results of the Hausman test in this paper strongly reject the original assumption, so the fixed effect model is selected, as expressed below:

$$\text{sueffic}_{it} = \alpha_0 + \beta_1 \text{fs}_{it} + \beta_2 D_{it} + \delta_i + \gamma_t + \varepsilon_{it} \quad (4)$$

where sueffic_{it} denotes the efficiency of the agricultural circular economy in the ith city (county) in the tth year; fs_{it} denotes the fiscal fund for supporting agriculture received by the ith city (county) in the tth year; α_0 is an intercept term; D_{it} is a control variable unaffected by the fiscal expenditure for supporting agriculture; δ_i is the regional effect; γ_t is the time effect; and ε_{it} is a stochastic error term.

3.2. Variable Selection and Data Sources

Referring to studies by Grosskopf et al. (2011) [23], this paper takes the efficiency of the agricultural circular economy in 28 cities (counties) of Henan Province in 2013–2019 measured using the super-efficiency DEA model as the explained variable. The fiscal expenditure for supporting agriculture is the financial support offered by national finance for "agriculture, rural areas, and farmers." The expenditure on agriculture, forestry, and water affairs, as a major account of fiscal support for agriculture, mainly covers the industries of agriculture, forestry, animal husbandry, and fisheries; rural poverty alleviation; and water conservancy development and is generally used to measure the scale of local fiscal support for agriculture. Referring to the study by Rotolo et al. (2022) [14], this paper takes the proportion of the expenditure on agriculture, forestry, and water affairs in the total output value of agriculture, forestry, and animal husbandry as the core explanatory variable to measure the strength of fiscal support for agriculture in various cities (counties). In addition, considering the effects of economic environment, social environment, human capitals, and the utilization efficiency of agricultural production resources on the efficiency of the agricultural circular economy, this paper sets the following control variables with reference to existing studies: land structure (landstru), measured by the proportion of the sown area of food crops in the sown area of crops; farmers' income (income), measured by the per capita net income of rural residents; agricultural economic level (ecolevl), measured by per capita total output value of agriculture; human capitals (labcapital), measured by the proportion of education expenditure in fiscal expenditure; urbanization rate (urban), measured by the proportion of urban population in the total population of the region; and utilization of agricultural production resources, characterized by the effective utilization rates of agricultural machinery (machpower), pesticides (chemical), agricultural films (plastic), fertilizers (fertili), and electric power (electric), which are measured by the proportion of their agricultural production inputs in the total output value of agriculture. Winsorization is performed for all variables within the range of 1–99% to ensure the stability of data and avoid the effect of extreme values.

Among the above data on the indices involved, the data on the explained variables are taken from the efficiency of the agricultural circular economy measured by the super-efficiency DEA model in Section 4 of this paper. The data on the explanatory and control variables are derived from the *Henan Statistical Yearbook*, *China Statistical Yearbook*, and *China Population & Employment Statistics Yearbook* (2013–2019) and the EPS database. A model is built using the panel data of 28 cities (counties) of Henan Province in 2013–2019 as the sample.

Table 7 indicates that there are differences between variables. Specifically, the maximum difference between the two ends of sueffic and its standard deviation indicates that the efficiency of the agricultural circular economy differs only slightly across various cities (counties) of Henan Province. An average value of 0.891 suggests that the sample, as a whole, tended to be DEA-efficient, but some cities (counties) still failed to achieve relative efficiency. The maximum difference between the two ends of fs was 0.6359, which indicates that there are considerable gaps in the fiscal support for agriculture enjoyed by various cities (counties). An average value of 0.202 suggests that the overall strength of fiscal support for agriculture in Henan Province is low. The standard deviation of 0.126 is approximately equal to that of sueffic, indicating the presence of a slight difference in discreteness between them and, to some extent, reflecting their correlation. There are considerable gaps between the control variables, except for land structure and human capital. The maximum difference between the two ends of the per capita net income of farmers is 16,697, which means that farmers' living standards differ greatly across various cities (counties). The maximum difference between the two ends of ecolevl is 0.6373, which is slightly greater than the average value of 0.422. This suggests that the efficiency level of the agricultural circular economy varies across various cities (counties) but is only slightly relative to other indices, and the environment required to develop the agricultural economy is relatively stable. In addition, among the five input indices used to characterize agricultural production resources, electric power has an effective utilization rate that differs greatly, while the other four indices (i.e., agricultural machinery, pesticides, agricultural films, and fertilizers) roughly indicate the same distribution of the effective utilization rate. Notwithstanding the presence of differences, they are generally stable, suggesting that the effective utilization of agricultural production resources does not vary greatly across various cities (counties).

Table 7. Descriptive statistics of variables.

Variable	Mean	Standard Deviation	Minimum	Maximum
sueffic	0.891	0.123	0.598	1.319
fs	0.202	0.126	0.0841	0.720
landstru	0.752	0.0707	0.604	0.896
income	12,600	3477	6839	23,536
ecolevl	0.422	0.145	0.0947	0.732
machpower	0.442	0.219	0.136	1.421
chemic	0.0409	0.0131	0.0182	0.0880
plastic	0.0385	0.0175	0.0118	0.0885
fertili	0.000655	0.000280	0.000219	0.00190
electic	20.31	13.69	0.557	60.74
labcapital	0.197	0.0302	0.118	0.275
urban	46.30	9.362	25.08	73.40

3.3. Analysis of Empirical Results

Models (1)–(6) are constructed in this section using Stata16 software by gradually adding control variables into the benchmark model based on previous analysis. We estimate two types of effects—individual fixed effects and time/individual two-way fixed effects—in succession, and the estimation results are provided in Tables 8 and 9, respectively.

As presented in Table 8, under individual fixed effects, Models (1)–(6) reveal the positive promoting effect of the fiscal expenditure for supporting agriculture on the efficiency of the agricultural circular economy, which remains at the significance level of 5% in each case. In addition, the goodness of fit (R^2) of Models (1)–(6) constantly improves when the control variables are continuously added, which proves the reliability of the regression results to a certain extent. The regression results of single variables reveal that the fiscal expenditure for supporting agriculture has a significant positive correlation with the efficiency of the agricultural circular economy, while land structure, the effective utilization rate of pesticides, and the effective utilization rate of agricultural machinery play prominent and stable roles in supporting the agricultural circular economy. Land structure and the effective utilization rate of pesticides both have large effect coefficients and high significance levels. On the one hand, this, to some extent, suggests that the development of the agricultural circular economy depends on high-level and high-quality agricultural land development, which indirectly affects the efficiency of the agricultural circular economy by affecting agricultural outputs. On the other hand, it reflects the direct supporting effect of the effective utilization rate of artificial agricultural preparations (represented by pesticides) on the efficiency of the agricultural circular economy. According to the regression results of Models (1)–(6), the addition of the effective utilization rate of agricultural machinery also exerts a significant promoting effect on the efficiency of the agricultural circular economy. This suggests that the increased mechanization degree of modern agriculture improves the level of agricultural outputs, on the one hand, and weakens the negative environmental impact of agricultural production; on the other hand, so agricultural development has sustainable and circular development modes.

Table 8. Results of the individual fixed-effect regression.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Sueffic	**Sueffic**	**Sueffic**	**Sueffic**	**Sueffic**	**Sueffic**
fs1	0.248 **	0.268 **	0.278 **	0.290 **	0.305 **	0.242 **
	(2.11)	(2.28)	(2.35)	(2.46)	(2.59)	(2.02)
landstru	0.637 ***	0.700 ***	0.719 ***	0.736 ***	0.722 ***	0.733 ***
	(2.81)	(3.07)	(3.13)	(3.23)	(3.17)	(3.26)
chemic	6.610 ***	6.404 ***	6.170 ***	5.973 ***	5.936 ***	6.338 ***
	(10.92)	(10.44)	(9.08)	(8.75)	(8.72)	(9.09)
plastic	1.137 *	0.769	0.698	0.697	0.446	0.636
	(1.66)	(1.08)	(0.97)	(0.97)	(0.61)	(0.87)
urban	0.001	0.001	0.001	0.000	−0.005	−0.002
	(0.64)	(0.73)	(0.53)	(0.01)	(−1.28)	(−0.43)
electic		0.002 *	0.002	0.001	0.002	0.003 *
		(1.72)	(1.41)	(0.81)	(0.98)	(1.81)
fertili			51.247	26.243	6.921	73.435
			(0.81)	(0.41)	(0.11)	(1.03)
machpower				0.105 *	0.117 **	0.130 **
				(1.88)	(2.08)	(2.33)
income					0.000	0.000
					(1.46)	(0.75)
ecolevl						−0.386 **
						(−2.19)
Constant	−0.009	−0.096	−0.110	−0.082	0.082	0.033
	(−0.06)	(−0.66)	(−0.75)	(−0.56)	(0.44)	(0.18)
Observations	196	196	196	196	196	196
Number of ct	28	28	28	28	28	28
R-squared	0.708	0.713	0.714	0.720	0.724	0.732
City FE	YES	YES	YES	YES	YES	YES
F test	0	0	0	0	0	0
r2_a	0.650	0.654	0.653	0.659	0.661	0.669

Note: ***, **, and * represent $p < 1\%$, $p < 5\%$, and $p < 10\%$, respectively. Standard errors are in parentheses.

Table 9 presents the results of the two-way fixed-effect regression performed for Models (1)–(6) using the individual fixed-effect regression obtained by controlling regions and years simultaneously. As presented in the table, the goodness of fit (R^2) of Models (1)–(6) under the two-way fixed effects constantly improves with the continuous addition of control variables, which further perfects model control. On the whole, the overall regression results of these models also significantly improved. Specifically, the effect coefficient of the core explanatory variable (i.e., the fiscal expenditure for supporting agriculture) on the efficiency of the agricultural circular economy increased to as large as 0.463 (Model (5)), suggesting that an increase of 1% in the strength of fiscal support for agriculture would drive the efficiency of the agricultural circular economy to improve by 0.463%. Moreover, the effect coefficient of fiscal support for agriculture remained at the significance level of 1% in each model, which indicates that the promoting effect of the fiscal expenditure for supporting agriculture on the efficiency of the agricultural circular economy becomes more significant after the time effect is controlled. The results of the individual control variables reveal that both the effect coefficient and significance level of land structure on the efficiency of the agricultural circular economy improved. The regression results of the urbanization rate changed very significantly. After the time effect was controlled, the urbanization level exerted a promoting effect on the efficiency of the agricultural circular economy at the level of 1%. The effect coefficient and significance level of the effective utilization rate of agricultural machinery also significantly improved.

Table 9. Results of the two-way fixed-effect regression.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Sueffic	**Sueffic**	**Sueffic**	**Sueffic**	**Sueffic**	**Sueffic**
fs1	0.354 ***	0.363 ***	0.385 ***	0.405 ***	0.463 ***	0.381 ***
	(2.96)	(3.03)	(3.21)	(3.42)	(3.97)	(3.43)
landstru	0.700 ***	0.739 ***	0.782 ***	0.807 ***	0.791 ***	0.827 ***
	(3.16)	(3.30)	(3.48)	(3.65)	(3.67)	(4.09)
chemic	6.433 ***	6.301 ***	5.924 ***	5.546 ***	5.376 ***	5.964 ***
	(10.20)	(9.83)	(8.71)	(8.08)	(8.03)	(9.29)
plastic	1.347 *	1.084	1.109	0.969	0.597	0.832
	(1.90)	(1.45)	(1.49)	(1.32)	(0.82)	(1.22)
urban	0.022 ***	0.020 **	0.024 ***	0.025 ***	0.023 ***	0.035 ***
	(2.73)	(2.49)	(2.88)	(3.02)	(2.89)	(4.37)
electic		0.002	0.001	−0.001	−0.001	0.002
		(1.11)	(0.46)	(−0.32)	(−0.36)	(1.39)
fertili			109.183	71.039	56.043	178.901 ***
			(1.60)	(1.03)	(0.83)	(2.61)
machpower				0.146 **	0.181 ***	0.245 ***
				(2.46)	(3.09)	(4.32)
income					0.000 ***	0.000 **
					(3.15)	(2.07)
ecolevl						−0.819 **
						(−4.64)
Constant	−0.915 **	−0.898 **	−1.144 ***	−1.186 ***	−1.272 ***	−1.563 **
	(−2.56)	(−2.51)	(−2.95)	(−3.10)	(−3.41)	(−4.40)
Observations	196	196	196	196	196	196
Number of ct	28	28	28	28	28	28
R-squared	0.733	0.735	0.740	0.749	0.765	0.794
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
F test	0	0	0	0	0	0
r2_a	0.669	0.669	0.672	0.683	0.700	0.736
F	39.22	36.11	33.86	32.90	33.15	36.58

Note: ***, **, and * represent $p < 1\%$, $p < 5\%$, and $p < 10\%$, respectively. Standard errors are in parentheses.

Overall, according to the regression results of the two fixed-effect models, the fiscal expenditure for supporting agriculture exerted a positive promoting effect on the efficiency of the agricultural circular economy in each model, and the degree of the effect remained above 0.24 in each case. This suggests that an increase of 1% in the level of fiscal support for agriculture would drive the efficiency of the agricultural circular economy to improve by no less than 0.24%. This conclusion remains reliable after considering individual and time effects and the regression estimation between different models.

3.4. Robustness Test

A model is built by controlling individuals and time successively based on panel data. To some extent, this reduces the endogenous effect caused by omitted variables and random errors. For the stringency of empirical results, the robustness of the above regression results is analyzed from the following two aspects. Logically, the development of the local agricultural circular economy is affected by the strength of fiscal support for agriculture. In turn, by optimizing the structure of supporting agriculture and benefiting farmers, fiscal support for agriculture increases subsidies for green factor inputs; improves the mode of agricultural production; encourages farmers to shift their attention from agricultural outputs to the improvement of agricultural green productivity; and guides the sustainable, scientific, and circular development of agriculture, thereby promoting the development of the agricultural circular economy and improving the efficiency of the local agricultural circular economy. On the other hand, the fiscal support provided by the state varies with specific economic structures in different regions. Regions with a higher efficiency level of the agricultural circular economy often have a more scientific, systematic, and sound system of agricultural circular production, which inevitably requires more agricultural production inputs and more fiscal, technical, and policy support. To ensure the stability of agricultural production bases at the home front, the state allocates more fiscal budgets to regions with high agricultural production inputs each year to support their agricultural development. Similarly, the state is also more likely to increase fiscal support for major agricultural provinces with larger growth spaces in terms of the efficiency of the agricultural circular economy to drive the development of the agricultural circular economy in these provinces as soon as possible and coordinate the high-quality, all-round, green, and sustainable development of agriculture between various regions. Therefore, the efficiency of the local agricultural circular economy always affects the fiscal expenditure for supporting agriculture, whether positive or negative. In summary, the dependent variable (the efficiency of the agricultural circular economy) and the independent variable (fiscal expenditure for supporting agriculture) may have a reciprocal causality, which leads to the occurrence of an endogenous problem. Based on this assumption and referring to other scholars' research methods, this paper adopts first-phase lag fs_1 as the instrumental variable for a two-step fixed-effect regression to weaken the possible endogenous effect, as presented in Table 10. For the robustness of the empirical conclusions, with the aid of the measurement results of the efficiency of the agricultural circular economy in the previous section, the efficiency value of the agricultural circular economy under the CCR model is selected as the explained variable to replace the efficiency result of the super-efficiency DEA model. The empirical model is consistent with the above, and regression is still performed under the two-way fixed-effect model, as detailed in Table 10.

Table 10. Results of robustness regression.

Variables	Endogeneity Considered Regression Results of the First Stage	Endogeneity Considered Regression Results of the Second Stage	Replacement of the Explained Variable
	fs1	Sueffic	ccr
fs1		2.154 **	0.143 **
		(2.08)	(2.08)
fs_1	0.212 **		
	(2.17)		
landstru	0.301 *	0.180	0.896 ***
	(1.85)	(0.38)	(7.11)
income	0.000	0.000 *	0.000
	(−0.83)	(1.78)	(0.92)
machpower	−0.019	0.251 **	0.202 ***
	(−0.39)	(2.24)	(5.69)
chemic	0.476	5.181 ***	2.629 ***
	(0.94)	(4.18)	(6.57)
plastic	0.070	0.557	0.875 **
	(0.12)	(0.42)	(2.06)
fertili	−51.421	279.627 **	112.090 ***
	(−0.89)	(1.97)	(2.62)
electic	0.001	0.002	−0.000
	(0.49)	(0.57)	(−0.20)
urban	−0.009	0.055***	0.020 ***
	(−1.31)	(3.21)	(4.07)
ecolevl	−0.192	−0.552	−0.506 ***
	(−1.35)	(−1.48)	(−4.59)
Constant	0.435	−2.565 ***	−0.790 ***
	(1.38)	(−3.08)	(−3.57)
Observations	168	168	196
Number of ct	28	28	28

Table 10. *Cont.*

Variables	Endogeneity Considered Regression Results of the First Stage	Endogeneity Considered Regression Results of the Second Stage	Replacement of the Explained Variable
	fs1	**Sueffic**	**ccr**
City FE	YES	YES	YES
Year FE	YES	YES	YES
R-sq	0.4591	0.4089	0.800

Note: ***, **, and * represent $p < 1\%$, $p < 5\%$, and $p < 10\%$, respectively. Standard errors are in parentheses.

According to the results of the robust regression, the fiscal expenditure for supporting agriculture still exerts a significant promoting effect on the agricultural circular economy after the endogenous effect was considered. In the regression results of the second stage, the effect coefficient of fiscal support for agriculture on the efficiency of the agricultural circular economy increased to 2.154 and remained at the significance level of 5%. In addition, the regression results after the replacement of the explained variable reveal that an increase of 1% in the fiscal expenditure for supporting agriculture would improve the efficiency of the agricultural circular economy by 0.143%, which was significant at the level of 5%. When the efficiency result under the CCR model is adopted as the substitution variable, the driving effect of fiscal support for agriculture on the efficiency of the agricultural circular economy weakens relative to that under the super-efficiency DEA model. However, this still proves the presence of a positive driving effect to some extent, so the empirical conclusions are reliable and robust.

Based on the efficiency of the agricultural circular economy measured above, a model is constructed using the strength of fiscal support for agriculture and the efficiency of the agricultural circular economy in Henan Province in 2013–2019 and is used for the fixed-effect regression analysis. The empirical results reveal that the strength of fiscal support for agriculture has a positive driving effect on the efficiency of the agricultural circular economy, especially when the time effect is considered. After considering the endogenous effect and replacing the explained variable, the empirical conclusions remained robust, suggesting that the conclusions of this paper are reliable and of referential significance.

4. Conclusions and Suggestions

4.1. Conclusions

First, the development status of fiscal support for agriculture and the agricultural circular economy in Henan Province is summarized and analyzed from the perspectives of policy review and status analysis. Second, referring to the input–output theory, the efficiency of the agricultural circular economy in Henan Province under BBC, CCR, and super-efficiency DEA models is measured using the DEA method, and the efficiency results are analyzed vertically and horizontally. Then, a two-way fixed-effect model is used to empirically test the correlation between the fiscal expenditure for supporting agriculture and the efficiency of the agricultural circular economy in Henan Province. Finally, the forward-looking policies intended to promote the development of the agricultural circular economy are examined. The following conclusions are drawn.

First, in the four historical stages of fiscal support for agriculture in Henan Province, the scale of the fiscal expenditure for supporting agriculture has expanded rapidly. Eastern, southern, and northern Henan Province were the key regions receiving fiscal support for agricultural development in Henan Province, and the scale of the fiscal expenditure for supporting agriculture varied greatly across various cities (counties) of Henan Province. In terms of expenditure structure, the expenditure on comprehensive agricultural development of Henan Province was mainly supported by government fiscal funds, and the proportion of fiscal funds from the central government exceeded 40% throughout the year and was a major force that drove comprehensive agricultural development. As far as the land governance and industrial management projects of comprehensive agricultural development are concerned, the fiscal expenditure of Henan Province lays particular stress on land governance projects. Second, the efficiency level of the agricultural circular economy in Henan Province needs to be improved. The efficiency of the agricultural circular economy in Henan Province was measured using the BCC, CCR, and super-efficiency DEA models. Specifically, notwithstanding their differences in the efficiency values obtained, both the CCR and BCC models indicate that the efficiency level of the agricultural circular economy in Henan Province is low; there are considerable gaps between cities (counties); and most of them failed to achieve relative efficiency. The super-efficiency DEA model is used to measure the efficiency values of various cities (counties), and they are ranked based on this criterion. Only Hebi City, which ranked first, achieved relative efficiency, which suggests that the overall development level of the agricultural circular economy in Henan Province is low, and the input–output efficiency of agriculture is also low. Both the government and the market should pay more attention to the agricultural circular economy and make greater efforts to improve the efficiency of resource utilization and promote the quality and efficiency improvement of agriculture. Finally, the fiscal expenditure for supporting agriculture has a positive promoting effect on the development of the agricultural circular economy in Henan Province. Under the individual fixed-effect model, the empirical results obtained based on the panel data of Henan Province for 2013–2019 reveal that the fiscal expenditure for supporting agriculture has a positive incentive effect on the efficiency of the agricultural circular economy, and the incentive effect is more significant after the time effect is controlled. Since 2013, China's national economy has entered a stage of high-quality development. The evaluation of the development level of an industry is no longer limited to economic indices. The support from public finance helps to rationally allocate agricultural production inputs, improve the input–output efficiency, and stimulate the improvement of the agricultural circular economy.

4.2. Suggestions

In view of the development status of fiscal support for agriculture and the agricultural circular economy in China, this paper offers the following policy suggestions.

(1) A circular economy-oriented approach should be taken to rationally allocate the fiscal funds for supporting agriculture and improve the performance level of the fiscal expenditure for supporting agriculture. Starting with the perspective of a circular economy, public finance should increase subsidies for green and pollution-free means of production, thus directly reducing the factor input costs of farmers and enterprises from the supply side; increase inputs in agricultural machinery and equipment; and provide subsidies to manufacturers of agricultural machinery and equipment to improve agricultural output efficiency, reduce unnecessary resource waste, and promote the development of agricultural modernization and integration. Moreover, "waste collection, processing, and recycling" in all aspects of rural production and life should be popularized. Regarding talent training, high subsidies or bonus incentives should be provided for talents who have made outstanding contributions in the field of the agricultural circular economy, or the reserves of outstanding talents in other related fields should be motivated to join research on the agricultural circular economy to constantly explore the future development direction of the agricultural circular economy from a professional perspective.

(2) The strength of fiscal support for agriculture should be increased to innovate the development mode of the agricultural circular economy. Under the composite industrial mode of agriculture, animal husbandry, and fisheries, biological populations, such as farmed animals, crops, and microorganisms, which are mutually independent, can be organically combined to create a coherent production process system, thereby achieving the ecological goal of reducing consumption and emission. Under the recycling mode of agricultural wastes, organic wastes such as straw and livestock manure can be transformed into useful resources through technological reprocessing to be reused in agricultural production or rural life.

(3) A long-term mechanism for supporting agriculture should be established to combine fiscal and financial support and drive the development of agricultural science and technology. Specific agricultural support projects are generally managed through the establishment of special funds for overall planning. In this regard, special funds for the agricultural circular economy can be established to realize the "use of funds as ear-marked" in the fields of input factor subsidies, resource recycling mechanism construction, etc., to improve the efficiency of fund use. In addition to fiscal support for agriculture, the introduction of policy finance will, to a certain extent, make up for the deficiency of fiscal support for agriculture. By reducing the loan interest rate and increasing the line of credit of the manufacturers of green pesticides, fertilizers, and agricultural machinery, policy finance supports the development of agricultural science and technology, thereby opening up another channel for the development of the agricultural circular economy. The publicity of the concept of the agricultural circular economy and related education and skill training should also be strengthened to remove obstacles to policy implementation. At present, the overall education level of Chinese farmers is still low, and individual quality is still uneven, making it necessary to increase the publicity of and education on the circular economy and ecological knowledge and advocate the concept of the circular economy. The purpose is to facilitate the landing and implementation of agricultural circular economy projects. In colleges and universities, "agriculture + environmental engineering," "agriculture + waste treatment," and other composite disciplines should be constructed to continuously refine research on the circular economy and improve professionalism in this regard. Enterprises involved in the agricultural circular process should be trained to realize the spread and practice of the concept of the circular economy through internal training and management and provide references for innovating development modes. Communities should organize relevant simulation activities to allow participants to experience the advantages and disadvantages of different agricultural circular modes in person, adapt to different application scenarios, and develop different agricultural circular systems.

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