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DYNAMICS, REGIONAL HETEROGENEITY AND ROBUSTNESS OF FISCAL POVERTY ALLEVIATION EFFICIENCY IN CHINA: DYNAMIC NETWORK DEA AND BOOTSTRAP RESAMPLING METHODS

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Abstract. This paper aims to tackle the issues of evaluating the dynamic performance of fiscal poverty alleviation in 22 Chinese provinces (regions) over 2016–2019. First, we open up the internal structure of the fiscal poverty alleviation system (FPAS) and clarify its input-output process as a two-stage series system consisting of the public investment process and poverty reduction process. On this basis, we construct dynamic network DEA models with and without carryover activities for measuring the period efficiency and overall efficiency of FPASs (*i.e.*, FPAS efficiency) and the period efficiency and overall efficiency of evaluation indicators (*i.e.*, indicator efficiency), and also prove the relationship between the two proposed models. Second, we combine the proposed dynamic network DEA models and Bootstrap resampling method to assess the robustness of FPAS efficiency for exploring the risk of returning to poverty for each FPAS. The results show that: (i) the carryover activities have some impact on the FPAS efficiency and indicator efficiency; (ii) the period efficiency shows an upward trend, and most of FPASs or evaluation indicators have been at high efficiency in the sample period, but there is still regional heterogeneity; (iii) there are some differences between the indicator efficiency and there are some inconsistencies between them and the FPAS efficiency; (iv) bootstrap resampling results indicate that several FPASs have a great risk of returning to poverty.

Mathematics Subject Classification. 90B30, 90B50, 90C05.

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1. Introduction

It is well known that winning the battle against poverty is an important strategic deployment in China to build a moderately prosperous society in all aspects. By the end of 2020, China has completed the task of poverty alleviation as scheduled, that is, under the current standard, China's rural poor population has been completely removed from poverty. However, getting out of poverty under the current standards does not mean the end of poverty alleviation work in China. On the one hand, it is necessary to reinforce the achievements made in the current poverty alleviation work and prevent the risk of returning to poverty for regions that have

Keywords. Data envelopment analysis, two-stage fiscal poverty alleviation system, dynamic network DEA, bootstrap resampling.

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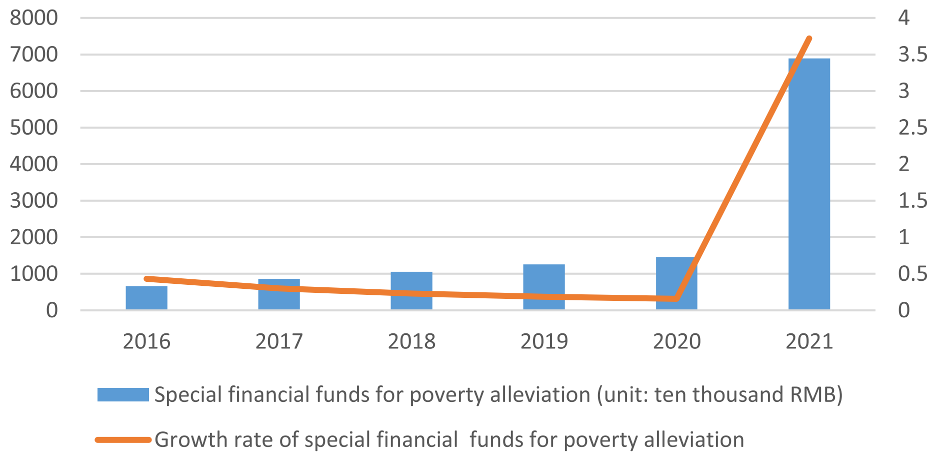

Figure 1. The amount and growth rate of the special fiscal funds for poverty alleviation.

already escaped from poverty. On the other hand, we need to effectively connect the poverty alleviation and rural revitalization strategies to lay the cornerstone for building a well-off society. In fact, whether to reinforce the effectiveness of current poverty alleviation or to dovetail with the rural revitalization strategy, decision-makers need to accurately measure the poverty alleviation efficiency to provide targeted optimization schemes for poor regions with inefficient poverty alleviation. To the best of our knowledge, the fiscal special funds for poverty alleviation, as the guarantee money for the battle against poverty, is increasing recently (see Fig. 1 for details). The expenditure performance of fiscal special funds in poverty alleviation has gained great concern for the government and the public. Therefore, how to analyze appropriately the efficiency of fiscal funds for poverty alleviation is a key issue to be resolved.

Performance appraisal of fiscal funds for poverty alleviation is also a task that meets national development requirements and has important practical guidance. This can identify the inefficiency problems of the current fiscal funds for poverty alleviation, serving to adjust and optimize the fiscal resource allocation associated with poverty alleviation. More importantly, although all of China's rural regions have been lifted out of poverty in terms of current standards, the Chinese government has invested heavily in human, material and fiscal resources. This also means that there may still be potential for improvement in terms of the input-output structure of poverty alleviation. Therefore, a rational measure for fiscal poverty alleviation system (FPAS) efficiency needs to accurately evaluate the performance of current poverty alleviation on the one hand, and investigate the rationality of the inputs of FPAS on the other.

As far as we know, the fiscal poverty alleviation has its unique characteristics, which should be taken into account when constructing FPAS efficiency measures. First, the FPAS has a complex production process and the assessment of FPAS efficiency involves the multidimensional performance of FPAS. Second, the fiscal poverty alleviation is a long-term task, and the proposed FPAS efficiency measure should be able to depict the dynamic characteristics of its performance. Third, the effectiveness of fiscal poverty alleviation is affected by regional characteristics, so it is necessary to discuss the regional heterogeneity of poverty alleviation efficiency. Finally, in addition to paying attention to the performance of FPAS, it is necessary to study the efficiency of input-output indicators of FPAS (*i.e.*, indicator efficiency), so that decision-makers can adjust the input-output structure in a targeted manner to improve the FPAS efficiency. Based on the above characteristics, it is not difficult to find that the FPAS has a complex process with one input and multiple outputs based on production theory. However, traditional production theory requires the specific form of production function of decision-making units (DMUs) when measuring production efficiency. In fact, due to the complex characteristics of FPAS, its production function is difficult to estimate accurately. Data envelopment analysis (DEA), as a data-driven evaluation method based on multiple inputs and outputs, is considered to be one of the useful tools for addressing the multidimensional evaluation [2, 5].

DEA models have been widely applied to measure the poverty alleviation efficiency, while the related literature still has several limitations: (i) the existing studies on the efficiency of fiscal poverty alleviation do not consider the dynamic network structure characteristics of the system [30]; (ii) the intensity of fiscal poverty alleviation in different regions in China is different, which means that there may be some regional heterogeneity in the FPAS efficiency, but this issue is not discussed in the above literature; (iii) the data used in the DEA-based poverty alleviation efficiency studies is observational, but these data may not fully describe the hidden characteristics of DMUs. What is more, DEA models are sensitive to input and output data, and this problem may be more serious when the data has different scales (*e.g.*, the percentage data and absolute data coexist in DEA models). Therefore, it is necessary to analyze the robustness of DEA efficiency measures. However, the existing studies do not analyze the robustness of the poverty alleviation efficiency [30, 33, 34, 36]. This also implies that there may be a potential risk of returning to poverty for some high-efficiency DMUs under the observation data.

To this end, we first account for the internal structure and dynamic evolution characteristics of FPAS and construct dynamic network DEA models to measure the dynamics and regional heterogeneity of the FPAS efficiency and the indicator efficiency in China. Given the importance of efficiency robustness testing [26], we further combine the proposed DEA models with Bootstrap resampling method to test the robustness of FPAS efficiency for exploring the risk of returning to poverty across DMUs.

Specifically, first, we open up the internal structure of FPAS and clarify its input-output process. The FPAS is considered as a two-stage series system consisting of the public investment process and poverty reduction process. Second, we employ the per capita net income (PCNI) as the carryover variable to connect production activities in adjacent periods, and construct a dynamic network production possibility set (PPS) for FPAS. On this basis, we propose dynamic network DEA models with and without carryover activities based on the directional distance function measure. The relationship between these two models is proved theoretically, arguing for the necessity of considering carryover activities in adjacent periods in the FPAS performance evaluation. Third, we combine the Bootstrap resampling method and the proposed dynamic network DEA models to investigate the dynamics, regional heterogeneity and robustness of FPAS efficiency in China, and then analyze the risk of returning to poverty across FPASs. Finally, this paper selects 22 provinces (regions) in China where key poverty alleviation counties exist as DMUs and analyzes the time-varying characteristics, regional heterogeneity and robustness of the FPAS efficiency and indicator efficiency.

The empirical results suggest that (i) the carryover variable has a certain effect on the FPAS efficiency and indicator efficiency, which verifies the rationality of considering the carryover activities in the proposed DEA model; (ii) in general, the period efficiency for a given FPAS or evaluation indicator tends to rise and reach a considerable level in 2019, but there is still some regional heterogeneity, where the efficiency ranges from high to low in the eastern, central and western regions; (iii) there are some differences between the indicator efficiency as well as inconsistency between the indicator efficiency and the FPAS efficiency; (iv) the Bootstrap resampling results show that several FPASs may suffer from a great risk of returning to poverty, such as Henan, Hubei, Hainan, Chongqing, Tibet, Xinjiang, etc.

Distinguishing from the existing literature, the contributions of this paper are as follows: (a) we open up the dynamic network structure of the FPAS at the inter-provincial level rather than the static network structure of FPAS used by Xiao *et al.* [30]; (b) we construct dynamic network DEA models with and without carryover activities, and argue for the necessity of considering carryover activities in the FPAS performance evaluation by theoretically demonstrating the relationship between the two models; (c) we combine the proposed DEA models and Bootstrap resampling method to analyze the risk of returning to poverty in different FPASs, which is not covered by existing literature on DEA-driven poverty alleviation efficiency evaluation; (d) we both measure the FPAS efficiency and the indicator efficiency, and the findings provide an accurate optimization path for the efficiency improvement of FPASs.

The remainder of this paper is organized as follows: Section 2 summarizes the progress of poverty alleviation efficiency evaluation and DEA-related literature. Section 3 clarifies the internal structure of FPASs and proposes dynamic network DEA models with and without considering carryover variable for measuring the dynamic FPAS efficiency. Then, we combine the proposed models with the Bootstrap resampling method to analyze the risk of returning to poverty of FPASs. Section 4 empirically illustrates the rationality of the proposed models and the dynamics, regional heterogeneity and robustness of FPAS efficiency. Conclusions, policy recommendations and possible directions for future research are formulated in Section 5.

2. Literature review

This paper is to study the efficiency of FPAS in China under the dynamic network input-output structure, therefore, this section makes a specific introduction to some poverty alleviation efficiency studies and the application of dynamic network DEA in other fields to further highlight our contributions. In particular, this section discusses three main areas of literature: the measurement of poverty alleviation efficiency based on traditional DEA models (*i.e.*, static black-box DEA models), the measurement of poverty alleviation efficiency by using the static network DEA models, and the recent developments of dynamic network DEA models.

2.1. Traditional DEA-based poverty alleviation efficiency measure

Habibov and Fan [15] compared the poverty reduction effects of social welfare programs in Canadian using DEA method. Their results show that DEA can be effectively used to assess and compare the poverty reduction performance of multiple jurisdictions. Zhong and He [40] measured the development efficiency of 592 national-level poverty-stricken counties in China from 2002 to 2012 based on DEA, and applied the geographic information system method to analyze the spatial differences in development efficiency. Chen *et al.* [7] proposed a new type-2 fuzzy DEA model by combining type-2 fuzzy sets with DEA to measure the rural poverty alleviation efficiency in Hainan Province of China. Dong *et al.* [12] employed the basic three-stage DEA and Tobit models to discuss the fiscal poverty alleviation efficiency and influencing factors of 21 impoverished counties in the destitute area of Liupanshan. Li *et al.* [18] combined principal component analysis, DEA with grey relation analysis to discuss the performance of solar photovoltaic poverty alleviation projects. Zameer *et al.* [38] combined the super-efficiency DEA with system generalized method of moments to conduct an empirical study based on the data of 30 provincial-level administrative regions in China from 2007 to 2018. Wang *et al.* [29] evaluated the tourism poverty alleviation efficiency of 40 districts and counties in Liupanshan area from 2009 to 2018 with the combination of super-efficiency DEA model and Malmquist index. Chen *et al.* [9] adopted DEA to gauge the consumption poverty alleviation efficiency by using data from 20 poverty counties in Guizhou from 2017 to 2020. Tirtosuharto [27] used the traditional DEA to measure the fiscal poverty alleviation efficiency of 26 Indonesian regions from 2001 to 2016.

2.2. Network DEA-based poverty alleviation efficiency measure

It is an important work to open the internal structure of the system in DEA theoretical research, which can effectively improve the validity and accuracy of the evaluation results [6, 16, 20, 24]. To our knowledge, in the field of poverty alleviation performance evaluation, Yang *et al.* [33] were the first to regard the agricultural poverty alleviation system as a two-stage system composed of production and poverty reduction processes. They proposed a two-stage DEA model to evaluate the agricultural production efficiency and poverty reduction efficiency in China. Yang *et al.* [34] considered the tourism poverty alleviation system as consisting of the tourism investment and tourism poverty alleviation processes, and then combined the two-stage DEA model with Malmquist index to calculate dynamic changes in tourism investment efficiency and tourism poverty reduction efficiency in China. In addition, Yang *et al.* [36] proposed a metafrontier-driven dynamic network DEA model based on the two-stage agricultural poverty alleviation system proposed by Yang *et al.* [33] to investigate the overall efficiency, period efficiency and indicator efficiency of 28 inter-provincial agricultural poverty alleviation systems in China. Xiao *et al.* [30] proposed global two-stage DEA models and global Malmquist productivity indices to measure the fiscal poverty alleviation efficiency.

2.3. Dynamic network DEA models

Although the existing literature has not investigated the dynamic efficiency based on the internal structure of FPAS, the recent developments in dynamic network DEA models provide a potential source of inspiration for our dynamic study of FPAS performance. Tone and Tsutsui [28] provided carryover variables to connect the production activities of two adjacent periods and constructed a dynamic network DEA model to evaluate the overall efficiency and period efficiency of DMUs during the observation period. Thereafter, the fundamental idea of dynamic network DEA models has been amply applied across sectors and disciplines. Zha *et al.* [39] divided the bank's operation process into productivity and profitability processes and constructed a dynamic network DEA model with non-performing loans as a carryover variable. Yu *et al.* [37] developed a dynamic network DEA model to study the efficiency of major airlines in China and India based on the airline's internal processes and the carryover activities between consecutive periods. Yang *et al.* [35] divided the internal structure of the industrial water system into water and wastewater treatment subsystems and proposed a dynamic network DEA model with the capacity of wastewater treatment facilities as a carryover variable for evaluating China's regional industrial water system. Based on a dynamic network DEA model with a carryover variable, Lu *et al.* [21] measured the internal management efficiency and investment performance of 37 investment trust companies in Taiwan. Meng and Pang [22] discussed the operational efficiency of China's power industry by using a dynamic network DEA model. In addition, dynamic network DEA models have also been estimated for sectors or industries varying from high-tech (*e.g.*, [1, 31]) to healthcare (*e.g.*, [23]), new energy vehicle [8], and banking [3, 13, 14]. To the best of our knowledge, there is only one literature based on dynamic network DEA model to measure the dynamic efficiency of agricultural poverty alleviation system [36].

2.4. Summary of existing literature

The characteristics of the above studies can be summarized as follows. First, although these studies have developed the traditional DEA-driven performance evaluation for poverty alleviation, which treat the poverty alleviation system as a "black box" and ignore the internal structural characteristics of the system. In addition, the traditional DEA-based poverty alleviation efficiency studies mainly focus on tourism poverty alleviation, photovoltaic poverty alleviation, and consumption poverty alleviation, while the efficiency evaluation on fiscal poverty alleviation has only been explored by Dong *et al.* [12] and Tirtosuharto [27]. Second, the network DEA-based poverty alleviation performance appraisal studies mainly focus on the efficiency measure of agricultural poverty alleviation and tourism poverty alleviation, while the discussion on the internal structure and efficiency evaluation of FPAS is only involved by Xiao *et al.* [30]. However, this work neither considers the carryover activities of the FPAS in adjacent time periods (*i.e.*, the dynamic network structure of FPAS is not taken into account in this study), nor measures the indicator efficiency, nor analyzes the regional heterogeneity of FPAS efficiency and indicator efficiency. Finally, the dynamic network DEA-based poverty alleviation performance assessment is concerned with the agricultural poverty alleviation [36], none of these existing articles systematically investigates the application of the dynamic network DEA models in the assessment of FPAS performance from a dynamic network perspective. Most importantly, all these studies do not consider the robustness of poverty alleviation efficiency. The differences between this paper and existing studies are shown in Table 1.

It is clear that the dynamic internal structures of different poverty alleviation systems are also different, and the dynamic internal structure of FPAS has several unique characteristics. In particular, the special fiscal funds for poverty alleviation are mainly used to support poor areas to accelerate economic and social development, improve the basic production and living conditions of poverty alleviation targets, and enhance their self-development capacity to raise their income levels. Obviously, the dynamic production structure of fiscal poverty alleviation is not identical to that of tourism and agricultural poverty alleviation mentioned above. In addition, there is heterogeneity in the natural endowments across different regions, so there are differences in the efficiency of fiscal poverty alleviation in each region. More importantly, although all poor areas in China are out of poverty under current standards, there is still a potential risk of returning to poverty. Therefore, it is

Table 1. A summary of DEA studies to appraise the poverty alleviation efficiency.

Author(s)	Dynamic network structure	Carryover activities	Regional heterogeneity analysis	Robustness analysis	Indicator efficiency analysis	Fiscal poverty alleviation
Habibov and Fan [15]	No	No	No	No	No	No
Zhong and He [40]	No	No	Yes	No	No	No
Chen *et al.* [7]	No	No	No	Yes	No	No
Dong *et al.* [12]	No	No	Yes	Yes	No	Yes
Li *et al.* [18]	No	No	Yes	No	No	No
Zameer *et al.* [38]	No	No	Yes	No	No	No
Wang *et al.* [29]	No	No	Yes	No	No	No
Chen *et al.* [9]	No	No	No	No	Yes	No
Tirtosuharto [27]	No	No	No	No	No	Yes
Yang *et al.* [33]	No	No	Yes	No	No	No
Yang *et al.* [34]	No	No	No	No	No	No
Yang *et al.* [36]	Yes	Yes	Yes	No	Yes	No
Xiao *et al.* [30]	Yes	No	No	No	No	Yes
Present study	Yes	Yes	Yes	Yes	Yes	Yes

of great research value to explore the internal structure of FPAS and the dynamic evolutionary characteristics, regional heterogeneity, and robustness of FPAS efficiency and indicator efficiency.

3. Problem and methodology

Dynamic network DEA is an evaluation model considering the internal structure and dynamic evolution characteristics of DMUs, and its model characteristics are exactly consistent with these of fiscal poverty alleviation in China (see Sect. 3.1 for details). Therefore, this paper uses the dynamic network DEA as the assessment tool to analyze the dynamic and regional heterogeneity characteristics of the fiscal poverty alleviation efficiency in China. In addition, we also analyze the robustness of fiscal poverty alleviation efficiency using Bootstrap resampling method to discuss the risk of returning to poverty for each DMU.

3.1. Problem description

As far as we know, the fiscal special funds for poverty alleviation in China are mainly used to support rural poor areas to accelerate economic and social development, improve the basic production and living conditions of the poverty alleviation targets, enhance their ability to develop themselves, help raise their income levels, and promote the elimination of the phenomenon of rural poverty. Specifically speaking, the fiscal special funds are mainly used for the construction of infrastructure and public service (IPS) in rural poor areas, thereby helping residents of poor areas to improve their income and living standards, which presents a two-stage production process. It is found that the construction of IPS in poor areas is the cornerstone of the fiscal poverty alleviation, which can be considered as the first stage of the proposed two-stage process. The construction of IPS increases the incomes of the rural residents, and thus improves the conditions of housing and household facilities (HHF) and durable consumer goods (DCG) in poor areas, which can be considered as the second stage of the proposed two-stage process. In addition, the net income of rural residents in the current year is used as an input into the following year to improve their standard of living and living conditions, which can be treated as the carryover activity of FPAS in adjacent time periods. Therefore, from the production perspective, the input-output process of FPAS has a dynamic network structure.

Further, we regard the FPAS as a two-stage process, namely the public investment process (Subsystem 1) including the construction of infrastructure and public services, and the poverty reduction process (Subsystem 2)

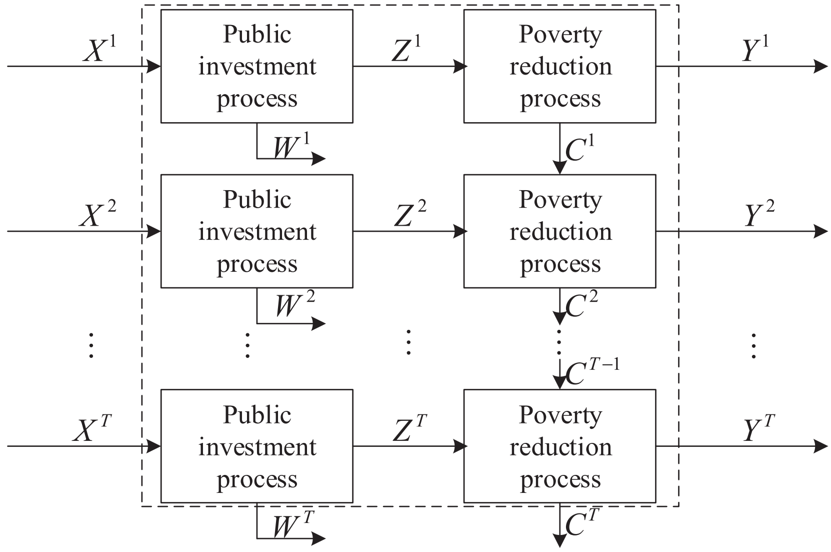

FIGURE 2. The dynamic network input-output progress of FPAS.

including the stage of improving self-development, income and living conditions. In view of this, this paper constructs the dynamic network fiscal poverty alleviation production process as shown in Figure 2.

3.2. Dynamic network DEA model

Based on the dynamic input-output process of FPAS shown in Figure 1, supposing that there are n DMU$_s$, and DMU$_j$ denotes the j-th inter-provincial FPAS in China, where $j = 1, \cdots, n$. For a given period t and DMU$_j$, let $X_j^t = (x_{1,j}^t, \cdots, x_{R,j}^t)$ and $W_j^t = (w_{1,j}^t, \cdots, w_{L,j}^t)$ denote the input and output vectors of Subsystem 1, $Z_j^t = (z_{1,j}^t, \cdots, z_{K,j}^t)$ as the intermediate measure, $Y_j^t = (y_{1,j}^t, \cdots, y_{S,j}^t)$ as the output vector of Subsystem 2, the carryover measure of two adjacent time periods is denoted as $C_j^t = (c_{1,j}^t, \cdots, c_{N,j}^t), t = 1, \cdots, T, j = 1, \cdots, n$. As shown in Figure 1, the linkage Z^t is used as the output of DMU in the first stage, and it is also used as an input to enter the next stage of production process. In addition, the carryover measure C^t is not only the output of Subsystem 2 in time period t, but also the input of Subsystem 2 in time period $t+1$. Based on the above settings, when the inputs and outputs of DUMs satisfy the classical assumptions of convexity, free disposability, and variable returns to scale, the dynamic network production possibility set for FPAS is constructed as follows.

$$P = \left\{ (X^t, W^t, Z^t, Y^t, C^t)_{t=1}^T \left| \begin{array}{ll} \sum_{j=1}^n \lambda_j^t X_j^t \leq X^t, & t = 1, \cdots, T, \\ \sum_{j=1}^n \lambda_j^t W_j^t \geq W^t, & t = 1, \cdots, T, \\ \sum_{j=1}^n \lambda_j^t Z_j^t \geq Z^t, & t = 1, \cdots, T, \\ \sum_{j=1}^n \lambda_j^t Z_j^t = \sum_{j=1}^n \mu_j^t Z_j^t, & t = 1, \cdots, T, \\ \sum_{j=1}^n \mu_j^t Y_j^t \geq Y^t, & t = 1, \cdots, T, \\ \sum_{j=1}^n \mu_j^t C_j^t \geq C^t, & t = 1, \cdots, T, \\ \sum_{j=1}^n \mu_j^t C_j^t = \sum_{j=1}^n \mu_j^{t+1} C_j^t, & t = 1, \cdots, T-1, \\ \sum_{j=1}^n \lambda_j^t = 1, \sum_{j=1}^n \mu_j^t = 1, & t = 1, \cdots, T, \\ \lambda_j^t, \mu_j^t \geq 0, & j = 1, \cdots, n, \ t = 1, \cdots, T. \end{array} \right. \right\} \tag{1}$$

For DMU$(X_d^t, W_d^t, Z_d^t, Y_d^t, C_d^t)_{t=1}^T$, we simultaneously take into account the contraction (expansion) of each input (output) and assume $((1-\theta_d^t)X_d^t, (1+\theta_d^t)W_d^t, (1+\theta_d^t)Z_d^t, (1+\theta_d^t)Y_d^t, (1+\theta_d^t)C_d^t)_{t=1}^T \in P$, where θ_d^t

reflects the proportion of the input (output) indicators of DMU to be evaluated that can shrink (expand) within the production possibility set P. In general, the decision-maker wants to find the maximum value of θ_d^t that satisfies the above requirement, because it means that the maximum efficiency improvement space of DMU to be evaluated is found. Then, the following dynamic network DEA model is constructed:

$$\max_{\lambda_j^t,\mu_j^t,\theta_d^t} \sum_{t=1}^{T} \phi^t \theta_d^t$$
$$\text{s.t.} \begin{cases} \sum_{j=1}^n \lambda_j^t X_j^t \leq (1-\theta_d^t) X_d^t, & t=1,\cdots,T, \\ \sum_{j=1}^n \lambda_j^t W_j^t \geq (1+\theta_d^t) W_d^t, & t=1,\cdots,T, \\ \sum_{j=1}^n \lambda_j^t Z_j^t \geq (1+\theta_d^t) Z_d^t, & t=1,\cdots,T, \\ \sum_{j=1}^n \lambda_j^t Z_j^t = \sum_{j=1}^n \mu_j^t Z_j^t, & t=1,\cdots,T, \\ \sum_{j=1}^n \mu_j^t Y_j^t \geq (1+\theta_d^t) Y_d^t, & t=1,\cdots,T, \\ \sum_{j=1}^n \mu_j^t C_j^t \geq (1+\theta_d^t) C_d^t, & t=1,\cdots,T, \\ \sum_{j=1}^n \mu_j^t C_j^t = \sum_{j=1}^n \mu_j^{t+1} C_j^t, & t=1,\cdots,T-1, \\ \sum_{j=1}^n \lambda_j^t = 1,\ \sum_{j=1}^n \mu_j^t = 1, & t=1,\cdots,T, \\ \lambda_j^t, \mu_j^t \geq 0, & j=1,\cdots,n,\ t=1,\cdots,T. \end{cases} \tag{2}$$

It is notice that the weight ϕ_t is the pre-given parameter, which represents the decision-makers' preference of the poverty alleviation performance in various time periods. The weights in different time periods satisfy the conditions: $\sum_{t=1}^T \phi_t = 1$ and $\phi_t \geq 0$.

To further investigate the impact of carryover activities on the poverty alleviation efficiency, refer to Briec *et al.* [4], this paper also constructs the corresponding fiscal poverty alleviation production possibility set without considering carryover activities.

$$P_1 = \left\{ (X^t, W^t, Z^t, Y^t, C^t)_{t=1}^T \middle| \begin{array}{ll} \sum_{j=1}^n \lambda_j^t X_j^t \leq X^t, & t=1,\cdots,T, \\ \sum_{j=1}^n \lambda_j^t W_j^t \geq W^t, & t=1,\cdots,T, \\ \sum_{j=1}^n \lambda_j^t Z_j^t \geq Z^t, & t=1,\cdots,T, \\ \sum_{j=1}^n \lambda_j^t Z_j^t = \sum_{j=1}^n \mu_j^t Z_j^t, & t=1,\cdots,T, \\ \sum_{j=1}^n \mu_j^t Y_j^t \geq Y^t, & t=1,\cdots,T, \\ \sum_{j=1}^n \mu_j^t C_j^t \geq C^t, & t=1,\cdots,T, \\ \sum_{j=1}^n \lambda_j^t = 1,\ \sum_{j=1}^n \mu_j^t = 1, & t=1,\cdots,T, \\ \lambda_j^t, \mu_j^t \geq 0, & j=1,\cdots,n,\ t=1,\cdots,T. \end{array} \right\} \tag{3}$$

Similarly, for DMU$(X_d^t, W_d^t, Z_d^t, Y_d^t, C_d^t)_{t=1}^T$, we also assume that $((1-\theta_d^t)X_d^t, (1+\theta_d^t)W_d^t, (1+\theta_d^t)Z_d^t, (1+\theta_d^t)Y_d^t, (1+\theta_d^t)C_d^t)_{t=1}^T \in P_1$. Then, the following dynamic DEA model is constructed.

$$\max_{\lambda_j^t,\mu_j^t,\theta_d^t} \sum_{t=1}^{T} \phi^t \theta_d^t$$

$$\text{s.t.} \begin{cases} \sum_{j=1}^{n} \lambda_j^t X_j^t \leq (1-\theta_d^t) X_d^t, & t=1,\cdots,T, \\ \sum_{j=1}^{n} \lambda_j^t W_j^t \geq (1+\theta_d^t) W_d^t, & t=1,\cdots,T, \\ \sum_{j=1}^{n} \lambda_j^t Z_j^t \geq (1+\theta_d^t) Z_d^t, & t=1,\cdots,T, \\ \sum_{j=1}^{n} \lambda_j^t Z_j^t = \sum_{j=1}^{n} \mu_j^t Z_j^t, & t=1,\cdots,T, \\ \sum_{j=1}^{n} \mu_j^t Y_j^t \geq (1+\theta_d^t) Y_d^t, & t=1,\cdots,T, \\ \sum_{j=1}^{n} \mu_j^t C_j^t \geq (1+\theta_d^t) C_d^t, & t=1,\cdots,T, \\ \sum_{j=1}^{n} \lambda_j^t = 1,\ \sum_{j=1}^{n} \mu_j^t = 1, & t=1,\cdots,T, \\ \lambda_j^t, \mu_j^t \geq 0, & j=1,\cdots,n,\ t=1,\cdots,T. \end{cases} \tag{4}$$

If the optimal solutions of Models (2) and (4) are recorded as $(\theta_d^{t^*}, \lambda_1^{t^*}, \cdots, \lambda_n^{t^*}, \mu_1^{t^*}, \cdots, \mu_n^{t^*})$ and $(\theta^{t^{**}}, \lambda_1^{t^{**}}, \cdots, \lambda_n^{t^{**}}, \mu_1^{t^{**}}, \cdots, \mu_n^{t^{**}})$, the conclusion shown in Theorem 1 is obtained.

Theorem 1. *The optimal values of Models (2) and (4) satisfy the following relationship:* $\sum_{t=1}^{T} \phi^t \theta_d^{t^*} \leq \sum_{t=1}^{T} \phi^t \theta_d^{t^{**}}$ *and* $\theta_d^{t^*} \leq \theta_d^{t^{**}}$.

Proof. From the form of Models (2) and (4), it found that the optimal solution of Model (2), *i.e.*, $\left(\theta_d^{t^*}, \lambda_1^{t^*}, \cdots, \lambda_n^{t^*}, \mu_1^{t^*}, \cdots, \mu_n^{t^*}\right)$, is also the feasible solution of Model (4). That is to say, the conclusion $\sum_{t=1}^{T} \phi^t \theta_d^{t^*} \leq \sum_{t=1}^{T} \phi^t \theta_d^{t^{**}}$ holds. In addition, Model (4) can be decomposed into T independent single-period models, we then set the decision variables of Model (4) as follows:

$$(\theta_d^t, \lambda_1^t, \cdots, \lambda_n^t, \mu_1^t, \cdots, \mu_n^t) = \begin{cases} (\theta_d^{t^*}, \lambda_1^{t^*}, \cdots, \lambda_n^{t^*}, \mu_1^{t^*}, \cdots, \mu_n^{t^*}), & \text{for } \forall t = t_0; \\ (\theta_d^{t^{**}}, \lambda_1^{t^{**}}, \cdots, \lambda_n^{t^{**}}, \mu_1^{t^{**}}, \cdots, \mu_n^{t^{**}}), & \text{for } \forall t \neq t_0. \end{cases}$$

It is not difficult to find that the above setting of decision variables are also the feasible solution of Model (4). Therefore, $\sum_{t=1, t\neq t_0}^{T} \phi^t \theta_d^{t^{**}} + \phi^{t_0} \theta_d^{t_0 *} \leq \sum_{t=1}^{T} \phi^t \theta_d^{t^{**}}$ is established, that is, $\theta_d^{t_0 *} \leq \theta_d^{t_0 **}$ is true. In summary, Theorem 1 holds. □

Further, the period efficiency and overall efficiency of FPAS (*i.e.*, FPAS efficiency) to be evaluated by different DEA models are defined as:

$$\hat{\theta}_d^t = \begin{cases} \frac{1-\theta_d^{t^*}}{1+\theta_d^{t^*}}, & \text{for Model (2)}, \\ \frac{1-\theta_d^{t^{**}}}{1+\theta_d^{t^{**}}}, & \text{for Model (4)}, \end{cases} \tag{5}$$

$$E_o = \begin{cases} \sum_{t=1}^{T} \phi^t \frac{1-\theta_d^{t^*}}{1+\theta_d^{t^*}}, & \text{for Model (2)}, \\ \sum_{t=1}^{T} \phi^t \frac{1-\theta_d^{t^{**}}}{1+\theta_d^{t^{**}}}, & \text{for Model (4)}. \end{cases} \tag{6}$$

In addition, the period efficiency of each evaluation indicator is defined as:

$$E_{x,i}^t = \begin{cases} \frac{\sum_{j=1}^{n} \lambda_j^{t^*} x_{i,j}^t}{x_{i,0}^t}, & \text{for Model (2)} \\ \frac{\sum_{j=1}^{n} \lambda_j^{t^{**}} x_{i,j}^t}{x_{i,0}^t}, & \text{for Model (4)} \end{cases} \tag{7}$$

$$E_{w,i}^t = \begin{cases} \frac{w_{l,0}^t}{\sum_{j=1}^{n} \lambda_j^{t^*} w_{i,j}^t}, & \text{for Model (2)} \\ \frac{w_{l,0}^t}{\sum_{j=1}^{n} \lambda_j^{t^{**}} w_{i,j}^t}, & \text{for Model (4)} \end{cases} \tag{8}$$

$$E_{z,h}^t = \begin{cases} \frac{z_{h,0}^t}{\sum_{j=1}^n \lambda_j^{t^*} z_{h,j}^t}, & \text{for Model (2)}, \\ \frac{z_{h,0}^t}{\sum_{j=1}^n \lambda_j^{t^{**}} z_{h,j}^t}, & \text{for Model (4)}, \end{cases} \tag{9}$$

$$E_{y,r}^t = \begin{cases} \frac{y_{r,0}^t}{\sum_{j=1}^n \mu_j^{t^*} y_{r,j}^t}, & \text{for Model (2)}, \\ \frac{y_{r,0}^t}{\sum_{j=1}^n \mu_j^{t^{**}} y_{r,j}^t}, & \text{for Model (4)}, \end{cases} \tag{10}$$

$$E_{c,r}^t = \begin{cases} \frac{c_{r,0}^t}{\sum_{j=1}^n \mu_j^{t^*} c_{r,j}^t}, & \text{for Model (2)}, \\ \frac{c_{r,0}^t}{\sum_{j=1}^n \mu_j^{t^{**}} c_{r,j}^t}, & \text{for Model (4)}. \end{cases} \tag{11}$$

Similarly, the overall efficiency of each evaluation indicator is defined as follows.

$$E_{o,x,i} = \sum_{t=1}^T \phi^t E_{x,i}^t, \tag{12}$$

$$E_{o,w,i} = \sum_{t=1}^T \phi^t E_{w,i}^t, \tag{13}$$

$$E_{o,z,h} = \sum_{t=1}^T \phi^t E_{z,h}^t, \tag{14}$$

$$E_{o,y,r} = \sum_{t=1}^T \phi^t E_{y,r}^t, \tag{15}$$

$$E_{o,c,r} = \sum_{t=1}^T \phi^t E_{c,r}^t. \tag{16}$$

From the definition of efficiency in (5)–(16), it is found that the overall efficiency reflects the comprehensive performance of FPASs and evaluation indicators in the evaluation time horizon, and the period efficiency characterizes the performance of FPASs and evaluation indicators at a specific time period. Further, the period efficiency over time can also be used to characterize the dynamic evolution of efficiency.

3.3. Robustness analysis of FPAS efficiency

Models (2) and (4) are both based on observational data to measure the performance of FPASs, but the observational data may not fully capture the performance of each FPAS, *i.e.*, the results of observational data-driven evaluation models may lack robustness. Therefore, for some FPASs that are high-efficiency under the observational data but lack robustness, they may be at some risk of returning to poverty. To address this problem, this paper uses the Bootstrap resampling method in Simar and Wilson [26] to further study the robustness of the FPAS efficiency obtained by the above DEA models. Bootstrap is a resampling statistical method with replacement, which can be used for parameter inference when the population distribution or statistical distribution is unknown. It is widely used in the robustness analysis of DEA efficiency [10, 11, 17]. Next, we take Model (2) as an example to show the specific steps of the Bootstrap resampling method.

(1) According to the smoothed Bootstrap process in Simar and Wilson [26], we build the following random variables $\hat{\theta}_1^{1^{**}}, \cdots, \hat{\theta}_n^{1^{**}}, \cdots, \hat{\theta}_1^{T^{**}}, \cdots, \hat{\theta}_n^{T^{**}}$:

$$\widehat{\theta}_d^{t^{**}} = \begin{cases} \widehat{\theta}_d^{t^*} + h\epsilon_d^t, \widehat{\theta}_d^{t^*} + h\epsilon_d^t \le 1, \\ 2 - \widehat{\theta}_d^{t^*} - h\epsilon_d^t, \widehat{\theta}_d^{t^*} + h\epsilon_d^t > 1, \end{cases} \tag{17}$$

where $\hat{\theta}_1^{1^*}, \cdots, \hat{\theta}_n^{1^*}, \cdots, \hat{\theta}_1^{T^*}, \cdots, \hat{\theta}_n^{T^*}$ is the group of Bootstrap sample generated by sampling with replacement from $\hat{\theta}_1^1, \cdots, \hat{\theta}_n^1, \cdots, \hat{\theta}_1^T, \cdots, \hat{\theta}_n^T$, ϵ_d^t follows the standard normal distribution, and the smoothing parameter h is a given value. It is worth noting that the optimal value of h as indicated by Silverman [25] is $h = 0.0140$.

(2) Based on the random variable $\hat{\theta}_d^{t^*}$ constructed above, a set of modified Bootstrap sequences $\tilde{\theta}_1^{1^{**}}, \cdots, \tilde{\theta}_n^{1^{**}}, \cdots, \tilde{\theta}_1^{T^{**}}, \cdots, \tilde{\theta}_n^{T^{**}}$ is generated, which satisfy the following conditions $\tilde{\theta}_d^{t^{**}} = \hat{\theta}^{**} + (\hat{\theta}_d^{t^{**}} - \hat{\theta}^{**})/\sqrt{1 + h^2/\sigma^2}$, $\hat{\theta}^{**} = \sum_{t=1}^T \sum_{j=1}^n \hat{\theta}_j^{t^{**}}/(n \times T)$, and σ^2 is the sample variance of $\hat{\theta}_1^1, \cdots, \hat{\theta}_n^1, \cdots, \hat{\theta}_1^T, \cdots, \hat{\theta}_n^T$.

(3) Let $\tilde{\theta}_j^{t^*} = \frac{1-\tilde{\theta}_j^{t^{**}}}{1+\tilde{\theta}_j^{t^{**}}}$, we can calculate the Bootstrap production possibility set $P_b^* = \{(X_j^{t^*}, W_j^{t^*}, Z_j^{t^*}, Y_j^{t^*}, C_j^{t^*}), j = 1, \cdots, n, t = 1, \cdots, T\}$, where $X_j^{t^*} = \frac{1-\theta^{t^*}}{1-\tilde{\theta}_j^{t^*}} X_j^t$, $W_j^{t^*} = \frac{1+\theta^{t^*}}{1+\tilde{\theta}_j^{t^*}} W_j^t$, $Z_j^{t^*} = \frac{1+\theta^{t^*}}{1+\tilde{\theta}_j^{t^*}} Z_j^t$, $Y_j^{t^*} = \frac{1+\theta^{t^*}}{1+\tilde{\theta}_j^{t^*}} Y_j^t$, $C_j^{t^*} = \frac{1+\theta^{t^*}}{1+\tilde{\theta}_j^{t^*}} C_j^t$, $j = 1, \cdots, n, t = 1, \cdots, T$.

(4) For DMU$(X_d^t, W_d^t, Z_d^t, Y_d^t, C_d^t)_{t=1}^T$, we can build model $\max_{\lambda_j^t, \mu_j^t, \theta_d^t} \{\sum_{t=1}^T \phi^t \theta_d^t | ((1-\theta_d^t)X_d^t, (1+\theta_d^t)W_d^t, (1+\theta_d^t)Z_d^t, (1+\theta_d^t)Y_d^t, (1+\theta_d^t)C_d^t)_{t=1}^T \in P_b\}$. Further, let the optimal decision variable of θ_d^t be $\theta_{d,b}^{t^*}$, then, we obtain the Bootstrap FPAS efficiency $\hat{\theta}_{d,b}^1, \cdots, \hat{\theta}_{d,b}^T$, where $\hat{\theta}_{d,b}^t = \frac{1-\theta_{d,b}^{t^*}}{1+\theta_{d,b}^{t^*}}$.

(5) Repeat steps 1–4 B times to obtain the Bootstrap estimation of group B.

Based on the above Bootstrap estimation $\hat{\theta}_{d,b}^t$, the mean and bias are recorded as $\bar{\theta}_d^t = \frac{1}{B}\sum_{b=1}^B \hat{\theta}_{d,b}^t$ and $Bias_d^t = \hat{\theta}_d^t - \bar{\theta}_d^t$. At this point, the corrected efficiency of $\hat{\theta}_d^t$ is defined as

$$\tilde{\theta}_d^t = \hat{\theta}_d^t - Bias_d^t = 2\hat{\theta}_d^t - \hat{\theta}_d^t.$$

In addition, we can correct the Bootstrap efficiency $\hat{\theta}_{d,b}^t$ by $\tilde{\theta}_{d,b}^t = \hat{\theta}_{d,b}^t - Bias_d^t$. In the following, we build the confidence interval $(\tilde{\theta}_{d,b}^{t(\alpha/2)}, \tilde{\theta}_{d,b}^{t(1-\alpha/2)})$ based on the empirical distribution function, where the confidence level is $1-\alpha$, $\tilde{\theta}_{d,b}^{t(\alpha/2)}$ and $\tilde{\theta}_{d,b}^{t(1-\alpha/2)}$ denote the lower and upper $\alpha/2$ quantiles of $\tilde{\theta}_{d,b}^t$. Obviously, the smaller the length of the confidence interval, the better the efficiency robustness of the FPAS.

4. Empirical analysis

4.1. Evaluation indicators and data preprocessing

Based on the dynamic network input-output process shown in Figure 2, this section discusses the specific input-output indicators of the FPAS, of which the rationale for the selection of each indicator is shown as follows.

(i) **The inputs in the first stage.** This paper studies the fiscal poverty alleviation efficiency, and the special fiscal funds for poverty alleviation (*i.e.*, PA funds) are regarded as the input of Subsystem 1. Specifically, the PA funds are mainly used for the construction of infrastructure and public services (IPS) in poor rural areas [30].

(ii) **The outputs in the first stage.** Based on the main uses of China's PA funds, it can be seen that the PA funds are used to support the construction of public welfare facilities, supporting facilities for rural drinking water safety, roads in poor areas, etc. In view of this, "The proportion of farmers who can easily take the bus in their natural villages", "The proportion of farmers who can centrally dispose the garbage in their natural villages", "The proportion of farmers with health posts in their natural villages", "The proportion of farmers who can easily access to kindergarten in their natural villages", and "The proportion of farmers who can easily access to primary school in their natural villages" are considered in this paper as the second-level evaluation indicators of IPS.

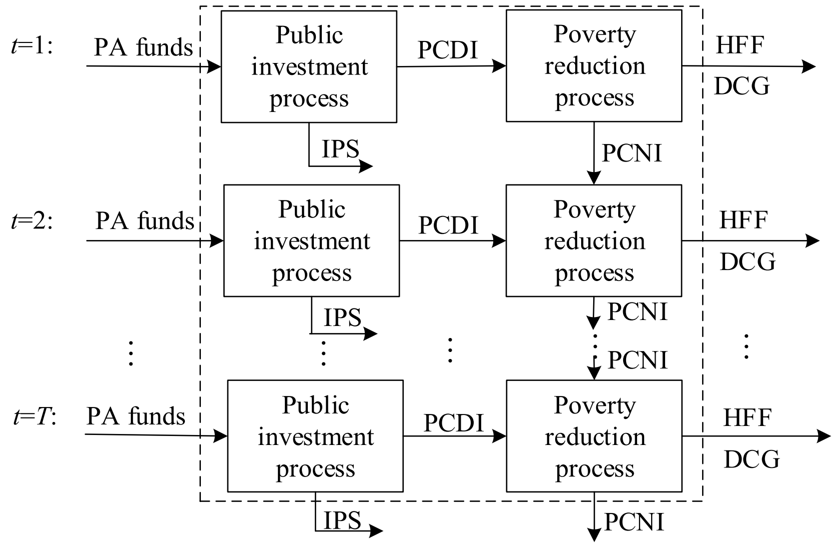

FIGURE 3. Specific input-output process of the dynamic network FPAS.

(iii) **The intermediate measure.** It is well known that the construction of IPS can facilitate the employment of rural residents, the sale of agricultural products and the development of specialized industries, thereby increasing the disposable income of rural residents. Moreover, the disposable income of the rural residents as an input indicator goes into Subsystem 2 to support the poverty reduction process. For this reason, we use per capita disposable income (PCDI) as an intermediate measure between Subsystem 1 and Subsystem 2.

(iv) **The outputs in the second stage.** The disposable income of the rural residents is mainly used to improve the conditions of housing and household facilities (HHF) and durable consumer goods (DCG). For this purpose, we construct the second-level indicators in terms of the HHF and DCG dimensions. In the case of HHF, the primary improvements for rural residents are housing conditions, piped water facilities, and toilet facilities, etc. To this end, we treat "The proportion of farmers living in bamboo and grass adobe houses", "The proportion of farmers using piped water supply", "The proportion of farmers using purified tap water", "The proportion of farmers who use the toilet alone", and "The proportion of farmers using firewood for cooking" as the secondary indicators of HHF. In the case of DCG, rural residents use their disposable income to purchase consumer durables such as car, washing machine, refrigerator, cell phone, and computer, etc., which can be considered as the second-level indicators of DCG.

(v) **The carryover measure.** In fact, the disposable income of the rural residents may have some surplus in addition to being used for HHF improvements and DCG purchases, which can be carried over to the next time period. To this end, we regard the per capita net income (PCNI) as the carryover measure for Subsystem 2 in two adjacent time periods.

Combined with the purpose of the special funds for poverty alleviation, this paper constructs the input-output indicators shown in Table 1.

Based on the input-output indicators shown in Table 2, the dynamic input-output structure of inter-provincial FPAS in China is shown in Figure 3.

In this paper, we selected 22 provinces (regions) in China where key poverty alleviation counties exist during 2016–2019 as DMUs, and the specific provinces (regions) are listed in the China Rural Poverty Monitoring

Table 2. The specific setting of input and output indicators of FPAS.

Indicator attributes	First level indicators	Second level indicators
Inputs in the first stage	PA funds	–
Intermediate measure	PCDI	–
Carryover measure	PCNI	–
Outputs in the first stage	IPS	The proportion of farmers who can easily take the bus in their natural villages (%)
		The proportion of farmers who can centrally dispose the garbage in their natural villages (%)
		The proportion of farmers with health posts in their natural villages (%)
		The proportion of farmers who can easily access to kindergarten in their natural villages (%)
		The proportion of farmers who can easily access to primary school in their natural villages (%)
Outputs in the second stage	HHF	The proportion of farmers living in bamboo and grass adobe houses (%)
		The proportion of farmers using piped water supply (%)
		The proportion of farmers using purified tap water (%)
		The proportion of farmers who use the toilet alone (%)
		The proportion of farmers using firewood for cooking (%)
	DCG	Car (cars per 100 households)
		Washing machine (units per 100 households)
		Refrigerator (units per 100 households)
		Mobile phone (department per 100 households)
		Computer (units per 100 households)

Report (CRPMR)[1]. The relevant data sources are as follows: the data on the poverty alleviation funds by province from the National Rural Revitalization Bureau (NRRB)[2], and other data from CRPMR.

However, each of the three output indicators (*i.e.*, IPS, HHF, and DCG) shown in Table 2 contains five second-level indicators, and there are also undesirable output indicators (*e.g.*, "the proportion of farmers living in bamboo and grass adobe houses", and "the proportion of farmers using firewood for cooking"). In fact, the number of DMUs and evaluation indicators in the DEA model need to meet certain requirements, that is, decision-makers cannot directly use all second-level indicators as the output indicators of the DEA model when there are too many second-level indicators. Moreover, we cannot only select some second-level indicators as the output indicators, because this reckless method affects the accuracy and fairness of evaluation results. Intuitively, therefore, for a given first-level indicator, decision-makers need to integrate the comprehensive performance of all second-level indicators as the output of the DEA model. In fact, DEA is a multi-indicator-driven evaluation method, which can be used to measure the comprehensive performance of the above-mentioned first-level indicators. It is worth noticing that the second-level indicators are outputs, and their comprehensive performance can be measured by the Index-DEA model (or the DEA model without explicit inputs) proposed by Liu *et al.* [19] and Yang *et al.* [32].

In addition, to avoid the influence of data magnitude differences (*i.e.*, the data in Tab. 2 has both percentage and absolute data) on the evaluation results, we perform the standardized processing on the collected panel data. Specifically, the above-mentioned desirable and undesirable outputs are preprocessed by the following

[1]The CRPMR has only published the data up to 2019, so our sample interval is 2016–2019.

[2]The website is http://www.cpad.gov.cn/col/col2360/index.html.

TABLE 3. Descriptive statistics of input-output indicators during 2016–2019.

Indicator	Mean	Standard deviation	5-th percentile	95-th percentile
PA funds	0.2916	0.2222	0.0601	0.7855
PCDI	0.4899	0.2179	0.1748	0.8735
PCNI	0.3765	0.2013	0.1434	0.8506
IPS	0.8444	0.1274	0.5633	1.0000
HHF	0.9375	0.0829	0.7252	1.0000
DCG	0.8455	0.1147	0.6404	1.0000

mappings:

$$\text{Desirable}_j^t \rightarrow \frac{\text{Desirable}_j^t - \min_{j,t}\left\{\text{Desirable}_j^t\right\}}{\max_{j,t}\left\{\text{Desirable}_j^t\right\} - \min_{j,t}\left\{\text{Desirable}_j^t\right\}} + \varepsilon, \tag{18}$$

$$\text{Undesirable}_j^t \rightarrow \frac{\max_{j,t}\left\{\text{Undesirable}_j^t\right\} - \text{Undesirable}_j^t}{\max_{j,t}\left\{\text{Undesirable}_j^t\right\} - \min_{j,t}\left\{\text{Undesirable}_j^t\right\}} + \varepsilon. \tag{19}$$

As shown in equations (18) and (19), we add an infinitesimal value ε to the processed data to avoid the results in a zero value. In the empirical evidence, the value of ε is set as 0.0001. In addition, to ensure that the resulting efficiency values are comparable in both time and spatial dimensions, the following non-convex global Index-DEA model is used to measure the performance of first-level indicators [30]. Based on the above standardized indicators, the following non-convex global Index-DEA model is proposed to measure the integrated performance of the h-th first-level indicator at the time period τ, where $h = 1, 2, 3$ and $\tau = 1, \cdots, T$[3].

$$\begin{aligned} &\varphi^*\left(\tilde{Y}_0^{\tau,h}\right) = \max \varphi \\ &\text{s.t.} \begin{cases} \sum_{t=1}^{T}\sum_{j=1}^{n} \nu_j^t \tilde{Y}_j^{t,h} \geq \tilde{Y}_0^{\tau,h} + \varphi g_{\tilde{Y}_0^{\tau,h}}, & \\ \sum_{j=1}^{n} \nu_j^t = \kappa^t,\ \sum_{t=1}^{T} \kappa^t = 1, & j = 1, \cdots, n \\ \nu_j^t \geq 0, \kappa^t = \{0, 1\}, & t = 1, \cdots, T, j = 1, \cdots, n. \end{cases} \end{aligned} \tag{20}$$

It is worth noting that $\tilde{Y}_j^{t,h} = (\tilde{Y}_{1,j}^{t,h}, \cdots, \tilde{Y}_{I_h,j}^{t,h})'$ and I_h denotes the number of second-level indicators associated with the h-th first-level indicator. Further, as shown in Model (20), $\tilde{Y}_{i,j}^{t,h}$ denotes the standardized value of the i-th second-level indicator of the j-th DMU in the time period t under the category of the h-th first-level indicator.

Let the projection direction $g_{\tilde{Y}_{i,0}^{\tau,h}}$ be $\tilde{Y}_{i,0}^{\tau,h}$, then the integrated performance of the above three first-level indicators (*i.e.*, $1/[1 + \varphi^*(\tilde{Y}_0^{\tau,h})] \in [0, 1]$) is measured, which in turn is used as the output indicators of the FPAS. Based on the preprocessed data, the descriptive statistics of the input and output indicators are shown in Table 3.

It can be seen from Table 3 that there is a large gap between indicators. The mean, standard deviation and percentiles of these indicators show a significant difference. In terms of the descriptive statistics of the three indicators, PA funds, PCDI and PCNI, it can be observed that, as a whole, most of the provinces are at a low level in these indicators, and there are large variations across provinces. In contrast, concerning the three output indicators (*i.e.*, IPS, HHF, and DCG), one can see that the means and quartiles for all three indicators are relatively high and the standard deviations are low, which indicates that most of the provinces

[3]Here the first-level indicators are IPS, HHF and DCG respectively, and the corresponding second-level indicators for each first-level indicator are shown in Table 2.

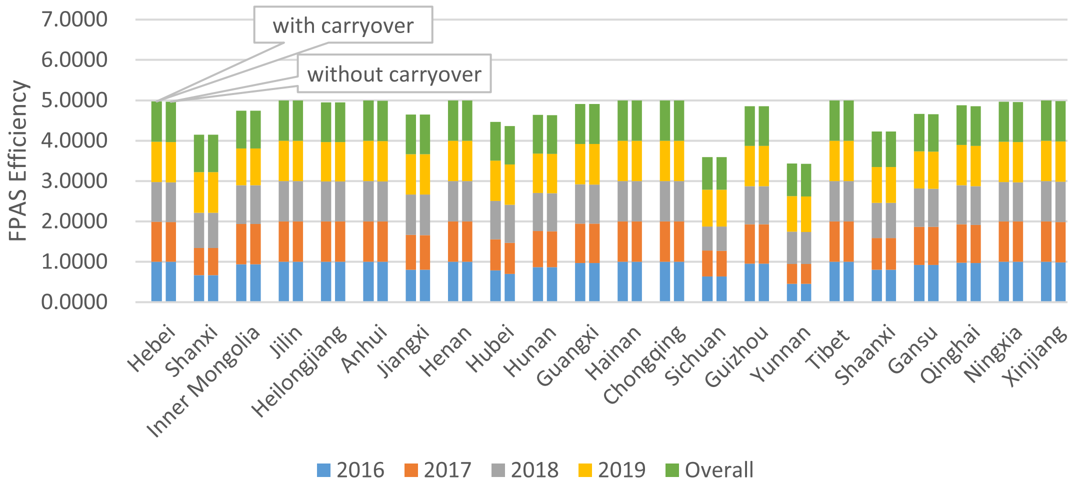

FIGURE 4. Comparative analysis of the FPAS efficiency.

have comparatively high levels in these three indicators in general, especially for the HHF indicator. From the descriptive statistical results of the indicators among provinces, it is necessary to study the regional heterogeneity of the efficiency of FPAS across provinces in China.

Combined with the methods in Section 3 and the collected data, we analyze the FPAS efficiency and indicator efficiency of the inter-provincial FPAS in China. However, the weight coefficient ϕ^t for Models (2) and (4) need to be set in advance. Generally speaking, decision-makers are more comfortable assigning higher weight to the period efficiency that are closer to the current time. To this end, we assume the weight ϕ^t is derived by the following exponential decay model: $\phi^t = [e^{\delta t}(1-e^{\delta})]/[e^{\delta}(1-e^{\delta T})], t = 1, \cdots, T$, and the value of parameter δ is set as 1[4]. In addition to this, since the time horizon for the evaluation has been set from 2016 to 2019, it means that the number of time periods T takes the value of 4. Specifically, $t = 1$ denotes the year 2016 and the remainder in that order. Based on Models (2)–(4), the obtained results are shown in Figures 4–12 and Tables 4–21. For convenience, our notations are defined as follows: "2016", "2017", "2018", and "2019" denote the period performance of DMU to be evaluated from 2016 to 2019, and "Overall" shows the overall performance of DMU to be evaluated over the evaluation time horizon.

In the following empirical analyses, we both show the comparisons of the results from the DEA models with and without carryover activities. The main purposes of comparing the results of these different DEA models are twofold. First, we aim to examine whether the consideration of the carryover activities has an impact on the FPAS efficiency and indicator efficiency, thereby validating the necessity of considering carryover activities in the inter-provincial FPAS appraisal in China. Second, we aim to further illustrate the discrepancy in the impact of carryover activities on the robustness of fiscal poverty alleviation efficiency in China, thus clarifying the extent to which the corrected FPAS efficiency is affected by carryover activities.

4.2. Efficiency analysis of FPASs

Based on Models (2) and (4), the dynamic efficiency of each FPAS is measured. The empirical results obtained are shown in Figure 4 and Tables 4 and 5.

[4]In the empirical analysis, the decay coefficient is set to 1, and the weight of each time period is computed as $[0.0321, 0.0871, 0.2369, 0.6439]$ by using the exponential decay model. In this setting, the weight of the last time period is 0.6439, while the sum of the weights of the first three time periods is 0.3561. It also shows that when decision makers have a trade-off between the performance of DMUs in the last time period and the performance in the first three time periods, they are more in favor of the former. This is because they believe that the performance of the last time period should be more informative. To this end, we roughly consider that this way of weight setting is relatively rational behavior in the real world.

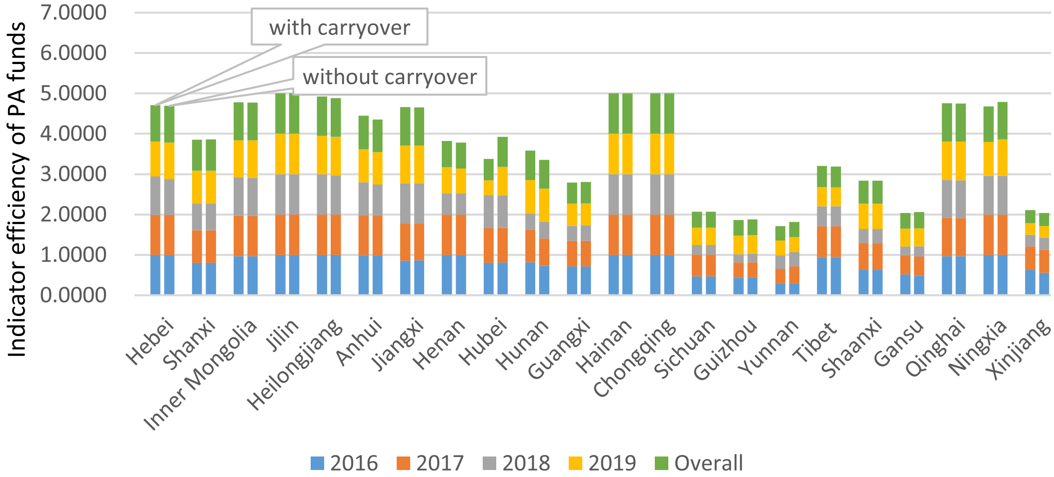

FIGURE 5. Comparative analysis of indicator efficiency of PA funds.

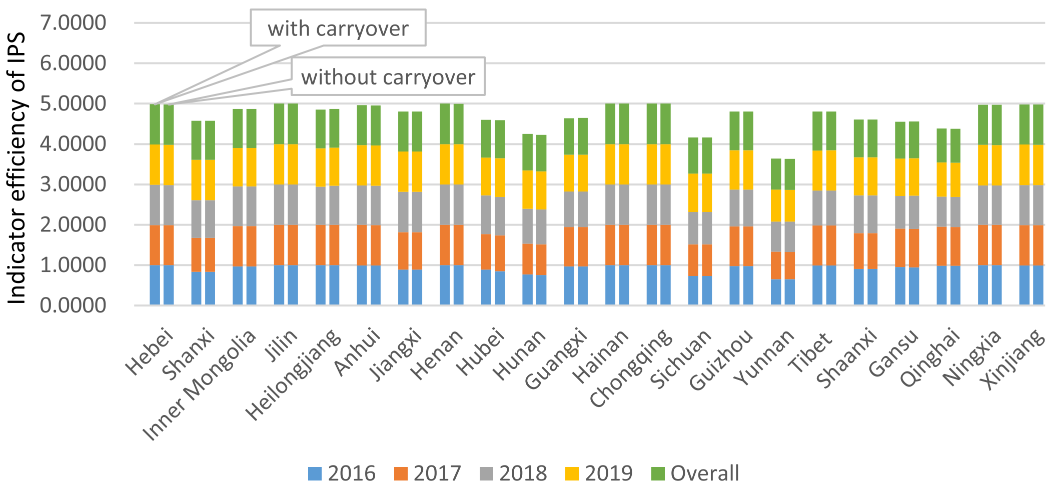

FIGURE 6. Comparative analysis of indicator efficiency of IPS.

The period efficiency and overall efficiency of the FPASs (*i.e.*, FPAS efficiency) obtained by different DEA models are shown in Figure 4. For a given province (region), the bottom-up sub-graphs of the histogram represent the period efficiency of each FPAS in 2016, 2017, 2018, and 2019 and the overall efficiency in the entire time horizon. And the larger the value, the better the effect of poverty alleviation. In general, whether in the framework of the DEA model with or without carryover activities, the FPAS efficiency is still quite impressive, and the effect is more obvious, but there are some differences in the FPAS efficiency among provinces (regions). In terms of individual performance, the results of different DEA models agree that the FPAS efficiency in Hebei, Jilin, Heilongjiang, Anhui, Henan, Guangxi, Hainan, Chongqing, Guizhou, Tibet, Qinghai, Ningxia, and Xinjiang are at or close to the effective state. However, the efficiency in Shanxi, Inner Mongolia, Jiangxi, Hubei, Hunan, Sichuan, Yunnan, Shaanxi and Gansu still has a certain potential for improvement, of which Sichuan and Yunnan have the largest room for improvement. Indeed, Xiao *et al.* [30] also found Sichuan and Yunnan to be the worst performers among 22 provinces or regions. This may be due to the fact that both are in the

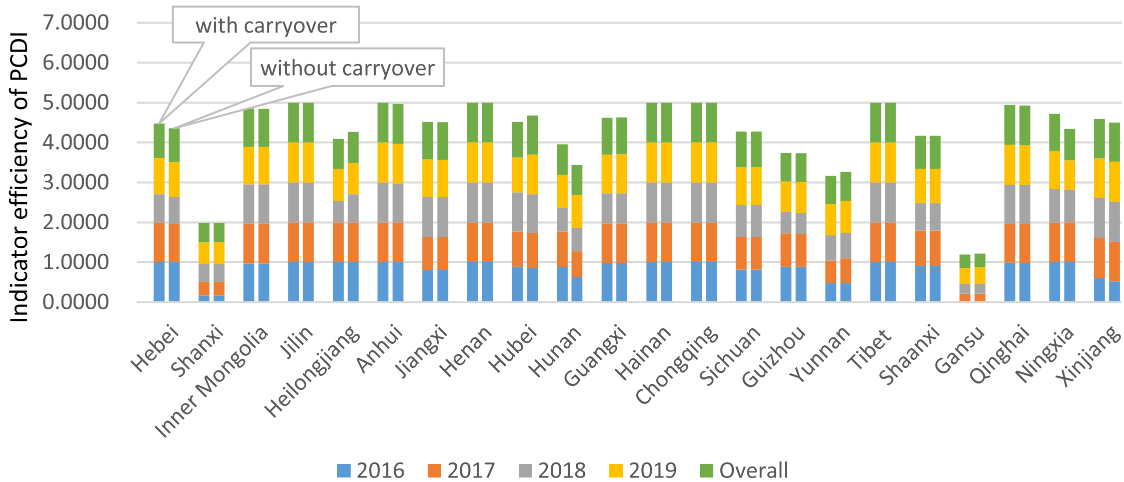

FIGURE 7. Comparative analysis of indicator efficiency of PCDI.

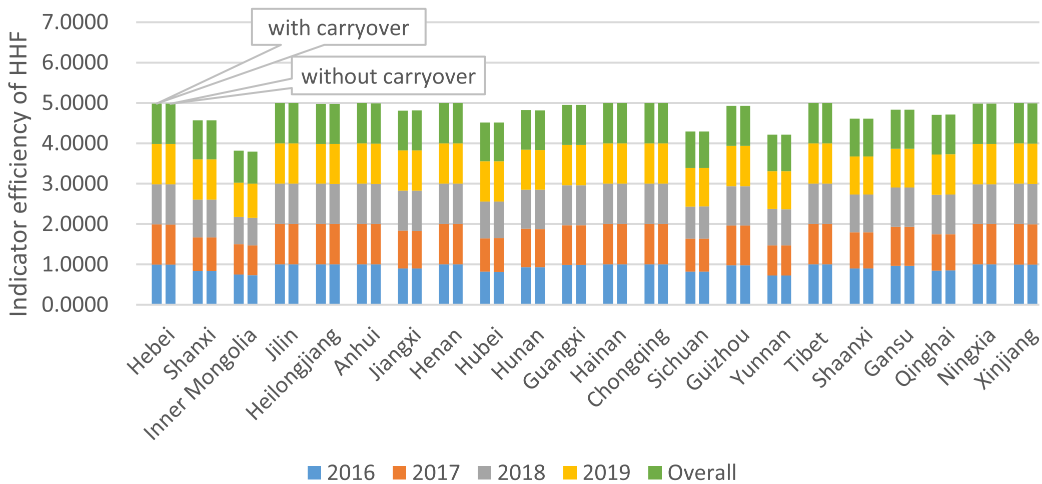

FIGURE 8. Comparative analysis of indicator efficiency of HHF.

western region of China, where the difficulty of poverty alleviation is inherently high owing to the constraints of the natural condition and geographic location, resulting in the efficiency still has a certain gap compared with other provinces (regions). However, the efficiency of fiscal poverty alleviation in Sichuan and Yunnan still shows an upward trend, that is, their fiscal poverty alleviation work is still worthy of recognition.

To further analyze the impact of carryover activities on the FPAS efficiency, this paper uses Kendall's τ correlation coefficient to test the difference in the FPAS efficiency obtained by Models (2) and (4) shown in Figure 4. As we all know, Kendall's τ correlation coefficient is a statistic used to measure the ordinal correlation between two groups of data, which reflects the difference in the ranking of test samples. And the smaller the value, the lower the correlation between them. The corresponding results are shown in Table 4.

As can be observed from Table 4, the carryover activities have some impact on the FPAS efficiency, and they have some different impact on the period efficiency and overall efficiency of FPASs. Specifically, compared with the impact of carryover activities on the overall efficiency, they have a greater impact on the period efficiency,

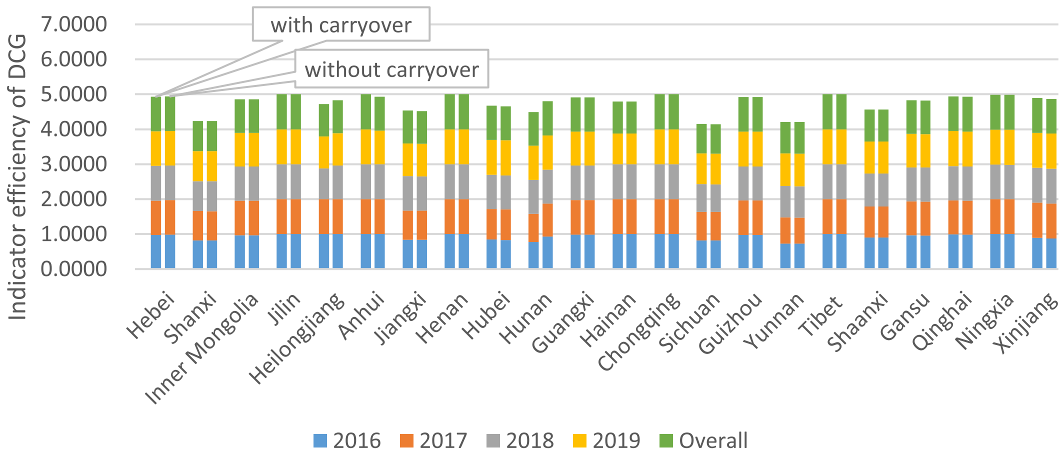

Figure 9. Comparative analysis of indicator efficiency of DCG.

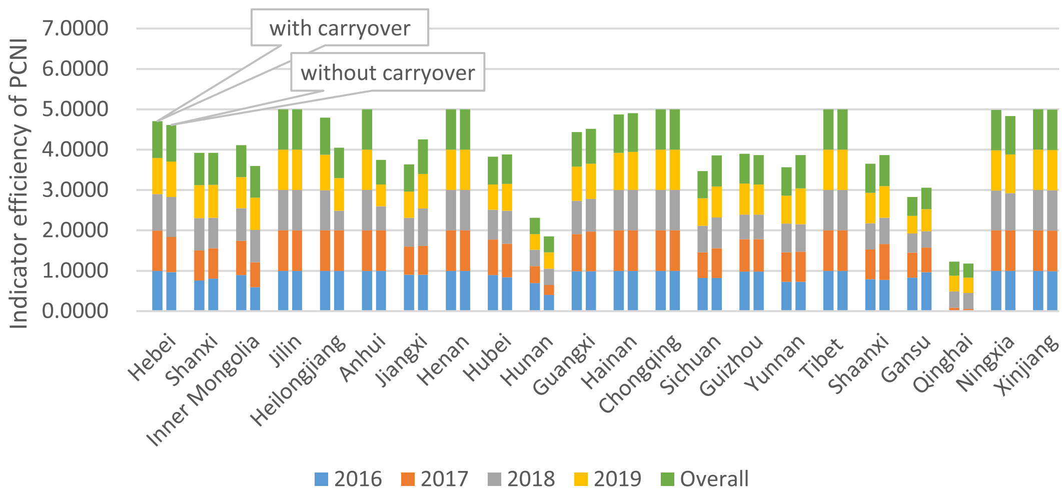

Figure 10. Comparative analysis of indicator efficiency of PCNI.

which is more obvious in 2019. This finding also further argues for the necessity of constructing a dynamic network DEA model on considering the carryover activities for measuring the FPAS efficiency in China.

In addition, in light of the poor performance of Sichuan and Yunnan and the fact that they are both in the western region of China, we believe that there may be some regional heterogeneity in the efficiency of fiscal poverty alleviation in China. To this end, this subsection also analyzes the regional heterogeneity of FPAS efficiency. In view of the existing regional division standards, this paper divides the tested provinces (regions) into the eastern, central and western regions[5]. Based on the division of the above regions, the empirical results shown in Table 5 are obtained.

The following conclusions are drawn from Table 5. From the national level, Models (2) and (4) consistently consider that the period efficiency has shown an increasing trend over the years in China. From the regional

[5]The eastern region includes: Hebei, Hainan; the central region contains: Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan; the western region includes: Sichuan, Chongqing, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, Inner Mongolia.

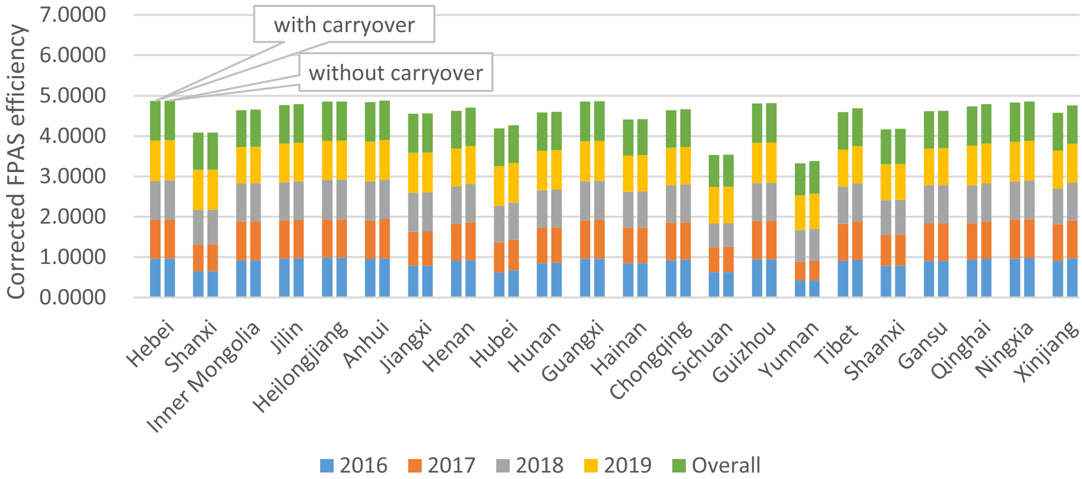

FIGURE 11. Comparative Analysis of the corrected FPAS efficiency.

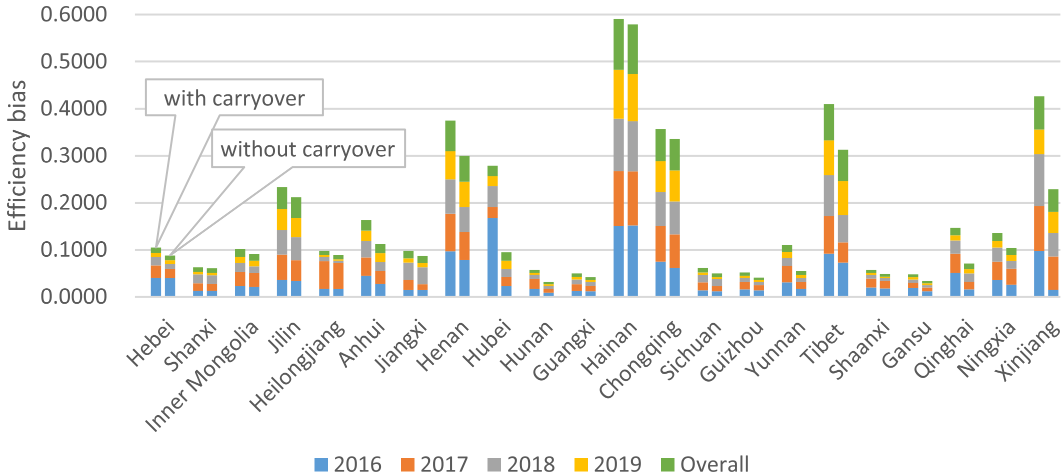

FIGURE 12. The bias between the corrected FPAS efficiency and the original FPAS efficiency.

perspective, the period efficiency obtained by Models (2) and (4) has basically shown an increasing trend over the years. Moreover, the eastern region has the best performance in both period efficiency and overall efficiency, followed by the central region, and the western region has the worst performance. In addition, the heterogeneity of period efficiency between the central and western regions is increasing year by year, while the heterogeneity of period efficiency between the central and eastern regions is decreasing year by year, and the efficiency difference between them is very small by the end of 2019.

The above conclusions show that there is a certain regional heterogeneity in the FPAS efficiency in China. Specifically speaking, the current pressure of fiscal poverty alleviation mainly comes from the western region, and there is a large room for improvement in the FPAS efficiency. Therefore, the Chinese government needs to pay more attention to the development of the western region and may need to formulate appropriate fiscal poverty alleviation strategies based on the characteristics of local industries. In addition, some inefficient provinces can

Table 4. Correlation coefficients of the FPAS efficiency from different DEA models.

FPAS efficiency	2016	2017	2018	2019	Overall
Correlation coefficient (Model 2 *vs.* Model 4)	0.7983	0.7462	0.8528	0.6124	0.9307

Table 5. Regional heterogeneity analysis of the FPAS efficiency.

FPAS efficiency	With carryover activities				Without carryover activities			
	Eastern region	Central region	Western region	Nation	Eastern region	Central region	Western region	Nation
2016	1.0000	0.8906	0.8892	0.8998	1.0000	0.8792	0.8868	0.8943
2017	0.9949	0.9002	0.8963	0.9067	0.9931	0.8991	0.8950	0.9054
2018	0.9933	0.9707	0.9192	0.9447	0.9921	0.9683	0.9187	0.9434
2019	1.0000	0.9938	0.9590	0.9754	1.0000	0.9938	0.9590	0.9754
Overall	0.9980	0.9768	0.9419	0.9597	0.9975	0.9758	0.9416	0.9591

Table 6. Correlation coefficients of indicator efficiency of PA funds from different DEA models.

Indicator efficiency of PA funds	2016	2017	2018	2019	Overall
Correlation coefficient (Model 2 *vs.* Model 4)	0.8961	0.8788	0.9394	0.8874	0.9394

Table 7. Regional heterogeneity analysis of indicator efficiency of PA funds.

Indicator efficiency of PA funds	With carryover activities				Without carryover activities			
	Eastern region	Central region	Western region	Nation	Eastern region	Central region	Western region	Nation
2016	1.0000	0.9078	0.7128	0.8098	1.0000	0.8980	0.7053	0.8022
2017	0.9958	0.9239	0.6944	0.8053	0.9965	0.9069	0.6992	0.8018
2018	0.9745	0.7788	0.5294	0.6605	0.9430	0.7670	0.5342	0.6560
2019	0.9326	0.7933	0.6125	0.7074	0.9507	0.8310	0.6187	0.7261
Overall	0.9502	0.8049	0.6032	0.7081	0.9545	0.8246	0.6085	0.7185

Table 8. Correlation coefficients of indicator efficiency of IPS from different DEA models.

Indicator efficiency of IPS	2016	2017	2018	2019	Overall
Correlation coefficient (Model 2 *vs.* Model 4)	0.9048	0.9221	0.9567	0.8268	0.9654

Table 9. Regional heterogeneity analysis of indicator efficiency of IPS.

Indicator efficiency of IPS	With carryover activities				Without carryover activities			
	Eastern region	Central region	Western region	Nation	Eastern region	Central region	Western region	Nation
2016	1.0000	0.9219	0.9261	0.9313	1.0000	0.9149	0.9257	0.9285
2017	0.9972	0.9265	0.9341	0.9370	0.9965	0.9257	0.9330	0.9361
2018	0.9959	0.9601	0.8881	0.9241	0.9946	0.9615	0.8890	0.9250
2019	1.0000	0.9786	0.9416	0.9604	1.0000	0.9815	0.9417	0.9615
Overall	0.9988	0.9679	0.9278	0.9488	0.9984	0.9698	0.9280	0.9496

Table 10. Correlation coefficient of indicator efficiency of PCDI from different DEA models.

Indicator efficiency of PCDI	2016	2017	2018	2019	Overall
Correlation coefficient (Model 2 *vs.* Model 4)	0.8009	0.6941	0.8615	0.7835	0.8788

Table 11. Regional heterogeneity analysis of indicator efficiency of PCDI.

Indicator efficiency of PCDI	With carryover activities				Without carryover activities			
	Eastern region	Central region	Western region	Nation	Eastern region	Central region	Western region	Nation
2016	1.0000	0.8433	0.8040	0.8361	1.0000	0.8065	0.7965	0.8186
2017	0.9975	0.8688	0.8568	0.8740	0.9803	0.8375	0.8595	0.8625
2018	0.8554	0.8188	0.7846	0.8035	0.8373	0.8356	0.7852	0.8083
2019	0.9527	0.8713	0.8873	0.8874	0.9395	0.8846	0.8709	0.8821
Overall	0.9350	0.8577	0.8576	0.8647	0.9208	0.8664	0.8472	0.8609

Table 12. Correlation coefficient of indicator efficiency of HHF from different DEA models.

Indicator efficiency of HHF	2016	2017	2018	2019	Overall
Correlation coefficient (Model 2 *vs.* Model 4)	0.8701	0.7922	0.8788	0.7115	0.9394

Table 13. Regional heterogeneity analysis of indicator efficiency of HHF.

Indicator efficiency of HHF	With carryover activities				Without carryover activities			
	Eastern region	Central region	Western region	Nation	Eastern region	Central region	Western region	Nation
2016	0.9987	0.9359	0.9143	0.9298	0.9987	0.9348	0.9127	0.9286
2017	0.9975	0.9432	0.9209	0.9360	0.9965	0.9437	0.9196	0.9354
2018	0.9967	0.9755	0.9342	0.9549	0.9961	0.9753	0.9340	0.9547
2019	1.0000	0.9967	0.9704	0.9827	1.0000	0.9967	0.9704	0.9827
Overall	0.9989	0.9851	0.9557	0.9703	0.9987	0.9850	0.9555	0.9702

learn from provinces with similar characteristics within the same region, *e.g.*, Sichuan and Yunnan can learn from the experience of Guizhou.

4.3. Efficiency analysis of inputs and outputs

This subsection discusses the indicator efficiency of each evaluation indicator, analyzes the differences between it and the FPAS efficiency, and further explores the specific paths for improving the indicator efficiency of each DMU. Similarly, the empirical results shown in Figures 5–10 and Tables 6–18 are obtained.

Figure 5 reports the period efficiency and overall efficiency of PA funds (*i.e.*, indicator efficiency of PA funds) obtained from Models (2) and (4). In general, Models (2) and (4) consistently concludes that the indicator efficiency of PA funds varies greatly among provinces (or regions), and the indicator efficiency of PA funds in most provinces (or regions) needs to be further optimized. Specifically, the provinces (regions) with better performance of PA funds include only: Hebei, Inner Mongolia, Jilin, Heilongjiang, Jiangxi, Hainan, Chongqing, Qinghai, and Ningxia; while most provinces (regions) have great room for improvement in the indicator efficiency of PA funds, such as Shanxi, Anhui, Henan, Hubei, Hunan, Guangxi, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, and Xinjiang. This also means that there may be some redundancy or misallocation of PA funds in the provinces (regions) mentioned above, thus making the indicator efficiency not very efficient. Therefore, the Chinese government may need to appropriately adjust the proportion of funds allocated to each province (region), while the local governments may need to take into account their own characteristics and utilize fiscal funds in projects that are more conducive to the development of poor areas.

Similarly, in order to further analyze the impact of carryover activities on the indicator efficiency of PA funds, we also calculate the Kendall's τ correlation coefficient of the indicator efficiency of PA funds from Models (2) and (4). The specific results are shown in Table 6.

As shown in Table 6, the carryover activities have some impact on the indicator efficiency of PA funds, but there are certain differences in their impact on the period efficiency and overall efficiency of PA funds. In addition, comparing the results in Tables 4 and 6, it is found that the effect of carryover activities on the indicator efficiency of PA funds is weaker than their effect on the FPAS efficiency. But in any case, it is still relatively necessary to consider the carryover activities in measuring the indicator efficiency of PA funds.

Similarly, this subsection also analyzes the regional heterogeneity of indicator efficiency of PA funds. The specific results are shown in Table 7.

From the results in Table 7, the following conclusions can be drawn whether the proposed DEA models consider carryover activities or not. From the national level, the indicator efficiency of PA funds has not been high in all years and to a certain extent shows a downward trend, which is exactly the opposite of the conclusion in Table 5. From the regional perspective, there is a large heterogeneity in the indicator efficiency of PA funds in various regions, which the indicator efficiency of PA funds is the best in the eastern region, followed by the central region, and the worst in the western region. This conclusion is consistent with Table 5. While the indicator efficiency of PA funds in each region has shown a downward trend over the years, which is also the opposite of the conclusion in Table 5. The above results indicate that the regional heterogeneity characteristics of the efficiency of PA funds differ from those of the FPAS efficiency, and that the former has more pronounced regional heterogeneity. Besides, the results in Table 7 also show that the carryover activities have some impact on the regional heterogeneity of the indicator efficiency of PA funds, which further argues for the need to consider the carryover activities in measuring the indicator efficiency.

Figure 6 reports the indicator efficiency of IPS obtained from Models (2) and (4), and they agree on the following conclusions. Generally speaking, the indicator efficiency of IPS has been at a high level, but there are also certain differences between individuals. In terms of individual performance, the indicator efficiency of IPS in Hebei, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hainan, Chongqing, Guizhou, Tibet, Ningxia, and Xinjiang is an effective or close to effective state, in other provinces, there is still room for improvement in the indicator efficiency of IPS. However, there is much less room for improvement in the indicator efficiency of IPS shown in Figure 6 compared to that of PA funds shown in Figure 5.

In order to discuss the impact of carryover activities on the indicator efficiency of IPS, we also present the Kendall's τ correlation coefficients between the indicator efficiency of IPS obtained by Models (2) and (4). The specific results are shown in Table 8.

As shown in Table 8, the carryover activities have some impact on the indicator efficiency of IPS, and the impact strength is different in each time period. However, the carryover activities do not have a significant impact on the indicator efficiency of IPS, which is consistent with their impact on the indicator efficiency of PA funds. The main reason for this is that PA funds and IPS are both evaluation indicators for Subsystem 1, but since Subsystem 1 has no carryover activity in the adjacent time period, the effect of carryover activities in Subsystem 2 on Subsystem 1 is not very significant.

In the following, this subsection also analyzes the regional heterogeneity of indicator efficiency of IPS. The specific results are shown in Table 9.

From Table 9, we obtain the following findings. From the national level, both Models (2) and (4) believe that the indicator efficiency of IPS is already in a relatively efficient state, although they do not show a strict monotonic trend, but its basic trend is still on the rise. From the regional perspective, the best indicator efficiency of IPS is in the eastern region, and the indicator efficiency of IPS in the central region is slightly lower than that of the western region in the early time period (*i.e.*, 2016 and 2017), but it is superior to the western region in the subsequent period and the whole-time horizon; there is a certain heterogeneity in the indicator efficiency of IPS in different regions. The indicator efficiency of IPS in the central region shows a monotonous increasing trend over the years. Although the indicator efficiency of IPS in the eastern and western regions does not show monotonicity, but there is still a zigzag upward trend. What is more, comparing the results in Tables 5, 7 and 9, it is not difficult to find that the regional nature of indicator efficiency of IPS is basically consistent with the nature of FPAS efficiency, while the regional characteristics of indicator efficiency of IPS differ significantly from those of indicator efficiency of PA funds.

Figure 7 shows the indicator efficiency of PCDI obtained by Models (2) and (4). From the national level, there are large differences in the indicator efficiency of PCDI. There are not many FPASs with high indicator efficiency of PCDI, and there is a large room for improvement in the PCDI dimension. In terms of individual performance, the indicator efficiency of PCDI in or close the effective state is Inner Mongolia, Jilin, Anhui, Henan, Hainan, Chongqing, Qinghai, Tibet, while other provinces (regions) in PCDI dimension still have certain potential productivity, among which the indicator efficiency of PCDI of the Shanxi, Gansu is most obvious improvement space. In addition, Figures 3–5 show that the potential for improvement in the indicator efficiency of PCDI is somewhat different from the potential for improvement in the FPAS efficiency and the indicator efficiency of IPS.

Similarly, this subsection also discusses the impact of carryover activities on the indicator efficiency of PCDI, and the Kendall's τ correlation coefficient is shown in Table 10.

The results in Table 10 show that the carryover activities have some impact on the indicator efficiency of PCDI, but this impact has certain differences in each time period. Moreover, the effect of carryover activities on the indicator efficiency of PCDI is to be significantly greater than their effect on the indicator efficiency of PA funds (or IPS). Therefore, the role of carryover activities cannot be ignored from the PCDI perspective, which further demonstrates the necessity of considering carryover activities.

Further, this subsection also analyzes the regional heterogeneity of indicator efficiency of PCDI, and the specific analysis results are shown in Table 11.

From Table 11, the following conclusions are obtained. From the national level, both Models (2) and (4) believe that the indicator efficiency of PCDI over the years is not high, but its change trend is unstable and shows an up-and-down trend. From the regional perspective, the highest indicator efficiency of PCDI is in the eastern region, and the indicator efficiency of PCDI in the central region is higher than that of the western region in the first three periods (*i.e.*, 2016, 2017, and 2018), while the efficiency in the last period (*i.e.*, 2019) is slightly worse than that of the western region. In addition, the results in Table 11 also show that there is no significant regional heterogeneity between the central and western regions in the efficiency of PCDI, but their performance is significantly different from that in the eastern region.

TABLE 14. Correlation coefficients of indicator efficiency of DCG from different DEA models.

Indicator efficiency of DCG	2016	2017	2018	2019	Overall
Correlation coefficient (Model 2 *vs.* Model 4)	0.8009	0.7229	0.8355	0.8528	0.8788

TABLE 15. Regional heterogeneity analysis of indicator efficiency of DCG.

Indicator efficiency of DCG	With carryover activities				Without carryover activities			
	Eastern region	Central region	Western region	Nation	Eastern region	Central region	Western region	Nation
2016	0.9899	0.9109	0.9358	0.9317	0.9906	0.9275	0.9332	0.9363
2017	0.9899	0.9171	0.9473	0.9402	0.9965	0.9357	0.9468	0.9473
2018	0.9967	0.9588	0.9588	0.9623	0.9961	0.9675	0.9582	0.9650
2019	0.9326	0.9630	0.9676	0.9628	0.9306	0.9587	0.9671	0.9607
Overall	0.9546	0.9564	0.9627	0.9597	0.9538	0.9578	0.9621	0.9598

Figure 8 shows the indicator efficiency of HHF obtained from Models (2) and (4). We can obtain the following conclusions. On the whole, the indicator efficiency of HHF is acceptable, but there are still some differences between individuals. Specifically, except Inner Mongolia, Sichuan, and Yunnan, the indicator efficiency of HHF in other provinces (regions) has reached a high level in recent years. In addition, comparing the results in Tables 5, 7, and 8, it is found that there is much less room for improvement on the indicator efficiency of HHF compared to that of PA funds and PCDI.

Table 12 shows the Kendall's τ correlations of the indicator efficiency of HHF from Models (2) and (4). The results show that the carryover activities have some impact on the indicator efficiency of HHF, and the impact on the period efficiency is more obvious than that on the overall efficiency. In addition, the impact of carryover activities on the indicator efficiency of HHF is more significant than their impact on the indicator efficiency of PA (or IPS). The above results further demonstrate the necessity of considering carryover activities.

Table 13 reports the regional heterogeneity analysis of indicator efficiency of HHF obtained by Models (2) and (4). From the national level, the indicator efficiency of HHF has been at a relatively high level, and the indicator efficiency of HHF has shown an upward trend over the years. From the regional level, there is a certain heterogeneity in the indicator efficiency of HHF at each region, among which the eastern region, central region and western region are in the order of higher to lower efficiency, and the indicator efficiency of HHF in each region basically shows an increasing trend in the years.

Figure 9 reports a comparative analysis of the indicator efficiency of DCG derived from Models (2) and (4). We derive the following conclusions. On the whole, the indicator efficiency of DCG in most inter-provincial FPASs has been at a high level, but there are still certain differences in the indicator efficiency of DCG in each system. For the individual performance, the indicator efficiency of DCG in Shanxi, Sichuan and Yunnan has a large room for improvement, while the indicator efficiency of DCG in other provinces (regions) is already in an effective state or has relatively little room for improvement.

Table 14 reports the Kendall's τ correlation coefficients of the indicator efficiency of DCG obtained by Models (2) and (4). The above results show that the carryover activities have some impact on the indicator efficiency of DCG, and their impact on the period efficiency in DCG is more obvious than that on the overall efficiency in DCG. Similarly, we find that the carryover activities have a more significant impact on the indicator efficiency of HHF than on the indicator efficiency of PA (or IPS). This also shows the necessity of considering carryover activities in measuring the indicator efficiency of HHF.

Table 16. Correlation coefficient of indicator efficiency of PCNI from different DEA models.

Indicator efficiency of PCNI	2016	2017	2018	2019	Overall
Correlation coefficient (Model 2 *vs.* Model 4)	0.7316	0.6797	0.6364	0.6797	0.6364

Table 17. Regional heterogeneity analysis of indicator efficiency of PCNI.

Indicator efficiency of PCNI	With carryover activities				Without carryover activities			
	Eastern region	Central region	Western region	Nation	Eastern region	Central region	Western region	Nation
2016	1.0000	0.9055	0.8355	0.8759	0.9811	0.8681	0.8189	0.8516
2017	0.9975	0.8430	0.7821	0.8238	0.9356	0.8187	0.7877	0.8124
2018	0.9503	0.8323	0.7599	0.8036	0.9961	0.7491	0.7530	0.7737
2019	0.9102	0.7935	0.7780	0.7957	0.9113	0.7608	0.8129	0.8029
Overall	0.9302	0.8106	0.7759	0.8026	0.9357	0.7665	0.7967	0.7984

Table 15 reports the regional heterogeneity analysis of the indicator efficiency of DCG obtained by Models (2) and (4). The above DEA models both agree the following conclusions. From the national level, the indicator efficiency of DCG is already at a relatively high level, and the indicator efficiency of DCG has shown an upward trend over the years. From the regional perspective, the indicator efficiency of DCG in the eastern region is better than that in the other two regions in the first three periods (*i.e.*, 2016, 2017, and 2018), while the indicator efficiency of DCG in the western region is better than the central region in all periods. In addition, in the most recent period (*i.e.*, 2019), the indicator efficiency of DCG in the western region is the best performer of the three regions.

Figure 10 reports the indicator efficiency of PCNI obtained by Models (2) and (4). It is not difficult to find that there are still large differences between the indicator efficiency of PCNI obtained by different models. However, Models (2) and (4) agree that the better performing FPASs only include Jilin, Henan, Hainan, Chongqing, Tibet, Ningxia, and Xinjiang, while most of the remaining FPASs have more room for improvement in the indicator efficiency of PCNI.

Table 16 reports the Kendall's τ correlation coefficients of the indicator efficiency of PCNI obtained from Models (2) and (4). The results show that the carryover activities have a greater impact on both period and overall efficiency in PCNI. Further, comparing the results in Tables 6, 8, 10, 12, 14 and 16, we find that the carryover activities have a greater impact on the indicator efficiency of PCDI and PCNI than their impact on the indicator efficiency of PA funds, IPS, HHF, and DCG. In addition, the above results also indicate that carryover activities have a greater impact on Subsystem 2 than they do on Subsystem 1.

Table 17 reports the regional heterogeneity analysis of the indicator efficiency of PCNI obtained by Models (2) and (4). We derive the following conclusions. From the national level, the indicator efficiency of PCNI is not too high, there is a large room for improvement, and the indicator efficiency of PCNI shows a decreasing trend. From the regional perspective, the indicator efficiency of PCNI shows obvious regional heterogeneity, where the best performance of indicator efficiency of PCNI is in the eastern region, followed by the central region, and the worst is in the western region. In addition, the indicator efficiency of PCNI in each region has shown a decreasing trend over the years. Comparing the results in Tables 6, 8, 10, 12, 14 and 16, it is found that there is a large regional heterogeneity in the indicator efficiency of PA funds, PCDI, and PCNI, so the Chinese government should focus on how to improve the utilization efficiency of PA funds as well as to improve the level of PCDI and PCNI in the poor areas. Obviously, the above findings also raise specific directions for shrinking

TABLE 18. Correlation coefficients of FPAS efficiency and indicator efficiency.

FPAS efficiency and indicator efficiency	2016	2017	2018	2019	Overall
Panel A: with carryover actives					
FPAS *vs.* PA funds	0.4892	0.4286	0.4719	0.1215	0.2554
FPAS *vs.* IPS	0.8528	0.8095	0.5671	0.3991	0.6104
FPAS *vs.* PCDI	0.7316	0.8182	0.6277	0.2430	0.6364
FPAS *vs.* HHF	0.7489	0.8095	0.7922	0.6855	0.8615
FPAS *vs.* DCG	0.7576	0.8615	0.8009	0.4338	0.6970
FPAS *vs.* PCNI	0.6883	0.6450	0.6190	0.2430	0.6104
Panel B: without carryover actives					
FPAS *vs.* PA funds	0.4425	0.3297	0.3853	0.0088	0.2294
FPAS *vs.* IPS	0.8156	0.7896	0.5152	0.3253	0.5931
FPAS *vs.* PCDI	0.7549	0.7609	0.6017	0.2550	0.6017
FPAS *vs.* HHF	0.8417	0.8243	0.8355	0.6829	0.9048
FPAS *vs.* DCG	0.8764	0.9111	0.7835	0.3341	0.6623
FPAS *vs.* PCNI	0.6855	0.5813	0.4545	0.0879	0.4892

the regional heterogeneity of FPAS efficiency in China, which is not available in the existing literature (*e.g.*, [12,30]).

To further test the consistency between the indicator efficiency and the FPAS efficiency, we also give the Kendall's τ correlation coefficient between the indicator efficiency and the FPAS efficiency, and the results are shown in Table 18.

Panel A in Table 18 presents the correlation coefficient between the FPAS efficiency and the indicator efficiency obtained from Model (2). The results show that the FPAS efficiency and the indicator efficiency are not completely consistent, especially the inconsistency in FPAS efficiency *vs.* indicator efficiency of PA funds, FPAS efficiency *vs.* indicator efficiency of PCDI, and FPAS efficiency *vs.* indicator efficiency of PCNI. Therefore, in order to provide an optimization path for improving FPAS efficiency and indicator efficiency, decision-makers can adjust the existing input-output structure to ensure they are more consistent. Panel B in Table 18 shows the correlation coefficients between the FPAS efficiency and the indicator efficiency obtained from Model (4), and it is found that the conclusions in Panel A and Panel B are in agreement. However, the values in Panel A of Table 18 are lower than those in Panel A of Table 18. This also implies that the carryover activities are able to shrink the inconsistency between indicator efficiency and FPAS efficiency to some extent.

4.4. Robustness analysis of FPASs

The above empirical analyses are all based on historical observation data to measure the poverty alleviation efficiency of each inter-provincial FPAS, which makes it difficult to describe the impact of uncertainty on the poverty alleviation efficiency. That is, the FPASs that perform well now may still be at risk of returning to poverty in the future. In view of this, this subsection analyzes the robustness of the FPAS efficiency by combining the proposed DEA models and Bootstrap sampling methods. In this subsection, the repeated sampling times B is set to 10 000. According to the steps in Section 3.2, the results in Tables 19–21 and Figures 11 and 12 are obtained.

Table 19 presents the descriptive statistics for the Bootstrap overall efficiency. The above results suggest that the uncertainty has an impact on the performance of each FPAS, but the strength of the impact varies. Specifically, from the volatility of Bootstrap efficiency, the impact of uncertainty on Jilin, Henan, Hainan, Chongqing, Tibet, Xinjiang, etc. is relatively large.

Figure 11 shows the corrected FPAS efficiency, which results the following findings. From the national perspective, there is still some variability in the corrected FPAS efficiency, and the carryover activities also have

Table 19. Descriptive statistics of Bootstrap overall efficiency of FPASs.

Province (Region)	With carryover activities				Without carryover activities			
	Mean	Standard deviation	Confidence interval ($\alpha = 0.05$)		Mean	Standard deviation	Confidence interval ($\alpha = 0.05$)	
			l.b.	u.b.			l.b.	u.b.
Hebei	1.0074	0.0049	1.0003	1.0192	1.0056	0.0047	0.9988	1.0168
Shanxi	0.9412	0.0063	0.9339	0.9581	0.9409	0.0062	0.9338	0.9574
Inner Mongolia	0.9479	0.0102	0.9364	0.9765	0.9457	0.0102	0.9354	0.9740
Jilin	1.0470	0.0561	1.0072	1.1648	1.0432	0.0486	1.0067	1.1622
Heilongjiang	0.9904	0.0056	0.9839	1.0028	0.9891	0.0056	0.9829	1.0015
Anhui	1.0229	0.0210	1.0043	1.0870	1.0179	0.0199	1.0019	1.0830
Jiangxi	0.9982	0.0089	0.9859	1.0173	0.9975	0.0088	0.9854	1.0160
Henan	1.0655	0.0534	1.0071	1.1916	1.0551	0.0444	1.0068	1.1663
Hubei	0.9830	0.0155	0.9655	1.0226	0.9740	0.0141	0.9597	1.0133
Hunan	0.9651	0.0022	0.9618	0.9703	0.9633	0.0019	0.9605	0.9680
Guangxi	0.9980	0.0030	0.9937	1.0049	0.9966	0.0026	0.9929	1.0027
Hainan	1.1082	0.1364	1.0068	1.4762	1.1050	0.1308	1.0069	1.4748
Chongqing	1.0683	0.0611	1.0067	1.2236	1.0672	0.0612	1.0067	1.2236
Sichuan	0.8137	0.0047	0.8076	0.8256	0.8122	0.0040	0.8069	0.8225
Guizhou	0.9898	0.0025	0.9860	0.9960	0.9884	0.0023	0.9851	0.9936
Yunnan	0.8265	0.0115	0.8152	0.8576	0.8194	0.0050	0.8138	0.8322
Tibet	1.0778	0.0787	1.0069	1.2848	1.0665	0.0688	1.0064	1.2587
Shaanxi	0.8809	0.0025	0.8770	0.8868	0.8797	0.0023	0.8762	0.8851
Gansu	0.9338	0.0028	0.9302	0.9405	0.9325	0.0024	0.9293	0.9386
Qinghai	1.0024	0.0078	0.9909	1.0216	0.9967	0.0068	0.9881	1.0145
Ningxia	1.0114	0.0086	0.9988	1.0313	1.0083	0.0082	0.9968	1.0285
Xinjiang	1.0704	0.0632	1.0068	1.2237	1.0472	0.0377	1.0052	1.1529

Table 20. Correlation coefficients of the corrected FPAS efficiency.

Corrected FPAS efficiency	2016	2017	2018	2019	Overall
Correlation coefficient (Model 2 *vs.* Model 4)	0.8268	0.9134	0.7835	0.9913	0.9221

some influence on the corrected FPAS efficiency. From the individual perspective, the corrected FPAS efficiency in Shanxi, Sichuan, and Yunnan has the most room for improvement. The conclusion is basically consistent with that in Figure 5.

Table 20 shows the Kendall's τ correlation coefficients of the corrected FPAS efficiency derived from Models (2) and (4) and Bootstrap resample method. The results show that when there is uncertainty in the input-output indicators, the carryover activities still have a certain impact on the corrected FPAS efficiency, which is basically consistent with that in Table 4. However, comparing the results in Tables 4 and 20, we find that the effect of carryover activities on the corrected FPAS efficiency is weaker than their effect on the original FPAS efficiency.

In addition, this paper also provides the gap between the corrected FPAS efficiency and the original FPAS efficiency to discuss the risk of returning to poverty in all inter-provincial FPASs. The specific results are shown in Figure 12. To the best of our knowledge, studying the risk of returning to poverty in the areas that have been lifted out of poverty is an important topic that has not been addressed in the existing literature (*e.g.*, [12, 27, 30]).

TABLE 21. Correlation coefficients of efficiency bias derived from different models.

Efficiency bias	2016	2017	2018	2019	Overall
Correlation coefficient (Model 2 *vs.* Model 4)	0.6104	0.7403	0.8355	0.9481	0.9134

Intuitively, the efficiency bias can be regarded as a measure for describing the risk of returning to poverty of FPASs. The larger the efficiency bias, the greater the risk of returning to poverty. As can be seen from Figure 12, Models (2) and (4) agree that there is still some basis between the original FPAS efficiency and the corrected FPAS efficiency, but the efficiency bias is more pronounced in the presence of carryover activities. Specifically, under the framework of Model (2), the FPASs with a large efficiency bias include Henan, Hubei, Hainan, Chongqing, Tibet, and Xinjiang. Under the framework of Model (4), the FPASs with a large efficiency bias include Henan, Hainan, Chongqing, Tibet, and Xinjiang. It is not difficult to find that Model (4) does not identify Hubei as a FPAS with a greater risk of returning to poverty, while Model (2) believes that Hubei has a greater risk of returning to poverty. Therefore, we argue that Model (2) is more sensitive to the identification of uncertainty and measures the risk of returning to poverty in a timelier manner than Model (4).

The above results show that several provinces may suffer from the risk of returning to poverty. This may be attributed to the following factors. First, the fragile ecological environment and small areas of arable land may be the sources of risk for returning to poverty in these provinces or regions (*e.g.*, Chongqing, Tibet and Xinjiang). Second, the lack of resilience of populations emerging from poverty to risks is a key factor in the generation of the risk of returning to poverty, especially for some highly populous provinces (*e.g.*, Henan). Due to various subjective and objective reasons, the sustainable livelihood capital (such as material capital, financial capital, etc.) of those populations in these provinces is experiencing weak growth or even a decrease, which is bound to affect the local population's ability to defend against the risk of returning to poverty. Third, the brain drain may be more severe in the central and western regions, which in turn may lead to a greater risk of returning to poverty in these provinces or regions (*e.g.*, Henan, Hubei, Chongqing, Tibet, and Xinjiang). Finally, some provinces are overly reliant on the less risk-resistant sectors such as tourism, which also contributes to the fact that they may be at greater risk of returning to poverty (*e.g.*, Hainan).

Similarly, to further quantify the difference between the efficiency bias obtained by Models (2) and (4), the Kendall's τ correlation coefficient is also provided, and the specific results are shown in Table 21.

It can be seen from Table 21 that the carryover activities have an impact on the efficiency bias, but there are certain differences in different time periods. Therefore, from the perspective of efficiency bias, it is also necessary to consider the carryover activities.

5. CONCLUSION

5.1. Summary of the work

Against the backdrop of profound concern over poverty alleviation issues and growing demand for the performance evaluation of fiscal funds for poverty alleviation, this paper assesses the efficiency and robustness of fiscal poverty alleviation for 22 provinces (regions) in China during 2016–2019. To this end, this paper opens the "black box" of the inter-provincial FPAS and treats it as a dynamic two-stage series system consisting of public investment and poverty reduction processes. By specifying the input-output process of FPAS, we construct two dynamic DEA models in the frameworks with and without carryover activities, where the relationship between the two models is proved theoretically. Moreover, our analysis accounts for the robustness of FPAS efficiency for exploring the risk of returning to poverty across FPASs by combing the proposed models with Bootstrap resampling method. Specifically, the paper includes the following findings.

First, the carryover activities have a clear impact on the FPAS efficiency and the indicator efficiency. The period efficiency of each FPAS basically shows an upward trend. Second, there is a significant variation between indicator efficiency, and there is a large divergence between some indicator efficiency (*i.e.*, indicator efficiency of PA funds and indicator efficiency of PCDI) and FPAS efficiency. Moreover, from a regional perspective, the efficiency ranges from high to low in the eastern, central and western regions in general. Finally, the Bootstrap resampling results show that the uncertainty has an impact on the FPAS performance, and this impact is particularly evident in Henan, Hubei, Hainan, Chongqing, Tibet, and Xinjiang. This means that the performance of poverty alleviation in these provinces (regions) is still relatively fragile and the risk of returning to poverty is high. Moreover, the dynamic network DEA model with carryover activities exhibits a stronger discriminatory power with respect to the risk of returning to poverty over the DEA model without carryover activities.

5.2. Policy recommendations

In light of the above findings, we put forward some policy recommendations. First, it has been found that carryover activities, as the important components of the production process of FPAS, cannot be ignored by government departments when evaluating the FPAS performance for each province (region). The dynamic network DEA with carryover activities allows for detecting the links among different periods, thus providing accurate efficiency results of each FPAS. The government is suggested to adjust the input-output structure of FPAS for each province in a targeted manner based on the DEA model with carryover activities.

Second, the indicator efficiency obtained by our models releases there is great room for improvement in some dimensions of FPAS performance in most provinces. Responding to this situation, the government can make good use of special projects and industries to increase rural employment and improve rural income, and thus promote the coordination among the multiple inputs and outputs of FPAS. In addition, it is suggested to strengthen the construction of the internet platform and digital technology, refine both management and supervision mechanisms for special funds in poverty alleviation. The policymakers need to constantly enhance the leading function of special fiscal funds to leverage fiscal and social capital for poverty alleviation programs.

Third, as it has been found that the development of fiscal poverty alleviation in central and western regions lags behind that in the eastern region, it is suggested that decision-makers should emphasize improving the FPAS performance in central and western provinces. It is necessary to fulfill local fiscal support for poverty alleviation, guide the flow of fiscal funds and advanced technologies across regions, and ensure the sustained infusion of fiscal poverty alleviation funds into poverty-stricken provinces in central and western regions.

Finally, several provinces may suffer from the risk of returning to poverty according to our empirical results. It is needed to continuously improve the productivity of the inter-provincial FPAS, prevent and resolve the risk of returning to poverty, and form a long-term mechanism to stabilize the effectiveness of poverty eradication. In addition, the government needs to strengthen the publicity and analysis of the risk of returning to poverty, enhance risk awareness in the areas that have escaped from poverty, and lay out schemes to resolve the risk of returning to poverty in advance.

5.3. Limitations and future research directions

Although this paper has systematically studied the dynamic characteristics, regional heterogeneity, and robustness of the fiscal poverty alleviation efficiency in China, it still has the following shortcomings. First, we do not specifically discuss the exogenous factors that affect the fiscal poverty alleviation efficiency. Second, the current work does not consider the difference in industrial structure across provinces or regions. In fact, when considering the variability in the industrial structure of the provinces, there are differences in the input-output indicators of the different FPASs. Finally, the dynamic evolution of FPAS efficiency is to be characterized by an in-depth quantitative analysis. To address the above issues, we believe that the future research directions can be conducted as follows. First, we can use panel econometric models to investigate the exogenous factors affecting the FPAS efficiency and the indicator efficiency. Second, we can consider the differences in the industrial structure of each province or region and propose non-homogeneous DEA models to reveal the internal structure of FPAS. Finally, we can construct dynamic network DEA-based total factor productivity to further investigate the dynamic evolution characteristics of FPAS efficiency.

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