Research Article

Performance Evaluation of China’s Basic Pension Insurance Based on a Three-Stage Superefficient SBM-DEA Model

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This study looks at the efficiency and effectiveness of the pension insurance system, thus establishing a pension insurance performance evaluation index system. Based on the SBM-DEA model with non-radial and non-angular outputs, the performance evaluation model of basic endowment insurance system was constructed using this index system. By studying the basic pension insurance for employees, this study analyses the basic pension insurance data of 31 provinces in China from 2016 to 2020 and conducts experiments. The results show that the overall performance of the basic endowment insurance system for urban workers in all provinces of China shows a downward trend. The development level of each province is obviously not balanced. The results also show clear regional characteristics and exhibit an east-high-high-low pattern with uncoordinated levels of development with each other. In view of this phenomenon, the Dagum is used to measure the spatial difference in the performance of the basic endowment insurance system. Finally, kernel is used to predict its dynamic evolution trend from the time dimension.

1. Introduction

With the strengthening of the old-age insurance system, the social security function and importance of the old-age insurance are increasing day by day. Because of the increasingly serious population aging, the system is facing the severe challenge of sustainable development, and how to objectively and scientifically evaluate the operation process and effect of the current old-age insurance system has become the further improvement and development of the system. These problems with the pension system need to be solved urgently. So, constructing a systematic and scientific evaluation index system of the endowment insurance system is important, and the operational efficiency of the endowment insurance system is quantitatively evaluated, its operation status is timely grasped, the existing problems are found out, and effective measures are taken to improve the operational capacity of the endowment insurance system and promote the sustainable development of the endowment insurance system. At present, the academic research on the performance of the old-age insurance system is limited to the research on the performance evaluation of social security, and there are few research results only on the evaluation of the performance of the old-age insurance system. In 2012, Shang Jinyun and Lee J [1] constructed a new-type rural social endowment insurance operation quality evaluation index system in five aspects and used the analytic hierarchy process to screen the indicators and determine the indicator weights. In 2012, Know [2] started from the international pension system evaluation system, analyzed China’s pension system from four aspects, and gave specific suggestions. In 2013, Zhang [3, 4] qualitatively analyzed the efficiency of China’s social system from macro-, meso-, and micro-levels and put forward ideas to improve the efficiency of the system. Li and Zhang [5], Zhong [6], and others used AHP to evaluate the effectiveness of China’s system and the performance of town basic pension expenditures, respectively. In 2017, Wang [7] established a “3E” index system for the performance expenditures and conducted a study on the expenditure performance of China’s basic pension by designing evaluation criteria for various scoring indicators.
The abovementioned research results mainly focus on the qualitative analysis level, and the constructed index system mainly focuses on comprehensive evaluation. The characteristics of performance are not obvious, the methods adopted are highly subjective, and the evaluation methods are relatively weak. The SBM-DEA model was created by Fried [8] in 2002. Its main idea is as follows: in the first stage, the input-output indicators are substituted into the traditional DEA model (BBC model or CCR model), and the slack variables of each decision-making unit are calculated [9–11]. Therefore, the SBM-DEA model of undesired outputs and the stochastic frontier analysis (SFA) method are used in the paper to construct a SBM-DEA model with non-radial, non-angular, and undesired outputs. This study establishes the performance evaluation index system from three aspects, economy, efficiency, and effectiveness of the system, and uses the index system combined with the generalized SBM-DEA method of panel data to construct the performance evaluation system of the system. The model, excluding external objective environmental variables, conducts an empirical analysis on the performance of workers in 31 provinces in China from 2016 to 2020.

2. Construction of Performance Evaluation Index System of BPI System

From the perspectives of economy, efficiency, and effectiveness of BPI system [12–14], this study selects indicators such as AGD P ratio of pension insurance fund expenditure, pension insurance fund balance rate, and pension insurance coverage rate. The ratio of GDP of expenditure (Exx./GD DP) [15]: this indicator reflects the strength of pension insurance participation in national income distribution.

Balance ratio (BR) of pension insurance fund [16]: this indicator reflects the sustainable development of the system, i.e., the accumulated balance of insurance fund-total expenditure of pension insurance fund.

\[
\min p = 1 - \frac{1}{m} \sum_{i=1}^{m} \frac{S_f^{-}}{x_{i0}} + 1 \frac{1}{S_1 + S_2} \left( \sum_{i=1}^{m} \frac{S_f^o}{y_{i0}} + \sum_{i=1}^{m} \frac{S_f^b}{y_{i0}} \right) x_0 = XL + S^- y_0^d = Y\lambda - S^d, y_0^b = Y\lambda + S^b, S^- \geq 0, S^d \geq 0, S^b \geq 0, \lambda \geq 0.
\]

In equation (2), \(0 \leq p \leq 1\) denotes the efficiency value of enterprise green technology innovation, which is a strictly monotonic decreasing function of slack variables about input elements, desired output, and non-desired output; \(S^-\) and \(S^d\) denote excess of input and non-desired output, respectively, and \(S^b\) denotes the deficiency of desired output. To avoid the problem of linear programming without feasible solutions, this study uses global covariance efficiency indicators for efficiency evaluation with reference to Li Zhanfeng et al. [22]. However, even if the slack is considered, the environmental factors still have an impact on the efficiency, and then, the second stage of measurement is needed to obtain more accurate results.

Coverage rate (CR) of pension insurance [17]: this indicator reflects the coverage and development level of the system, i.e., the number of insured persons/number of urban employed persons.

Pension replacement rate (RR) [18]: this indicator reflects the level of pension insurance payment, i.e., per capita pension/average wage of employees in employment.

Pension support rate (DR) [19]: this indicator measures the extent of the support burden and reflects the ability to pay, i.e., the number of retirees/insured employees.

3. Construction of Performance Evaluation Model of Basic Endowment Insurance System

As a way to analyze the relative of similar organizations, the DEA method is mainly used for the efficiency evaluation among decision-making units in a long period of time [20]. In this study, the SBM-DEA method is applied to the method with multiple inputs and multiple factors. The specific calculation steps of the three-stage SBM-DEA model are as follows [21].

Stage 1: the SBM model of undesired output proposed by Tone is used to measure the efficiency of system in each province in the first stage. Each province is a production (DMU). A DMU has \(m\) inputs \(X = (x_1, x_2, \ldots, x_m) \in R^m_\leq \) and \(S\) outputs, in which \(S_1\) has an expected output \(Y = (y_1, y_2, \ldots, y_S) \in R^S_\leq\) and \(S_2\) has an undesired output \(Z = (z_1, z_2, \ldots, z_\bar{S}) \in R^\bar{S}_\leq\). We assume that the nondesired output \(Z\) is weakly disposable, and the desired output \(Y\) with input \(X\) is strongly disposable; then, the desired output \(Y\) and the nondesired output \(Z\) are the convex and closed sets. The possible set \(P\) is as follows:

\[
P = \{(x, y, z) \mid x \geq X\lambda, y \leq Y\lambda, z = Z\lambda, \lambda \geq 0\}.
\]

Equation (1) represents the weight vector of cross-sectional observations. The specific SBM model for a specific production decision unit DMU is constructed as follows:

Stage 2: the above calculation results consider the role of input-output slack variables, but they are also influenced by the combination of internal factors. Traditional DEA models do not distinguish between the effects of internal and external environments and random errors on efficiency values but are uniformly classified as internal effects, which is undoubtedly not an accurate analysis of the results. As the data for each DUM input and output slack are truncated at zero, this paper uses the stochastic frontier SFA model to fit the input slack and environmental variables in the first stage [23].

The amount of slack \(S_{ij}\) in the \(j\)th decision unit on the \(i\)th input is assumed to be influenced by the \(K\) observable environmental variables \(Z_{ij} = [z_{1ij}, z_{2ij}, \ldots, z_{Kij}], j = 1, 2,\)
calculation method is as follows: \( S_{ij} = f \left( Z_{ij}; \beta_i \right) + \nu_{ij} + \mu_{ij}, \) where \( \beta_i \) is the vector of parameters to be estimated when the corresponding dependent variable is the \( ith \) input slack, \( \nu_{ij} \) is the mixed error term, and the statistical noise is \( \nu_{ij} \sim N(0, \sigma_{ij}^2), \) \( \mu_{ij} \) is the effect of factors that the firm itself can control on the input slack variables, and a larger \( \mu_{ij} \) means the greater the level of inefficiency of the firm, assuming that \( \mu_{ij} \sim N(\mu_i, \sigma_{ij}^2), \nu_{ij}, \) and \( \mu_{ij} \) are independent of each other. After estimating the unknown parameters with great likelihood, the initial input data are adjusted according to the following equation:

\[
x_{ij}^{\Delta} = x_{ij} + \left[ \max \{ z_j \beta_i \} - z_j \hat{\beta}_i \right] + \left[ \max \{ \nu_{ij} \} - \bar{\nu}_{ij} \right],
\]

where \( x_{ij}^{\Delta} \) is input variable and \( x_{ij} \) is the original input variable. After the above processing, all DMU will be at the same environmental level, which helps to truly reflect the DMU and facilitate the subsequent comparison of the differences among the decision-making units themselves after removing external pressure.

Stage 3: using the adjusted data instead of the original data, the efficiency is estimated using the non-expected output SBM model from stage 1. Here, the effects of environmental factors and random errors on the results are removed, and the new efficiency values reflect more accurately than the actual innovation efficiency level of the decision unit.

3.1. Indicator Selection and Processing. Referring to the practice of Yang Shuwang et al., this study selects input indicators from three aspects of labor force, innovative practice of Yang Shuwang et al., this study selects input slack, \( \nu_{ij} + \mu_{ij} \) is the mixed error term, and the statistical noise is \( \nu_{ij} \sim N(0, \sigma_{ij}^2), \) \( \mu_{ij} \) is the effect of factors that the firm itself can control on the input slack variables, and a larger \( \mu_{ij} \) means the greater the level of inefficiency of the firm, assuming that \( \mu_{ij} \sim N(\mu_i, \sigma_{ij}^2), \nu_{ij}, \) and \( \mu_{ij} \) are independent of each other. After estimating the unknown parameters with great likelihood, the initial input data are adjusted according to the following equation:

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4. Empirical Analysis of the Performance of the Basic Pension Insurance System for Urban Employees

Considering that urban basic pension insurance is the most important component of the current social pension insurance system in China, this study selects the performance of the basic pension insurance system for urban workers in 31 provinces in China from 2016 to 2020 for empirical analysis.

4.1. Data Sources. According to the system, raw data are obtained from the China Statistical Yearbook and the China Labor Yearbook in 2016 and 2020, respectively, and the index values are calculated for each region in each year to construct the corresponding panel data set. The performance evaluation model of the system is used to reflect the differences and trends of basic pension insurance in each region.

4.2. Performance Evaluation of the Basic Pension Insurance System for Urban Workers. The performance evaluation model of the system is applied to measure the performance of the system in each province from 2016 to 2020, and the performance evaluation values of the system for workers in each province are shown in Tables 1–4.

A comparison of the performance value evaluations for the national average, the eastern, the central, and the western regions is shown in Figure 1.

4.3. Analysis of the Performance Level of the Basic System for Urban Workers in Each Province. From the performance evaluation values in Figure 2, we can see that only the performance values of Guangdong in 2016–2020, Fujian in 2016, and Xizang in 2019 are greater than or equal to 1, and the performance levels of the above regions are effective in the corresponding years relative to the performance levels of urban workers’ basic pension insurance in 2016. Except for the specified regions in the above years, the performance values of the remaining regions in other years are less than 1. The performance levels are ineffective in the long term. The remaining regions all have performance levels less than 1, with Fujian, Henan, Yunnan, and Tibet having near long-term valid performance, and the remaining regions will have lower validity. The results indicate that the overall performance of these provinces is poor and also suggest that the indicators still need further improvement.

4.4. Analysis of Changes and Fluctuations in the Performance of the Basic System for Urban Workers in Various Provinces. The longitudinal analysis of provinces shows that only Beijing and Guangdong show an increase in performance, while the rest of the regions basically show a year-on-year decrease. According to the average performance of each province from 2016 to 2020 in Table 1, the average performance of Guangdong, Tibet, Fujian, and other three regions is relatively high, followed by Shandong, Henan, and Yunnan, and the average performance of the rest of the regions is relatively low at 0.2–0.56.

From the horizontal comparison among provinces, it can be seen from Figure 3 that the difference between the performance values of the highest and lowest regions of the system in China in each year from 2016 to 2020 is between 0.76 and 0.97, reflecting the uneven development of the system for workers in each province in China. The gap between the relative advantages and disadvantages is more obvious.

It can be seen that the regional characteristics of the performance of the worker system in China are clear: the eastern region shows a higher level than the western region. The average performance in the western region is higher than that in the central region, showing an overall pattern of high and low levels in the east. The average performance level of Yong, central, and western regions all shows a clear downward trend from 2016 to 2020, in which the average performance of boiling region is higher than the average performance level. The average performance of the system in central China has a large gap compared with that in eastern China. This also reflects that the way of economic development in the central region does not necessarily govern the level of performance of the system.

Figure 4 shows that the performance in China shows an unbalanced spatial distribution pattern. However, the above analysis does not provide enough valuable information on the spatial and temporal variation of the performance of the system for workers and its dynamic evolution. Therefore, we use the Dagum to measure the spatial variation of the performance system for urban workers and then use the kernel density estimation method to predict its dynamic evolution from the time dimension.

Compared with the traditional Gini coefficient, the Dagum and its subgroup method not only add the consideration of the subsample distribution state but also effectively solve the problem of crossover phenomenon between samples and the source of regional disparity, making the analysis conclusion more accurate [15]. The Dagum Gini coefficient is defined by the following equation:

$$G = \frac{\sum_{j=1}^{k} \sum_{h=1}^{k} \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} (y_{ji} - y_{hr})}{2n^2 \bar{y}},$$

where $G$ is the Gini coefficient; the larger the coefficient, the larger the gap. $k$ is the total number of regions, $j$ and $h$ are two different regions within $k$ regions, $i$ and $r$ are provinces.
Figure 1: Comparison of performance value evaluation in different regions. (a) National average. (b) Eastern region. (c) Central region. (d) Western region.

Figure 2: Comparison of performance evaluation values of employee pension insurance in multiple provinces.
Figure 3: Comparison of performance differences in pension insurance systems among different provinces.

Figure 4: Comparison of the three major economic regions with the national average performance level in 2016–2020.
within different regions, respectively. \( n_j(n_h) \) indicates the number of provinces within \( j(h) \) regions, \( y_{ji}(y_{hr}) \) indicates the efficiency of the system for urban workers in \( i(r) \) provinces in \( j(h) \) regions, \( \overline{y} \) indicates the arithmetic efficiency of the system for workers in each province mean value. The spatial differences in the efficiency of the system for urban workers in 2016–2020 were measured and decomposed using the coefficient and method proposed by Dagum, and the calculation results are shown in Table 5.

As can be seen from Table 5, the contribution rates of the east, west, central, and national average are shown in Figure 5.

As can be seen from Figure 5: in terms of the magnitude of contribution, the contribution of interregional variation is the largest, and the contribution of super-variable density is the lowest. Among them, the contribution rate is the largest at 69.29%, the lowest at 35.45%, and the majority of years are above 50%, which indicates that interregional differences are the main source of spatial differences in the efficiency of urban workers’ basic pension insurance system.

In the following, to describe the development pattern of institutional efficiency in the time dimension, the kernel density curve of its distribution pattern is estimated here using the kernel function, and the results show the dynamic evolution characteristics of institutional efficiency. The period 2016–2020 is selected as the sample observation time point, and Figures 6(a) and 6(b) represent the three-dimensional plots of kernel density for the whole country and the eastern, central, and western regions, respectively.

### Table 5: Dagum Gini coefficient and its decomposition results.

<table>
<thead>
<tr>
<th>Years</th>
<th>Interregional Gini coefficient ( G_{nb} )</th>
<th>Regional Gini coefficient ( G_{\omega} )</th>
<th>Contribution rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>East</td>
<td>Central</td>
<td>West</td>
</tr>
<tr>
<td>2016</td>
<td>0.299</td>
<td>0.327</td>
<td>0.179</td>
</tr>
<tr>
<td>2017</td>
<td>0.350</td>
<td>0.361</td>
<td>0.213</td>
</tr>
<tr>
<td>2018</td>
<td>0.338</td>
<td>0.308</td>
<td>0.261</td>
</tr>
<tr>
<td>2019</td>
<td>0.236</td>
<td>0.237</td>
<td>0.234</td>
</tr>
<tr>
<td>2020</td>
<td>0.208</td>
<td>0.229</td>
<td>0.202</td>
</tr>
</tbody>
</table>

![Figure 5: Comparison of Dagum’s Gini coefficient and its decomposition results in pie charts. (a) East. (b) West. (c) Central. (d) Average.](image-url)
The spatiotemporal divergence in the efficiency of the system for workers is very obvious as shown in Figure 6. Among them, the differences between east-central and east-west show a significant trend of narrowing in general, and the differences between central and western regions also show a small trend of narrowing. In the time dimension, the polarization of efficiency tends to slow down although it is obvious. The future development efficiency projections for the east, west, and central regions are shown in Figure 7.
5. Conclusion

This study constructs a performance evaluation model of the basic pension insurance system based on a three-stage SBM-DEA method with panel data and empirically analyses the performance of the system for workers in China. Based on the performance of the basic pension insurance system in China from 2016 to 2020, the following conclusions are obtained.

(1) The overall performance of the basic pension insurance system for urban workers in China is decreasing, and the performance is on the low side, and there is still room for further improvement of the indicators.

(2) The development of the system for workers has a large gap between the relative merits and demerits of each province, and there is an obvious unevenness.

(3) The performance of system for workers has obvious K-domain characteristics; it basically shows a pattern of high, middle, and low in the east.

(4) The performance level of each province in China is not coordinated with its economic development, and the level of economic development of the local K region does not necessarily restrict the performance development level of the basic pension insurance system.

The problems are found in the performance evaluation process, and this study puts forward the following relevant policy recommendations.

(1) Relevant departments should formulate and implement the policy of gradual delayed retirement as soon as possible to cope with the negative impact of population aging on the basic pension insurance fund, reduce the burden of basic pension insurance support, and improve the basic pension insurance performance level.

(2) We will strengthen the operation and management of the old-age insurance system, increase the collection of old-age insurance funds, expand the coverage of the old-age insurance system, adjust the replacement rate of old-age insurance, improve the security of the old-age insurance system, and further improve the basic old-age insurance system.

(3) The economy of region K should be integrated in order to promote the coordinated development of region K, bearing in mind that the pursuit of individual indicators and effects should not be pursued in isolation and that the degree of variation in absolute terms among the indicators should be rationalised.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest or personal relationships that could have appeared to influence the work reported in this study.

References


