

RESEARCH ARTICLE

Resilience of Operational Performance in China's Insurance Companies: A Dynamic Data Envelopment Analysis

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ABSTRACT In the rapidly changing business world, insurance companies should observe long-term operational performance and focus on its resilience. Existing studies rarely investigate the resilience issue of performance under the context of the insurance sector. Hence, this study develops a dynamic data envelopment analysis (DEA) model to measure the operational performance of insurance companies by considering multiple periods. Different from the existing works adopting traditional static DEA, our work develops a dynamic DEA model to estimate performance by incorporating multiple periods via a common objective function. Besides, the measurement for estimating the resilience of performance is further developed. The proposed approach in this study is applied to 25 Chinese insurance companies for three years from 2017 to 2019. The results reveal that most insurance companies' performances still have improvement potential. And there exists a distinct difference in performance between property and casualty insurance companies and life insurance companies during the observed period. Additionally, the resilience of the performance of most inefficient insurance companies is at a weak level. Finally, some management implications are provided for improving operational performance.

INDEX TERMS Operational performance, resilience, insurance companies, data envelopment analysis.

I. INTRODUCTION

The insurance industry is a significant part of each country's economy. The premium income, huge investment, and a great deal of employment of insurance companies are vital to the development of other industries and even the entire country [1]. Since the implementation of reform and opening up policy in China, the Chinese insurance industry has developed rapidly. Over the past decade, China's insurance market experienced particularly strong growth, with industry premium income increasing from 1722.2 billion Yuan in 2013 to 4695.7 billion Yuan in 2022 [2]. Although the

market size of the insurance industry continues to expand, the competition among insurance companies is also becoming fiercer due to today's global competitive environment [3], [4], [5]. Commercial insurance companies are crucial players in the insurance market. Competitive pressures are forcing them to lower operation costs while keeping or improving service quality. Namely, insurance companies must operate effectively in such an environment to survive [3], [6], [7], [8]. Measuring and comparing the performance of an insurance company with that of others, and constantly achieving substantial growth are the appropriate ways to achieve the goal of efficient operation [9]. However, low productivity and inefficiency could hinder the further development of the Chinese insurance industry [7]. Therefore, there is a need to

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evaluate the operational performance of Chinese insurance firms.

It is imperative to choose an appropriate approach to facilitate managers to identify which companies operate best and take them as benchmarks to respond and thrive in a changing environment. In existing studies related to the insurance industry, researchers constantly use two primary approaches to evaluate performance [10]. One is data envelopment analysis (DEA), a nonparametric method. The other is an econometric or parametric method (i.e., stochastic frontier analysis (SFA)). Differing from the SFA, by using a single score without pre-determined formulas, DEA can perform a holistic evaluation of a product system's performance [10], [11]. Prior studies have employed the DEA approach to perform analysis on the benchmarking of efficiency in the insurance sector [12], [13], [14].

Although the performance evaluation in the context of insurance has been discussed in existing studies, the operational performance of China's insurance companies from a resilience perspective is yet to be explored. In the rapidly changing business world, insurance companies should observe long-term operational performance and focus on the changes. Effective resource allocation can provide insurance companies with competitive advantages and sustainable business development. Hence, the important role of time dimension cannot be ignored in the resilience analysis of operational performance. The service process of insurance companies primarily encompasses premium collection from customers, investment of premiums in commercial ventures, customer loss compensation, and profit generation, constituting a lengthy operational trajectory spanning several years [15], [16]. Evaluating performance within a singular year or period, devoid of temporal considerations, could yield biased results, particularly under unique circumstances. An illustrative instance is the impact of the COVID-19 pandemic on insurance companies' premium income. In this case, evaluating the performance of insurance companies in one year is likely to obtain a lower performance result. Hence, the measurement without time dimension may impact the fairness and objectivity of performance. In this sense, the conventional DEA model cannot be used to assess changes in long-term efficiency without taking the effect of consecutive terms into account. To address this issue, the dynamic DEA model can be employed to obtain a more precise efficiency estimation across different periods [17]. There are few studies on dynamic performance evaluation in the Chinese insurance industry. Two relevant studies are Lu et al. [3] and Kweh et al. [18]. The performance of Chinese life insurance firms and non-life insurance firms was measured in these two studies using the dynamic slack-based measure (SBM) model, but the resilience of performance was not further examined. Simply put, resilience is defined as the inherent ability of a system to absorb the impact of disruption on its performance and the recovery of its performance [19]. In the dynamic observation, the change in operational performance can reflect the state of resilience better. To close

the research gap, this paper aims to develop a dynamic DEA model to investigate the operational performances of Chinese insurance companies and propose a measure to investigate resilience.

In addition, the contributions of this study are twofold. First, by developing a dynamic DEA model to evaluate operational performance and measurement to assess the resilience of performance, this work may extend the theoretical understanding of performance evaluation in the insurance sector. Second, using the proposed model, this study estimates the operational performance of Chinese insurance companies. The empirical study may offer some implications for performance improvements in insurance companies and sustainable industrial development policies.

The remaining part of the research is structured as follows. The literature review is included in Section II. Section III describes the method for measuring operational performance and its resilience. Section IV employs the proposed method in 25 Chinese insurance companies and presents the analysis of the results. Section V illustrates the conclusion of this work with a potential research agenda.

II. LITERATURE REVIEW

This section is separated into two parts: The first one introduces the DEA method. The second one reviews the literature on performance studies in the insurance field.

A. DEA METHOD

DEA was created by Charnes, Cooper, and Rhodes to assess the performance of decision-making units (DMUs). In particular, the DMUs are with multiple inputs and outputs. Based on its advantages (i.e., the nature of a non-parameter and without a pre-determined production function), it can be applied to measure the production or service systems' performance in many different industries [20], [21]. In the context of management decisions, time dimension is one of the most critical influential factors. Yet, it cannot be addressed by traditional DEA models [17]. In addition, the traditional DEA model fails to consider the connecting activities between two successive terms [17]. To address this issue, the dynamic DEA has been proposed. For instance, Färe et al. [22] proposed a DEA method to measure the Malmquist productivity index and decomposed it into technological change and technical efficiency change. Furthermore, by considering time as one of the influential factors of performance, the window DEA was developed [23]. To measure the performance across different periods, DMUs in multiple periods are regarded as different DMUs in the window DEA. By doing so, the performance of a DMU can be compared with itself and other DMUs across different periods. Following the prior works, based on the network theory, a dynamic model connecting periods via intermediate outputs was developed by Färe and Grosskopf [24]. Likewise, by incorporating network DEA and dynamic SBM, Tone and Tsutsui [25] designed a dynamic network SBM model. Taken as a whole, the studies mentioned above made significant contributions to the

literature regarding dynamic DEA and extended the understanding of performance evaluation in practice.

B. PERFORMANCE EVALUATION IN THE INSURANCE SECTOR

Performance estimation works in the insurance sector are growing rapidly. In the existing works, DEA and SFA have been adopted to compute the performance in the insurance industry [10]. Eling and Luhn [12] measured 6,462 insurance companies' performances in 36 countries by using DEA and SFA and found only minor variations when comparing the results of these two approaches. As mentioned earlier, based on the advantages of DEA (i.e., non-parametric and without pre-determined formulas), DEA has been widely employed in performance assessment in the context of the insurance sector [13].

Studies on performance evaluation applying the DEA method in the insurance industry started in the early 1990s. For instance, Donni and Fecher [26] estimated the technical efficiency of the insurance industry across several Organization for Economic Co-operation and Development (OECD) nations during the period 1983 to 1991 and discovered that the efficiency growth is largely attributable to technical improvement. Cummins et al. [27] calculated the cost and revenue efficiency of US life insurance companies between 1988 and 1995 and revealed that acquired companies have greater scores than those that were not involved in mergers. Recent studies also use DEA models to measure performance. For instance, Zhao et al. [14] used the DEA method to investigate the profit ratio efficiency of 53 property insurance companies in China from 2013 to 2017, and the empirical results showed the importance of reasonable arrangement of cost and income for insurance operations. Anandarao et al. [28] utilized the two-stage DEA method to estimate the performance of 17 Indian life insurance companies and revealed that companies that dominate in the investment stage maintain greater overall efficiencies than those that dominate in the premium stage during the study period. Utilizing a three-stage DEA model, Li et al. [29] conducted an analysis to evaluate the operational efficiency of basic pension insurance in various provinces of China between 2014 and 2019. Their findings indicated a relatively high level of operational efficiency, with notable variations observed across different regions. Siddiqui [30] employed the SBM model to analyze the efficiency and productivity performance of 27 Indian health insurance companies from 2015 to 2019 and found that the average efficiency has fluctuated significantly and nearly 30% of health insurance companies have achieved effective operations during the observed period.

The studies mentioned above on the insurance industry mostly use traditional static DEA models. However, due to the limitation of the static DEA model, it failed to assess long-term performance dynamics as the impact of time dimension is not included. In response to this, some scholars apply dynamic DEA models to assess the per-

formance of focal organizations. For example, Sinha [31] applied a dynamic SBM model to calculate the performance of 15 Indian firms in the life insurance sector, finding that there exist distinct fluctuations in average performance over the observed period. Nourani et al. [8] applied dynamic network SBM to compute the performance of Malaysian insurance companies considering ownership types over the period 2007-2014. The results show that compared with foreign insurance companies, local insurance companies are less efficient in the investment capacity function. Tone et al. [15] developed a dynamic two-stage network DEA model to estimate the performance of 30 Malaysian insurance companies from 2008 to 2016, and discovered that the discriminatory force of overall performance is high when investment asset is considered as a carry-over variable. Gharakhani et al. [32] proposed a dynamic network DEA to evaluate the efficiency of 30 non-life insurance companies in Iran during 2013-2015. The results indicated that the model can identify the dynamic changes in time period efficiency and stage efficiency.

Some researchers have also investigated the dynamic estimation of the insurance industry in China in recent years. For example, Lu et al. [3] assessed 34 Chinese life insurance enterprises' performance from 2006 to 2010 by using a dynamic SBM model. The results revealed that average performance is relatively stable and intellectual capital positively and significantly affects enterprise operational performance. Similarly, Kweh et al. [18] also applied dynamic SBM to assess the operations of 32 non-life insurance enterprises in five years in the Chinese context. This research discovered that insurance companies' operational performance fell almost monotonously during the study period. Nourani et al. [33] utilized dynamic SBM and dynamic network SBM to appraise the performance of 32 Chinese insurance companies between 2014 and 2018, providing valuable methodological insights into the assessment of profitability and investment performance.

In the above-mentioned studies, dynamic DEA is used to explore the consistent performance of insurance companies over time. However, these studies have not delved into the concept of performance resilience. Thus, there is a need to develop a measurement to assess resilience in long-run performance. An appropriate approach should focus on the resilience of performance to obtain more perceived insights. In addition, most studies evaluate the operational performance of (non) life insurance companies separately. While the comprehensive measurement of operational performance for Chinese life and non-life insurance firms is scarce. Measuring the operational performance of these two types of insurance companies together may make theoretical and managerial contributions to the insurance industry's long-term sustainable development.

III. METHODOLOGY

In the following section, the evaluation model of operational performance is introduced. Firstly, the selected variables of the operation process in insurance companies are described.

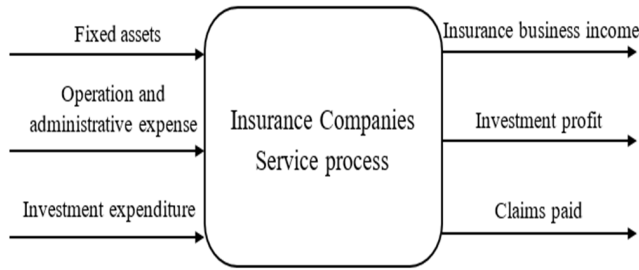


FIGURE 1. Service process of insurance companies.

Secondly, the model proposed for performance assessment is developed based on dynamic DEA. Finally, the measurements for assessing the resilience and the improvement potential are illustrated respectively.

A. INPUTS AND OUTPUTS VARIABLES

A set of well-selected measurements on the input and output sides should be used to adopt the DEA method to assess operational performance. Broadly speaking, the inputs include the resources utilized during the services, while the service outcomes should be considered as outputs [34]. Practically, insurance companies' service process mainly includes receiving premiums from clients, investing the premiums in other commercial activities, paying for clients' losses, and earning profits.

Based on prior literature, this paper selects three inputs and three outputs to compute the operational performance of insurance firms. Specifically, fixed assets [30], [35], operation and administrative expense [4], [16], [30], [36], and investment expenditure [16], [37], [38], [39] are considered as inputs. Fixed assets represents tangible assets with a long life cycle that a company uses for production and operation. Operation and administrative expense refers to the various expense incurred in operation activities, including business service expenses and employee benefit expenses. Investment expenditure denotes the expenditure of an insurance company in all investment activities. While insurance business income [9], [30], [40], [41] and investment profit [3], [4], [41], [42], [43] are treated as two desirable outputs, and claims paid [9], [30], [37], [42], [44] is taken as an undesirable output. Insurance business income is the gross premium obtained from insured clients. Investment profit expresses the profits acquired from investment activities for the year. Claims paid means the gross claims paid to assured. Below, in Figure 1, it illustrates the service process of insurance companies, where fixed assets, operation and administrative expenses, and investment expenditure are utilized to generate insurance business income, investment profit, and claims paid.

B. DYNAMIC DEA MODEL FOR MEASURING OPERATIONAL PERFORMANCE

As mentioned above, fixed assets (XK), operation and administrative expense (XE), and investment expenditure (XI) are three inputs. Insurance business income (YG) and investment profit (YR) are two desirable outputs, while claims paid (YB)

is one undesirable output. Each insurance company utilizes XK , XE and XI , and then yields YG , YR , and YB . To compute operational performance, each insurance company is denoted as DMU_j ($j = 1, 2, \dots, n$).

In DEA theory, there are two crucial models, that is, CCR (Charnes, Cooper, and Rhodes) and BCC (Banker, Charnes, and Cooper). These two models are radial. CCR assumes that returns to scale (RTS) are constant, while BCC assumes the opposite. Based on Noulas et al. [41], this paper adopts the CCR model to assess the operational performance of insurance firms. Based on the above-mentioned input and output variables, a performance evaluation model is constructed as follows:

$$\begin{aligned} & \min \theta_i \\ & \text{s.t. } \sum_{j=1}^n \lambda_j XK_j \leq \theta_i XK_i, \sum_{j=1}^n \lambda_j XE_j \leq \theta_i XE_i, \sum_{j=1}^n \lambda_j XI_j \leq \theta_i XI_i, \\ & \sum_{j=1}^n \lambda_j YG_j \geq YG_i, \sum_{j=1}^n \lambda_j YR_j \geq YR_i, \sum_{j=1}^n \lambda_j YB_j \leq YB_i, \\ & \lambda_j \geq 0, \quad j = 1, 2, \dots, n. \end{aligned} \tag{1}$$

In Model (1), θ_i denotes the operational performance score, belonging to $(0, 1]$. λ_j is the weight variable. The constraints $\sum_{j=1}^n \lambda_j XK_j \leq \theta_i XK_i$, $\sum_{j=1}^n \lambda_j XE_j \leq \theta_i XE_i$, and $\sum_{j=1}^n \lambda_j XI_j \leq \theta_i XI_i$ represent that the optimal fixed assets, operation and administrative expense, and investment expenditure are not greater than the actual inputs. The constraints $\sum_{j=1}^n \lambda_j YG_j \geq YG_i$, $\sum_{j=1}^n \lambda_j YR_j \geq YR_i$ express that the optimal insurance business income and investment profit are not less than the actual outputs. The constraint $\sum_{j=1}^n \lambda_j YB_j \leq YB_i$ means that the optimal claims paid is not higher than the actual output. When $\theta_i^* = 1$, the operational performance of an insurance company can be regarded as efficient; otherwise, it is inefficient. When an insurance company has a larger θ_i than others, this shows that this insurance company operates better than others.

In reality, the operation activities of insurance companies are consistent. In other words, the performance cannot be accurately assessed until time dimension is considered during the evaluation. In this sense, a dynamic DEA evaluation model is presented below for estimating performance. In our context, the service process of an insurance firm is regarded as an input and output system containing three periods with the consideration of the above-mentioned nature of operation activities.

In model (2), as shown at the bottom of the next page, t ($t = 1, 2, \dots, T$) represents time period. λ_j^t , λ_j^{t+1} , λ_j^{t+2} are the weight variables in three periods. θ_i^t , θ_i^{t+1} , θ_i^{t+2} represent the operational performance scores in three periods. The objective function expresses the optimal performance in three

| | | |
|---------------------|----------------------------|----------------------------|
| Top 50% S_i | The second quadrant | The first quadrant |
| | The third quadrant | The fourth quadrant |
| Bottom 50% S_i | DRS Stage | IRS/CRS Stage |

Note: DRS=Decreasingly returns to scale; IRS=Increasing returns to scale; CRS=Constant returns to scale.

FIGURE 2. The typology for the analysis of resilience.

periods. Similar to model (1), the constraints stipulate that the optimal inputs for three periods must not exceed the actual inputs, the optimal outputs must not fall below the actual outputs, and the optimal undesired output must not surpass the actual output. When $\theta_i^{t*} = 1$ ($\theta_i^{t+1*} = 1$ or $\theta_i^{t+2*} = 1$), the operational performance of an insurance company could be deemed as efficient in period t ($t+1$ or $t+2$). Besides, if the operational performances are efficient in all periods, the resilience of the operational performance can be viewed as perfect by default.

C. MEASURE FOR THE RESILIENCE OF OPERATIONAL PERFORMANCE

Broadly speaking, resilience performance is determined by the growth and fluctuation of operational performance in a

certain period. In this sense, our work proposes a novel measure to assess the resilience for the operations of inefficient insurance companies. First, an indicator of the intensity of change in operational performance, expressed by S_i in the following equation 3, is proposed to analyze the resilience.

$$S_i = \frac{\theta_i^{t+2} - \theta_i^t}{s_i^2} (t = 1, 2, \dots, T) \tag{3}$$

where s_i^2 denotes the variance of operational performance over certain periods.

Furthermore, deep insights into resilience can be acquired by analyzing the RTS status of DMUs to optimize their potential. In the realm of economic studies, constant return to scale (CRS) can be identified when the increase proportion of outputs is equal to that of production inputs, while increasing returns to scale (IRS) and decreasing returns to scale (DRS) can be found when the increase proportion of outputs is greater or smaller than that of production inputs. The pre-conditions to recognize RTS are provided below. It is believed that IRS and CRS conditions with greater outputs would conducive to achieving better resilience performance.

- (i) When $\sum \lambda_j^* < 1$ for all alternate optima, DMU_j should be in the IRS stage;
- (ii) When $\sum \lambda_j^* = 1$ in any alternate optimum, DMU_j should be in the CRS stage;
- (iii) When $\sum \lambda_j^* > 1$ for all alternate optima, DMU_j should be in the DRS stage.

Collectively, indicator S_i and RTS condition are used to assess the resilience of operational performance reasonably. Figure 2 shows a four-quadrant classification analysis to further make sense of the findings. For one thing, inefficient insurance firms are split into two groups equal proportionally based on the ordering of S_i . For another thing, these

$$\begin{aligned}
 & \min(\theta_i^t + \theta_i^{t+1} + \theta_i^{t+2}) \\
 & \text{s.t.} \left. \begin{aligned}
 & \sum_{j=1}^n \lambda_{1j} X K_j^t \leq \theta_i^t X K_i^t, \sum_{j=1}^n \lambda_{1j} X E_j^t \leq \theta_i^t X E_i^t, \sum_{j=1}^n \lambda_{1j} X I_j^t \leq \theta_i^t X I_i^t, \\
 & \sum_{j=1}^n \lambda_{1j} Y G_j^t \geq Y G_i^t, \sum_{j=1}^n \lambda_{1j} Y R_j^t \geq Y R_i^t, \sum_{j=1}^n \lambda_{1j} Y B_j^t \leq Y B_i^t,
 \end{aligned} \right\} \text{periodt} \\
 & \left. \begin{aligned}
 & \sum_{j=1}^n \lambda_{2j} X K_j^{t+1} \leq \theta_i^{t+1} X K_i^{t+1}, \sum_{j=1}^n \lambda_{2j} X E_j^{t+1} \leq \theta_i^{t+1} X E_i^{t+1}, \sum_{j=1}^n \lambda_{2j} X I_j^{t+1} \leq \theta_i^{t+1} X I_i^{t+1}, \\
 & \sum_{j=1}^n \lambda_{2j} Y G_j^{t+1} \geq Y G_i^{t+1}, \sum_{j=1}^n \lambda_{2j} Y R_j^{t+1} \geq Y R_i^{t+1}, \sum_{j=1}^n \lambda_{2j} Y B_j^{t+1} \leq Y B_i^{t+1},
 \end{aligned} \right\} \text{periodt} + 1 \\
 & \left. \begin{aligned}
 & \sum_{j=1}^n \lambda_{3j} X K_j^{t+2} \leq \theta_i^{t+2} X K_i^{t+2}, \sum_{j=1}^n \lambda_{3j} X E_j^{t+2} \leq \theta_i^{t+2} X E_i^{t+2}, \sum_{j=1}^n \lambda_{3j} X I_j^{t+2} \leq \theta_i^{t+2} X I_i^{t+2}, \\
 & \sum_{j=1}^n \lambda_{3j} Y G_j^{t+2} \geq Y G_i^{t+2}, \sum_{j=1}^n \lambda_{3j} Y R_j^{t+2} \geq Y R_i^{t+2}, \sum_{j=1}^n \lambda_{3j} Y B_j^{t+2} \leq Y B_i^{t+2},
 \end{aligned} \right\} \text{periodt} + 2 \\
 & \sum_{j=1}^n \lambda_{1j} X K_j^{t+1} \leq \sum_{j=1}^n \lambda_{2j} X K_j^{t+1}, \sum_{j=1}^n \lambda_{2j} X K_j^{t+1} \leq \sum_{j=1}^n \lambda_{3j} X K_j^{t+1}, \\
 & 0 \leq \theta_i^t \leq 1, 0 \leq \theta_i^{t+1} \leq 1, 0 \leq \theta_i^{t+2} \leq 1, \lambda_{1j} \geq 0, \lambda_{2j} \geq 0, \lambda_{3j} \geq 0, \quad j = 1, 2, \dots, n, t = 1, 2, \dots, T. \tag{2}
 \end{aligned}$$

TABLE 1. Sample insurance companies and categorization.

| Type | Insurance Company Name | Registered Address |
|---------------------------------|---|--------------------|
| Property and Casualty Insurance | An Cheng Property and Casualty Insurance (APCI) | Chongqing |
| | Bohai Property and Casualty Insurance (BPCI) | Tianjin |
| | China Continent Property and Casualty Insurance (CCPCI) | Shanghai |
| | Sinosafe Property and Casualty Insurance (SSPCI) | Shenzhen |
| | Hua Tai Property and Casualty Insurance (HTPCI) | Shanghai |
| | Tai Shan Property & Casualty Insurance (TSPCI) | Jinan |
| | Sunshine Property and Casualty Insurance (SPCI) | Beijing |
| | Yong An Property and Casualty Insurance (YAPCI) | Xi’an |
| | Zhe Shang Property and Casualty Insurance (ZSPCI) | Hangzhou |
| | China United Property and Casualty Insurance (CUPCI) | Beijing |
| Life Insurance | Taiping Life Insurance (TPLI) | Shanghai |
| | Bohai Life Insurance (BLI) | Tianjin |
| | Sun Life Everbright Life Insurance (SLELI) | Tianjin |
| | Guo Lian Life Insurance (GLLI) | Wuxi |
| | Min Sheng Life Insurance (MSLI) | Beijing |
| | Foresea Life Insurance (FLI) | Shenzhen |
| | Shanghai Life Insurance (SHLI) | Shanghai |
| | Tian An Life Insurance (TALI) | Beijing |
| | New China Life Insurance (NCLI) | Beijing |
| | Sunshine Life Insurance (SSLI) | Sanya |
| | Great Wall Life Insurance (GWLI) | Beijing |
| | China Post Life Insurance (CPLI) | Beijing |
| | Pearl River Life Insurance (PRLI) | Guangzhou |
| | Happy Life Insurance (HLI) | Beijing |
| Soochow Life Insurance (SCLI) | Suzhou | |

companies can also be categorized into two parts based on the RTS conditions. It’s noteworthy that insurance companies in the IRS and CRS stages can be grouped into one category, whereas the remaining companies in the DRS stage fall into a different category. Hence, a four-quadrant typology is proposed to assess the resilience of performance.

(1) When an insurance company’s S_i is in the top 50% and the IRS or CRS stage, namely, this company belongs to the first quadrant. The resilience of the company’s operational performance is at the high level. The company is recommended to make more resource investments to maximize outputs and operational performance.

(2) When an insurance company’s S_i is in the top 50% and the DRS stage, namely, this company belongs to the second quadrant. The resilience of operational performance for this company is at the middle level. A prudent resource investment strategy should be adopted by the company to enhance performance and its resilience.

(3) When an insurance company’s S_i is in the bottom 50% and the DRS stage, namely, this company belongs to the third quadrant. The resilience of operational performance for this company is at the low level. The company should signifi-

cantly increase operational performance and take a prudent increasing resource investment strategy to improve resilience.

(4) When an insurance company’s S_i is in the bottom 50% and the IRS or CRS stage, namely, this company belongs to the fourth quadrant. In this regard, the resilience of operational performance for this company is at the middle level. The company should first steadily improve operational performance and take an increasing resource investment strategy to obtain more outputs.

D. MEASURE FOR PERFORMANCE IMPROVEMENT

Based on the technique of DEA, the projected frontier is the benchmark for inefficient DMUs to achieve. In this sense, DEA is usually utilized to set objectives for inputs and outputs for the improvement of performance. In this study, the optimal target of claims paid could be computed by the following Equation (4):

$$TB_i^t = \sum_{j=1}^n \lambda_{1j} YB_j^t \tag{4}$$

where $\sum_{j=1}^n \lambda_{ij} YB_j^t$ denotes the optimal claims paid output. The target claims paid output TB_i^t expresses a minimum level of claims paid output to be taken as a target to achieve optimal operational performance. Therefore, the index of potential claims paid improvement PB_i^t is considered as the ratio of the difference between its actual value and target value to its actual value, measured by Equation (5).

$$PB_i^t = \frac{YB_i^t - TB_i^t}{YB_i^t} \tag{5}$$

Likewise, the optimization targets of insurance business income and investment profit of inefficient insurance companies can be computed by the following equations:

$$TG_i^t = \sum_{j=1}^n \lambda_{ij} YG_j^t \tag{6}$$

$$TR_i^t = \sum_{j=1}^n \lambda_{ij} YR_j^t \tag{7}$$

Accordingly, the improvement potentials of insurance business income and investment profit can be measured by Equation (8) and Equation (9).

$$PG_i^t = \frac{TG_i^t - YG_i^t}{YG_i^t} \tag{8}$$

$$PR_i^t = \frac{TR_i^t - YR_i^t}{YR_i^t} \tag{9}$$

According to these equations, the improvement potential of output indicators can be calculated to improve operational performance for the resilience in future.

IV. EMPIRICAL ANALYSIS

Our work employs the previously mentioned method to evaluate Chinese insurance firms' operational performance from 2017 to 2019.

A. DATA SOURCE

The sample data is collected from the annual reports of 25 Chinese insurance firms. According to the type of main business, these samples could be divided into two categories: property and casualty insurance companies (PCICs) and life insurance companies (LICs), as reported in Table 1. Moreover, Table 2 demonstrates the descriptive statistics of the dataset.

B. PERFORMANCE RESULTS ANALYSIS

By adopting the collected data from 2017 to 2019, operational performance scores can be obtained by the model (2). Table 3 displays the results.

The empirical findings indicate that the average performance of the 25 insurance companies over the study period was 0.8938. Eleven insurance companies' performance values are 1.0000, that is, BPCI, CCPCI, SSPCI, HTPCI, SPCI,

YAPCI, BLI, SHLI, TALI, CPLI, and PRLI. These companies can be considered efficient. The performances of four companies are higher than the average value, that is, ZSPCI (0.9611), CUPCI (0.9647), GLLI (0.9628), and FLI (0.9974). The remaining ten companies' (APCI, TSPCI, TPLI, SLELI, MSLI, NCLI, SSLI, GWLI, HLI, and SCLI) performance scores are below the overall average level. It can be inferred that the operational performances of many insurance companies have still not reached the ideal level, and the potential for their performance is not maximized.

In terms of the performance of different categories, the average performance of PCICs is 0.9519. Among 10 PCICs, 6 companies' performance values are 1.0000; while the performance of the remaining 2 companies is below average, the performance of 2 companies fared higher than average. According to the results, the LICs perform on average at 0.8503. Of the performance of 15 LICs, 5 of which are 1.0000. Yet, only 2 of them are above the overall average performance and the rest of 8 companies are lower than the average performance. It suggests that the average performance level of LICs is lower compared with the performance of PCICs. Hence, it is more urgent for LICs to improve operational performance.

China's top-tiered cities (i.e., first-tier cities) are Beijing, Guangzhou, Shenzhen, and Shanghai [45]. In terms of the performance of 15 insurance companies in first-tier cities, 8 of them are fully optimized (i.e., the performance score is 1.0000), while 2 of them perform better than the overall average level. The rest of 5 companies, however, perform worse than the overall average level. Among 10 insurance companies in non-first-tier cities, i.e., Chongqing, Tianjin, Jinan, Xi'an, Hangzhou, Wuxi, Sanya, and Suzhou, 3 companies' performance values are 1.0000. Yet, the performance of 7 companies does not reach the ideal level (2 of them perform better than the overall average level, while the other 5 of them are worse than the average performance). The average performance score of insurance companies registered in first-tier cities is 0.8976, and that of insurance companies registered in non-first-tier cities is 0.8882. Broadly speaking, it indicates that the insurance companies registered in first-tier cities perform better than those registered in non-first-tier cities. One of the reasons might be that those registered in first-tier cities have more opportunities to access financial resources and qualified human resources. It allows the insurance companies to enhance their practice (e.g., introduce management and technological techniques) to improve operational performance.

C. PERFORMANCE RESILIENCE ANALYSIS

For the insurance industry, the resilience of performance can be reflected by dynamic change trends. The dynamic changes in operational performance are illustrated in Figure 3. The overall average performance value of insurance companies is in the trend of fluctuating growth within the observed period. It slightly decreases from 0.8822 in 2017 to 0.8734 in

TABLE 2. Descriptive statistics^a.

| Year | Indicator | Fixed Assets | Operation and Administrative Expense | Investment Expenditure | Insurance Business Income | Investment profit | Claims Paid |
|------|-----------|--------------|--------------------------------------|------------------------|---------------------------|-------------------|-------------|
| 2017 | Maximum | 15278.43 | 14050.00 | 644203.00 | 113948.59 | 35649.00 | 38379.00 |
| | Minimum | 16.59 | 217.89 | 2892.96 | 890.19 | 116.98 | 21.36 |
| | Average | 2210.30 | 3467.32 | 78705.56 | 24816.31 | 4556.20 | 6647.66 |
| | Std. Dev. | 3951.33 | 3987.89 | 137650.06 | 30494.73 | 7636.63 | 9229.37 |
| 2018 | Maximum | 15083.47 | 12601.30 | 625199.09 | 119017.12 | 32526.95 | 49204.67 |
| | Minimum | 14.89 | 217.84 | 2729.63 | 1673.80 | 26.94 | 43.58 |
| | Average | 2486.33 | 3442.68 | 81469.52 | 26038.45 | 4143.80 | 7632.04 |
| | Std. Dev. | 4247.98 | 3834.63 | 138494.90 | 33117.93 | 7110.29 | 11395.71 |
| 2019 | Maximum | 16851.64 | 14162.01 | 738780.97 | 133388.56 | 33754.79 | 57296.88 |
| | Minimum | 15.82 | 233.86 | 2362.16 | 1561.07 | 169.64 | 64.79 |
| | Average | 2771.24 | 3709.14 | 95040.18 | 29453.46 | 4551.52 | 7976.36 |
| | Std. Dev. | 4804.25 | 4328.36 | 166725.08 | 37409.92 | 7782.44 | 12887.71 |

^a Note: The unit is million CNY.

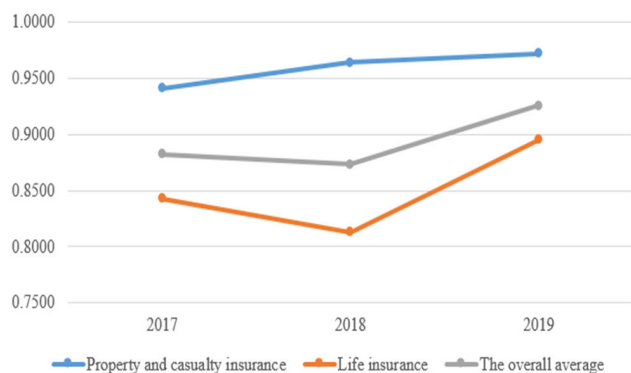
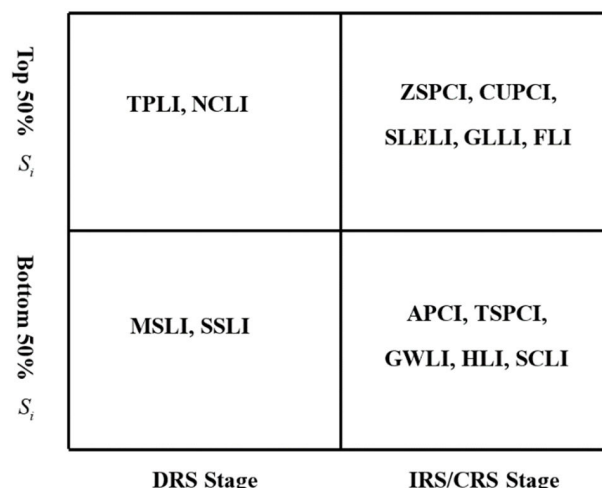


FIGURE 3. Performance change trend during 2017-2019.

2018 and then rises to 0.9259 in 2019. Due to the high volatility, the resilience of performance is weak. The reason for the decline in performance may be that the China Banking and Insurance Regulatory Commission strengthened supervision and regulation in the insurance sector after its establishment in 2018, which to some extent affected the operating activities at the industry level. From a category perspective, the average performance of LICs has decreased from 0.8427 to 0.8129 and then returned to 0.8952. Nevertheless, such a performance of PCICs is on the rise from 0.9413 to 0.9642, and then declines slightly to 0.9629. In addition, the performance gap between PCICs and LICs expands from 0.0986 (2017) to 0.1513 (2018), and then narrows to 0.0767 (2019). This indicates that PCICs fared better than LICs in terms of resilience.

For a specific inefficient insurance company, the indicator proposed to measure the change intensity S_i and the RTS condition are adopted to assess the resilience of performance.



Note: DRS=Decreasingly returns to scale; IRS=Increasing returns to scale; CRS=Constant returns to scale.

FIGURE 4. The distribution of inefficient insurance companies.

Below, the results of the indicator S_i and RTS are listed in Table 4. In addition, the distribution of inefficient insurance companies is presented in Figure 4.

According to the results, five insurance companies (ZSPCI, CUPCI, SLELI, GLLI, FLI) belong to the first quadrant. This indicates that the resilience of these companies' operational performances is at a high level. In terms of the two insurance companies in the second quadrant (i.e., TPLI and NCLI), the resilience of their performance is at the middle level. Since TPLI and NCLI belong to the DRS stage, the expansion of resource inputs would decrease outputs. It is suggested that the operators should control the expansion of resource inputs, and enhance the integration and effective

TABLE 3. Results generated by model (2).

| Type | Company | θ_i | | | |
|---------------------------------|---------------|------------|--------|--------|--------|
| | | 2017-2019 | 2017 | 2018 | 2019 |
| Property and Casualty Insurance | APCI | 0.7997 | 0.8339 | 0.8465 | 0.7187 |
| | BPCI | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | CCPCI | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | SSPCI | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | HTPCI | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | TSPCI | 0.8658 | 0.8021 | 0.7953 | 1.0000 |
| | SPCI | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | YAPCI | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | ZSPCI | 0.9611 | 0.8832 | 1.0000 | 1.0000 |
| | CUPCI | 0.9647 | 0.8941 | 1.0000 | 1.0000 |
| | PCICs Average | 0.9591 | 0.9413 | 0.9642 | 0.9719 |
| Life Insurance | TPLI | 0.8179 | 0.8162 | 0.7813 | 0.8562 |
| | BLI | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | SLELI | 0.7230 | 0.6786 | 0.7323 | 0.7581 |
| | GLLI | 0.9628 | 0.8885 | 1.0000 | 1.0000 |
| | MSLI | 0.5935 | 0.4958 | 0.5403 | 0.7445 |
| | FLI | 0.9974 | 0.9923 | 1.0000 | 1.0000 |
| | SHLI | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | TALI | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | NCLI | 0.7253 | 0.6855 | 0.7738 | 0.7167 |
| | SSLI | 0.7617 | 0.7812 | 0.7126 | 0.7914 |
| | GWLI | 0.5730 | 0.4726 | 0.4939 | 0.7524 |
| | CPLI | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | PRLI | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | HLI | 0.7915 | 0.9956 | 0.3857 | 0.9931 |
| | SCLI | 0.8079 | 0.8346 | 0.7737 | 0.8154 |
| LICs Average | 0.8503 | 0.8427 | 0.8129 | 0.8952 | |
| Average | 0.8938 | 0.8822 | 0.8734 | 0.9259 | |

utilization of current resources. By doing so, the operational performance can be roughly improved. Within the third quadrant, the resilience of operational performance of two case companies for MSLI and SSLI is at a low level. They should smoothly improve operational performance and reduce performance fluctuation. Specifically, as these companies are in the DRS stage, the utilization efficiency of the existing resources should be improved and the resource inputs need to be prudently increased. Within the fourth quadrant, the results of five case insurance companies (APCI, TSPCI, GWLI, HLI, SCLI) demonstrate that the resilience of these companies' operational performances is at the middle level. The outputs of the case companies in the IRS/CRS stage can be improved by moderating the expansion of resource inputs. The priority for them is to improve operational performance without too much fluctuation as three of the five companies have seen their operating performances decline during the observation.

D. IMPROVEMENT POTENTIAL ANALYSIS

In addition to the analysis of operational performance, the ineffectiveness of the operation in insurance companies can be identified. The main reasons for ineffectiveness may be caused by high levels of inputs, undesirable outputs, and low levels of desirable outputs. In practice, insurance companies rarely reduce investment, worrying that it might lead to lower service quality and revenue. In this sense, our work concerns the analysis of inefficient insurance companies' improvements in outputs. By calculating the equations (4-8), the specific proportion of each output adjustment potential can be summarized in the following Table 5.

Based on the results of claims paid, there are 13 inefficient insurance companies with potential for further improvement. This indicates that these insurance companies need to take measures to reduce claims paid. For instance, NCLI, MSLI, and SSLI should reduce the proportions of claims paid by

TABLE 4. Results of S_i and RTS.

| Type | Company | S_i | $\sum \lambda_j^*$ | RTS (2019) |
|---------------------------------|---------|--------|--------------------|------------|
| Property and Casualty Insurance | APCI | -48.49 | 0.8100 | IRS |
| | TSPCI | 21.96 | 1.0000 | CRS |
| | ZSPCI | 38.53 | 1.0000 | CRS |
| | CUPCI | 42.49 | 1.0000 | CRS |
| Life Insurance | TPLI | 49.88 | 7.5905 | DRS |
| | SLELI | 95.56 | 0.5114 | IRS |
| | GLLI | 40.36 | 0.0712 | IRS |
| | MSLI | 28.50 | 1.7173 | DRS |
| | FLI | 583.21 | 1.0000 | CRS |
| | NCLI | 32.60 | 10.0459 | DRS |
| | SSLI | 10.59 | 2.5018 | DRS |
| | GWLI | 22.99 | 0.3363 | IRS |
| | HLI | -0.03 | 0.9348 | IRS |
| | SCLI | -36.53 | 0.2728 | IRS |

TABLE 5. Adjustment potential for outputs during the observed period.

| Type | Company | Claims paid (RR) | Insurance business revenue (IR) | Investment profit (IR) |
|---------------------------------|---------|------------------|---------------------------------|------------------------|
| Property and Casualty Insurance | APCI | 22.32% | 25.70% | 35.99% |
| | TSPCI | 4.83% | 11.82% | 12.02% |
| | ZSPCI | 7.75% | 4.13% | 19.06% |
| | CUPCI | 8.66% | 3.67% | 3.73% |
| Life Insurance | TPLI | 0.00% | 20.30% | 19.83% |
| | SLELI | 2.94% | 32.88% | 33.12% |
| | GLLI | 2.42% | 12.29% | 17.81% |
| | MSLI | 39.64% | 71.14% | 67.16% |
| | FLI | 1.39% | 0.16% | 0.30% |
| | NCLI | 66.53% | 37.90% | 38.25% |
| | SSLI | 30.46% | 37.46% | 30.92% |
| | GWLI | 10.85% | 67.05% | 68.68% |
| | HLI | 20.77% | 35.71% | 18.38% |
| | SCLI | 9.26% | 21.52% | 22.66% |

Note: RR= Reduction rate; IR= Improvement rate.

66.53%, 39.64%, and 30.46% respectively compared with the ideal level. Three insurance companies (APCI, GWLI, HLI) should fall their claims paid by between 10% and 30%, and the other 7 companies (TSPCI, ZSPCI, CUPCI, SLELI, GLLI, FLI, SCLI) should fall their claims paid by less than 10%. According to the loss caused by claims paid, reducing claims paid is an ideal way for most inefficient insurance companies to improve their operational performance.

Concerning insurance business revenue, it is evident that 14 insurance companies have room for further enhancement. This indicates that most insurance companies' business revenues do not reach an ideal level. In terms of the differences between PCICs, the growth potentials of APCI and TSPCI are 25.70%, and 11.82% respectively, while those of ZSPCI and CUPCI are 4.13%, and 3.67% respectively. For LICs, the growth potentials of two companies (MSLI and GWLI) are greater than 60%, and those of six companies (TPLI, SLELI, NCLI, SSLI, HLI, and SCLI) are between 20% and 40%. The growth potentials of two companies (GLLI and FLI) are less than 20%. On the whole level, the average insurance business revenue growth potentials of PCICs and LICs are 11.33% and 33.64% respectively. The latter are almost three times as many. This suggests that compared with PCICs, LICs have a greater potential in this respect. Hence, most life companies should increase their insurance business profitability to improve operational performance.

With respect to investment profit, it can be observed that all insurance companies have improvement potential. For PCICs, APCI, TSPCI, ZSPCI, and CUPCI should take measures to increase investment profit by 35.99%, 12.02%, 19.06%, and 3.73% respectively. For LICs, MSLI and GLLI should improve investment profit by more than 60%. SLELI, NCLI, SSLI, and SCLI should improve investment profit by 20-40%. The improvement potentials of TPLI, GLLI, FLI, and HLI are under 20%. The average investment profit growth potentials of PCICs and LICs are 17.71% and 31.71% respectively. Obviously, LICs have more potential in investment profit for increasing operational performance.

Most companies need to make more efforts to tap into their potential for optimizing outputs, thereby improving performance and ensuring resilience in future competitive scenarios.

E. DISCUSSION

Based on the sample of 25 selected Chinese insurance companies between 2017 and 2019, this paper utilizes the proposed dynamic DEA model to measure and analyze operational performance from a resilience perspective. The important empirical findings can be conducted as follows. First, the operational performances of most insurance companies have improvement room. Second, a distinct difference in operational performance is observed between PCICs and LICs in the study period. Specifically, the former's average performance is higher than the latter. Third, insurance companies registered in first-tier cities have a higher average performance score than those registered in non-first-tier cities. Fourth, the resilience of operational performance of most inefficient insurance companies is weak, which needs to be further improved.

The sustainable development of the insurance industry is of great significance to China's economy, while the operational performance of insurance companies still needs to be further improved. Based on the findings, to improve operational

performance, several managerial implications can be developed as follows.

(1) Improving the capital operation of insurance funds investment should be emphasized to obtain more profit. In the case of intensified competition and scale expansion, the capital operation of insurance funds investment plays a critical role in increasing the profitability of the insurance sector. No matter for PCICs or LICs, it is necessary to change the management idea of emphasizing the underwriting system but neglecting capital operation. The coordinated development of the underwriting system and capital operation system should be emphasized. Improving capital operation capacity signifies increasing investment profit, which can be helpful in strengthening operational performance.

(2) For insurance companies with weak resilience, emerging technology investments, such as for the Internet and big data technology, should be increased to improve operational performance. For one thing, customers' data can be integrated into the Internet, and big data algorithms can be used to solve thorny problems under the traditional mode such as identity identification, risk pricing, demand analysis, and loss prevention, to help develop new insurance products. For another, emerging technologies can provide strong technical support for insurance companies' infrastructure improvement, operation optimization, and precise service, which is conducive to strengthening competitiveness and improving operational performance.

(3) Enhancing risk management capacity should be paid more attention to realize the sustainable development of the insurance industry. As the market environment becomes more and more complex, insurance companies are facing more and more risks. Therefore, insurance companies should enhance their risk management capability to ensure the safety of insurance funds and capital gains by improving the organizational structure of risk management, strengthening personnel allocation, and building and perfecting risk management systems. In addition, the undesirable output claims paid should be paid more attention to. Excessive claims paid output may result in more inefficiency. Strengthening risk management can help insurance companies control claims paid at a reasonable level to increase operational performance.

V. CONCLUSION

This study proposes a dynamic DEA model to explore the operational performance of insurance companies' service processes in China from a resilience angle. The operational performance in this study is the transfer efficiency between the input system and the output system of an insurance company, and the undesirable output is considered. On this basis, the measures for resilience analysis and output improvement potential are proposed according to the optimal solutions obtained from performance assessment. Finally, the proposed approach is applied to the Chinese insurance sector and the effectiveness is verified.

Yet, this study is not free from limitations, which can be the research agenda for further studies. Firstly, the analysis is

based on the data from 25 samples during 2017-2019. In this sense, studies in the future can extend the observation period to obtain deeper insights into insurance companies' operational performances (e.g., longitudinal data can be employed to provide more facilitated managerial implications). Secondly, the influential factors of operational performance are yet to be explored in this paper. Thirdly, this study only adopted a limited number of samples. The proposed methods in this work can assess the performance of numerous insurance companies in the big data context to acquire more insights. Fourthly, considering that this study is conducted using Chinese samples, the findings might not directly apply to insurance operations in other countries. To enhance the generalizability of the conclusions, it is recommended to perform a comparative analysis of insurance company performance between China and other nations.

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