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Measuring Logistics Efficiency in China Considering Technology Heterogeneity and Carbon Emission through a Meta-Frontier Model

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Abstract: Due to the differences in the economic and social environment, production technology heterogeneity exists in the logistics industry among provinces in China. If this fact is ignored, the evaluation result of logistics efficiency may be biased. To this end, this study developed a new analysis framework for evaluating logistics efficiency with the consideration of technology heterogeneity and carbon emission through a metafrontier data envelopment analysis (DEA) method. Furthermore, the source of logistics inefficiency were identified. The proposed method was employed in the regional logistics industry in China from 2011 to 2017. The following empirical findings could be drawn: (1) The overall logistics efficiency is low in China, and great potential exists in improving logistics efficiency. (2) Significant disparities exist in logistics efficiency and the technology gap among the three areas. The east area has higher logistics efficiency with advanced technology, while the central area and the west area have lower logistics efficiencies. (3) The technology gap and management issues in the utilization of logistics resources are the two primary reasons resulting in the logistics efficiency loss in China. The effect of the management factor is significant in the east area, while the impact of the technology gap is dominant in the central area and the west area. Some policy suggestions for enhancing logistics efficiency are provided.

Keywords: logistics efficiency; technology heterogeneity; carbon emission; slack-based measure

1. Introduction

Accelerated by the policy of reform and opening-up, China has achieved an astonishing economy expansion in the past four decades, which has brought the prosperity of the logistics industry. To a certain extent, freight turnover can reflect logistics scale. Figure 1 represents the change trends of freight turnover and gross domestic product (GDP) from 2001 to 2019 in China. To be specific, China's GDP increased by approximately 9.05 times in this period, and the freight turnover volume increased by 4.18 times, reaching up to 19,928.71 billion ton-km [1]. This indicates that the development of the logistics industry has made some achievements benefiting from GDP growth. However, it still resides at a lower level compared with developed countries [2]. A notable characteristic is that the logistics performance is low, while the logistics cost is high. To address this issue, China's government has launched serial policies to improve logistics performance. Some specific measures are advocated, such as establishing a national logistics hub system to match the modern industrial system, building an efficient multimodal logistics system, and promoting the interconnection and sharing of logistics information. It is often quoted that "if you cannot measure it, you cannot manage it". The performance evaluation of the logistics industry is the first step to improve logistics efficiency. Following Fugate et al. [3], the term "logistics efficiency" is defined as the ratio of the actual values of the inputs and outputs of the logistics system to the optimal values of them in this study, which can reflect the operational performance of logistics system. Effective performance evaluation can provide decision support for the government to develop better policies to allocate resources and improve logistics performance. Consequently, it is necessary to investigate logistics efficiency in China.

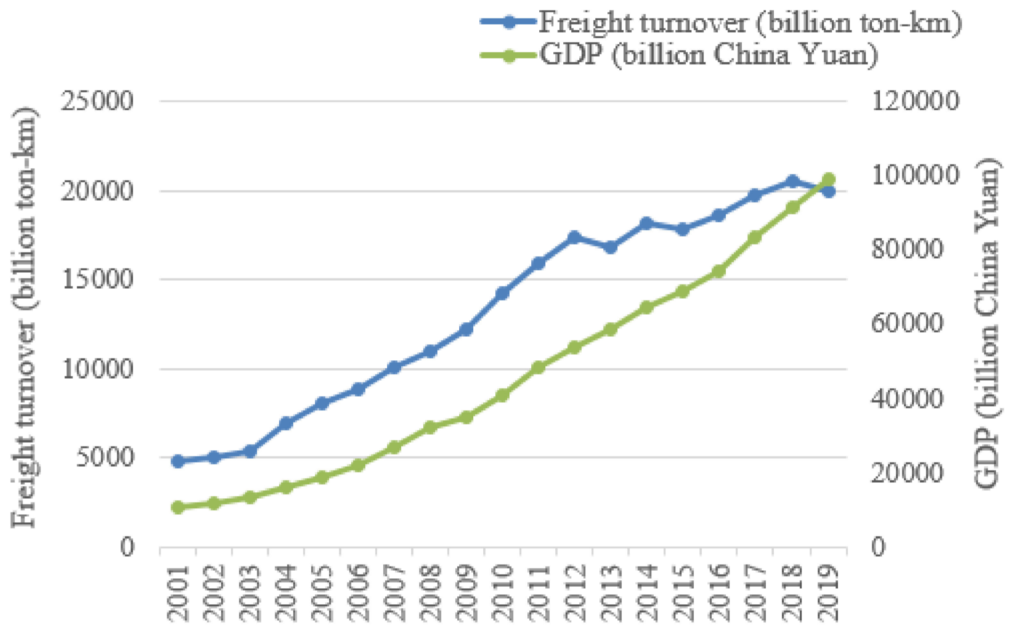

Figure 1. Freight turnover and GDP in China from 2004 to 2019.

As a crucial comprehensive service sector, the logistics industry connects the buyers and the sellers in the market. Generally, the logistics industry includes internal logistics and external logistics [4]. The former term refers to the activities involved in moving materials and parts in the production system in the industry. The latter term refers to a transport system that comprehends transport and logistics related to infrastructures and services at nodes (e.g., Russo et al. [5]) and links (e.g., Russo et al. [6]), which aims to move products from the origin to the destination for meeting the demands of customers [7]. Considering that the data on internal logistics and nodes in external logistics are unavailable, this study only considered transport, representing the logistics industry. In practice, transport and warehousing are closely related. Increasing the transport scale leads to the growth of the corresponding warehouse business since warehouses carry out ancillary activities to support transportation operations. Hence, transport activities can reflect the actual situation of the logistics industry to a certain extent.

Transport is one core activity in the logistics industry, which consumes a large amount of petroleum fuel. From the perspective of environmental protection, massive petroleum consumption would inevitably generate numerous carbon dioxide (CO_2) emissions. Excessive CO_2 emission would cause the greenhouse effect, which consequently results in natural disasters [8]. In practice, logistics production consumes enormous energy, which makes the logistics industry become one significant energy consumer and CO_2 emitter due to the rapid increase in the scale of logistics in China [9]. In 2015, China's government pledged to peak CO_2 emission by 2030 and to reduce the carbon intensity by 60–65% over the 2005 level [10]. Therefore, the carbon emission reduction should be advocated in China's logistics industry [11,12]. Given this circumstance, carbon emission should be considered in logistics performance evaluation.

The improvement of logistics performance is conducive to making full use of logistics resources, reducing logistics costs and carbon emission, and achieving sustainable development [9]. The efficiency issue of the logistics industry has drawn much attention from academic circles [9,12–16]. However, although significant progress on the evaluation issues of logistics efficiency has been made, further investigation is still required. Firstly, traditional studies on estimating logistics efficiency assume that each province has consistent production technologies based on the same reference production frontier. However, due to the significant disparities under different economic and social conditions, the technology heterogeneity of logistics resource utilization is inevitable. The regional technology heterogeneity may be induced by economic development [13] and industrial structures [12]. In this paper, the technology heterogeneity in logistics production can be explained by two reasons. The first refers to the technology gap determined by economic development. The technology level, impacted by the application of low emission logistics means and energy-saving green storage facilities, advanced management, and high-educated labor, can result in the differences in logistics performance. The second refers to the disparities of the industrial structure of the regional logistics industry. The production of the regional logistics industry may be affected by energy-intensive road logistics and low-energy waterway logistics and railway logistics. Different logistics industrial structures have different production technologies, which ultimately influence logistics efficiency. It may result in biased evaluation neglecting this fact. Consequently, the existence of technology heterogeneity should be considered while measuring logistics efficiency. In addition, the study of logistics efficiency loss has not been paid enough attention. In particular, the analysis of logistics inefficiency has not been investigated. Furthermore, some measurements of logistics efficiency only consider desirable output (e.g., freight turnover), ignoring the undesirable output (e.g., CO_2 emission). Carbon emission reduction is still of great concern for sustainable development. Therefore, logistics efficiency should be measured with the consideration of technology heterogeneity and CO_2 emission.

To this end, this paper emphasizes the existence of technology heterogeneity in logistics production with the consideration of CO_2 emission. Hence, an analytical framework for evaluating logistics efficiency integrating the metafrontier and slacks based measure (SBM) is proposed. The core concept of the metafrontier aims to emphasize that production technology heterogeneity exists among decision-making units (DMUs), which is determined by the intrinsic attributes of DMUs, such as region, type, and scale [17,18]. An evaluated object can be regarded as a DMU. Based on the sources of technology heterogeneity, all DMUs can be classified into several groups. Each group has an independent production frontier, called group frontier. A global production frontier can be constructed to include all group frontiers, called a metafrontier. Subsequently, the metafrontier concept is widely used in the studies of efficiency estimation [18–21]. Furthermore, logistics inefficiency is also broken down in this study.

The contributions to the literature are drawn into two aspects. First, this paper aimed to evaluate the logistics performance in China's regions with the consideration of technology heterogeneity and CO_2 emission. This may be the first attempt for the application of the logistics industry at the regional level based on the proposed metafrontier model. Besides, this study breaks down logistics inefficiency into technological inefficiency and managerial inefficiency. This provides new management implications for improving logistics performance.

The rest of this study is organized as follows. The literature review is introduced in Section 2. Section 3 presents the methodology of this study. An application of the proposed model in 30 regional logistics industries in China is given in Section 4. Section 5 summarizes conclusions, suggestions, and limitations.

2. Literature Review

Studies evaluating efficiency in the logistics industry are reviewed in this section. Generally, logistics efficiency evaluation research can be categorized into three classifications. The first classification employs the survey method to estimate the performance [22,23]. The most typical example is the global logistic performance index (LPI) survey employed by the World Bank, which is based on a worldwide survey of global freight forwarders and express carriers, providing feedback on the logistics "friendliness" of the countries in which they operate and those with which they trade [24].

The LPI focuses on estimating each country's logistics performance. The process of survey and estimation is complicated. Hence, it is not suitable for evaluating the efficiency of regional logistics industry within a country. The second classification adopts the production function method to assess performance [25–27]. Implementing the production function method needs the assumption of the production relationship between the inputs and the outputs in advance, which may be less reliable and reasonable for the complexity of the production operation in practice [28]. The third type is based on the data envelopment analysis (DEA) method to estimate logistics performance. The DEA method does not require modelling production function form or adding any parameter in the efficiency evaluation [29]. As a dominant nonparametric approach, DEA can construct a virtual optimal production frontier according to the original data and judge the relative performance of DMUs through measuring the distance away from the optimal production frontier [30]. As a result of these strengths, many academics have utilized the DEA method to investigate the efficiency issues within the logistics field [13,31–35]. According to the difference of research objects, the applications of the DEA method in the logistics industry can be categorized into two groups.

The first group investigated the operation efficiency of distribution centers or logistics companies. For instance, Ross and Droge [32] adopted the DEA method to measure the operational efficiency of distribution centers in a network of petroleum distribution facilities in the USA. The empirical study discovered three different causes of inefficiency, i.e., managerial effectiveness, the scale of operations and potential for a given market area, and resource heterogeneity. This paper also emphasized that different types of input–output and DEA models would yield different efficiency results. Hackman et al. [33] measured the operational efficiency of 57 warehouses and distributions in different industries in the USA. This article found that smaller warehouses tended to be more efficient than larger warehouses and that unionization may contribute to higher efficiency. Hamdan and Rogers [34] proposed a revised DEA model incorporating weight restriction and value judgment to measure the efficiency of 19 warehouses that were controlled by the same third-party logistics provider (3PL) in the USA in 2014. The proposed model can detect the impact of each input and output on the efficiency, providing management insights for the improvement of the efficiency. Similarly, Min and Joo [35] implemented the DEA model to estimate the operational performance of 3PLs with the consideration of financial factors in America and concluded that the long-term financial strength of 3PLs could impact on the performance. These studies analyzed the operation efficiency of specific logistics companies and distribution centers by DEA models at a microlevel and set the same benchmark for inefficiency DMUs for improving logistics performance. The technology heterogeneity of logistics production has not been discussed yet.

The second group focused on the performance measurement in the logistics industry in countries or regions. Representative samples are Markovits-Somogyi and Bokor [14] and Yu and Hsiao [15]. Markovits-Somogyi and Bokor [14] proposed an approach integrating DEA with the analytic hierarchy process to estimate the logistics efficiency of 29 countries and found that no correlation existed between the results obtained from the proposed model and the LPI. Yu and Hsiao [15] considered the heterogeneity of logistics technologies among countries and estimated the logistics efficiency of each country through the metafrontier DEA model. The empirical results were comparable to the LPI rankings and provided some management suggestions for the inefficient countries. Additionally, Tang et al. [12] proposed a parallel SBM approach for assessing the operational performance of the freight sector in China considering the internal industrial structure. This paper identified that the primary inefficiency source of the Chinese freight sector was the poor performance of the waterway subsector. These studies investigated the efficiency of the logistics industry at a macro level. Only Yu and Hsiao [15] took into account technology heterogeneity in the measurement of logistics efficiency at the country level. However, this issue at the regional level has not been investigated yet.

The majority of existing DEA studies on the logistics efficiency applied different models that took one production technology frontier as a benchmarking reference in the estimation. In practice, there exist essential differences in logistics technology with different economic and social conditions [15]. China covers a vast geographic area with 34 provincial regions, which have different levels of economic development. Hence, production technology heterogeneity exists in the regional logistics industry. According to the division of regional economic development degree by the National Development and Reform Commission of China [36], this paper classifies provincial regions into three areas, that is, east, central, and west, to estimate logistics efficiency with the consideration of the heterogeneity of production technology.

In the existing literature, the investigation on logistics efficiency evaluation at the regional level is still scarce. Chen [13] is an exception, who developed a new approach integrating DEA and Shannon entropy to measure logistics efficiency in China's regions in multiple contexts. Unfortunately, carbon emission is not taken into consideration in the measurement, which makes the evaluation insufficient for lacking environmental factors. Additionally, the work of Yang et al. [9] was similar to this study. This work explored the carbon emission performance in the logistics industry in Yunnan's sixteen cities in China, which focused on measuring carbon emission performance, instead of logistics efficiency. The production technology heterogeneity was also neglected. To this end, an efficiency evaluation extension for the regional logistics industry is investigated in this study.

3. Method

First, the indicators of inputs and outputs were determined to measure logistics performance. Following the description of this process, we propose a logistics efficiency evaluation approach based on the metafrontier SBM model with consideration of technology heterogeneity [19]. Besides, the inefficiency is further broken down from the dimensions of managerial inefficiency and technical inefficiency.

3.1. Input and Output Indicators

Before measuring logistics efficiency, the input and output indicators needed to be determined. It is worth noting that the indicators cannot be arbitrarily selected. Generally, the selection principle should follow production practice. In other words, the corresponding outputs can be yielded by utilizing or consuming some actual inputs.

Based on the operation practice of the logistics industry, five variables were adopted as inputs and outputs, which have been broadly used in the works of [9,19,28,37]. The three inputs (i.e., labor, capital, and energy) are the primary resources to provide logistics services [9,19]. One desirable output is freight turnover, referring to freight volume multiplied by the distance it has been transported [12,13]. Considering the importance of environmental protection in the logistics industry, energy-related CO_2 is taken as an undesirable output in the measurement [9,37,38]. The operational process of the logistics industry is exhibited in Figure 2.

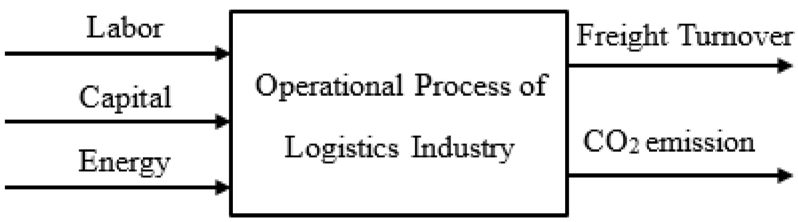

Figure 2. The operational process of the logistics industry.

3.2. Logistics Efficiency Evaluation Model

In this study, we assumed that there exist n DMUs, denoting the regional logistics industries. As shown in Figure 2, logistics production can be regarded as the process that utilizes the inputs of labor (XL), capital (XK), and energy (XE) to yield the outputs of freight turnover (YF) and carbon emission (YC). All DMUs can be categorized into h groups ($G_1, G_2, \ldots, G_h$).

The SBM model calculates the efficiency based on the measure of slacks. The slacks indicate the "input excess" and "output shortfall" of DMUs compared with the efficient DMU. The SBM model can find the maximum slacks to identify the inefficiency [39]. For this advantage, it has been broadly employed in performance evaluation [37,40]. Inspired by previous literature, a logistics efficiency evaluation model based on SBM-DEA under the group frontier can be constructed as:

$$\begin{aligned}
\rho_i \quad = \quad & \min\left(1-\frac{1}{3}\left(\frac{S_l^-}{XL_i}+\frac{S_k^-}{XK_i}+\frac{S_e^-}{XE_i}\right)\right)\Big/\left(1+\frac{1}{2}\left(\frac{S_f^+}{YF_i}+\frac{S_c^-}{YC_i}\right)\right) \\
\text{s.t.} \quad & \sum_{j=1}^{n}\lambda_j XL_j + S_l^- = XL_i, \\
& \sum_{j=1}^{n}\lambda_j XK_j + S_k^- = XK_i, \\
& \sum_{j=1}^{n}\lambda_j XE_j + S_e^- = XE_i, \\
& \sum_{j=1}^{n}\lambda_j YF_j - S_f^+ = YF_i, \\
& \sum_{j=1}^{n}\lambda_j YC_j + S_c^- = YC_i, \\
& \sum_{j=1}^{n}\lambda_j = 1, \\
& \lambda_j, S_l^-, S_k^-, S_e^-, S_f^+, S_c^- \geq 0, j = 1,2,\ldots,n.
\end{aligned} \tag{1}$$

In Equation (1), the objective function calculates ρ_i, which expresses the logistics efficiency score for DMU$_i$ with the range of {0, 1}. $s_l^-, s_k^-, s_e^-, s_f^+, s_c^-$ are the slacks corresponding to XL, XK,XE, YF, and YC, respectively. λ expresses the participation degree of each evaluated DMU. The constraint $\sum_{j=1}^{n}\lambda_j XL_j + s_l^- = XL_i$ represents the best solution to the labor input, belonging to a production frontier [41]. The following four constraints have similar meanings. The last constraint $\sum_{j=1}^{n}\lambda_j = 1$ represents Equation (1) is under the supposition of variable returns to scale. i expresses the evaluated DMU. It is worth noting that Equation (1) is nonlinear. It can be changed to a linear form:

$$\begin{aligned}
\rho_i \quad = \quad & \min\left(t-\frac{1}{3}\left(\frac{S_l^-}{XL_i}+\frac{S_k^-}{XK_i}+\frac{S_e^-}{XE_i}\right)\right) \\
\text{s.t.} \quad & t+\frac{1}{2}\left(\frac{S_f^+}{YF_i}+\frac{S_c^-}{YC_i}\right) = 1 \\
& \sum_{j=1}^{n}\eta_j XL_j + S_l^- = tXL_i, \\
& \sum_{j=1}^{n}\eta_j XK_j + S_k^- = tXK_i, \\
& \sum_{j=1}^{n}\eta_j XE_j + S_e^- = tXE_i, \\
& \sum_{j=1}^{n}\eta_j YF_j - S_f^+ = tYF_i, \\
& \sum_{j=1}^{n}\eta_j YC_j + S_c^- = tYC_i, \\
& \sum_{j=1}^{n}\eta_j = t, \\
& \eta_j, S_l^-, S_k^-, S_e^-, S_f^+, S_c^- \geq 0, j = 1,2,\ldots,n.
\end{aligned} \tag{2}$$

In Equation (2), t is a transform variable. The variables in the Equation (1) are changed as $\lambda t = \eta$, $ts_l^- = S_l^-, ts_k^- = S_k^-, ts_e^- = S_e^-, ts_f^+ = S_f^+, ts_c^- = S_c^-$. η_j, S_l^-, S_k^-, S_e^-, S_f^+, and S_c^- are the converted variables of λ_j, s_l^-, s_k^-, s_e^-, s_f^+, s_c^-, respectively. The optimal η_j^*, S_l^{-*}, S_k^{-*}, S_e^{-*}, S_f^{+*}, S_c^{-*}, and t^* are obtained for calculating the logistics efficiency ρ_i^*. If $\rho_i^* = 1$ and all slacks are equal to 0, the DMU_i would be evaluated as efficient.

The logistics efficiency evaluation model under the metafrontier is shown as follows:

$$
\begin{aligned}
\rho_i^{\mathrm{meta}} \quad & = \min\left(1 - \frac{1}{3}\left(\frac{S_l^{m-}}{XL_i^m} + \frac{S_k^{m-}}{XK_i^m} + \frac{S_e^{m-}}{XE_i^m}\right)\right) \Big/ \left(1 + \frac{1}{2}\left(\frac{S_f^{m+}}{YF_i^m} + \frac{S_c^{m-}}{YC_i^m}\right)\right) \\
\text{s.t.} \quad & \sum_{m=1}^{h}\sum_{j=1}^{n^m} \lambda_j^m XL_j^m + S_l^{m-} = XL_i^m, \\
& \sum_{m=1}^{h}\sum_{j=1}^{n^m} \lambda_j^m XK_j^m + S_k^{m-} = XK_i^m, \\
& \sum_{m=1}^{h}\sum_{j=1}^{n^m} \lambda_j^m XE_j^m + S_e^{m-} = XE_i^m, \\
& \sum_{m=1}^{h}\sum_{j=1}^{n^m} \lambda_j^m YF_j^m - S_f^{m+} = YF_i^m, \\
& \sum_{m=1}^{h}\sum_{j=1}^{n^m} \lambda_j^m YC_j^m + S_c^{m-} = YC_i^m, \\
& \sum_{m=1}^{h}\sum_{j=1}^{n^m} \lambda_j^m = 1, \\
& \eta_j^m, S_l^{m-}, S_k^{m-}, S_e^{m-}, S_f^{m+}, S_c^{m-} \geq 0, j = 1,2,\ldots,n^m, m = 1,2,\ldots,h.
\end{aligned} \tag{3}
$$

In Equation (3), m represents the group. For instance, XE_i^m expresses the XE of DMU_i in the group m. $\sum_{m=1}^{h}\sum_{j=1}^{n^m} \eta_j^m XE_j^m$ expresses the optimal XE under the metafrontier. The remaining variables have similar meanings in Equations (1) and (3). Following O'Donnell et al. [42], the models follow the important principle: T^m and T^{meta} express the production technologies under the group frontier and the metafrontier, respectively. For any group m, if $(XL, XK, XE, YF, YC) \in T^m$, then $(XL, XK, XE, YF, YC) \in T^{meta}$, $T^{meta} = \left\{T^1, T^2, \ldots, T^m\right\}$, and $m = 1,2,\ldots,h$. Similarly, the nonlinear Equation (3) can be transformed into a linear model:

$$
\begin{aligned}
\rho_i^{\mathrm{meta}} \quad & = \min\left(t^m - \frac{1}{3}\left(\frac{S_l^{m-}}{XL_i^m} + \frac{S_k^{m-}}{XK_i^m} + \frac{S_e^{m-}}{XE_i^m}\right)\right) \\
\text{s.t.} \quad & t^m + \frac{1}{2}\left(\frac{S_f^{m+}}{YF_i^m} + \frac{S_c^{m-}}{YC_i^m}\right) = 1, \\
& \sum_{m=1}^{h}\sum_{j=1}^{n^m} \eta_j^m XL_j^m + S_l^{m-} = t^m XL_i^m, \\
& \sum_{m=1}^{h}\sum_{j=1}^{n^m} \eta_j^m XK_j^m + S_k^{m-} = t^m XK_i^m, \\
& \sum_{m=1}^{h}\sum_{j=1}^{n^m} \eta_j^m XE_j^m + S_e^{m-} = t^m XE_i^m, \\
& \sum_{m=1}^{h}\sum_{j=1}^{n^m} \eta_j^m YF_j^m - S_f^{m+} = t^m YF_i^m \\
& \sum_{m=1}^{h}\sum_{j=1}^{n^m} \eta_j^m YC_j^m + S_c^{m-} = t^m YC_i^m, \\
& \sum_{m=1}^{h}\sum_{j=1}^{n^m} \eta_j^m = t^m, \\
& \eta_j^m, S_l^{m-}, S_k^{m-}, S_e^{m-}, S_f^{m+}, S_c^{m-} \geq 0, j = 1,2,\ldots,n^m, m = 1,2,\ldots,h.
\end{aligned} \tag{4}
$$

The efficiency value calculated by Equation (1) is based on the group frontier, denoted as *GLE* (group frontier logistics efficiency), while the efficiency value obtained from Equation (3) is based on the metafrontier, denoted as *MLE* (metafrontier logistics efficiency). Both efficiency values are between 0 and 1. If the region has a higher efficiency value than other regions, it indicates this region performs better in the logistics industry than other regions do.

Referring to O'Donnell et al. [42], the technology gap ratio (*TGR*) for logistics efficiency between the group frontier and the metafrontier can be calculated by the following equation:

$$TGR_i = MLE_i/GLE_i. \tag{5}$$

MLE_i and GLE_i are evaluated independently based on the metafrontier and the group frontier. The production technology of the latter is a subset of the former. Hence, $MLE_i \leq GLE_i$ is permanently valid and *TGR* is in the range of {0, 1}. *TGR* reflects the technology gap of logistics production between two frontiers. The closer the *TGR* is to 1, the smaller the technology heterogeneity, indicating that the logistics efficiency under the group frontier is closer to that under the metafrontier. The closer the *TGR* is to 0, the greater the technology heterogeneity, implying that the logistics efficiency under the group frontier is farther from that under the metafrontier [43].

3.3. Decomposition of Logistics Inefficiency

As mentioned, GLE_i and MLE_i are measured under two frontiers. The difference represented by *TGR* provides valuable implication concerning the source of logistics inefficiency. Referring to the work of [44], The logistics inefficiency based on the metafrontier (*MLI*) could be further broken down into two indicators: technological inefficiency (*TGI*) and group frontier managerial inefficiency (*GMI*). *TGI* represents the loss of logistics efficiency deriving from the technology gap between the two frontiers. This efficiency loss is mainly caused by technological differences, which can be measured as follows:

$$TGI_i = GLE_i \times (1 - TGR_i). \tag{6}$$

GMI expresses the loss of logistics efficiency based on the group frontier. In general, the DMUs in the same group have the same or similar logistics production technology. Consequently, the loss of logistics efficiency under the group frontier is mainly derived from the ill management issue rather than production technology, which is expressed as follows:

$$GMI_i = 1 - GLE_i. \tag{7}$$

Finally, the entire logistics inefficiency can be measured by aggregating MLE_i and GLE_i, which is expressed as follows:

$$MLI_i = TGI_i + GMI_i. \tag{8}$$

Figure 3 shows the general concepts of the measure of logistics efficiency, which considers three groups. These group frontiers are under the metafrontier. For instance, DMU A belongs to Group 2. Point A shows that the logistics efficiency of DMU A is measured based on the group frontier 2. The measures of logistics efficiency based on the metafrontier and the group frontier are $MLE = OF/OD$ and $GLE = OE/OD$, respectively. The *TGR* can be described as $TGR = OF/OE$. The technological inefficiency and managerial inefficiency are measured as $TGI = FE/OD$ and $GMI = ED/OD$. The logistics inefficiency under the metafrontier is $MLI = TGI + GMI = FD/OD$.

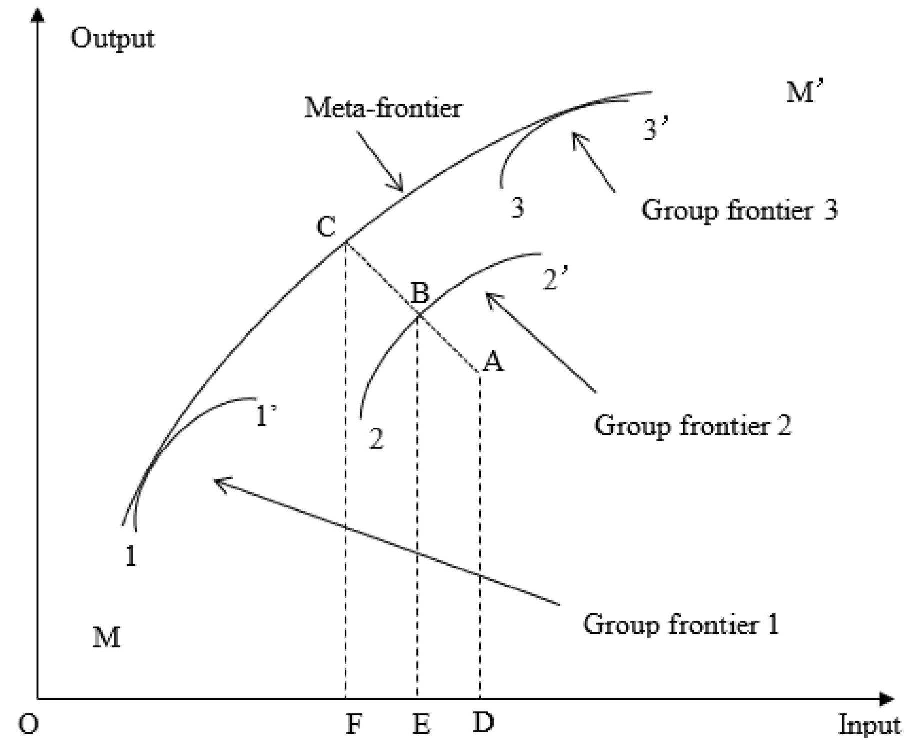

Figure 3. General concepts for measuring logistics efficiency.

4. Empirical Study

This study used the proposed model to measure logistics efficiency in China at the regional level from 2011 to 2017. Furthermore, logistics inefficiency was broken down and analyzed for the improvement of logistics performance.

4.1. Data Set

There exist 31 provincial-level administrative regions in mainland China, which can be categorized into three areas, as shown in Table 1. Due to lacking the data of Tibet, only 30 regions were taken as samples in this study.

Table 1. The classification of provincial regions in mainland China.

Area	Regions
East	Beijing, Guangdong, Shanghai, Hebei, Liaoning, Zhejiang, Fujian, Shandong, Hainan, Tianjin, Jiangsu
Central	Hunan, Shanxi, Henan, Heilongjiang, Anhui, Jiangxi, Hubei, Jilin
West	Ningxia, Guizhou, Tibet, Qinghai, Shaanxi, Xinjiang, Sichuan, Inner Mongolia, Chongqing, Guangxi, Gansu, Yunnan

As mentioned above, this paper considered three inputs (labor, capital, energy) and two outputs (freight turnover, CO_2 emission) for the measurement of logistics efficiency. Given that there exist no specialized and completed statistics in China's logistics industry, this study used the sample data of the transport, storage, and post sectors to evaluate regional logistics efficiency. This is a common practice in the studies on China's logistics industry issues, which can be witnessed in many works, such as [9,13,45].

Labor refers to the number of employed persons at the end of the year.

Capital refers to the accumulated fixed asset that provides essential support for logistics activities. However, official data on the capital of the regional logistics industry in China do not exist. Following Liu and Lin [19], this study estimated capital with the perpetual inventory method [46]. The method of estimating capital is as follows:

$$K_t = I_t / p_t + (1 - \delta) \times K_{t-1}. \quad (9)$$

In Equation (9), I_t expresses the fixed asset investment in period t, p_t represents the price indices of investment in fixed assets in period t, δ represents the depreciation rate, K_t and K_{t-1} express the capital in period t and period $t-1$. Following Liu and Lin [19], we also used each province's fixed asset investment in the logistics industry in 2004 as the initial capital and set the depreciation rate as 6.9%. The data of labor, fixed asset investment, and price indices were derived from the China Statistical Yearbooks 2012–2018 [47]. Additionally, capital was transformed into a constant price for the year 2011 to remove the inflation impact.

Energy refers to the energy consumed in the process of freight transport, which is the main energy consumer in the logistics industry. The data were obtained based on the unit energy consumption statistics for freight turnover, which were published by the National Railway Administration and the Ministry of Transport of China [48,49]. We measured the energy through multiplying freight turnover by the unit energy consumption.

Freight turnover is a vital output in the logistics industry, representing the actual completed logistics tasks. The data of freight turnover were also collected from the China Statistical Yearbooks 2012–2018.

It is also worth noting that there exist no statistics on CO_2 emission in China's provincial logistics industry. Consequently, this study calculated CO_2 emission based on the fuel-based carbon footprint method. This method has been widely employed in the literature, e.g., Wu et al. [28] and Liu et al. [37]. The descriptive statistics of all indicators are listed in Table 2 for the years 2011, 2014, and 2017 to provide a simple illustration.

Table 2. Descriptive statistics.

Year.	**Variable.**	***XL***	***XK***	***XE***	***YF***	***YC***
Unit		10^4 People	10^8 CNY [1]	10^4 TCE [2]	10^8 Ton-km	10^4 Tons
2011	Max	59.62	7134.82	1702.35	20,309.56	3617.72
	Min	3.13	427.66	67.64	486.38	143.74
	Mean	21.24	3051.34	508.50	4951.01	1080.64
	Std. Dev.	13.37	1564.37	445.04	4528.23	945.77
2014	Max	85.40	10,916.05	1673.01	18,633.36	3555.37
	Min	3.94	690.58	67.35	506.94	143.13
	Mean	28.68	4840.31	529.77	5494.66	1125.84
	Std. Dev.	17.99	2502.84	427.95	4820.55	909.46
2017	Max	83.33	16,093.54	1635.73	27,919.79	3476.15
	Min	3.75	1236.84	33.11	519.46	70.36
	Mean	28.10	7520.92	514.95	6322.44	1094.34
	Std. Dev.	17.29	3891.30	404.70	6628.16	860.04

Notes: [1] CNY stands for China Yuan, the official currency in China; [2] TCE stands for ton of standard coal equivalent.

4.2. Metafrontier Logistics Efficiency Analysis

In this subsection, the logistics efficiencies under the metafrontier and group frontier in each year were measured using a previously developed approach. The average logistics efficiencies during 2011–2017 are provided in Table 3.

Table 3. Average logistics efficiencies during 2011–2017.

Region	*MLE*	*GLE*	Region	*MLE*	*GLE*
Beijing	0.3095	0.3976	Hubei	0.2775	1.0000
Tianjin	0.6606	0.6606	Hunan	0.2544	0.7205
Hebei	0.5559	0.8084	Inner Mongolia	0.3157	1.0000
Liaoning	0.4919	0.5174	Guangxi	0.3124	0.9655
Shanghai	1.0000	1.0000	Chongqing	0.3036	1.0000
Jiangsu	0.3580	0.3580	Sichuan	0.1650	0.4066
Zhejiang	0.4701	0.4766	Guizhou	0.3151	0.6785
Fujian	0.3890	0.3890	Yunnan	0.2222	0.4412
Shandong	0.2643	0.2649	Shaanxi	0.2572	0.7178
Guangdong	0.4966	0.4966	Gansu	0.4442	1.0000
Hainan	1.0000	1.0000	Qinghai	1.0000	1.0000
Shanxi	0.3025	1.0000	Ningxia	1.0000	1.0000
Jilin	0.2617	1.0000	Xinjiang	0.2986	0.6242
Heilongjiang	0.2313	1.0000	East area	0.5451	0.5790
Anhui	0.8464	1.0000	Central area	0.3458	0.9214
Jiangxi	0.3185	1.0000	West area	0.4213	0.8031
Henan	0.2741	0.6506	All	0.4465	0.7525

Here, we took Henan province as an illustration example. The average logistics efficiency of Henan under the group frontier was 0.6506 during the observed period. This means that the improvement potential of logistics performance in Henan was 34.94%, taking the optimal production technology in the central area as a reference. Based on the metafrontier, the average logistics efficiency of Henan was 0.2741. It indicates that Henan has an improvement room of 72.59% based on the optimal production technology in all areas. Obviously, it is greater than the prior value obtained under the group frontier. The situations of most provinces were analogous to Henan. This is because the metafrontier was constructed on the basis of the data of all DMUs, enveloping all group frontiers. In this case, the optimal technological level under the metafrontier cannot be lower than that under the group frontier determined by group DMUs. The eastern provinces, Shanghai and Hainan, had highest logistics efficiencies under two frontiers. It reflects that these two provinces had the best logistics operation within the area and nationwide.

It was found that the average logistics efficiency of the national level was 0.4465. This signifies that China's regional logistics efficiency was low during 2011–2017. Besides, there existed significant regional disparities in China's logistics industry. Under the metafrontier, it was discovered that the east area had the greatest efficiency (0.5451), the west area was second (0.4213), and the central area was the least efficient (0.3458). To specific regions, the average logistics efficiencies of Shanghai and Hainan were 1.0000, tied for the first place in the east area. The average efficiency of Anhui was 0.8464, which ranked first in the central area. The average efficiencies of Qinghai and Ningxia were 1.0000, which were the top two in the west area. The efficiencies of most provinces were less than the national level. These inefficient provinces should address improving logistics performance, especially of Heilongjiang, Sichuan, and Yunnan.

As shown in Figure 4, logistics efficiencies under the metafrontier were rising slowly in the whole country during the observed period. Overall, the logistics efficiency at the national level increased from 0.4109 in 2011 to 0.4449 in 2017. The efficiency was presented at the regional level as follows: in the east and central areas, it rose from 0.5074 to 0.5889, and from 0.2668 to 0.2975 respectively, while in the west area it slightly reduced from 0.4191 to 0.4081.

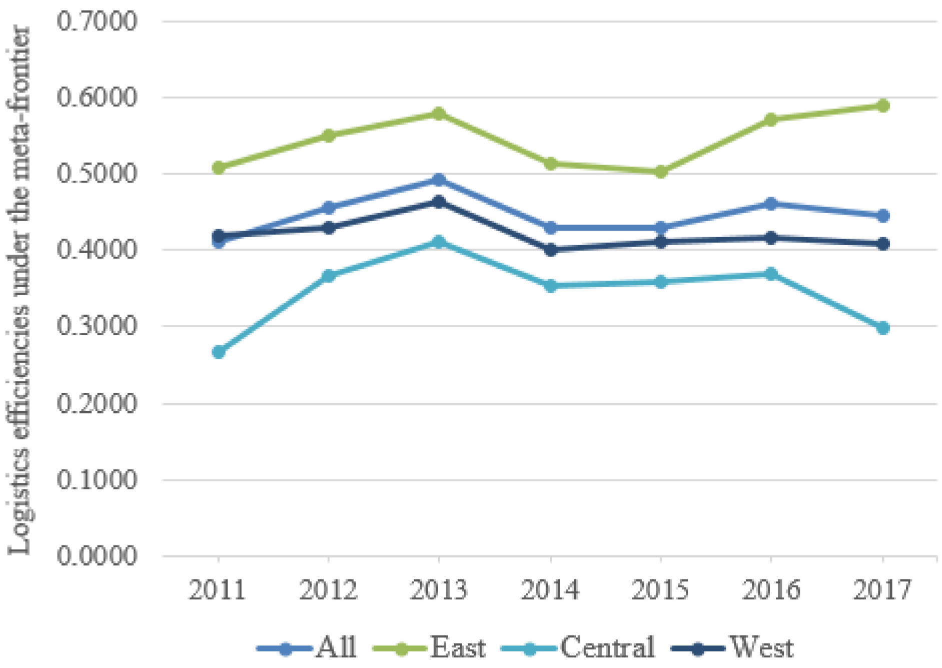

Figure 4. Logistics efficiencies in the three areas.

Given that different groups have different production frontiers, it is meaningless to compare the logistics efficiencies based on the group frontier between the provinces in the different groups. Only provinces in the same group could be compared meaningfully. As shown in Table 3, under the separate group frontiers, the logistics efficiencies of the east area, central area, and west area were 0.5790, 0.9214, and 0.8031, respectively. The distribution of logistics efficiencies indicates that the differences between the eastern regions were the largest, followed by the western regions and the central regions. To regions, Shanghai and Hainan were at the east group frontier. Shanxi, Jilin, Heilongjiang, Anhui, Hubei, and Jiangxi were on the central group frontier. Inner Mongolia, Chongqing, Qinghai, Gansu, and Ningxia were on the west group frontier.

Compared with the other two group frontiers, the east group frontier was the closest to the metafrontier. Nevertheless, the logistics efficiency under the group frontier of the east area was low. The main reason for this was that the efficiencies of the eastern regions were scattered. In contrast, the central group frontier was farthest from the metafrontier. Although the efficiencies under the metafrontier were low, the central regions had higher scores under the group frontier because of their relatively concentrated distribution. The efficiency value of the west area was between the east area and the central area. This phenomenon can be explained from the view of technology gap ratio.

Based on Equation (5), *TGR* can be measured. Figure 5 portrays the dynamic change of the *TGR* values in the three areas from 2011 to 2017.

As shown in Figure 5, the *TGR* value of the east area was greater than the values of the central area and the west area, which remained above 0.9000 during the observed period. This indicates that the east area possessed the best logistics production technology. The reason for this is that most eastern regions were at a relatively high level of economic development, investing massive resources in the logistics industry. These investments have brought developed logistics networks, advanced management systems, and technology applications. This is in line with the finding that the eastern provinces have higher efficiencies under the metafrontier mentioned above. The *TGR* value of the west area lagged behind the east area, though it kept ahead of the central area. Therefore, the two lagging areas need to improve the production technology level for the improvement of logistics performance.

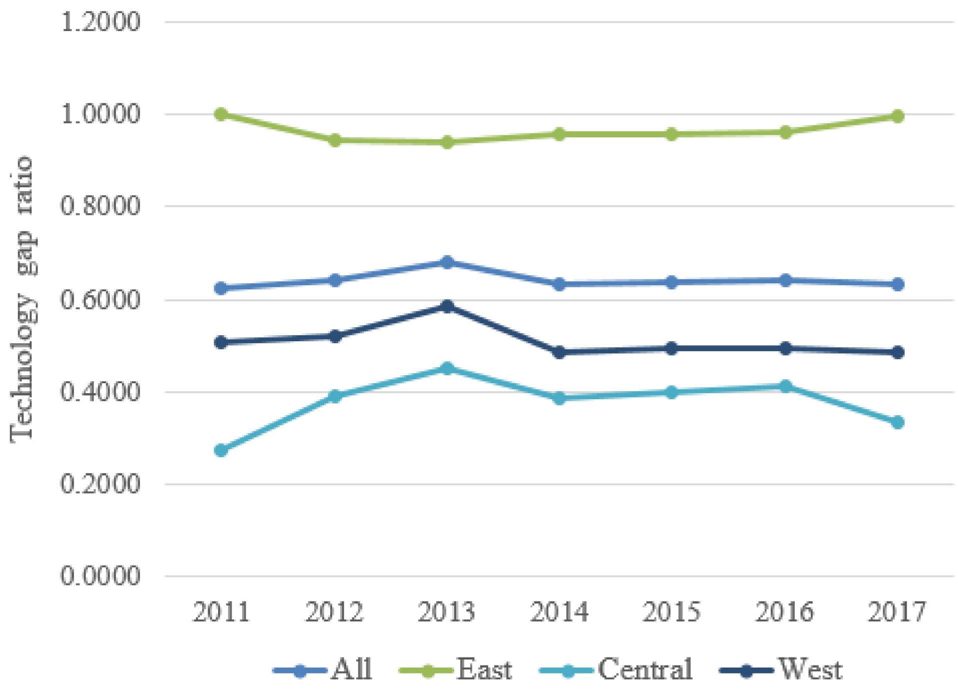

Figure 5. Technology gap ratio in the three areas.

4.3. *Provincial Logistics Inefficiency Analysis*

In this study, logistics inefficiency can be further broken down into *TGI* and *GMI*, which are measured based on Equations (6) and (7). Table 4 shows the results of *TGI* and *GMI*. Here, Hunan province is taken as an illustration example. The logistics inefficiency of Hunan was 0.7456, of which *TGI* was 0.4661 and *GMI* was 0.2795. The *GMI* was greater than the *TGI* in Hunan. It shows that the technology gap was the primary reason for the loss of logistics efficiency. In some provinces, the management issue was the main factor for the loss of logistics efficiency, e.g., Sichuan province in the west area. Notably, Shanghai, Hainan, Qinghai, and Ningxia were regarded as efficient under both frontiers. Hence, the values of *TGI* and *GMI* in these four provinces were equal to 0.

Table 4. Decomposition of logistics inefficiencies for regions.

Region	*TGI*	*GMI*	Region	*TGI*	*GMI*
Beijing	0.0881	0.6024	Hubei	0.7225	0.0000
Tianjin	0.0000	0.3394	Hunan	0.4661	0.2795
Hebei	0.2525	0.1916	Inner Mongolia	0.6843	0.0000
Liaoning	0.0256	0.4826	Guangxi	0.6531	0.0345
Shanghai	0.0000	0.0000	Chongqing	0.6964	0.0000
Jiangsu	0.0000	0.6420	Sichuan	0.2417	0.5934
Zhejiang	0.0065	0.5234	Guizhou	0.3634	0.3215
Fujian	0.0000	0.6110	Yunnan	0.2190	0.5588
Shandong	0.0006	0.7351	Shaanxi	0.4606	0.2822
Guangdong	0.0000	0.5034	Gansu	0.5558	0.0000
Hainan	0.0000	0.0000	Qinghai	0.0000	0.0000
Shanxi	0.6975	0.0000	Ningxia	0.0000	0.0000
Jilin	0.7383	0.0000	Xinjiang	0.3256	0.3758
Heilongjiang	0.7687	0.0000	East area	0.0339	0.4210
Anhui	0.1536	0.0000	Central area	0.5756	0.0786
Jiangxi	0.6815	0.0000	West area	0.3818	0.1969
Henan	0.3765	0.3494	All	0.3059	0.2475

Based on the metafrontier, the logistics efficiency of the east area was 0.5451 and the inefficiency is 0.4549. The values of *TGI* and *GMI* were 0.0339 and 0.4210. This indicates that managerial inefficiency was the main reason for logistics efficiency loss and the inefficiency induced by the technology gap was negligible. On the contrary, the logistics inefficiencies of the central area and the west area caused by the technology gap were 0. 5756 and 0.3818, while the contribution degrees of ill management for the inefficiencies were small, i.e., 0.0786 and 0.1969. Generally, the lags in technology and management caused the logistics inefficiencies in these two areas.

As a whole, technology gap and poor management were two critical factors for the efficiency loss in China's logistics industry. For future improvement of logistics performance, the efforts should be made in two aspects. First, it is essential to upgrade the production technologies (e.g., artificial intelligence and big data analysis) continuously for the utilization of logistics resources and intensify the promotion of energy-saving equipment in the logistics sector of all provinces to narrow the technology gap among regions. Second, it is necessary to enhance the management of logistics resource, transportation capacity, and practitioners.

4.4. Discussion

According to the empirical findings, some management implications can be acquired. As a whole, the logistics inefficiencies have been discerned to spread across most of China's regions, showing a significant region disparity. This implies that logistics efficiency improvement policies may not be suitable for all regions identically. Regional disparity should be considered in the improvement of logistics efficiency at the national level. Different regions have various performances, which should be treated differently. For regions that are evaluated as efficient, it is unnecessary to invest excessive resources to improve logistics performance. More financial funds for the logistics industry from the central government should be allocated to the inefficient regions. In this way, the development of the logistics industry in the east, central, and west area could be balanced.

Based on the logistics inefficiency decomposition results, managerial inefficiency was the main reason for the logistics inefficiency in the east area, while technological inefficiency was mainly responsible for the efficiency loss in the central area. For the west area, the impact of technological inefficiency on the logistics inefficiency was more significant than that of managerial inefficiency. This provides a managerial insight that the local government should formulate more specific policies based on the causes of local logistics inefficiency. The results suggest that managerial improvement may have a more positive impact on increasing logistics performance for most eastern regions, while technological improvement plays a more significant role for the central and western regions.

A new vision was explored in this study based on the efficiency analysis. In general, the national benchmark is targeted to increase logistics efficiency for inefficient regions [13]. This study suggests that regional logistics inefficiency should be reinforced first to achieve the group benchmark target, then the national benchmark target. Due to the disparities in economic, social, and geographical conditions, there exists technical heterogeneity in logistics production in different regions. The performance improvement in the inefficient regions based on the optimal production level nationwide cannot be achieved in the short term. Therefore, the inefficient region should first enhance logistics efficiency based on the group benchmark.

5. Conclusions

The improvement of logistics performance is a crucial way to decrease logistics costs and alleviate the excessive growth of CO_2 emission. The significant disparities in the level of economic development among China's provinces induce the technology heterogeneity in logistics production. Considering technology heterogeneity and carbon emission, this study developed a metafrontier SBM approach for the estimation of logistics efficiency. An application of the proposed approach in China's logistics industry was also shown at the regional level.

Under the group frontier, the logistics efficiency was measured with the consideration of technology heterogeneity, which shows the available improvement potential in the group context. Under the metafrontier, the logistics efficiency mirrors the improvement room based on the best production technology in the global context. Specifically, Shanghai, Hainan, Qinghai, and Ningxia displayed high logistics operational performances under two frontiers. Some provinces, such as Anhui, Jiangxi, Inner Mongolia, and Chongqing, showed high efficiencies based on the group frontier, while low efficiencies based on the metafrontier.

Overall, China's logistics efficiency was still at a low level. The logistics efficiency of the east area was the highest, followed by the west area, and the central area. In addition, the technology gap ratio values of the three areas presented significant disparities. The east area was the leader with better production technologies for the utilization of logistics resource nationwide. The west area ranked second, and the central area was the last. This can be explained by the fact that the logistics industries in the eastern regions have invested many resources and used more advanced production technology. Technological inefficiency and managerial inefficiency were the two sources for the loss of logistics efficiency in China. The effect of managerial inefficiency was significant in the east area, while the impact of technical inefficiency was dominant in the central area and the west area.

Based on the findings, some policy suggestions could be obtained. Firstly, the improvement strategy of logistics efficiency at the regional level should obey the rule of "common but differentiated". This is necessary as there exist significant differences in logistics performance among the three areas and provinces. Therefore, the potential performance improvement for each region is different. The government should consider not only the national condition but also the reality in specific regions, and then develop reasonable policies for enhancing the logistics performance. The central and west areas should be paid more attention due to their low logistics efficiencies. For inefficient provinces, the logistics efficiency improvement should be managed to achieve the areal target first and then the national target.

Secondly, based on the source of logistics inefficiency, the east area should focus on improving management capacity to weaken logistics inefficiency, while the central area should highlight the way of improving the technology level. The west area should strive in both aspects for the improvement of logistics efficiency. For instance, considering the contribution of managerial inefficiency, most eastern provinces, such as Shandong, Jiangsu, and Fujian, should develop the managerial level of the logistics industry by providing financial support. Anhui and Jiangxi should improve the technical level of the logistics industry, while Shaanxi and Guizhou should make efforts to improve the managerial and technical level and achieve a balance between them. If the policy cannot aim at an improvement emphasis, it may trigger resource misallocation, ultimately leading to resource waste and unsatisfactory effectiveness.

Thirdly, regional cooperation should be strongly advocated in China's logistics industry. In this case, the advanced logistics technology and management experience can be spread quickly. The policymakers in logistics administering authority in the central area and the west area can learn the industrial management experience from the east area. Additionally, the local government should create favourable conditions for regional cooperation, such as guiding business communication among logistics enterprises in different regions. This cooperation can not only make enterprises learn the operational experiences from each other and share logistics resources, but also promote industrial innovation, thus improving the holistic logistics performance.

It is worth noting that this paper still has some limitations. Firstly, this paper did not consider certain pollutants (e.g., sulfur dioxide and nitrogen oxides) that are emitted in the logistics industry. A study with the consideration of these pollutants can provide a better environmental vision on the estimation of logistics performance. Besides, the observation dataset for the empirical study was from the period 2011–2017. More management perceptions in heightening logistics performance may be acquired in a study with a longer observed data sample. Finally, the empirical dataset has a limitation. In this study, the statistics of labor and capital inputs were based on the whole logistics industry, while energy input only considered the consumption of the transport activities. The energy consumption (e.g., electricity), output (e.g., throughput), and carbon dioxide emission of warehousing activities were not taken into account in the measurement due to lack of relevant data. If the official statistics of these indicators are available in the future, the evaluation results for regional logistics efficiency would be more accurate. The above-mentioned research extensions can be further explored.

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