Research Looking at Geographical Differences When Measuring Distribution Efficiency in China

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Abstract. As a pioneer industry of the national economy, the Distribution industry can guide China's consumption and investment, and the Distribution efficiency can effectively reflect the construction effect of China's Distribution system, which is of great significance to China's economic development. Based on this, this paper uses the MinDW-MML index model to measure China's DCE based on the data of 30 provinces (cities) from 2004 to 2020, and the results show that (1) China's DCE shows an overall upward trend, and its growth mainly relies on technological progress. (2) DCE has obvious spatial differences, and the eastern region has obvious advantages in technology and talent. (3) DCE under the common frontier is lower than that under the group frontier. based on the above findings, targeted policy recommendations are proposed for each region to improve DCE, considering the actual national conditions of China.

Keywords: scale difference, distribution industry, distribution efficiency, MinDW-MML model

1 Introduction

The distribution industry is a link between production and consumption, and the basic situation of commodity distribution has significant differences in the phenomenon[1]. Different regions have obvious heterogeneity in infrastructure development, labor quality, pillar industries, capital investment, and urbanization level. This paper applies the MinDW-MML (Minimum distance to weak efficient frontier-Metafrontier Malmquist Luenberger) model to comprehensively evaluate the change of total factor productivity of China's distribution efficiency from 2004 to 2020 under the condition of considering scale heterogeneity, which is important for the development of China's commodity distribution industry and the improvement of distribution efficiency.

The second part of this paper introduces the research of related literature, the third part presents the theoretical foundation and data description, mainly including indicator selection and data sources, the empirical analysis is in the fourth part, and the conclusion and policy recommendations are in the fifth part.

Y. Jiao et al. (eds.), *Proceedings of the 3rd International Conference on Internet Finance and Digital Economy (ICIFDE 2023)*, Atlantis Highlights in Economics, Business and Management 1,
https://doi.org/10.2991/978-94-6463-270-5_56

2 Review of the literature

Marx on the capital economy details the capital circuit of commodity production and Distribution, arguing that capital as private wealth generates internal conflicts with socio-economic activities and is detrimental to capital Distribution and industry development[2]. And Distribution efficiency is considered to be in the same direction as resource allocation efficiency, if resource allocation efficiency is high then Distribution efficiency must be high[3].

For the methods of Distribution efficiency measurement, most of the existing research methods focus on the stochastic frontier production function (SFA) method, total factor productivity (TFP), Divisia index method, DEA method, etc. Kendrick (1961), through his study of economic growth in the United States, found that the growth of efficiency in the service sector relies mainly on the input of capital and labor factors[4]. Gouyette and Perelman (1997), and Mahadevan (2000) use the SFA approach to measure total factor productivity in the services sector for OECD countries and Singapore, respectively, and argue that rising growth rates in the distribution sector are necessary to maintain high productivity growth rates in the future[5][6]. Espoir and Ngepah (2021) examine data from 1990-2014 across countries and find a consistent pattern where low productivity inhibits total factor productivity growth[7]. Based on this, the text uses the MinDW model to measure distribution efficiency

In summary, the innovations of this paper are mainly reflected in the following three aspects: (1) The data selected in this paper has a larger time span and newer years than the data of previous studies, which can more accurately evaluate the current situation of circulation efficiency in China. (2) In terms of research methodology, this paper considers regional heterogeneity and constructs the MinDW model based on a common frontier to evaluate different scale DCE. (3) In terms of research perspectives, this paper analyzes and evaluates China's circulation efficiency in time and space, compares circulation efficiency horizontally and vertically, and highlights the circulation efficiency pull factors in different regions.

3 Methodology

3.1 Minimum distance to the weak efficient frontier

Data envelopment analysis (DEA) is a non-parametric approach that evaluates numerous inputs and outputs. According to Briec (1999), a MinDW model can be created in this article if each production system consists of n DMUs, each of which contains m input variables denoted x and p output variables denoted y. $m + n$ linear programming (m is the number of input indicators and n is the number of output indicators)[8].

$$max\, \beta_z, z = 1,2, \dots, m + n \tag{1}$$

$$s.t. \quad \sum_{j=1}^{p} \alpha_j x_{ij} + \beta_z e_i \le x_{ik}, i = 1,2, \dots, m$$

$$\sum_{j=1}^{p} \alpha_j y_{rj} - \beta_z e_r \ge y_{rk}, r = 1,2, \dots, n \tag{2}$$

$$\alpha \geq 0$$

3.2 Metafrontier-Malmquist-Luenberger index

The traditional DEA model assumes that "all DMUs do not have a group relationship" and is uniform across all regions. By using Oh (2010) method[9], the global reference set established in this article is:

$$Q^G(x) = Q^1(x^1) \cup Q^2(x^2) \cup \ldots \cup Q^T(x^T) \tag{3}$$

$$Q^t(x^t) = \{(y^t) | x^t \; can \; produce(y^t)\} \tag{4}$$

The result of the MML index is MI, and the value of MI is the DCE. The circulation efficiency indicator under the common border and the intergroup frontier are respectively the common frontier as follows:

$$metaMI_{t-1}^t = \sqrt{\frac{1-D_{t-1}^m(x^t,y^t;y^t)}{1-D_{t-1}^m(x^{t-1},y^{t-1};y^{t-1},)} \times \frac{1-D_t^m(x^t,y^t;y^t)}{1-D_t^m(x^{t-1},y^{t-1};y^{t-1})}} \tag{5}$$

$$groupMI_{t-1}^t = \sqrt{\frac{1-D_{t-1}^g(x^t,y^t;y^t)}{1-D_{t-1}^g(x^{t-1},y^{t-1};y^{t-1})} \times \frac{1-D_t^g(x^t,y^t;y^t)}{1-D_t^g(x^{t-1},y^{t-1};y^{t-1})}} \tag{6}$$

3.3 Data and variables

Based on the existing literature, this paper uses the wholesale and retail trade and the transportation, storage, and postal industry to represent the distribution industry, and a total of eight indicators are selected to construct the input-output indicator system as follows.

Input variables.

(1) Employment of urban collective units in wholesale and retail trade (10,000 people)

(2) Urban collective unit employment in transportation, storage, and postal and telecommunication industry (10,000 people)

(3) Capital investment in the wholesale and retail industry (billion yuan)

(4) transportation, storage, and postal industry capital investment (billion yuan)

(5) the length of transport routes (10,000 km)

Output variables.

(1) Total retail sales of social consumer goods (tens of billions of yuan)

(2) Wholesale and retail trade value added (billion yuan)

(3) added value of transportation, storage, and postal industry (billion yuan)

Due to the serious data deficiency in Xinjiang Production and Construction Corps, Taiwan, Hong Kong, and Macao, 30 provinces in China were selected as the sample for the study.

4 Empirical Study and Analysis

4.1 Analysis of the overall change of Distribution of commodities effectively DCE (MI) Nationwide

The DCE and its decomposition indicators TC and EC for the three scales of the composite total factor productivity index of change (MI) for 2004-2020 are shown in Table 1 below. As shown in Figure 1, under the common frontier, China's DCE has been fluctuating around 1. From 2004 to 2005, 2008 to 2009, and 2011 to 2013, DCE declined three times, with the last decline being the largest at -6.24% and the first decline being the smallest at -1.30%.

Table 1. DCE and its decomposition index from 2004-2020

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
MetaMI	1.0002	0.9872	1.0012	1.0246	1.0313	1.0137	1.0285	1.0296	0.9817	0.9661	1.0127	1.0078	1.0275	1.0366	1.0377	1.0206	1.0125
MetaEC	0.9989	1.0065	1.0010	1.0062	1.0012	0.9972	1.0047	0.9962	1.0020	1.0053	0.9999	1.0011	0.9935	1.0046	1.0018	1.0051	0.9965
MetaTC	1.0014	0.9809	1.0002	1.0185	1.0302	1.0161	1.0238	1.0335	0.9796	0.9611	1.0128	1.0065	1.0341	1.0317	1.0358	1.0154	1.0160
GroupMI	1.0135	0.9826	0.9881	1.0368	1.0580	1.0290	1.0468	1.0380	0.9906	0.9573	1.0100	1.0099	1.0359	1.0554	1.0671	1.0653	1.0101
GroupEC	1.0017	1.0058	0.9986	0.9995	0.9995	1.0028	1.0018	0.9988	1.0005	1.0015	0.9980	0.9998	0.9999	1.0000	0.9957	1.0010	0.9996
GroupTC	1.0119	0.9768	0.9895	1.0373	1.0585	1.0261	1.0450	1.0392	0.9899	0.9559	1.0120	1.0100	1.0361	1.0554	1.0715	1.0642	1.0104

The extreme values over the 17 years occurred in 2008 (1.0313) and 2018 (1.0377), and the minimum value occurred in 2013 (0.9661). Both DCE (MI) and TC peaked in 2018, with a 0.10% increase in DCE and a 0.40% increase in TC under the common frontier, after 2018 DCE is showing a downward trend again. The DCE of China in 2020 is 1.0125, a decrease of 0.80%, which is a small value, but still indicates the decrease of DCE of commodity distribution efficiency due to the slowdown of COVID-19 on China's national economic growth.

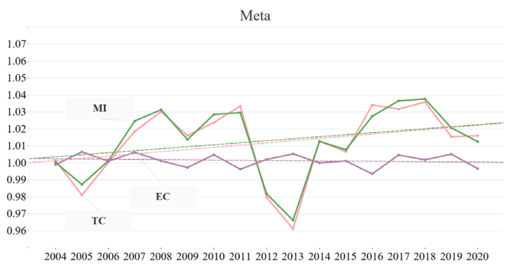

Fig. 1. DCE and its decomposition index under meta-frontier from 2004-2020

The three-scale integrated DCEs under the cluster frontier (scale frontier) for 2004-2020 are shown in Figure 2. From Figure 1 and Figure 2, it can be found that the overall fluctuation trends under the common frontier and cluster frontier are the same, and the fluctuation magnitude is somewhat larger under the common frontier. The fluctuation trend of DCE under the cluster frontier is the same as that under the common frontier, but the peaks are different.

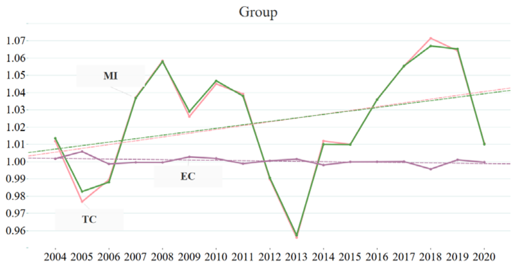

Fig. 2. DCE and its decomposition index under group-frontier from 2004-2020

4.2 Analysis of the change of DCE in different regions

The combined DCEs of the three scales under the common frontier and the scale frontier are shown in Figure 3. In general, the DCE under the cluster frontier is higher than that under the common frontier. in terms of individual provinces, the DCE is relatively higher in Liaoning Province (1.0278), Inner Mongolia Autonomous Region (1.0324), Shandong Province (1.0403), Beijing City (1.0444), Jiangsu Province (1.0518), Shanghai City (1.0677) under the common frontier, and the cluster frontier Jiangsu Province (1.0518), Hunan Province (1.0585), Henan Province (1.0615), Shanghai Municipality (1.0677), and Inner Mongolia Autonomous Region (1.0718) have relatively high DCEs, and three of the top six provinces under the common frontier and cluster frontier are in agreement among the 30 provinces.

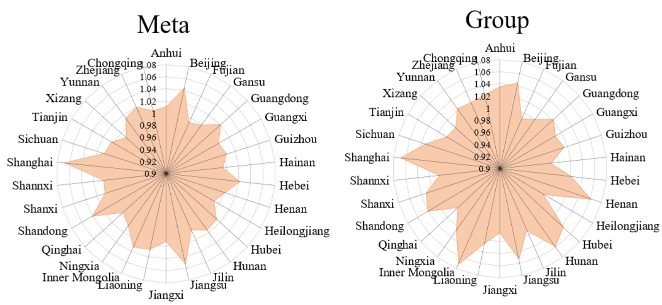

Fig. 3. Average DCE in each province

At the regional level, the eastern region has a TGR closest to 1, the eastern region has a TGR of 0.9993, the central region has a TGR of 0.9663, and the western region has a TGR of 0.9647. All three regions have not reached the best frontier technology level, with a gap of 0.65%, 3.37%, and 3.53% from the common frontier, respectively.

5 Conclusions and policy implications

This paper draws the following conclusions.

(1) China's DCE shows growth overall from 2004 to 2020, with decomposition indicators showing technological progress and declining efficiency. the growth of DCE relies mainly on the acceleration of technological progress.

(2) DCE shows large spatial and temporal variation characteristics. The eastern region has obvious advantages in technology and talent in DCE, and the central region has obvious advantages in population concentration and geographical superiority.

(3) The results under the common frontier and the cluster frontier are different, and the DCE under the common frontier is lower than that under the cluster frontier.

Based on the above empirical results, we propose the following policy recommendations.

(1) Strengthen the construction of Distribution infrastructure. Improving modern transportation corridors and systems and enhancing the efficiency of logistics and transportation.

(2) Promote industry innovation and industrial structure optimization and upgrading. Improving the level of technological innovation and the application rate of innovation can effectively help China to increase the efficiency of the distribution.

(3) Improve the level of information technology in Distribution. The use of information technology in the circulation industry can reduce operating costs, innovate circulation methods, realize omni-channel circulation and improve circulation efficiency.

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