

A Study of Regional Variability in Port Transport Efficiency in China - Based on A Three-Stage DEA-Malmquist Index Model

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Abstract. To study the impact of COVID-19 on China's port logistics efficiency, this paper uses a three-stage DEA and Malmquist model to measure the efficiency of China's port logistics industry in 38 coastal and inland river cities under environmental constraints from 2016-2021, and analyses its spatial and temporal characteristics and evolutionary dynamics. The study shows that the comprehensive technical efficiency of port logistics in coastal cities is higher than that of inland river ports. The progress in port logistics efficiency stems from the increase in scale efficiency, and the dependence of port logistics on scale expansion is high. In addition, COVID-19 has had some hit on port operational efficiency, where the reduction in total factor productivity is mainly caused by a lower technological progress index. Compared to coastal ports, inland ports are more affected by COVID-19. Meanwhile, the impact of COVID-19 on the productivity of Chinese ports is characterised by a clear short-term pattern. The paper then makes recommendations for further improving the efficiency of port logistics and the ability to cope with major contingencies in China and globally.

Keywords: Port Logistics Efficiency, Three-stage DEA Model, Malmquist model, COVID-19.

1. Introduction

As an important link in the supply chain logistics network system, port logistics occupies an extremely important position in the process of domestic and foreign material circulation and turnover. According to statistics, China's port cargo throughput will be 15.55 billion tons in 2021, an increase of 1 billion tons compared to 2020, an increase of 6.8% year-on-year, ranking first in the world in the recent years [1]. During the 14th Five-Year Plan period, China accelerated the construction of a comprehensive transport system, and ports, as an important part of water transport construction, received national policy support. 2021, the Outline of the National Comprehensive Three-Dimensional Transport Network Plan was issued, emphasising the need to accelerate the construction of a shipping hub that radiates globally. However, the development of domestic ports still suffers from some problems of unreasonable resource allocation. For example, in 2021, the port cargo throughput of Ningbo Zhoushan reaches 122,405,000 tons, while the port cargo throughput of five cities such as Huangshi, Weihai and Shantou is less than 50 million tons, and the development between ports in different cities is unbalanced. To address the existing problems, this paper selects the DEA three-stage model to measure the efficiency of port logistics, find out the influencing factors that restrict the efficiency of port logistics, and provide a theoretical basis for the decision of port logistics development, which is of great significance to improve the construction of port logistics in China.

2. Literature Review

As scholars in various fields pay more and more attention to the logistics industry, research results and practices have been emerging in recent years. Port logistics is a crucial link in the global supply chain and an important driver of regional economic development. How to objectively evaluate a city's port logistics efficiency is an important topic. In the study of efficiency evaluation, the DEA model

decomposes efficiency into pure technical efficiency and scale efficiency, giving researchers two perspectives on efficiency improvement. The literature review in this paper will start from both logistics efficiency measurement and the DEA three-stage model.

From a research perspective, many scholars have conducted research on measuring the performance level of the logistics industry from different perspectives, and DEA methods have been widely used. In cold chain logistics, Shang [2] used the DEA model of CCR, BCC model and Malmquist index to find that what restricts the efficiency of cold chain logistics of agricultural products in Chinese provinces are reasons such as too large scale of inputs and insufficient scientific and technological innovation and weak information operation. Based on the improved three-stage super-efficiency SBM-DEA model and the global Malmquist-Luenberger index model, Pu [3] included the carbon emissions of cold chain logistics in 13 municipalities in Jiangsu Province as non-expected outputs in the analysis framework and constructed a comprehensive measurement model of regional cold chain logistics efficiency that combines static and dynamic measures. In terms of port logistics, Chen [4] substituted the index data of Huanghua port, Tangshan port and Qinhuangdao port into the comprehensive evaluation model for port logistics efficiency measurement analysis. Liu et al. [5] studied the relationship between port logistics and the development of GDP and three major industries in the Beibu Gulf regional economy based on DEA analysis and concluded that logistics efficiency grew positively with the regional economy. In terms of regional logistics, Zhang [6] used the DEA-BCC model to evaluate the logistics efficiency of Xuzhou City from 2005 to 2018 vertically and horizontally and found that Xuzhou City had high overall and scale efficiency and low pure technical efficiency. Wu et al. [7] used the DEA-BCC model and the Malmquist model to study the operational efficiency of the logistics industry in the Yangtze River Delta in the smart era from 2015 to 2020 and found that the overall comprehensive efficiency of the 26 cities in the sample developed well overall, but the impact of the new crown epidemic in 2020 made its total factor productivity slightly lower. In terms of agricultural logistics, Song [8] studied the cold chain logistics efficiency of fresh agricultural products in Hubei Province with the help of DEAP2.1 software, combining static and dynamic analysis to give corresponding countermeasure suggestions.

In terms of research methods, most scholars choose a three-stage DEA model. Ba et al. [9] conducted an example study on the logistics efficiency of China's top ten coastal ports in 2017, using a three-stage DEA model, and concluded that scale efficiency is the core influencing factor of comprehensive efficiency. Wang et al. [10] adopted a three-stage DEA approach to analyse and compare the efficiency of the logistics industry in the regions along China's "Belt and Road" from 2010 to 2016 and found that it was strongly influenced by the external environment. These studies show that the three-stage DEA model can provide a feasible assessment method for port logistics.

As the above studies show, port logistics is an integral part of international trade and supply chain management and plays a key role in the development of the entire logistics industry and the growth of the national economy. However, compared to other studies in the field of logistics efficiency, there is a lack of research on the efficiency measurement of port logistics, which mostly does not exclude environmental factors and distorts the efficiency measurement. Therefore, based on previous studies, this paper selects 21 coastal port cities and 17 inland river port cities across China from 2016-2021 to evaluate the logistics efficiency of port systems using the DEA three-stage model. Through a joint horizontal and vertical inter-temporal analysis of the ports in each region, the reasons for the impact on the efficiency of port logistics are investigated, ways to enhance and improve them are explored, and suggestions and countermeasures to improve the efficiency of port logistics in the cities are given.

3. Research Methodology and Model Construction

3.1 DEA - SFA model

To overcome the shortcomings of traditional DEA models, which are susceptible to environmental, random variables and management inefficiencies, this paper adopts the three-stage DEA model

proposed by Fried to remove the influence of random disturbance terms and environmental variables and improve the accuracy of the measurement [11].

(1) SFA model

The slack variables in the first stage were used as the dependent variables, and the independent variables were selected as the errors in the environmental and the random variables, which were used to develop the regression analysis. In addition, the SFA model was used to measure input redundancy due to managerial inefficiency, and the following SFA model which was based on input variables was constructed:

$$S_{in} = f(z_i; \beta^n) + V_{in} + \mu_{in}, i = 1, 2, \dots, I, n = 1, 2, \dots, N \quad (1)$$

where, z_i represents the environmental explanatory variables; β^n is a pre-assessment parameter for the environmental explanatory variables; $f(z_i; \beta^n)$ represents the effect of the slack variables based on the environmental variables; V_{in} represents the input of factor i in the n port logistics industry, that is, the random error value in port logistics production; μ_{in} represents the input of factor i in the n port logistics industry, that is, the random variable of management efficiency; $V_{in} + \mu_{in}$ represents the error term of other unrelated factors.

After the SFA regression, their factor inputs were adjusted according to the results obtained, with the following expression:

$$x_{ni}^A = x_{ni} + [\max(f(z_i; \beta_n)) - f(z_i; \beta_n)] + [\max(v_{ni}) - v_{ni}] \quad (2)$$

Where, x_{ni}^A represents inputs after adjustment for slack variables; x_{ni} represents inputs before adjustment for the effects of slack variables.

3.2 Malmquist Index Model

The combination of Malmquist, a theoretical non-parametric linear programming method, and data envelopment analysis by RolfFare has led to the widespread use of this index analysis. Malmquist index analysis allows the analysis of the dynamic efficiency of data for each decision unit over time and the measurement of panel data over time. Total factor production indices, that is, $tfpch$, includes $effch$ and $techch$, which can provide a breakdown of productivity changes and identify the main sources of changes in Malmquist index values. The expression is as below:

$$M(x^{t+1}, y^{t+1}, x^t, y^t) = EC \times TEC = \frac{D_v^{t+1}(x^{t+1}, y^{t+1})}{D_v^t(x^t, y^t)} \times \left[\frac{D_v^t(x^{t+1}, y^{t+1})}{D_v^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_v^t(x^t, y^t)}{D_v^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \quad (3)$$

4. Selection of indicators and data sources

Based on the principle of three-stage DEA model, this paper uses the ratio of port transport output to port logistics resource input to measure logistics efficiency and establishes an indicator system from the three perspectives of input, output and impact, set as input indicators, output indicators and environmental variable indicators. The selection of indicators follows the principles of comprehensiveness, balance, reasonableness and accessibility.

4.1 Selection of input indicators

This paper combines the port's own characteristics, comprehensive DEA model to analyse the relevant literature on port efficiency, and the principles of selecting evaluation indicators, using the number of port berths X1, the length of port quays X2, the number of port berths above 10,000 tons X3 and the total mileage of city roads X4 of the six years from 2016 to 2021 of the research subject

as input indicators. The input indicators are all chosen from the specific data of infrastructure construction in each port city from 2016-2021, reflecting the level of modernization of the port area and the importance that the local government attaches to the construction of hardware facilities in the port area.

4.2 Selection of output indicators

Port city freight volume, port cargo throughput and port container throughput can, to a large extent, directly and objectively reflect a city's port logistics capacity, while the data is open, transparent and easily accessible. For this reason, this paper selects port city freight volume Y1, port cargo throughput Y2 and port container throughput Y3 as output indicators to measure the efficiency of port logistics in a city.

4.3 Selection of environmental indicators

Given that the gross regional product (GDP) Z1 and the total import and export Z2 directly or indirectly influence the development of the regional logistics industry, and thus the efficiency of port logistics, this paper uses them as environmental influencing factors. The specific production indicators and environmental indicators are shown in Table 1.

Table.1. Port productivity evaluation indicators and environmental indicators

Indicator Type	Index name	Units	Symbol
Input indicators	Number of berths in the port terminal	units	X1
	Length of Port Quay	metres	X2
	Number of quayside berths above 10,000 tonnes	units	X3
	Total number of road miles	Kilometres	X4
Output indicators	Port city freight volume	million tonnes	Y1
	Port cargo throughput	million tonnes	Y2
	Port Container Throughput	million TEU	Y3
Environmental indicators	Gross Regional Product	billion	Z1
	Total Import and Export Trade	billion	Z2

4.4 Source of data

The research period of this paper was selected as 2016-2021, and 40 port cities in China were selected as the initial sample. Due to the lack of data of some port cities, 38 port cities were finally selected for the study, including 21 coastal port cities and 17 inland river port cities, and the sample is generally representative. Data were obtained from the 2016-2021 statistical yearbooks of provincial and municipal statistical bureaus, the China Statistical Yearbook, official websites of port areas and relevant papers.

5. Empirical results

5.1 Analysis of Phase 1 DEA results

The DEAP 2.1 software was used to analyse the overall efficiency of port logistics in 38 coastal and inland cities in China from 2016-2021. The results are shown in Table 2. The overall efficiency of coastal ports is slightly higher than that of inland ports, mainly due to the fact that coastal ports, as international hubs and major nodes in the dual domestic and international cycle, have a wider range of trade targets, larger volumes of import and export trade and more mature trade technologies. In 2021, coastal ports reach a total of 9.93 billion tonnes of cargo throughput, while inland ports reach a total of 5.57 billion tonnes. The diseconomies of scale and waste of resources caused by the lack of output of inland ports lead to their lower operational efficiency.

Table.2. Integrated logistics efficiency and ranking of 38 major ports in China in 2016 - 2021

	DMU	2016	2017	2018	2019	2020	2021	Means	Rank
Coastal ports	Dalian	0.791	0.805	1.000	0.485	0.462	0.421	0.661	16
	Yingkou	1.000	1.000	1.000	0.780	0.886	0.877	0.924	7
	Qinhuangdao	0.550	0.779	0.336	0.872	0.509	0.469	0.586	19
	Tianjin	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
	Yantai	0.736	0.544	1.000	0.467	0.653	0.473	0.646	17
	Weihai	1.000	0.362	0.611	0.755	0.759	0.298	0.631	18
	Qingdao	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
	Rizhao	1.000	1.000	0.804	1.000	1.000	1.000	0.967	5
	Shanghai	0.902	0.935	0.795	0.946	1.000	0.853	0.905	9
	Lianyungang	0.627	0.721	1.000	0.735	0.664	0.825	0.762	12
	Ningbo-Zhoushan	1.000	1.000	0.506	1.000	1.000	1.000	0.918	8
	Taizhou	0.715	0.764	0.934	1.000	0.827	0.869	0.852	10
	Wenzhou	0.393	0.400	0.714	0.531	0.528	0.720	0.548	20
	Fuzhou	0.576	1.000	1.000	0.420	0.744	0.625	0.728	14
	Xiamen	0.871	0.842	1.000	1.000	1.000	1.000	0.952	6
	Shantou	0.363	0.351	0.858	0.250	0.667	0.471	0.493	21
	Shenzhen	1.000	1.000	0.854	1.000	0.983	1.000	0.973	4
	Guangzhou	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
	Zhanjiang	0.819	0.955	0.463	0.685	0.645	0.646	0.702	15
	Beihai	0.383	0.448	1.000	0.984	1.000	1.000	0.803	11
	Haikou	0.728	0.646	0.990	0.693	0.893	0.480	0.738	13
Coastal Average		0.784	0.788	0.851	0.791	0.820	0.763	0.799	
Inland ports	Chongqing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
	Yichang	0.546	0.391	0.134	1.000	0.341	0.634	0.508	16
	Wuhan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
	Huangshi	0.375	0.386	0.380	1.000	1.000	1.000	0.690	12
	Jiujiang	0.598	0.588	0.385	0.552	0.475	1.000	0.600	14
	Anqing	0.667	0.786	0.376	1.000	1.000	0.565	0.732	7
	Chizhou	0.453	0.452	0.419	1.000	1.000	1.000	0.721	9
	Tongling	0.627	0.720	0.345	1.000	1.000	0.698	0.732	7
	Wuhu	0.770	0.797	0.904	1.000	0.956	0.802	0.872	5
	Maanshan	0.574	0.659	0.309	0.405	0.473	0.365	0.464	17
	Nanjing	0.579	0.631	0.570	0.657	0.883	0.833	0.692	11
	Zhenjiang	0.373	0.420	0.365	0.690	0.435	1.000	0.547	15
	Taizhou	0.533	0.619	0.579	0.719	0.821	0.766	0.673	13
	Yangzhou	0.767	0.833	0.510	0.958	1.000	0.961	0.838	6
	Jiangyin	0.795	0.849	1.000	0.685	0.984	0.970	0.881	4
	Changzhou	1.000	1.000	0.646	1.000	1.000	1.000	0.941	3
	Nantong	0.695	0.728	0.764	0.766	0.639	0.732	0.721	9
Mean value of inland ports		0.668	0.698	0.570	0.849	0.824	0.843	0.742	
Overall mean value		0.732	0.748	0.725	0.817	0.822	0.799	0.774	

5.2 Analysis of stochastic frontier regression

In the second stage, the external environmental variables of gross regional product and total import and export trade were used as independent variables, and the input slack variables obtained in the first stage were used as dependent variables. A stochastic frontier regression analysis was conducted and the panel data for 2016 - 2021 were analysed year by year. The regression results are shown in Table 3: (For space reasons, the regression results for 2016 were selected for presentation in this paper)

Table.3. SFA model regression results

Variables	Slack variable for port terminal berth count	Slack variables for the length of the port quay	Slack variables for the number of berths in terminals over 10,000 tonnes	Slack variables for the total number of road miles
Constant	-15.315*** (-10.796)	-2808.793*** (-2808.778)	-7.331*** (-6.697)	-1792.540*** (-1792.686)
Gross regional product (GDP)	0.0008*** (11.023)	0.155*** (14.295)	0.0002 (1.182)	0.110*** (129.482)
Total import and export trade	-0.0004*** (-6.074)	-0.066 (-1.544)	-0.00004 (-0.176)	-0.085 (-1.182)
sigma-squared	1783.659*** (1783.72)	42770006*** (42770006)	389.772*** 389.771	17656195*** 17656195
gamma	0.999*** (2339815)	0.999*** (4370945)	0.999*** (2201026.5)	0.999*** (86172.77)
log	-167.458	-359.395	-139.809	-341.725
LR	22.131	21.484	19.634	23.203

Note: Results in brackets indicate t-tests for coefficients, ****, ***, ** indicate significant between 1%, 5% and 10% respectively

Analyzing the measured results in Table 3, the slack γ values for the number of berths at port terminals, length of port terminals, number of berths at terminals over 10,000 tonnes and total road mileage are greater than 0.5 and pass the significance test at the 1% level. the LR one-sided likelihood ratio test effectively rejects the OLS estimation results, therefore the panel data results of the stochastic frontier are considered credible. From the above analysis it can be concluded that:

(1) Gross regional product: Gross regional product represents the combined socio-economic level of the region. The regression coefficient between GDP and the number of port terminal berths, the length of port terminals, the number of terminal berths over 10,000 tonnes and the number of total road miles is positive, indicating that an increase in GDP has a negative impact on the reduction of redundant variables. As the regional port logistics industry develops, it will stimulate investment in port infrastructure accordingly, leading to an increase in fixed asset investment. This indicates that gross regional product reduces the efficiency of port logistics operations to a certain extent and that its increase is sloppy.

(2) Overall import and export trade: The regression coefficients of the slack variables of total import and export trade on the number of berths at port terminals, the length of port terminals, the number of berths at terminals over 10,000 tonnes and the total number of road miles are all negative, indicating that the total import and export trade has caused a change in redundancy during the period, and that the increase in total import and export trade has reduced the redundancy of fixed asset investment. As an external stimulus, the rise in the volume of import and export trade contributes to a certain degree to the efficient development of ports. The increase in total trade volume encourages each port to make full use of its resources and rationalise its inputs. In addition, the value of γ is close to 1, when managerial inefficiency becomes the main influence. Therefore, the impact of management inefficiency is more significant for the 38 major port cities in China.

5.3 Analysis of stage three

The paper continues with the BCC model analysis again using Deap2.1 based on the adjusted input variables and the original output variables from the second stage. The efficiency frontier of the DEA

three-stage model varies from year to year, and therefore the efficiency values cannot be compared across years. Therefore, the DEA three-stage approach can only reflect the static efficiency of the decision unit and cannot measure the change in efficiency quantitatively. Therefore, this section decomposes the total factor productivity of China's major ports for 2016-2021 using the Malmquist index method based on panel data in the longitudinal time dimension. And comparing inland waterways and coasts to provide a dynamic and quantitative analysis of total factor productivity and its decomposition indicators. Tables 4, 5 and 6 show the results of the Malmquist Index decomposition for major ports, coastal ports and inland ports respectively.

Table.4. Port Malmquist Index and its decomposition indicators

Year	EFFCH	TECHCH	PECH	SECH	TFPCH(M Index)
2016-2017	1	1.028	0.977	1.003	1.028
2017-2018	0.706	0.851	0.931	0.758	0.601
2018-2019	1.448	1.252	1.083	1.338	1.813
2019-2020	0.993	0.974	0.994	0.998	0.967
2020-2021	0.998	1.162	0.984	1.014	1.16
Average	1.003	1.044	0.997	1.006	1.047

Table.5. Malmquist Index for coastal ports and its decomposition indicators

Year	EFFCH	TECHCH	PECH	SECH	TFPCH(M Index)
2016-2017	0.993	1.016	0.993	0.989	1.011
2017-2018	0.868	1.015	0.929	0.920	0.921
2018-2019	1.271	1.133	1.075	1.159	1.487
2019-2020	1.046	0.959	0.988	1.053	0.995
2020-2021	0.982	1.168	0.980	1.003	1.148
Average	1.032	1.058	0.993	1.025	1.112

Table.6. Malmquist Index for Inland Waterway Ports and its decomposition indicators

Year	EFFCH	TECHCH	PECH	SECH	TFPCH(M Index)
2016-2017	1.048	1.051	1.008	1.040	1.101
2017-2018	0.653	0.744	0.955	0.688	0.497
2018-2019	2.132	1.524	1.128	1.902	3.357
2019-2020	0.968	1.005	1.006	0.960	0.966
2020-2021	1.071	1.187	0.994	1.073	1.282
Average	1.174	1.102	1.018	1.133	1.441

5.3.1 Coastal and inland port development dynamics

The Port's Total Factor Productivity Index for 2016 to 2021 is 1.047, or an average annual growth rate of 4.7% in total factor productivity. In terms of disaggregated indicators, the composite technical efficiency index is 1.003, i.e. an average annual increase of 0.3%. Its decomposition index, the pure technical efficiency index, is 0.997, an average annual decrease of 0.3%, indicating that the management and technical level of the port is not high and is declining year by year. The mean value of scale efficiency is 1.006 greater than 1, indicating that the annual progress in port logistics efficiency stems from the increase in scale efficiency, the high dependence of port logistics on scale expansion and the traction effect of integrated technical efficiency by scale efficiency. Malmquist index is 0.601 in 2018, 0.967 in 2020 both decreased from its previous year, the rest of the years Malmquist index is increasing, indicating that the efficiency of port logistics in these two years is seriously affected by the external environment, the possible reasons are: the beginning of the trade war between China and the United States in July 2018, the United States imposed huge tariffs on Chinese goods, resulting in the import and export a decrease in total trade and thus a decline in total factor productivity. The impact of the COVID-19 on port logistics in late 2019 has reduced import and export trade and regional GDP,

leading to a reduction in the efficiency of port logistics. The trends in total factor productivity in different ports are shown in Figure 1 below.

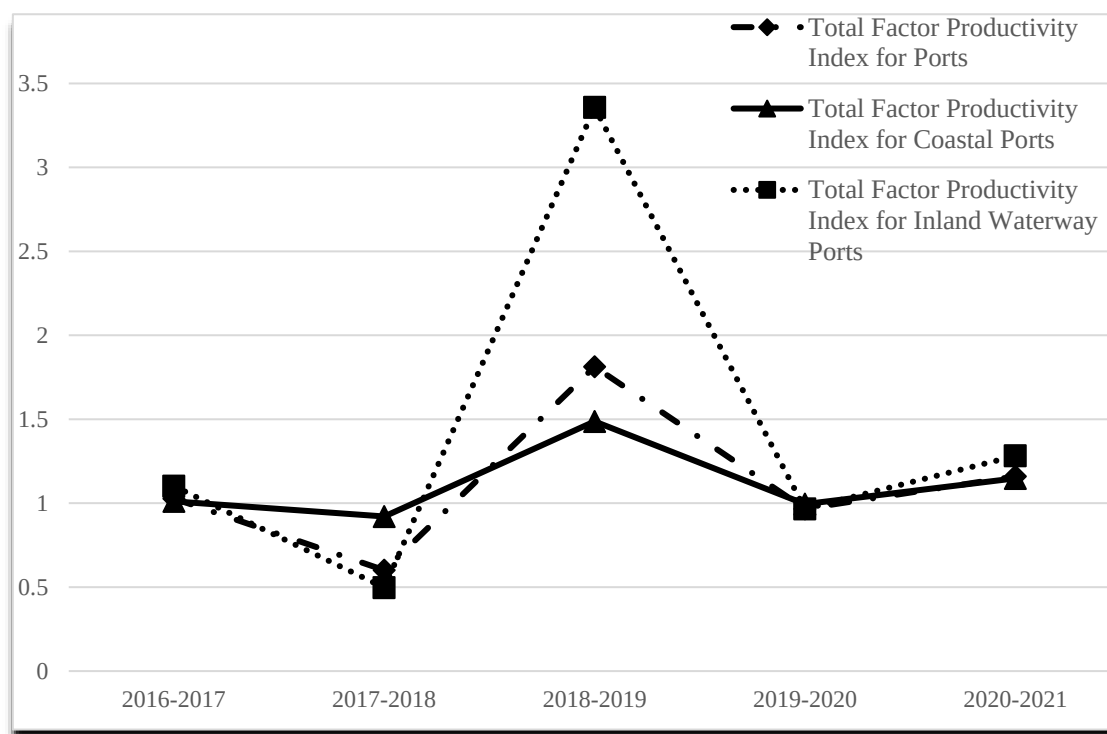


Figure. 1. Total factor productivity in ports

By region, as shown in Figure 1, the trend in the movement of the total factor productivity index is essentially the same for coastal and inland river ports. All efficiency change indices for ports in coastal cities are lower than those for ports in inland river cities. This indicates that the inland river ports have a good foundation and fast improvement in resource allocation ability and management level, and a strong capacity for technological innovation. The pure technical efficiency of coastal ports is 0.993, i.e. an average annual decrease of 0.7%, indicating the lack of resource allocation and management capacity of ports in coastal cities. Overall, the M average for 2016-2021 is 1.047 indicating that it is still an upward trend, indicating that a major epidemic will not shake the development of China's port operations and that the development of China's port industry is on a long-term positive trend.

5.3.2 Impact of the COVID-19 on the port

The COVID-19 ended 2019 with the Port's Total Factor Productivity Index for 2019-2020 at 0.967, or a decrease of 3.3%. The decomposition index looks at a composite technical efficiency index of 0.993, or 0.7% lower, and its decomposition index of pure technical efficiency of 0.994, or 0.6% lower, and a scale efficiency index of 0.998, or 0.2% lower. This indicates that external environmental factors such as the COVID-19, import and export trade and regional production have had an impact on the port, causing both the management level and scale of the port to show a decline in 2020 compared to 2019. In addition, the technological progress index was 0.974, a decrease of 3.6% compared to 2019, also showing a decline, indicating that the epidemic also had an impact on the port's technological innovation capacity.

For coastal ports, the TFP index for 2019-2020 is 0.995 for coastal ports and 0.966 for inland river ports, with the TFP index for both being less than 1 and both declining to some extent. However, the TFP index for coastal ports is greater than that for inland ports, indicating that inland ports were hit to a greater extent by the epidemic, probably stemming from the fact that domestic controls were more stringent than foreign controls due to the impact of the epidemic, resulting in a greater negative impact on the operations and transport capacity of inland ports. Disaggregated indicators show that the overall technical efficiency index for coastal ports was 1.046, i.e. an increase of 4.6%, while the technical

progress index was 0.959, a decrease of 4.1%. This indicates that the decline in logistics efficiency in coastal ports is due to the lack of technological innovation capacity in ports. The decomposition index pure technical efficiency is 0.988, a decrease of 1.2%, while the scale efficiency index is 1.053, an increase of 5.3%. It indicates that the increase in the overall efficiency index of coastal ports relies on the expansion of scale and the deficiency of organizational management capacity.

For inland ports, the Total Factor Productivity Index for inland ports is 0.966 for 2019-2020, a decline of 3.4%. The decomposition index looks at an overall efficiency index of 0.968, or a decline of 3.2 per cent. Its decomposition index pure technical efficiency index is 1.006, up 0.6%, and scale efficiency index is 0.960, down 4%. It shows that the comprehensive technical efficiency of inland ports is hindered by the effect of scale efficiency, indicating that the COVID-19 has a large impact on the scale efficiency of inland ports. The technological progress index, on the other hand, was 1.005, up 0.5%, indicating that the technological innovation capacity of inland river ports was not significantly affected by the COVID-19.

In addition, the impact of the Newcastle pneumonia epidemic on Chinese port production was markedly short-term in nature, with large stocks accumulating during the epidemic, followed by a short period of digestion and a quick recovery in port production efficiency. Total factor productivity in port logistics grows by an average of 16% over the period 2020-2021 and is largely due to advances in technology ; The average annual growth in total factor productivity for coastal port logistics was 14.8% and 28.2% for inland ports, indicating that the epidemic had a limited efficiency impact on the medium and long-term production of ports. Although major COVID-19 can have a short-term, irreversible impact on the development of China's port operations, they have not affected the long-term trend of a stable and positive development of China's port industry.

6. Conclusions and Recommendations

This paper uses DEA and Malmquist index analysis to investigate the impact of COVID-19 on port efficiency. The main conclusions that can be drawn are as follows:

(1) During the period 2016-2021, the technical efficiency of China's port logistics shows an overall upward trend, except for a decline in 2018 and 2020. In addition, there is an overall input redundancy in port logistics, with scale efficiency being the main constraint on overall technical efficiency. The overall technical efficiency of port logistics in coastal cities is higher than that of inland river ports.

(2) The growth of gross regional product (GRP) as an environmental variable is sloppy and reduces the operational efficiency of port logistics to a certain extent. The increase in total import and export trade, as an external stimulus, contributes to some extent to the efficiency of port development.

(3) COVID-19 has a certain impact on the efficiency of port operations, and the lower total factor productivity is mainly caused by the lower index of technological progress. Inland ports are more affected by COVID-19, and this impact is mainly in terms of scale efficiency. In addition, the impact of COVID-19 on the productivity of Chinese ports has a clear short-term nature.

Based on the results of the above analysis, this paper makes the following recommendations:

(1) Improve the degree of intensification and co-ordination of port development. At present, the port logistics industry needs to change its crude development mode and promote intensive economic development. In response to the uncoordinated spatial distribution of ports and the relatively scattered use of resources, the government should strengthen the co-ordination of port planning and land use.

(2) Strengthen the construction of port infrastructure and allocate resources scientifically. The key factor affecting the number of ships berthing and the volume of goods transported is the completeness and operational stability of the port infrastructure. Railway, highway and other transportation networks should be scientifically planned to meet the needs of modern ships in deep water and large scale.

(3) Improve the stability of the port supply chain. From the above analysis, it can be seen that the port logistics supply chain system in China and the world does not have a sound mechanism to deal with epidemics. Therefore, it is necessary to establish a risk mechanism that can respond quickly. Cloud computing technology can be used to integrate information on market demand, industrial

production and port logistics. For uncertain risk factors, the spread of risk can be limited through an early warning mechanism.

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