Research on Improving Logistics Efficiency by Digital Economy from the Perspective of High-Quality Development

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Abstract. Building a modern industrial system is an important focus point for promoting high-quality development. The logistics industry is an important part of the modern industrial system, and the improvement of logistics efficiency is the key to the high-quality development of the modern industrial system. The digital economy has become a new driving force for economic growth in countries around the world. This paper combines China's provincial panel data from 2014–2019, innovatively constructs an evaluation index system to measure the development level of the digital economy, and applies the super DEA-SBM method to measure logistics efficiency to empirically test the effect of digital economy-driven logistics efficiency improvement. The study shows that the digital economy promotes the improvement of logistics efficiency. The development of urbanization and the growth of the general economic environment are also important factors to enhance logistics efficiency. China should promote logistics efficiency improvement in the future through four major policy mechanisms: integrated promotion, collaborative development, cooperation and sharing, and local adaptation, and give full play to the new advantages of the digital economy.

Keywords: High-quality development · digital economy · logistics efficiency · DEA-SBM model

1 Introduction

The report of the 20th National Congress of the Communist Party of China proposed that "high-quality development is the primary task of comprehensively building a modern socialist country". The modern industrial system is an important focus point for promoting high-quality development. The Fourteenth Five-Year Plan for the Development of the Digital Economy emphasizes "promoting the digital transformation of traditional industries in all aspects and chains, and improving total factor productivity". Logistics industry is an important part of the modern industrial system, and the improvement of logistics efficiency is the key to the high-quality development of the modern industrial system. Therefore, it is of theoretical and practical significance to study the effect of digital economy driving logistics efficiency.

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Scholars have found that industrial agglomeration, economic development level [1], location advantage [2], logistics resource utilization, marketization, technological progress [3], human capital structure [4], enterprise management level, openness, R&D investment, government support [5], and urban innovation [6] all have an impact on logistics efficiency, but studies on the impact of digital economy on logistics efficiency are still relatively rare. Therefore, this paper empirically analyzes the effect of digital economy driving China's logistics efficiency improvement.

2 Methods and Data

2.1 Model Specification

This paper explores the impact of the digital economy on logistics efficiency, and constructs the basic regression model as follows:

$$tfp_{it} = \beta_0 + \beta_1 dig_{it} + \beta_2 Control_{it} + c_i + v_t + \varepsilon_{it} \tag{1}$$

Equation (1), i denotes the province, t denotes the year, β is the parameter to be estimated, c is the individual effect, v is the time effect, ε denotes the random disturbance term. *tfp* is the explanatory variable of this paper, i.e., logistics efficiency. *dig* is the core explanatory variable of this paper, i.e., the level of digital economy development. *Control* denotes the control variables.

2.2 Variable Measurement

The explanatory variable (*tfp*). According to China's National Economic Classification of Industries (2017), the logistics industry includes transportation, storage, and postal industries. In this paper, the super-efficient DEA-SBM model is used to measure logistics efficiency, and the logistics efficiency evaluation index system is constructed from the input-output perspective. The output indicator is the added value of logistics industry. Input indicators include the total employment scale of logistics industry, infrastructure input calculated by the sum of mileage of roads, railroads, and inland waterways, and capital input estimated by the perpetual inventory method. The capital stock is calculated by the following formula.

$$K_{it} = K_{it-1}(1 - \delta) + I_{it} \tag{2}$$

K_{it}, K_{it-1} are the capital stock of region i in year t and $t-1$ respectively, I_{it} is the fixed capital investment amount of region i in year t, δ is the depreciation rate. This paper uses 2013 as the base period and estimates the capital stock in the base period by using the sum of the 2014 gross capital formation over depreciation rate and the average growth rate of fixed asset investment from 2014–2019 [7]. The depreciation rate of fixed assets was selected as 8.6% [8], Price deflator for nominal fixed asset investment using the fixed asset investment price index for the base period of 2013. Data are from the China Statistical Yearbook.

Core explanatory variable (*dig*). Based on the Statistical Classification of Digital Economy and Its Core Industries (2021) and existing studies [9]. The four dimensions of digital R&D innovation and digital governance environment are used to build the indicator system of digital economy development level, using entropy weight method, as shown in Table 1. The data were obtained from the China Statistical Yearbook, the China Electronic Information Industry Statistical Yearbook, and the platform of Qichacha.

Table 1. Digital economy development level indicator system.

Level I indicators	Secondary indicators and their decomposition
digital infrastructure	Cloud: length of fiber optic cable lines (km), number of IPv4 addresses (million)
	Web side: number of domain names (million), number of web pages (million)
	Terminal: internet broadband access ports (million), number of computers in use at the end of the period (units)
digital industry development	Economic output: total telecommunications business (billion yuan), electronic information manufacturing (million yuan), software industry revenue (million yuan), e-commerce transactions (billion yuan)
	Benefit quality: number of employees in information transmission, computer service and software industry (million), proportion of enterprises with e-commerce trading activities (%)
digital R&D innovation	Technology R&D: full-time equivalent of R&D personnel (person year), R&D funds (million yuan)
	Innovation transformation: number of patent applications (pieces), technology turnover (million yuan), number of patent authorizations (pieces)
digital governance environment	Market environment: cell phone call minutes (billion minutes), cell phone exchange capacity (million households), cell phone base stations (million households), cell phone penetration rate (min. Per 100 people), cell phone users (million households), mobile internet users (million households), mobile internet access traffic (million G)
	Public service and management: urban broadband access users (million households), government enterprise broadband access users (million households), general public service expenditure (100 million yuan), public management, social security and social organization employment number (million people), public management, social security and social organization average wages (yuan)
	Network security: number of new network security enterprises, public security expenditure (100 million yuan)

Note: This table is compiled and drawn by the author

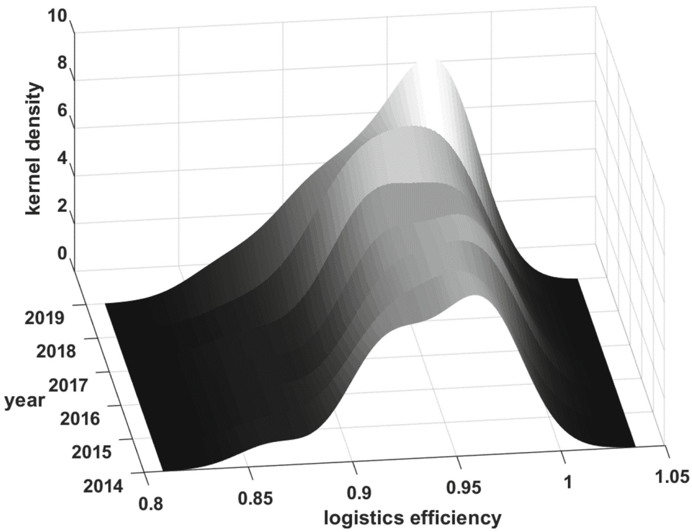

Fig. 1. Change of logistics efficiency's kernel density.

Control variables. The control variables in this paper are selected as urbanization level, human capital level, economic development level, and trade openness level. Urbanization level is expressed as the proportion of the urban population to the total population at the end of the year. The human capital level is measured by average years of education. The level of economic development is measured by the growth rate of real GDP per capital using 2013 as the base period. The level of trade openness is expressed by the proportion of total import and export of goods to GDP.

2.3 Summary Statistics

In this paper, 30 provinces (except Tibet) in China from 2014–2019 are selected as the sample. The human capital level is logarithmically treated to avoid heteroskedasticity. This paper plots the three-dimensional dynamic kernel density estimation of logistics efficiency values from 2014–2019, as shown in Fig. 1; and plots the radar map of the digital economy development level of each province in China in 2014 and 2019, as shown in Fig. 2.

3 Results and Discussion

3.1 Baseline Regression Analysis

In this paper, the unit root test of each indicator variable was conducted by HT test, and the original hypothesis of "the existence of panel unit root" was rejected at the 1% significance level for all variables, which means that the panel data are stable. The results of the multicollinearity test concluded that there was no multicollinearity. The heteroskedasticity and autocorrelation tests found that the panel data had between-group heteroskedasticity and within-group autocorrelation. According to the econometric model (1), the

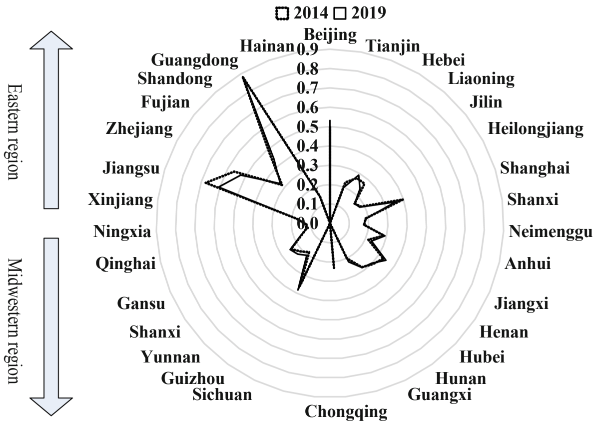

Fig. 2. Digital economy development levels in 2014 and 2019.

baseline regression results of digital economy development on logistics efficiency are tested, as shown in Table 2. This paper reports the OLS model, and PCSE model estimation results in turn. Combining the R^2 values and model settings in the estimation results, the estimated results in column (4) of the PCSE model, which has better fitting results and is more robust, are finally selected for interpretation.

Table 2. Baseline regression results

Variables	OLS Model		PCSE Model	
	(1)	(2)	(3)	(4)
dig	0.1373*** (0.0358)	0.1227*** (0.0405)	0.1175*** (0.0259)	0.0618*** (0.0190)
urban		0.3606*** (0.1272)		0.3222*** (0.0723)
ln *edu*		-0.1346 (0.1007)		-0.1562** (0.0736)
pcgdp		0.0035 (0.0034)		0.0019** (0.0009)
open		-0.0733 (0.0453)		-0.0306 (0.0199)
_cons	0.9124*** (0.0179)	1.0041*** (0.2048)	0.9198*** (0.0097)	1.0931*** (0.1353)
Fixed year	YES	YES	YES	YES
N	180	180	180	180
R^2	0.2099	0.3342	0.9941	0.9938

Note: Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1, as below

From the estimation results of column (4) of the PCSE model in Table 2, the level of digital economy development drives the improvement of logistics efficiency and is significant at the 1% level with a force level of 0.0618, indicating that for every 1 increase in the level of digital economy development, logistics efficiency increases by 0.0618. Considering the control variables, both the level of urbanization and the level of economic development have a positive force on logistics efficiency and are significant at least at the 5% level with coefficients of 0.3222 and 0.0019, respectively, indicating that urbanization development and the growth of the general economic environment significantly enhance logistics efficiency.

3.2 Robustness Test

Replacing of key variables. In this paper, we adopt replacing the explanatory variables for robustness validation and use the stochastic frontier production approach (SFA) to replace the explanatory variables by frontier4.1 to calculate the technical efficiency index of the logistics industry (*te*). The estimation results are shown in column (1) (2) of Table 3, where the development of the digital economy positively affects the technical efficiency index of the logistics industry and is significant at the 1% level. It proves that the regression results are still robust after replacing the key variables.

Reverse causality test. Regressions are performed with a *dig*-lag of one period as the core explanatory variable. The estimation results in Table 3 find that the estimation results do not change significantly compared to the previous paper.

Endogeneity problem treatment. In this paper, *dig* lagged by one period is chosen as the instrumental variable for the current period *dig* to deal with the endogeneity problem. The GMM method is used to estimate the corresponding dynamic panel model. The results of the unidentifiable test for instrumental variables are shown in columns (4) and (5) of Table 3, where the Kleibergen-Paap rk LM statistic has a p-value of 0.000, rejecting the original hypothesis of "insufficient identification of instrumental variables. The Cragg-Donald Wald F-statistic and Kleibergen-Paap rk Wald F-statistic are both greater than the Stock-Yogo 10% threshold, i.e., there are no weak instrumental variables. The results of the variable regression show that the level of digital economy development enhances logistics efficiency. Therefore, the empirical findings remain robust after considering the endogeneity issue.

Adjustment of sample intervals. In this paper, the variables are subjected to 1% bilateral tailing. The regression results in columns (6) and (7) of Table 3 show that the results remain robust after excluding the effect of outliers.

Table 3. Robustness test.

Variables	Replacing the explanatory variable		Reverse causality test	IV (*L.dig*)		Double-sided indentation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
dig	0.2192*** (0.0476)	0.2071*** (0.0616)		0.1447*** (0.0181)	0.1355*** (0.0233)	0.1190*** (0.0255)	0.0564*** (0.0205)
L.dig			0.0910*** (0.0171)				
Control variables	NO	YES	YES	NO	YES	NO	YES
Fixed year	YES	YES	YES	YES	YES	YES	YES
Kleibergen-Paap rk LM statistic				37.887***			
Cragg-Donald Wald F statistic				2920.505***			
Kleibergen-Paap rk Wald F statistic				1515.403***			
Stock-Yogo 10% Threshold value				16.38			
N	180	180	150	150	150	180	180
R^2	0.8309	0.8152	0.9946	0.2113	0.3498	0.9941	0.9940

4 Conclusion and Suggestion

This paper combines the panel data of 30 provinces (except Tibet) in China from 2014–2019, constructs an evaluation index system from the digital infrastructure dimension, digital industry development dimension, digital R&D innovation dimension, and digital governance environment dimension, and measures the development level of the digital economy using the entropy weight method. This paper constructs a logistics efficiency index system from the input-output perspective and uses the super DEA-SBM model to measure the logistics efficiency. A linear regression model is established for empirical testing, and it is concluded that the coefficient of the effect of the digital economy on logistics efficiency is 0.0618. Considering the control variables, both the urbanization level and economic development level have a significant positive force on logistics efficiency with coefficients of 0.3222 and 0.0019, respectively, indicating that the growth of urbanization development and the general economic environment can improve logistics efficiency. The findings of this study remain robust after replacing key variables and endogeneity problem treatment.

Therefore, to promote the improvement of China's logistics efficiency and promote the high-quality development of the logistics industry, it is recommended that: (1) Coordinate and promote. Formulate development strategies and action plans for digital economy-driven logistics efficiency change from the national level, form a demonstration and promotion mechanism of model innovation-pilot application-experience summary-model promotion, and promote digital economy-driven logistics efficiency improvement in a coordinated manner. (2) Collaborative development. Build a logistics digital platform, strengthen cooperation among logistics entities, establish an inter-regional collaborative development mechanism, and promote the coordinated development of the logistics industry in the region. (3) Cooperation and Sharing. Strengthen the sharing of data resources in the logistics industry, explore the development mode of sharing and mutual benefit of logistics enterprises, promote the free and orderly flow of innovation resources, build a digital technology innovation cooperation platform, and implement the cooperation method of industry-university-research. (4) Make local conditions appropriate. Formulate policy measures according to local conditions, and build industrial digital empowerment platforms for the central and western regions where the level of digital infrastructure construction is relatively backward.

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