The Impact of Industrial Agglomeration on Supply Chain Efficiency in Manufacturing

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Abstract. The 20th National Congress of the Communist Party of China pointed out that China's high-quality economic development needed to improve the stability and resilience of the supply chain. And the improvement of manufacturing supply chain efficiency affected markedly on this. Firstly, this paper quantified the supply chain efficiency by using the three-stage DEA model, and established an evaluation system of digital capability from the perspective of green economy. Secondly, the bidirectional fixed effect model was used to further analyze the influence of specialized agglomeration, diversified agglomeration on supply chain efficiency and the moderating effect of digital capability. Based on the above, the conclusion was drawn specialized agglomeration and diversified agglomeration affected positively on manufacturing supply chain efficiency, and digital capability moderated them positively. Then, the result of the robustness analysis showed the model is robust. Finally, this paper put forward suggestions from the aspects of government and enterprise, advocating the development of specialized agglomeration, diversified agglomseration and digital capability.

Keywords:industrial agglomeration ; supply chain efficiency ; digital capability ; three-stage DEA ; bidirectional fixed effect model.

1. Introduction

Although China is a big manufacturing country, we should realize soberly that China's manufacturing industry is "big but not strong". The development of the manufacturing supply chain is still facing the problem of structural and regional overproduction at a low level. At the same time, considering the sudden outbreak of the epidemic in 2020, the vulnerability and low efficiency of the supply chain were revealed. In this regard, the 20th National Congress of the Communist Party of China stressed the importance of improving the resilience and safety of industrial supply chains, ensuring unimpeded supply chains, improving the turnover efficiency of supply chains, enhancing the internal driving force and reliability of the domestic great cycle, improving the quality and level of the international cycle. Especially in the manufacturing industry, the manufacturing supply chain is a key factor supporting the development of the manufacturing industry ,an important source of the core competitiveness of the manufacturing industry. The improvement of the manufacturing supply chain efficiency is an effective way to better promote the transformation and upgrading of manufacturing enterprises, and plays a decisive role in the stable development of China's economy. Therefore, this paper focused on the question of how to improve the efficiency of manufacturing supply chain based on the DEA method.

2. Literature Review

Industrial agglomeration is the embryonic form of industrial innovation ecosystem. Industrial agglomeration affects the external environment mainly through externalities. Industrial agglomeration can be divided into diversified agglomeration and specialized agglomeration according to whether the source of externalities comes from the same industry. Specialized agglomeration, also known as Marshall Externality (MAR), originated from the externality theory represented by Marshall. He mentioned the same industry can create an environment for collaborative innovation, reduce the information cost of enterprises, contribute to technological innovation and information exchange, and improve the efficiency of innovation [1]. Diversified agglomeration, also known as Jacobs externality, came from Jacobs' view. He believed externalities, knowledge spillovers, mainly occurred between different industries, and knowledge spillovers between complementary industries can better promote industrial innovation storms [2]. Compared with specialized agglomeration, diversified agglomeration pays more attention to the sparks of innovation generated by the knowledge collision of different industries, rather than the social benefits brought by technology diffusion [3]. Martin et al. found the specialized agglomeration externality had a short-term effect on the total factor productivity of French manufacturing industry, while the diversified agglomeration externality didn’t affected obviously [4]. Glaeser et al. showed diversified agglomeration externality promoted the development of labor distribution in American cities, while specialized agglomeration didn’t play a role [5]. Yanfen Qu found both diversified and specialized agglomeration promoted the improvement of enterprises' green technology innovation efficiency, and diversified agglomeration influenced more significantly [6]. Zhonghua Cheng believed specialized agglomeration didn’t affect obviously on innovation performance of manufacturing enterprises, but diversified agglomeration influenced markedly on innovation performance of manufacturing enterprises. It can be seen that the current research on externality mainly focuses on the economic development of cities and enterprises [7].

A supply chain is defined as an organization that connects the upstream and downstream of an industry and provides products and services to the final customer [8]. SCM in the United States proposed the concept of supply chain management for the first time in 1996: based on the comprehensive competitiveness of each subject, the supply chain can be integrated and utilized, so as to minimize the total cost of the supply chain and realize the win-win situation of each subject in the supply chain [9]. Supply chain mainly integrates upstream and downstream resources, including suppliers, distributors, other logistics, information flow and capital chain, so as to rationally allocate production and reduce inventory backlog. From a macro view, the improvement of supply chain efficiency is to ensure the supply chain is not broken, not blocked, not rigid, and each link of the internal circulation of the national economy is effectively connected. From the micro view, continuous technological innovation should improve the efficiency of enterprises in all links and ensure the smooth of supply chain [10]. In addition to minimizing inventory backlog, reducing enterprise costs without affecting service level is the key to improving supply chain efficiency [11]. At present, the factors affecting supply chain efficiency studied by scholars mainly focus on industrial agglomeration, enterprise innovation and digital capability. Drucker and Feser took manufacturing enterprises as research objects and found industrial agglomeration could improve the efficiency of supply chain [12]. Fu et al. suggested we should promote the development of industrial agglomeration to improve the efficiency of supply chain [13]. However, few people study the impact of specialized agglomeration and diversified agglomeration on the supply chain efficiency.

Weizhong Fu and Yao Liu found the coupling coordination level of industrial digitalization and high-quality development of manufacturing industry rose [14]. Hui Xu found digital economy can directly promote the high-quality development of manufacturing industry, and the innovation effect of digital technology can indirectly promote the high-quality development of manufacturing industry [15]. Zhuangyu Wei et al. found digital economy significantly promoted the total factor productivity of manufacturing industry, and the effect had obvious spatial heterogeneity [16]. Yingjie Li and Ping Han found the extensive integration of digital economy and manufacturing development can promote the innovation and upgrading of manufacturing industry [17]. The manufacturing supply chain develops into a digital supply chain that is deeply integrated with digital technology [18]. The level of digital capability affects the supply chain efficiency greatly. Currently, many scholars confirm the impact of digital capability on supply chain efficiency, but there is a lack of studies on the moderating effect of digital capability on supply chain efficiency. In addition, most scholars measure digital capability from the view of infrastructure, empowering society, innovation ability, economies of scale, etc. while rarely consider it from the view of green economy development. At present, the problem of high energy consumption and pollution of manufacturing enterprises needs to be solved urgently. More and more enterprises rely on digital capability to achieve green transformation which attracts wide attention. Therefore, it’ s necessary to measure ecological capability such as energy conservation and emission reduction in digital capability. In this paper, green innovation indicators were added into the measurement system of digital capability. See the following for details.

Based on the existing studies, this paper further explored the influence of industrial agglomeration on supply chain efficiency and the moderating role of digital capability. Compared with previous studies, the marginal contributions of this paper include: Firstly, the panel data of 913 manufacturing enterprises, 198 prefecture-level cities and 30 provinces in China from 2012 to 2020 were used for empirical test. It was to analyze the impact of specialized agglomeration and diversified agglomeration on supply chain efficiency. Secondly, from the perspective of green economy, this paper constructed the evaluation system of digital capability, studied the moderating effect of digital capability, and provided experience reference and policy enlightenment for further improving the manufacturing supply chain efficiency.

3. Research Hypothesis

Specialized agglomeration and diversified agglomeration both have spillover effects. However, specialized agglomeration usually has the knowledge spillover within industries, while diversified agglomeration usually has the knowledge spillover between industries [19]. According to Poter's externality theory, knowledge spillover mainly occurred in vertically integrated industries, and he emphasized the spillover effect of specialized agglomeration can improve efficiency. Although Poter didn’ t confirm the spillover effects of diversified agglomeration, he did argue diversified agglomeration supports innovation. Wahyu Widodo et al. confirmed part of Poter's view with the data of Indonesian manufacturing industry, that specialized agglomeration affected the technical efficiency of enterprises positively, while diversified agglomeration had a negative impact on the technical efficiency of enterprises [20]. Both specialized agglomeration and diversified agglomeration can promote urban economic development by reducing transaction costs, optimizing resource allocation and promoting technological innovation [3]. Scholars prove diversified agglomeration and specialized agglomeration promote regional innovation obviously [21]. Therefore, we proposed the following hypotheses:

Hypothesis 1: Specialized agglomeration affects the manufacturing supply chain efficiency positively.

Hypothesis 2: Diversified agglomeration affects the manufacturing supply chain efficiency positively.

In addition to the problems of high energy consumption and pollution, the traditional supply chain management of manufacturing enterprises has the pain points of low information sharing degree, slow market response speed and high operating risk cost, which seriously restricts the efficient operation. Digital technology relies on the information transmission and exchange speed of upstream and downstream supply chain to solve the problem of information asymmetry and improve the accuracy of matching supply and demand. Digital technology integrates information, which greatly improves information transparency and reduces the supervision cost of enterprises. Meanwhile, cloud computing, big data and other technologies optimize logistics layout and resource allocation, improve logistics efficiency and reduce logistics costs. In addition, Blockchain and other digital technology have the features of immutable data and permanent tracking as well as automatic contract management, which effectively reduces the cost of enterprise default [22]. It can be seen that digital capability can affect the path of industrial agglomeration on economic development, and digital capability can improve the efficiency of supply chain by reducing enterprise operating costs. Therefore, we proposed the following hypotheses:

Hypothesis 3: Digital capability moderated the relationship between specialized agglomeration and manufacturing supply chain efficiency positively.

Hypothesis 4: Digital capability moderated the relationship between diversified agglomeration and manufacturing supply chain efficiency positively.

4. Measurement Model ,Variable Selection and Data Source

4.1 Construction of Measurement Model

In this paper, the influence of specialied agglomeration and diversified agglomeration on manufacturing supply chain efficiency was discussed from the company leve. After model testing, this paper chose to introduce the bidirectional fixed effect model as the econometric model, and combined it with the moderating effect model to form a model suitable for this paper.

$$\begin{aligned}\mathrm{MCE_{it}} &= \beta_0 + \beta_1 \mathrm{isa_{it}}(\mathrm{ida_{it}}) + \beta_2 \mathrm{dcapa_{it}} \times \mathrm{isa_{it}}(\mathrm{ida_{it}}) \\ &+ \beta_3 \mathrm{dcapa_{it}} + \sum_{j=4}^{9} \beta_j \mathrm{con_{it}} + \mu_i + \theta_i + \varepsilon_{it} \#(1)\end{aligned}$$

In the above equation, i represented individual and t represented time. MCE represented manufacturing supply chain efficiency, isa represented specialized agglomeration, ida represented diversified agglomeration, dcapa represented digitalization capability, and $\mathrm{dcapa} \times \mathrm{isa(ida)}$ represented the interaction term. In addition, con represented control variables, including control variables at the firm level, enterprise scale (esc) and equity structure (equ), control variables at the city level, foreign investment (ffi), trade openness (open), government intervention (gov) and education expenditure (edu). $\beta_j (j = 1, \ldots, 9)$ represented the parameter to be estimated. μ_i and θ_i represented individual fixed effect and time fixed effect, respectively. ε_{it} was a random disturbance term. In this paper, Model A took specialized agglomeration (isa) as the independent variable, and Model B took diversified agglomeration (ida) as the independent variable.

4.2 Variable Selection

4.2.1 Explained Variables

Manufacturing supply chain efficiency (MCE). According to the production process, this paper divided the manufacturing supply chain into three stages, which were production, processing and sales. Referring to the existing studies [11,23,24], this paper established indicators in accordance with the input, output and environment of the three-stage DEA model. See Table 1 for specific indicators.

Table 1. Input, output and environmental indicators at three-stages

Stage	Input index	Output index	Environmental index
Production	Number of active employees (10,000)	Number of active employees (10,000) Operating income (ten thousand Yuan) Inventory turnover ratio (%) Operating profit (ten thousand Yuan)	Government subsidy (ten thousand yuan) Proportion of GDP in sample (%) Enterprise age (year)
	Fixed assets (ten thousand yuan)		
Processing	Operating cost (ten thousand yuan)		
Sales	Sales expenses (ten thousand yuan)		

The input indexes selected in this study reflected supply chain input from both human and material aspects. Among the output indexes, inventory turnover ratio is the most important indicator to measure the operation level of the enterprise supply chain. [23] In this paper, three-stage DEA model was used to evaluate the supply chain efficiency. In first stage, BCC model with Variable Returns to Scale was selected. In second stage, the input-oriented regression model like SFA was selected. In third stage, the adjusted input value was used.

4.2.2 Core Explanatory Variables

Specialized Agglomeration Index (isa). Referring to the measurement index [24,25] widely used in relevant studies, this paper adopted the maximum location quotient of cities to measure specialized agglomeration. In the equation, i represented city, j represented industry, and t represented year. s_{ijt} represented the proportion of the employment of industry j in city i to the total employment of all industries in city i in year t. s_{jt} referred to the proportion of the employment of industry j in all cities to the total employment of all industries in all cities in year t. The larger the index, the higher the specialized agglomeration level.

$$isa_i = max_j \frac{s_{ijt}}{s_{jt}} \#(1)$$

Diversified Agglomeration Index (ida). In this paper, the relative diversified agglomeration index was adopted. It was a variant of the Herfindahl Index (HDI), which was favored by most scholars due to its two advantages of absolute concentration and relative concentration. The symbolic meaning was the same as that of the specialized agglomeration. The larger the index, the higher the diversification agglomeration level.

$$ida_i = \frac{1}{\sum |s_{ijt} - s_{jt}|} \#(2)$$

4.2.3 Moderating Variables

Digital capability (dcapa). There are always some problems of high energy consumption, heavy pollution and low efficiency in the manufacturing enterprises. Under the development trend of dula-cycle economy and green economy, digital capability becomes an important measure to promote the green transformation of enterprises. Therefore, it is also very important to measure energy saving, emission reduction and digital ecological capability in digital capability. Combined with the concept of digital capability [26] and referring to the construction of other evaluation systems of digital capability, this paper evaluated digital capability from three dimensions: digital transformation capability, digital ecological capability and digital economies of scale, as shown in Table 2. There were four second grade indexes: digital talent, digital innovation, digital ecology and digital scale. From the logic of "input-transformation-output", infrastructure was input, and digital talents made enterprises or regions carry out digital transformation by relying on continuous innovation of advanced technology achievements. Therefore, enterprises or regions can gradually promote the economic development of low energy consumption, low pollution and low cost, and the digital scale was constantly expanding to produce abundant digital benefits. The dimension of digital ecology was mainly manifested as empowering society. With reference to Green Development Indicator System [27], there were three third grade indexes, namely energy consumption, pollution emission and digital inclusion. This paper used entropy weight method to measure.

Table 2. Digital capability evaluation system and weight

First index	Second index	Third index	Explanation of index	Direction of index	Unit of index	Weight of index
Digital transformation capability	Digital talent	Human capital	Proportion of college students to total population at the end of the year	+	%	0.1120
		Talent employment	Number of employees in the information transmission,	+	10,000	0.0991

			computer services and software industries			
	Digital innovation	Patent innovation	Number of authorized patent applications	+	1	0.1032
		Innovation input	Expenditure on science and technology	+	10,000	0.1010
Digital ecological capability	Digital ecology	Energy consumption	Total energy consumption of prefecture-level cities	-	10,000	0.1204
		Pollution emisson	Total carbon emissions of prefecture-level cities	-	10,000	0.1204
		Digital inclusion	Digital Financial Inclusion Total Index	+	%	0.1189
Digital economies of scale	Digital scale	Digital service	Total volume of telecommunication service	+	10,000	0.1114
		Internet scale	Number of international Internet users	+	1	0.1137

4.2.4 Control variables

In order to minimize the endogeneity of the model, control variables were selected from two levels: enterprise and city. Table 3 showed the descriptive statistics of the main variables. The names of the variables, meanings, sample size, mean value, standard deviation, 25% quantile, 75% quantile, minimum value and maximum value were arranged from left to right.

Table 3. Descriptive statistics of main variables

Variable	Meaning	N	Mean	Sd	P25	P75	Min	Max
MCE	Supply chain efficiency of manufacturing enterprises	8217	-0.0700	0.760	-0.770	0.340	-1.710	2
isa	Specialized agglomeration	8217	-0.0800	0.910	-0.700	0.490	-1.450	2.980
ida	Diversified agglomeration	8217	0.110	0.910	-0.610	0.650	-1.200	3.190
dcapa	Digital capability	8217	-0.160	0.860	-0.730	0.300	-1.820	2.640
equ	Shareholding of the first largest shareholder	8217	-0.0200	0.960	-0.760	0.610	-1.710	2.720
esc	Total assets of the enterprise	8217	-0.0500	0.660	-0.320	-0.100	-0.370	4.700
ffi	Ratio of actually utilized foreign investment to GDP	8217	-0.0300	0.950	-0.800	0.580	-1.440	2.960
open	Ratio of total imports and exports to GDP	8217	-0.0500	0.940	-0.750	0.360	-0.980	3.280
gov	Ratio of regional budget expenditure to GDP	8217	0.0300	0.920	-0.400	0.210	-0.680	5.730
edu	Ratio of regional education expenditure to total fiscal expenditure	8217	0.0500	0.950	-0.540	0.640	-1.930	2.480

4.3 Data Source

Considering the availability and completeness of the data, the data of manufacturing enterprises, Sansha City, Nyingchi City and other regions with serious omissions were excluded from the sample. Partial missing data was completed by interpolation method. Finally, this paper obtained panel data of 913 manufacturing enterprises, 198 prefecture-level cities and 30 provinces from 2012 to 2020 for empirical analysis. The data used were mainly from statistical yearbook of China City, Tertiary Industry, China Science and Technology, China Energy and other statistical yearbooks, local statistical bureau and Wind, EPS and other databases.

5. Empirical Analysis

5.1 Data Preprocessing and Correlation Analysis

All the variable data are preprocessed before empirical analysis: (1) In order to make the data more stable and the results more comparable, all variables were standardized. (2) In order to avoid the influence of outliers on the model, all continuous variables were reduced at the level of 1% and 99%. (3) In order to avoid the influence of multicollinearity, the interaction variables were processed centrally.

As can be seen from Table 4 and Table 5, the correlation coefficient between supply chain efficiency (MCE) and specialized agglomeration (isa) was 0.084($p<0.01$). The correlation between supply chain efficiency (MCE) and diversified agglomeration (ida) was -0.157($p<0.01$). The results of correlation analysis also preliminarily verified the conclusions of this paper. In addition, the results of correlation matrix showed there was no strong correlation between other variables. The possibility of multicollinearity problem was less. It can be followed by regression analysis.

Table 4. Sectional correlation coefficient matrix

	MCE	isa	ida	equ	esc	dcapa
MCE	1					
isa	0.084***	1				
ida	-0.157***	-0.055***	1			
equ	0.030***	-0.073***	-0.025**	1		
esc	0.064***	-0.012	0.003	0.027**	1	
dcapa	-0.232***	-0.169***	-0.136***	-0.035***	0.01	1
ffi	0.041***	0.093***	0.026**	0.095***	0.01	0.160***
open	0.059***	0.375***	-0.385***	0.088***	-0.018	0.155***
gov	-0.004	-0.111***	-0.053***	0.046***	-0.011	0.059***
edu	0.130***	0.031***	-0.007	-0.021*	-0.033***	-0.375***
isa×dcapa	0.090***	-0.026**	0.135***	-0.046***	0.004	-0.314***
ida×dcapa	0.218***	0.126***	-0.188***	-0.020*	-0.029***	-0.209***

Table 5. Sectional correlation coefficient matrix

	ffi	open	gov	edu	isa×dcapa	ida×dcapa
ffi	1					
open	0.325***	1				
gov	0.081***	0.236***	1			
edu	-0.330***	-0.280***	-0.190***	1		
isa×dcapa	-0.259***	-0.189***	-0.028**	0.046***	1	

ida×dcapa	-0.070***	0.031***	-0.011	0.118***	0.172***	1

5.2 Regression Test of the Model

In order to find a suitable model between the random effects model and the fixed effects model, a series of tests were carried out in this paper. First, the significance test of the individual effect was conducted. The results showed model A and model B both rejected the null hypothesis($p<0.1$), that was, the individual effect was significant. Secondly, the robust Hausman test and Hausman test based on bootstrap method were conducted. The results showed model A and model B both rejected the null hypothesis($p<0.01$), that was, fixed effect model could be selected. Finally, the joint significance test of annual dummy variables was conducted. The results showed model A and model B both rejected the null hypothesis($p<0.01$), that was, time effect existed. The result was that the bidirectional fixed-effect model was selected and the cluster robust standard error was used to eliminate heteroscedasticity.

5.3 Baseline Regression Analysis

Table 6. Results of baseline regression

	Model A		Model B	
	(1)	(2)	(3)	(4)
isa	0.0684***	0.0658***		
	(0.0179)	(0.0177)		
isa×dcapa		0.0454***		
		(0.0069)		
ida			0.0500***	0.0576***
			(0.0131)	(0.0140)
ida×dcapa				0.0232***
				(0.0090)
dcapa	0.0292**	0.0428***	0.0327**	0.0380***
	(0.0136)	(0.0142)	(0.0135)	(0.0133)
equ	-0.0009	0.0012	-0.0008	-0.0012
	(0.0117)	(0.0116)	(0.0118)	(0.0117)
esc	0.0336**	0.0303**	0.0334**	0.0339**
	(0.0153)	(0.0153)	(0.0154)	(0.0153)
ffi	0.0235**	0.0381***	0.0227**	0.0245**
	(0.0109)	(0.0111)	(0.0109)	(0.0109)
open	0.0614***	0.0799***	0.0638***	0.0518***
	(0.0158)	(0.0165)	(0.0158)	(0.0171)
gov	-0.0106***	-0.0062**	-0.0099***	-0.0101***
	(0.0030)	(0.0030)	(0.0030)	(0.0029)
edu	0.0349***	0.0362***	0.0308***	0.0322***
	(0.0112)	(0.0111)	(0.0112)	(0.0112)
Cons	0.2676***	0.2766***	0.2605***	0.2647***
	(0.0146)	(0.0148)	(0.0148)	(0.0146)
N	8217	8217	8217	8217
Adjusted R2	0.8051	0.8063	0.8054	0.8056
F	1.4e+03	1.3e+03	1.4e+03	1.3e+03

*Note: The estimating standard error of robust heteroscedasticity adjusted for urban clustering is reported in brackets, where ***, ** and * represent significance levels of 1%, 5% and 10%, respectively. Due to space, the regression results of dummy variables are omitted.*

Table 6 reported the results of baseline regression for Model A(with isa as the independent variable) and Model B(with ida as the independent variable). The first column of models A and B in the table reported the regression results of independent variables and control variables on supply chain efficiency, and the second column reported the regression results after adding interaction terms. In model 1, it was found specialized agglomeration affected supply chain efficiency positively(β =0.0684， p<0.01). The reason may be that specialized agglomeration promoted technological competition and diffusion within industry, thus promoting technological innovation. Meanwhile, specialized agglomeration promoted cooperative innovation among enterprises, realized knowledge spillover and technological upgrading, which had industrial scale effect and reduced transaction costs thus promoting the improvement of supply chain efficiency [28].

In model 2 with the addition of interaction terms, it was found specialized agglomeration still affected supply chain efficiency positively (β=0.0.0658， p<0.01). The standard error of coefficient estimation became smaller, which indicated the independent variable coefficient was more explanatory after the interaction term was added. The coefficient of the interaction term (β=0.0454， p<0.01) was consistent with the direction of the independent variable coefficient, indicating the moderating effect of digital capability strengthened the positive influence of specialized agglomeration on supply chain efficiency. It can be judged digital capability moderated it positively. The reason may be that digital capability promoted the green transformation and upgrading of manufacturing enterprises. Digital technology reduced the cost of communication, cooperation and innovation among enterprises, promoted the knowledge spillover benefits brought by specialized agglomeration. Therefore, digital capability promoted the positive effect of specialized agglomeration on supply chain efficiency. At this point, Hypothesis 1 and Hypothesis 3 were verified.

In the model 3, we found that diversified agglomeration affected supply chain efficiency positively (β =0.05 ， p<0.01). The reason may be that diversified agglomeration promoted technology and knowledge complementarity of different industries, optimized resource allocation, created a good innovation environment, promoted cooperative innovation among enterprises in different industries, and thus promoted the improvement of supply chain efficiency [29]. In model 4 with interaction terms, it was found that diversified agglomeration still affected supply chain efficiency positively (β=0.0576，p<0.01). The coefficient of the interaction term (β=0.0232，p<0.01) was consistent with the direction of the coefficient of the independent variable, indicating the moderating effect of digital capability strengthened the positive influence of diversified agglomeration on supply chain efficiency. It can be judged that digital capability moderated it positively. The reason may also be that digital capability facilitated the communication and cooperation between enterprises in different industries, promoted the benefits brought by cooperative innovation, and thus strengthened the positive effect of diversified agglomeration on supply chain efficiency. At this point, Hypothesis 2 and Hypothesis 4 were verified.

5.4 Robustness analysis

First, this article added missing control variables. Han Li and Limiao Tang found improving traffic levels can improve supply chain efficiency [30]. Therefore, traffic level (tran) was added as a control variable in the robustness test and there was no multicollinearity problem. The results were consistent with those obtained by the baseline regression in Table 7. It can be judged that the conclusion of this paper was still robust after the inclusion of the missing control variables.

Table 7. Regression results after adding missing variables

	Model A		Model B	
	(1)	(2)	(3)	(4)
isa	0.0675***	0.0648***		
	(0.0178)	(0.0176)		

isa×dcapa		0.0455***		
		(0.0069)		
ida			0.0513***	0.0590***
			(0.0131)	(0.0140)
ida×dcapa				0.0233***
				(0.0090)
dcapa	0.0283**	0.0420***	0.0319**	0.0372***
	(0.0136)	(0.0143)	(0.0135)	(0.0133)
equ	-0.0013	0.0009	-0.0012	-0.0017
	(0.0117)	(0.0116)	(0.0117)	(0.0117)
esc	0.0339**	0.0306**	0.0338**	0.0343**
	(0.0153)	(0.0153)	(0.0154)	(0.0153)
ffi	0.0214**	0.0360***	0.0203*	0.0221**
	(0.0108)	(0.0110)	(0.0108)	(0.0108)
open	0.0545***	0.0729***	0.0558***	0.0437**
	(0.0159)	(0.0166)	(0.0159)	(0.0172)
gov	-0.0102***	-0.0057*	-0.0094***	-0.0096***
	(0.0030)	(0.0030)	(0.0029)	(0.0029)
edu	0.0360***	0.0373***	0.0321***	0.0335***
	(0.0113)	(0.0111)	(0.0112)	(0.0112)
tran	0.0317*	0.0323*	0.0373**	0.0375**
	(0.0179)	(0.0178)	(0.0178)	(0.0178)
Cons	0.2735***	0.2827***	0.2673***	0.2716***
	(0.0148)	(0.0150)	(0.0150)	(0.0148)
N	8217	8217	8217	8217
Adjusted R2	0.8052	0.8064	0.8056	0.8058
F	1.3e+03	1.3e+03	1.3e+03	1.2e+03

*Note: The estimating standard error of robust heteroscedasticity adjusted for urban clustering is reported in brackets, where ***, ** and * represent significance levels of 1%, 5% and 10%, respectively. Due to space, the regression results of dummy variables are omitted.*

Secondly, the sample period was changed in this paper. Considering the impact of the epidemic, samples excluding 2020 data were used in the robustness test. The regression results were shown in Table 8. The results were consistent with those obtained by the baseline regression, indicating the conclusions of this paper were still valid after the sample period was changed.

Table 8. Regression results of changing sample period

	Model A		Model B	
	(1)	(2)	(3)	(4)
isa	0.0290**	0.0339**		
	(0.0132)	(0.0140)		
isa×dcapa		0.0135*		
		(0.0080)		
ida			0.0218**	0.0312***
			(0.0102)	(0.0114)
ida×dcapa				0.0232***
				(0.0085)
dcapa	0.0197	0.0259*	0.0199*	0.0227*
	(0.0121)	(0.0136)	(0.0120)	(0.0119)

equ	0.0075	0.0079	0.0076	0.0071
	(0.0106)	(0.0106)	(0.0107)	(0.0107)
esc	0.0262**	0.0253*	0.0259**	0.0260**
	(0.0131)	(0.0131)	(0.0132)	(0.0131)
ffi	-0.0192***	-0.0145**	-0.0200***	-0.0177**
	(0.0070)	(0.0073)	(0.0071)	(0.0071)
open	0.0266*	0.0296**	0.0262*	0.0120
	(0.0136)	(0.0138)	(0.0136)	(0.0158)
gov	-0.0068***	-0.0061**	-0.0058**	-0.0057**
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
edu	0.0185*	0.0223**	0.0159*	0.0165*
	(0.0098)	(0.0106)	(0.0095)	(0.0096)
Cons	0.2777***	0.2805***	0.2743***	0.2764***
	(0.0125)	(0.0128)	(0.0127)	(0.0126)
N	7304	7304	7304	7304
Adjusted R2	0.8727	0.8728	0.8728	0.8730
F	1.3e+03	1.2e+03	1.3e+03	1.2e+03

*Note: The estimating standard error of robust heteroscedasticity adjusted for urban clustering is reported in brackets, where ***, ** and * represent significance levels of 1%, 5% and 10%, respectively. Due to space, the regression results of dummy variables are omitted.*

Finally, in order to avoid the influence of sample outliers as much as possible, this paper expanded the sample tail shrinkage interval. In the baseline regression, the sample was treated with tail shrinkage at 1% and 99%. Besides, in the robustness test, the sample was treated with tail shrinkage at 3% and 97%. The regression results were shown in Table 9, which were consistent with the results obtained by the baseline regression, indicating the conclusion of this paper was still valid after the sample's tail shrinkage interval was expanded.

Table 9. Regression results after expanding the tail shrinkage interval

	Model A		Model B	
	(1)	(2)	(3)	(4)
isa	0.0472**	0.0523***		
	(0.0185)	(0.0187)		
isa×dcapa		0.0380***		
		(0.0065)		
ida			0.0411***	0.0486***
			(0.0123)	(0.0133)
ida×dcapa				0.0211**
				(0.0083)
dcapa	0.0247*	0.0271**	0.0302**	0.0371***
	(0.0129)	(0.0130)	(0.0128)	(0.0127)
equ	-0.0031	-0.0014	-0.0029	-0.0034
	(0.0118)	(0.0117)	(0.0118)	(0.0118)
esc	0.0234	0.0187	0.0241	0.0248
	(0.0260)	(0.0259)	(0.0259)	(0.0258)
ffi	0.0246**	0.0394***	0.0238**	0.0254**
	(0.0113)	(0.0114)	(0.0113)	(0.0113)
open	0.0712***	0.0636***	0.0805***	0.0694***
	(0.0195)	(0.0191)	(0.0195)	(0.0203)
gov	-0.0033	0.0050	-0.0023	-0.0033
	(0.0090)	(0.0091)	(0.0089)	(0.0089)

edu	0.0381***	0.0406***	0.0358***	0.0362***
	(0.0113)	(0.0112)	(0.0113)	(0.0113)
Cons	0.2675***	0.2687***	0.2641***	0.2692***
	(0.0139)	(0.0139)	(0.0140)	(0.0139)
N	8217	8217	8217	8217
Adjusted R2	0.8112	0.8121	0.8115	0.8117
F	1.4e+03	1.4e+03	1.4e+03	1.3e+03

Note: The estimating standard error of robust heteroscedasticity adjusted for urban clustering is reported in brackets, where ***, ** and * represent significance levels of 1%, 5% and 10%, respectively. Due to space, the regression results of dummy variables are omitted.

6. Summary

Based on the panel data, this paper used the three-stage DEA model to measure the efficiency of manufacturing supply chain. From the perspective of green economy, it used the entropy weight method to construct the digital capability evaluation system. Furthermore, the bidirectional fixed effect model was further used to analyze the influence of specialized agglomeration and diversified agglomeration on manufacturing supply chain efficiency and the moderating effect of digital capability.The main conclusions were drawn as follows: First, specialized agglomeration and diversified agglomeration had significant positive effects on manufacturing supply chain efficiency. Second, digital capability can adjust the positive effects of specialization agglomeration on supply chain efficiency and diversification agglomeration on supply chain efficiency. Based on the empirical results, this paper had the following suggestions:

On the one hand, at the government level, the government should build diversified clusters such as industrial innovation ecosphere and industrial and residential innovation aggregation circle to promote diversified development of industries to produce more innovative results. In addition, the government should also encourage the development of single-industry innovation clusters, promote the professional development of the industry, support the diffusion of knowledge and joint innovation within the industry, and promote the upgrading of specialized technologies. It was suggested to set up incentive policies for industrial cooperative innovation. For example, the government bore part of the enterprise innovation expenditure, and relevant departments encouraged technology sharing and exchange among enterprises. In terms of digital capacity building, this paper suggested government could increase the investment in digital construction to promote the digital green transformation of manufacturing enterprises. The government can also set up a reward and punishment system, reduce taxes on enterprises that actively do the green transformation, and implement the suspension and adjustment policy for enterprises with negative development.

One the other hand, at the corporate level, in addition to actively responding to national policies, the company can actively carry out technical exchanges and learning with other enterprises in the same or different industries, hold some sharing meetings, or contact famous enterprises to establish digital alliances, so as to promote the spread of technology and the output of innovation results. In addition, the company should carry out regular training on the digital ability of the staff and encourage the digital ability to be included in the evaluation index as well as pay attention to the combination of company management and digital means, actively connect with the upgrade of digital technology and accelerate the enterprise's own digital transformation. Besides, the company should also pay attention to the path relationship between enterprise performance and energy consumption and pollution, and strive to reduce energy consumption and pollution without changing the quality level, so as to promote the development of green economy.

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