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How Does Industrial Agglomeration Affect Total Factor Energy Efficiency in China? Perspectives on the Collision of Digital and Green

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Industrial agglomeration is an important way to affect total factor energy efficiency (TFEE), and digitalization level (DL) and green technology innovation (GTI) can help improve the effect of industrial agglomeration. This research examines the impact of specialized industrial agglomeration (SIA) and diversified industrial agglomeration (DIA), the two main forms of industrial agglomeration, on TFEE under the mediating role of GTI and the moderating role of DL. Three main results were obtained based on the China's provincial data from 2010 to 2021. (1) Both SIA and DIA can significantly promote TFEE, but their effects are different. (2) GTI plays a mediating role in the positive promotion effect of DIA and SIA on TFEE. In addition, GTI not only has obvious inertial effects in time, but also has significant spillover effects in space. (3) DL not only strengthens the impact of SIA or DIA on TFEE, but also enhances the impact of SIA or DIA on GTI. The results show that DL and GTI are effective ways for industrial agglomeration to build a sustainable economy. The article finally puts forward policy recommendations, emphasizing accelerating digital transformation, strengthening industrial agglomeration planning, promoting green technology innovation, and adopting a multi-path development model.

1. Introduction

China is one of the largest coal consumers and carbon dioxide emitters, it is very important to ensure the sustainable growth of economy. In the past few decades, China has relied on resource consumption to promote economic growth, especially traditional energy such as coal. Therefore, the key to solving the above problems lies in improving energy efficiency. Industrial agglomeration areas have become an important engine for China's rapid economic growth by relying on the concentrated production of enterprises in geographical space. At the same time, they have inevitably become a source of environmental pollution due to the concentrated emission of greenhouse gases such as carbon (Lu and Jiao, 2018). Industrial agglomeration can provide the geographic basis for technology diffusion and knowledge spillovers among firms in the agglomeration area, thereby improving overall energy use efficiency. On the contrary, industrial agglomeration can also trigger environmental problems such as production expansion and pollution concentration, which will accelerate energy consumption. At present, industrial agglomeration is mainly divided into SIA and DIA, whose different modes will also bring different results. However, existing studies have ignored the heterogeneous ways of industrial agglomeration. This research trying to responses the following questions. What would be the same trends and different characteristics of SIA or DIA impacts on TFEE? Especially from the perspective of spatial spillover, what characteristics will these impacts present? At the same time, in response to climate challenges, countries have encouraged the development of GTI to promote the green and low-carbon development of local industries. Therefore, does GTI act as a mediating variable in the impact of SIA or DIA on TFEE?

In addition, as an important driving force for social change and an important carrier of technological change, the digital economy have an important impact on industrial agglomeration areas (Yan et al., 2023). The digitalization will improve the production methods and resource acquisition channels of enterprises in the cluster area. Therefore, this article further explores the following two questions: Can increased digitization play a moderating role in the mechanism of industrial agglomeration's impact on TFEE? At the same time, can the digitalization help firms in the agglomeration area to better apply green technological innovations and thus increase TFEE?

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2. Literature review and research hypothesis

2.1 The direct path of SIA and DIA to influence TFEE

Industrial agglomeration will inevitably bring about changes in production methods and pollution emissions, thereby leading to changes in energy efficiency. Industrial agglomeration can bring about the agglomeration of labor, production linkages between enterprises in the agglomeration area, and knowledge spillovers (Wang and Wang, 2019). On the contrary, industrial agglomeration will also lead to the concentration of production within a certain geographic area, and the growth of scale within the limited scope of the agglomeration area is prone to produce a congestion effect, which will make the industrial agglomeration area become a larger source of pollution (Hao et al., 2022). However, it is still important to point out that despite the existing literature on industrial agglomeration and TFEE, most of these studies have ignored the fact that differences in the mode of industrial agglomeration may also give rise to differences in agglomeration effects. The results based on SIA and DIA may be different due to the differences in industries and production behaviors engaged by firms in the agglomeration area. Therefore, this article proposes the first hypothesis.
Hypothesis 1: Both SIA and DIA have a strong connection to TFEE, and both of these connections are positive.

2.2 The indirect path from GTI

Due to the significant role of GTI in long-term sustainable growth (Dory, 2023), industrial agglomeration plays a crucial role in driving GTI. On the one hand, supporters of SIA believe that SIA can generate homogeneous knowledge, promote the absorption and dissemination of homogeneous knowledge by enterprises in the region, and thus drive regional industrial innovation (Mariotti et al., 2010). On the other hand, supporters of DIA believe that DIA can lead to diversified and heterogeneous knowledge output. Through cross-industry knowledge exchange, enterprises in the agglomeration area can use complementarity to improve innovation benefits (Shen et al., 2018). Furthermore, Xu and Zhang (2023) found that manufacturing agglomeration has a substantial influence on improving GTI's efficiency. The hypothesis 2 is proposed.
Hypothesis 2: GTI can play an important mediating role in the influence of SIA and DIA on TFEE, both SIA and DIA can improve TFEE through GTI.

2.3 The moderating role of DL

As an emerging form of information technology, digital economy can break the limitations of the space of agglomeration area, integrate physical resources and information resources (Zhong et al., 2024). In addition, Dian et al. (2024) emphasized that the digital economy can change the access to information and the way companies manage their production, which can significantly change the perception and acceptance of green innovation in the pursuit of green transformation. The advancement of the Internet and related innovative applications have had a significant impact on energy conservation and pollution avoidance. Furthermore, positive media coverage can significantly promote green innovation, which has become crucial for green production in the digital era. Therefore, this article proposes the following hypothesis.
Hypothesis 3: DL not only strengthen the impact of SIA and DIA on TFEE, also enhance the impact of SIA and DIA on GTI.

3. Methodology and Research Design

3.1 Basic model estimation of SIA and DIA

This paper constructed the Eq (1) and (2) following equation to explores the impact of SIA and DIA on TFEE.

$$TFEE_{it} = \alpha_0 + \alpha_1 SIA_{it} + \alpha_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (1)$$

$$TFEE_{it} = \alpha_0 + \alpha_1 DIA_{it} + \alpha_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (2)$$

where *i* represents province, and *t* represents year. X_{it} represents the control variables.

3.2 Measurement of variables

Explained variable: TFEE. (1) Labor input, expressed by the stock of human capital. Capital input, indicated as the fixed capital stock, which is calculated by the perpetual inventory method. Energy input, expressed by converting energy consumption in production and life, such as coal, natural gas and petroleum, into standard coal (tons of standard coal). (2) Desirable output. Includes economic and environmental benefits. The economic benefits employed the nominal GDP of each province, and the percentage of forest cover is used to represent the environmental benefits. (3) Undesirable output. In this study, the standardized indices of the four pollutants are used to measure the undesirable outputs through the index weight entropy method. This article measures

TFEE in China based on a super SBM model with undesirable output (Zhao et al., 2020), and the sample is drawn from the data of 30 provinces in China (excluding Taiwan, Hong Kong, Macao, and Tibet due to large data gaps) from 2010 to 2021.The spatial and temporal distribution of TFEE of China were shown in the Fig. 1.

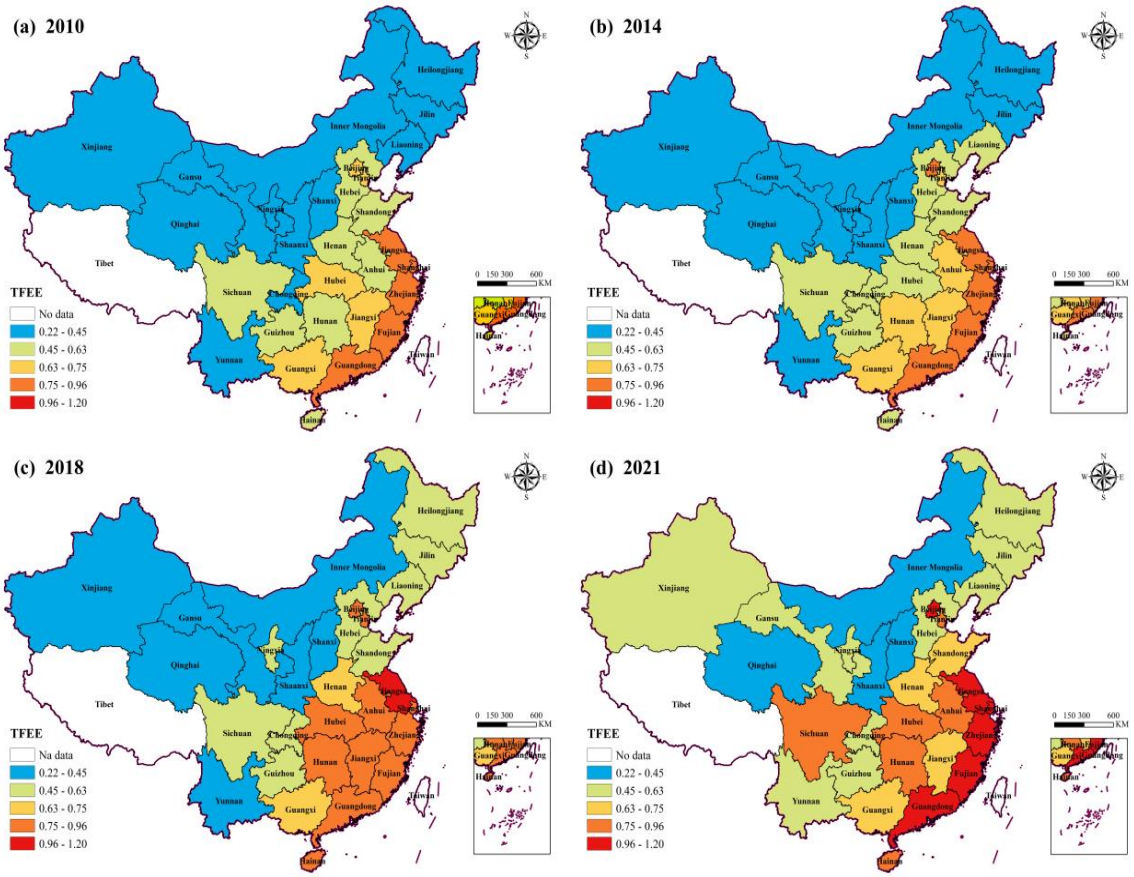

Figure 1: The TFEE of China at (a) 2010, (b) 2014, (c) 2018 and (d) 2021

Core explanatory variable: SIA and DIA. In this study, the Herfindahl-Hirschman Index is utilized to fully characterize the SIA and DIA, and it can be drawing from Peng et al., (2023).

Mediating variable: GTI. The GTI is selected referring the research of Liu et al., (2021). Those patents for inventions and utility models that have been granted are counted and assigned to different provinces and years by using known information about the inventor's place of residence and the date of patent publication.

Moderating variable: DL. Referring the research of Zhang et al., (2022), this article measures digitalization level from the industrial digitalization and digital industrialization.

Control variables. (1) Energy structure (ES): calculated as energy consumption divided by overall energy consumption. (2) Urbanization level (UL): expressed as the urban population divided by the total population. (3) R&D investment (RD): the proportion of the regional annual R&D investment to GDP. (4) Trade openness (OP): foreign direct investment divided by GDP. (5) Market competition (COM): the percentage of the industrial output value of non state-owned enterprises in total industrial output. (6) Industrial structure (IS): the tertiary industry's share of GDP. The above data all originate in the China Statistical Yearbook, Chinese Energy Statistics Yearbook and provincial statistical yearbooks and so on.

4. Results analysis and discussion

4.1 Basic analysis of SIA or DIA and TFEE

Table 1 shows the baseline regression results. Among them, Model 1~Model 3 are the analysis results based on ordinary least squares (OLS), random effects (RE) and fixed effects (FE) respectively. At the same time, this study further tests the impact of SIA and DIA employed the generalized method of moments (GMM) and dynamic GMM, and results are shown in Model 4~5. This paper finds the time inertia and snowball effect of TFEE are established. And all five models above tentatively show that SIA or DIA can effectively enhance TFEE, and the effect is different.

Table 1: The results of basic model estimation of SIA and DIA

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
	OLS	FE	RE	SYS-GMM	SYS-GMM
TFEEt-1					0.737***
SIA	0.112**	0.120**	0.224***	0.181*	0.165**
DIA	0.175**	0.154*	0.103**	0.142**	0.187**
ES	-0.204**	-0.261**	-0.199*	-0.210*	-0.168*
UL	-0.131*	-0.108**	-0.117*	-0.196*	-0.158*
UL2	0.093*	0.101*	0.094**	0.105*	0.081**
RD	0.183**	0.099***	0.108*	0.117**	0.167*
OP	-0.087	-0.075*	-0.058	-0.052**	-0.069*
OP2	0.091*	0.088*	0.107*	0.133	0.096*
COM	0.050	0.033*	0.047	0.045	0.061*
IS	0.146*	0.117**	0.189**	0.203*	0.197**
Constant	0.388**	0.406*	0.310*	0.501**	0.523***
F/wald-test	46.630**	55.489***	60.847**	112.362***	208.464***
R-squared	0.502	0.661	0.573		
AR(2)[P]				1.223[0.133]	1.201[0.146]
Hansen[P]				20.354[0.299]	18.377[0.314]
Observations	360	360	360	360	330

Notes: ***, **, * indicates significance at the 1%, 5%, 10%, respectively. The following table is the same.

4.2 Analysis of the spatial effect of SIA and DIA

This research employs the spatial weight matrix and the Moran'I index to verify the spatial correlation of TFEE, SIA, DIA, GTI and DL. Table 2 demonstrates the regression results from the spatial perspective. A series results show the SDM model is fit. Model 1~2 show the regression of SIA and DIA respectively. Specifically, the coefficient of SIA on TFEE is 0.108, and the DIA is 0.166. The estimated coefficients of the spatial terms of SIA and DIA is 0.165 and 0.180 respectively. This shows that the TFEE in this region will be affected by the SIA and DIA in adjacent provinces. In addition, the coefficients of spatial terms of TFEE were 0.261 and 0.196 respectively. This shows that the TFEE in this province will also be affected by the TFEE in neighboring provinces, and the demonstration effect and synergy effect are significant.

Table 2: The results of spatial spillover effect

Variables	EV=TFEE	EV=TFEE
	Model 1	Model 2
TFEEt-1	0.877***	0.806***
SIA	0.108***	
DIA		0.166**
W*TFEE	0.261***	0.308***
W*SIA	0.165***	
W*DIA		0.180**
Constant	0.216**	0.196***
LM test lag	100.91**	116.27*
LM test error	86.36**	79.10**
LR test for SAR	25.33***	27.16***
LR test for SEM	19.28***	17.30***
Wald-test	1032.081**	1181.762***
AR(2)[P]	1.23[0.228]	1.38[0.301]
Hansen[P]	18.34[0.668]	15.72[0.596]
Observations	330	330

4.3 Analysis of GTI as the mediate variable

Table 3 shows the influence of SIA and DIA on GTI, and GTI on TFEE. In Model 1 and 3, the regression results show that both SIA and DIA can promote GTI, and the formation of agglomeration areas is conducive to the flow and sharing of green technology. In addition, the spatial regression results of SIA and DIA on GTI are positive, 0.115 and 0.099 respectively. This shows that the GTI in this region will be affected by the industrial agglomeration in adjacent regions. Furthermore, Model 2 and 4 show the regression results of GTI on TFEE

under the SIA and DIA scenario, and the coefficient is 0.172 and 0.168, respectively. Therefore, GTI is the mediating variable that affects TFEE due to industrial agglomeration. It is worth mentioning that in Model 1 and Model 3, the results of the lag term of GTI are 0.215 and 0.146 respectively, indicating that GTI also be affected by the previous issue. At the same time, in Model 2 and Model 4, the spatial term of GTI is also significantly positive, 0.218 and 0.197 respectively. This suggests that GTI has a strong spatial spillover effect within a certain geographic range, and that GTI in one region is affected by GTI in neighboring regions.

Table 3: The mediating effect of GTI

Variables	EV=GTI	EV=TFEE	EV=GTI	EV=TFEE
	Model 1	Model 2	Model 3	Model 4
TFEEt-1		0.803***		0.908***
GTIt-1	0.215***		0.146***	
SIA	0.206**	0.157***		
DIA			0.133***	0.184**
IS	0.039*	0.121*	0.031*	0.117**
GTI		0.172**		0.168***
W*TFEE		0.204***		0.210***
W*SIA	0.115**	0.127**		
W*DIA			0.099***	0.119***
W*GTI		0.218***		0.197***
Constant	0.705**	0.511**	0.628**	0.356**
LM test lag	105.22**	148.36***	121.31***	130.82**
LM test error	78.21**	77.99**	81.22**	69.37***
LM test for SAR	41.83**	38.95***	50.25**	45.56***
LM test for SEM	25.49**	30.57**	28.46**	27.13**
Wald-test	1956.303***	1496.641**	2013.285**	1507.393***
AR(2)[P]	1.99[0.167]	1.60[0.192]	1.80[0.155]	1.86[0.143]
Hansen[P]	18.67[0.662]	17.09[0.501]	19.66[0.708]	20.11[0.637]
Observations	330	330	330	330

Table 4: The moderating effect of DL

Variables	EV=TFEE	EV=GTI	EV=TFEE	EV=TFEE	EV=GTI	EV=TFEE
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
SIA	0.166**	0.204**	0.153***			
DIA				0.124**	0.185*	0.171**
DL	0.107**	0.157***	0.112**	0.104***	0.161***	0.110**
DL*SIA	0.283**	0.246***	0.279**			
DL*DIA				0.260**	0.301***	0.292**
GTI			0.218**			0.201**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.357**	0.509***	0.567***	0.319**	0.458***	0.494***
Wald-test	1128.263***	1079.645**	1530.582**	1452.297***	1107.942**	1096.837***
AR(2)[P]	1.23[0.166]	1.59[0.203]	1.55[0.192]	1.09[0.143]	1.57[0.217]	1.72[0.209]
Hansen[P]	19.65[0.291]	18.66[0.255]	20.13[0.188]	19.57[0.204]	19.06[0.199]	18.71[0.182]
Observations	360	360	360	360	360	360

4.4 Analysis of DL as the moderate variable

Next, the table 4 shows the results that the moderating effect of DL in the influence of SIA or DIA on TFEE. Model 1 show that both SIA and DL can promote the TFEE, and the coefficient of SIA*DL is 0.283. Model 4 shows that both DIA and DL can promote the growth of TFEE, and the coefficient of DIA*DL is 0.260, It shows that DL can improve the influence of SIA or DIA on TFEE. In addition, Model 2~3 demonstrated the moderating effect of DL on GTI. In Model 2, the influence of DL on GTI is positive, and the coefficient of SIA*DL is 0.246. The coefficients of SIA*DL and GTI are 0.279 and 0.218 respectively shown by model 3. In Model 5, the impact of DL on GTI is positive, the coefficient is 0.161. The coefficient of SIA*DL is 0.301. It shows that DL can positively regulate the effect of DIA on TFEE. In Model 6, the coefficients of DIA*DL and GTI are 0.292 and

0.201, respectively. These show that both the moderating effect of DL on SIA or DIA's influence on GTI and the mediating effect of GTI are established.

5. Conclusions

This paper explores the relationship between industrial agglomeration and TFEE from the perspective of collision of DL and GTI. After the elaboration of theoretical mechanisms and the measurement of quantitative analysis, the three hypotheses proposed in this paper have been effectively verified. Firstly, both SIA and DIA can enhance TFEE to a certain extent, but there are differences in the degree of promotion between them, and industrial agglomeration can be regarded as a powerful means to improve energy efficiency. Secondly, both SIA and DIA can play a facilitating role on TFEE through GTI. Finally, DL can enhance the influence of SIA or DIA on TFEE, as well as improve the influence of SIA or DIA on GTI. Both GTI and DL can be regarded as an effective initiative to amplify the promotional effect of industrial agglomeration on energy efficiency.

In response to the above findings, this paper can draw some relevant policy inspiration. (1) Vigorously promote the digitalization process. The government should be committed to the rapid development of the digital economy and encourage the application of digital technology in the firms in the agglomeration area. (2) Implement a dynamic differentiation strategy of specialization and diversified agglomeration. A series of policies and measures that are conducive to industrial agglomeration can be formulated. Meanwhile, it can guide industrial agglomeration to transform into high-end, green and green directions, which profits both industrial agglomeration and carbon emission efficiency. (3) Encourage local governments and enterprises to jointly promote GTI. Strengthening support and promotion of green technology, enterprises can be encouraged to form a sharing and diffusion mechanism for green technologies in industrial agglomerations. (4) Promote regional collaborative governance. The promotion of inter-regional collaborative governance mechanisms can also play an important role in improvement of TFEE.

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