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RESEARCH ON THE INFLUENCE AND MECHANISM OF DIGITAL INDUSTRY AGGLOMERATION ON REGIONAL QUALITY COMPETITIVENESS

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Abstract

With the arrival of the quality economy era, quality competition has gradually become the core competition field and strategic focus of regional development towards high quality. Digital industry agglomeration is particularly critical to the improvement of regional quality competitiveness. This paper uses panel data of 283 cities in China from 2005 to 2021. It verifies the impact of digital industry agglomeration on the improvement of regional quality competitiveness by constructing a two-way fixed effect model. The robust and endogenous results of this paper show that the results are robust. The results reveal the following: (1) Digital industry agglomeration significantly promotes regional quality competitiveness. However, the influence of digital industry agglomeration on regional quality competitiveness is non-linear. When the degree of digital industry agglomeration breaks through a certain threshold, its promoting effect on regional quality competitiveness gradually weakens, showing an inverted U-shaped influence relationship. (2) The impact of digital industry agglomeration on regional quality competitiveness shows significant heterogeneity in different locations and resource endowments. (3) Regional innovation activities, industrial collaboration quality, and industrial collaboration depth are the mechanism path of digital industry agglomeration affecting regional quality competitiveness. This study clarifies the impact of digital industry agglomeration on regional quality competitiveness and its mechanism, enriches the existing research framework, and offers valuable insights for the effective implementation of the national quality power strategy.

Keywords: *Digital industry agglomeration, Industrial synergy, Regional quality competitiveness, Nonlinear effect*

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1 INTRODUCTION

Improving regional quality competitiveness has become a critical starting point for sustainable development in many countries. As the world's largest emerging economy, China is striving to optimize its economic structure and enhance growth quality while maintaining steady economic growth. In this context, the new development concept, focusing on building a strong country with quality and enhancing regional competitiveness, has become a new strategy to lead China's future economic development. At the same time, as a key engine driving the transformation of old and new economic drivers and optimizing the layout of industrial structure, digital industry has become an important source of power to solve development problems and cultivate new growth drivers (Wang et al., 2024). The rapid rise of China's emerging digital industry groups, with big data and artificial intelligence as engines, has not only formed an initial industrial agglomeration effect, but also gradually established its advantages and core industry position as a driver of high-quality economic development (Wang et al., 2021). Therefore, how to make efficient use of the scale effect, technology spillover effect and innovation leading effect of digital industry agglomeration (DIAGG) to comprehensively enhance the regional quality competitiveness index (RQCI) has become a major issue for China’s economic development.

The concept of regional competitiveness was first proposed by Porter (1990). In terms of research on developed countries, Kresl and Singh (1999) defined regional competitiveness within a city in terms of employment, income, culture, and quality governance. In terms of measuring regional competitiveness, developed countries mostly measure the competitiveness of a country or a region from the aspects of technological ability, innovation level and talent support. José et al. (2012) constructed a scientific and technological innovation index system from the perspective of R&D personnel, R&D funding and other inputs, and used this system to evaluate the competitiveness of regional scientific and technological innovation in Spain. Krstic and Gawel (2023) applied a multiple linear regression model, finding that international exchanges, human resources, and innovation levels all positively influence regions. In developing countries, scholars tend to focus more on industrial development, government support and policy impacts. Feng et al. (2015) used the data of 31 provinces in China to study the status of related and supporting industries, provincial factor conditions, and the impact of telecom industry competition on the quality competitiveness of regional telecom industries using factor analysis. Moirangthem and Nag (2022) used India panel data from 2008 to 2017 to measure India’s regional competitiveness from the quality of regional entrepreneurship, technological innovation and institutional development. Wang and Li (2024) investigated the competitiveness of China’s listed manufacturing companies based on the development strategy of China’s manufacturing power, and the results showed that carbon emissions and supply chain digitalization policies were positively correlated with the competitiveness of manufacturing enterprises.

Industrial agglomeration is a spatial organization form of industrial spatial layout adjustment in the process of industrial evolution, which is mainly manifested as the relative concentration of the same industry or related enterprises within a certain geographical range (Wang et al., 2023). Many scholars have conducted research on industrial agglomeration, and their measurement methods have covered industrial concentration, the Herfindahl index, location entropy and so on (Ren & Tang, 2024; Martin et al., 2010). At present, two opposing views have emerged regarding the impact of industrial agglomeration on regional high-quality development: promotion theory and withdrawal theory (Andersson et al., 2014; Gonzalez et al., 2016). In terms of the promotion theory, the existing research finds that industrial agglomeration strengthens the cooperation and division of labor among enterprises at the micro level, forms resource sharing to a certain extent, and improves the utilization of urban public facilities (Wang et al., 2023). However, as far as the theory of industrial agglomeration promoting retreat is concerned, some studies have shown that industrial agglomeration will produce serious crowding-out effect, leading to regional homogeneous production and further squeezing production profits. Other studies have found that there may be an inverted U-shaped relationship between the impact of industrial agglomeration on regional development, i.e., excessive industrial agglomeration will also bring serious crowding out problems, which is not conducive to regional development. For instance, the study of Cai and Hu (2022) shows that the initial stage of industrial agglomeration is conducive to reducing regional pollution emissions, while when the industrial agglomeration continues to increase, it will significantly increase regional pollution emissions.

To summarize, while some scholars have examined the impact of industrial agglomeration on regional competitiveness, several gaps remain in the current research: (1) Despite the rapid development of the digital economy, the economic impact of DIAGG has received limited attention; (2) Research on RQCI is insufficient, and the influence and mechanism of DIAGG on RQCI are still inconclusive. (3) Most evaluations of regional competitiveness are qualitative, with limited quantitative research. To address these research gaps, this study constructs the RQCI index, uses data from 283 cities in China from 2005 to 2021, empirically tests the relationship and mechanism through which DIAGG affects urban quality competitiveness in China, and further explores the potential nonlinear effects of DIAGG on the development of quality competitiveness.

The marginal contribution of this study is mainly reflected in three aspects: (1) This paper innovatively constructs the RQCI index, providing a comprehensive and detailed measurement method for this important concept, and filling the research gap in the existing literature. (2) It clarifies the impact of DIAGG on RQCI and its influence path. (3) It examines the nonlinear impact of DIAGG on RQCI. The findings of this study demonstrate a nonlinear relationship between DIAGG and quality competitiveness.

The remaining chapters are organized as follows: the second chapter is theoretical basis and research hypothesis; chapter three is the research design; the fourth chapter is the empirical analysis; chapter five is for further analysis; the last section is the conclusion of the study.

2 THEORY AND HYPOTHESIS

2.1 Theoretical analysis of digital industry agglomeration and regional quality competitiveness

Compared with traditional industries, digital industries, with high technology as the core driving force and data elements as the key carrier, exhibit unprecedented penetration and influence, becoming a strong engine for driving regional high-quality development and transformation (Jie et al., 2024). First, DIAGG can optimize the regional innovation environment. According to the endogenous growth theory, DIAGG effectively gathers scientific and technological talent and promotes the optimal allocation and flow of labor resources through the guidance of digital technology (Du et al., 2024). This not only promotes synergy and consensus among regional enterprises in areas such as energy conservation, emission reduction, product and service innovation, and business model innovation, but also accelerates the dissemination of basic innovation achievements, thereby significantly improving the overall production efficiency and innovation capabilities of the region (Zhang et al., 2023). In addition, the agglomeration effect intensifies both competition and cooperation within the digital industry, builds a closer and deeper innovation ecosystem among innovation agents, accelerates the iterative development of new technologies and new models, and injects sustained innovation momentum into the regional economy (Henderson, 2000).

Secondly, DIAGG can improve regional production efficiency. According to Marshall’s theory of external economic agglomeration, DIAGG factors enhance the integration of key innovation factors, such as technology, talent, capital, and enhance the efficiency of innovation achievement transformation within a region (Eswaran & Kotwal, 2002). The centralized layout of digital industries promotes the deep integration and efficient utilization of core innovation elements such as technology, talent and capital, and accelerates the transformation of innovation achievements into productive forces. (Lengyel & Rechnitzer, 2013). Thus, this paper puts forward hypothesis 1:

H1: DIAGG plays a significant role in promoting the development of RQCI.

2.2 Theoretical analysis of influence mechanism

DIAGG can significantly promote urban entrepreneurial activity, further promoting the RQCI. First, from the perspective of knowledge spillover and technology exchange, DIAGG has built a highly concentrated innovation ecosystem. Within this ecosystem, the convergence of sophisticated enterprises and top talent accelerates the flow and sharing of technical knowledge, while fostering technological exchanges and cooperation in the region, forming a significant knowledge spillover effect. Second, DIAGG enhances enterprise innovation, power, and efficiency through resource sharing and cost reduction mechanisms. In the agglomeration area, enterprises can easily share basic R&D resources, such as data centers and experimental facilities, thus effectively reducing the innovation cost of a single enterprise. At the same time, the market environment where competition and cooperation coexist, has stimulated the internal potential of enterprises, prompting them to constantly pursue breakthroughs in new technologies and products, and promoting the overall leap of regional innovation capacity (Ke et al., 2014). This comprehensive support system not only reduces the threshold and risk of entrepreneurship, but also accelerates the commercialization process of innovation achievements, injecting strong impetus into the continuous enhancement of urban entrepreneurship activity. With the continuous increase of innovation and entrepreneurship activities, new technologies, new products and new forms of business emerge in a region, and innovation and entrepreneurship become the main driving force of regional economic growth, providing more growth points for the development of urban quality competitiveness (Lanaspa et al., 2016). Based on these theories, this paper proposes hypothesis 2a:

H2a: DIAGG can promote regional entrepreneurial activity.

DIAGG can promote the coordinated development of manufacturing and producer services. Collaborative agglomeration refers to the collaborative agglomeration of related and supporting industries, which is a transformation from single-wheel drive to two-wheel drive (Burchfield et al., 2006). This concept emphasizes the close connection and common growth between related and supporting industries, and its core is to achieve the optimal allocation of resources and a significant improvement in efficiency. When discussing the dimensions of collaborative development, the quality and the depth of collaborative are indispensable aspects. In terms of collaborative quality, the initial stage of DIAGG may negatively affect the collaboration between manufacturing and producer services. According to Baumol's cost disease theory, manufacturing, as a progressive sector, is highly motivated to innovate (Baumol, 1967). During technological upgrading, manufacturing industries often require higher quality and more efficient services from producer services (such as high-end logistics, precision processing, digital management). On the other hand, however, producer services may lack sufficient innovation momentum, making it difficult to meet the manufacturing sector's high demands, which results in a mismatch between the technology and services provided by both industries. Consequently, the promotion effect of DIAGG on RQCI is weakened (Ren & Tang, 2024; Liu & He, 2022). However, as DIAGG matures, its long-term effects become more apparent. With its advantages in technological innovation and talent intensity, DIAGG promotes the transformation and upgrading of the manufacturing sector. The digital industry within the agglomeration area promotes the manufacturing industry to adopt advanced production equipment, management systems, and intelligent technologies through technology spillovers and innovative resource sharing, improving production efficiency and product quality (Nie et al., 2022). This not only modernizes the manufacturing sector but also expands its, increasing the demand for high-quality producer services. As a result, producer services can further expand and enhance their overall scale and quality to meet these new demands (Peng et al., 2021). Based on this analysis, this paper proposes hypotheses 2b and 2c:

H2b: DIAGG contributes to the industrial collaborative quality.

H2c: DIAGG may not be conducive to the industrial collaborative quality.

Furthermore, in terms of collaboration depth, the initial stage of DIAGG may have a negative impact on the depth of collaboration. This is because, during the initial stage of agglomeration, technological progress in manufacturing often outpaces that in producer services, leading to a mismatch between the high-quality service demands of the manufacturing sector and the capabilities of the producer services sector, creating a service supply-demand mismatch (Xu et al., 2024). As a result, the depth of collaboration in the initial stage may be low, and even form a certain degree of disconnection phenomenon. This potential dislocation may not only weaken the synergy effect between industries but also hinder the improvement of RQCI.

However, with the further deepening of industrial agglomeration, DIAGG promotes the transformation of producer services from basic to high value-added and technology-intensive services by improving the manufacturing sector’s scale, efficiency, and technological capabilities. As the manufacturing sector upgrades, the demand for more efficient, customized and intelligent producer services grows. To meet these demands, producer services must innovate and upgrade, adapting to rapidly changing market needs (Chen et al., 2024). At this point, DIAGG facilitates the development of producer services, advancing them to higher levels of technology and service capabilities through resource sharing, technological innovation, and talent flow, which further deepens collaboration between industries. The technological transformation of the service sector increases the depth of collaboration, thereby enhancing RQCI (Wu and Lin, 2021; Zhou et al., 2024). Based on this, this paper proposes hypotheses 2d and 2e:

H2d: DIAGG contributes to the depth of industrial collaboration.

H2e: DIAGG may not be conducive to the depth of industrial collaboration.

2.3 The nonlinear impact of digital industry agglomeration on regional quality competitiveness

The influence of DIAGG on RQCI is not a single linear relationship but demonstrates a clear nonlinear effect (Cai & Hu, 2022). The influence of DIAGG on RQCI may vary at different development stages. In particular, DIAGG contributes to the efficient allocation of resources, attracts innovative talent and promotes technology spillovers, thereby stimulating the innovation vitality and economic potential of the region. However, with the deepening of agglomeration, negative effects within the region gradually appear (Balland et al., 2020). First, the rapid development of agglomeration increases pressure on infrastructure, especially in the case of insufficient carrying capacity of infrastructure, which may lead to inefficient use of resources and a decline in operational efficiency. Secondly, in the initial stage of DIAGG, collaboration quality and depth are low, and the internal output within the industrial agglomeration area rises slowly. In addition, industrial homogenization begins to emerge. As digital industries concentrate further, enterprises may become overly reliant on existing production modes and technologies, neglecting industrial diversification and technological innovation (Jin et al., 2025). This trend limits regional production diversity and innovation depth, reducing the elasticity and long-term growth potential of the regional economy, ultimately inhibiting RQCI improvement.

Over time, as industrial agglomeration deepens, DIAGG’s influence on RQCI gradually demonstrates a late-stage advantage. Driven by technological and service innovation, enterprises in the agglomeration area gradually transform to high-quality and high value-added products and services (Huo et al., 2024). Technological renewal and intelligent processes in the manufacturing industry have driven a leap in productivity, while producer services have further enhanced synergies by providing customized and intelligent services. Therefore, in the later stage of agglomeration, DIAGG not only brings technological progress but also promotes deeper cooperation and complementary development among industries, and promotes the overall improvement of RQCI (Brinkman, 2016; Liu et al., 2024). Based on this analysis, this paper proposes hypothesis 3:

H3: The impact of DIAGG on the development of RQCI may have a nonlinear effect.

3 RESEARCH DESIGN

3.1 Data sources

Considering the research of this paper and the availability of relevant data, this paper uses data from 283 Chinese cities between 2005 and 2021, sourced from the China City Statistical Yearbook, China Statistical Yearbook on Science and Technology, and China Statistical Yearbook. Considering that some individual data are missing, this paper uses the artificial neural network model to predict and supplement the missing data.

3.2 Variable selection

(1) Dependent variable

Regional quality competitiveness (RQCI): Considering that RQCI is the direct indicator to measure the construction of a regional quality power, based on the existing research (Krstic & Gawel, 2023; Wang et al., 2023), this paper selects 17 indicators closely related to RQCI from the three dimensions of quality supply, quality demand and quality development, and constructs an index system of quality competitiveness, as shown in Table 1. Since the RQCI index is composed of multiple indicators, in order to objectively reflect the overall level of RQCI, this paper refers to the practice of Satı (2024) and adopts the technique for order preference by similarity to an ideal solution (TOPSIS) entropy weight method for weighting.

Tab. 1 – Evaluation system of RQCI. Source: own research

Category	Species	Variable	Attribute
Supply of quality	Quality technology supply	Number of patents granted in prefecture-level cities	+
	Quality capital supply	Investment in fixed assets in prefecture-level cities	+
	Quality talent supply	Scientific research and technology practitioners in prefecture-level cities	+
	Quality and safe supply	Loss rate of product quality in prefecture-level cities	-
Demand for quality	Competitiveness in the market	Retail sales in prefecture-level cities/total national retail sales	+
		Export volume of prefecture-level cities/total national export	+
	Market adjustment power	Industrial enterprises above designated size	+
		Change rate of the domestic market	+
		Change rate of the international market	+

	Customer satisfaction	Product sampling inspection quality excellent rate	+
		Product sampling inspection failure rate	-
Development of quality	Support for related industries	Fiscal expenditure / GDP	+
		Local financial loan balance at the end of the year / GDP	+
		Road capacity per 10,000 people	+
	Quality management ability	Internal government R&D spending	+
		Sampling inspection intensity of products	+
	Quality input efficiency	Output per unit of new product input	+

(2) Independent variable

Based on the definition of digital industry in the Statistical Classification of Digital Economy and Its Core Industries (2021) and the research of Martin et al. (2010) and Wang and Wang (2019), the DIAGG index of each city is calculated using the location entropy and the number of employees in information transmission, software and information technology service industries. The regional DIAGG index is calculated as follows:

$$DIAGG_{it} = \frac{Inforem_{it}/EM_{it}}{\sum_{t=1}^{n} inforem_{it} \,/\, \sum_{i=1}^{n} EM_{it}} \tag{1}$$

Where $DIAGG_{it}$ is the degree of digital industry agglomeration in the t-th city in the i-th year, where $Inforem_{it}$ is the number of computer and software service employees, $\mathrm{EM}_{\mathrm{it}}$ is the total number of employment, n is total the number of cities, and $\sum_{t=1}^{n} Inforem_{it}$ is the total number of computer and software service employees, and $\sum_{i=1}^{n} EM_{it}$ is the number of employment.

(3) Mediating variable

1) Region entrepreneurial activity (RENTACT): From this analysis, regional innovation activity may play the role of intermediary variable between DIAGG and RQCI. Therefore, referring to the research of Wang et al. (2024c), the increase of entrepreneurial enterprises per 100 people in cities is used to measure the innovation activity of enterprises.

2) Industrial synergy quality (INDSQ): The scale of industrial synergy can measure the integration of local manufacturing and producer service after DIAGG, which is reflected in the quality of industrial integration. Referring to Wang and Wang (2019), this paper calculates the agglomeration of manufacturing industry ($AGGMI_{it}$) based on location entropy.

$$AGGMI_{it} = \frac{Manuem_{it}/EM_{it}}{\sum_{t=1}^{n} Manuem_{it} \,/\, \sum_{i=1}^{n} EM_{it}} \tag{2}$$

In model 2, $AGGMI_{it}$ is the manufacturing agglomeration, and $Manuem_{it}$ is the number of manufacturing employees.

According to the Statistical Classification of Producer Services (2019) of the National Bureau of Statistics, this paper selected the number of employees of producer services such as transportation, warehousing, post and telecommunications, finance, leasing and commercial services, and geological exploration as the representative of producer services, and used model 2 to calculate the agglomeration of producer services ($AGGSI_{it}$).

Referring to the methods of Liu and He (2024), this paper calculates the industrial synergy quality as follows:

$$INDSQ_{it} = 1 - \frac{|AGGMI_{it} - AGGSI_{it}|}{AGGMI_{it} + AGGSI_{it}} \quad (3)$$

$INDSQ_{it}$ is the industrial synergy quality of manufacturing and producer service.

Industrial synergy depth (INDSD): The depth of industrial synergy can measure the integration degree of digital industrial agglomeration on manufacturing and producer service. This paper refers to Liu and He's (2024) methods to calculate the depth of industrial synergy as follows:

$$INDSD_{it} = |AGGMI_{it} + AGGSI_{it}| \quad (4)$$

$INDSD_{it}$ is the depth of integration of manufacturing and producer services.

(3) Control variable

In order to prevent the omission of major variables from affecting the robustness of empirical results, we refer to existing studies (Bai et al. 2024; Liu & Chen, 2024; Zhang et al., 2023), controlling the following variables:(1) growth rate of regional GDP (GRRGDP), telecommunication service volume (TELSV), gross output value of all above designated size industrial enterprises (GOVADSIE), number of registered unemployed individuals (NRUIU), number of college students (NCSTU), regional fiscal expenditure (RFEXP), and rate of urbanization (RURBAN).

3.3 Model setting

In order to test the impact of DIAGG on RQCI, this paper uses the panel two-way fixed effects model for testing. The specific regression model is as follows:

$$RQCI_{it} = \alpha_0 + \alpha_1 DIAGG_{it} + \alpha_2 Control_{it} + \sigma_i + \delta_t + \varepsilon_{it} \quad (5)$$

In model (5), $RQCI_{it}$ is the quality competitiveness of city i in year t, $DIAGG_{it}$ is the digital industrial agglomeration of city i in year t, α_0 is a constant, α_1 is the coefficient of $DIAGG_{it}$, $Control_{it}$ is the choice of control variable in this paper, and α_2 is its coefficient. σ_i is the individual control effect, δ_t is the year control effect, and ε_{it} is the random disturbance term.

4 EMPIRICAL ANALYSES

In order to preliminarily grasp the data characteristics of the variables in this paper, this paper conducts descriptive statistics on these selected variables, as shown in Table 2.

Tab. 2 – Statistical characteristics of variables. Source: own research

	Variable	Observations	Mean	Std. Dev.	Min	Max
Dependent variable	RQCI	4811	0.063	0.063	0.013	0.701
Independent variable	DIAGG	4811	0.698	0.489	0.034	5.302
Mediating variable	RENTACT	4811	1.070	1.121	0.029	20.24
	INDSQ	4811	0.718	0.196	0.054	1.00
	INDSD	4811	1.660	0.532	0.310	3.695
Control variable	GRRGDP	4811	2.340	0.486	-2.303	4.700
	TELSV	4811	12.04	1.409	2.639	16.45
	GOVADSIE	4811	16.46	1.382	8.941	19.88
	NRUIU	4811	0.144	5.817	0.00	350

	NCSTU	4811	10.41	1.433	3.850	14.00
	RFEXP	4811	14.46	1.021	10.81	18.25
	RURBAN	4811	0.519	0.169	0.114	1.00

4.1 Benchmark regression

After controlling for city and year fixed effects, control variables are gradually added, and the benchmark regression results are shown in Table 3. As more control variables are added, the impact of DIAGG on RQCI remains significantly positive at the 5% significance level. In terms of control variables, the results in column (5) of Table 3 show that the GRRGDP growth has a significantly positive impact on RQCI, which is consistent with the previous analysis. The impact of industrial enterprise output on RQCI is significantly negative. The reason for this phenomenon may be that most of these enterprises are traditional industrial sectors, and their production mode is often resource-intensive and polluting. Therefore, an increase in its output may exacerbate the negative impact on RQCI. The coefficient of RFEXP is significantly positive, indicating that increasing government fiscal expenditure plays a crucial role in promoting the construction of RQCI, highlighting the key role of government policies in enhancing city competitiveness. The regression results in Table 3 verify Hypothesis 1 in this paper, indicating that DIAGG has a significantly positive impact on RQCI. This is crucial for Chinese cities to promote the construction of RQCI by promoting the agglomeration of digital industries in the future development process, and for the needs of the construction of China's quality power and modern power.

Tab. 3 – Results of benchmark regression. Source: own research

VARIABLES	(1)	(2)	(3)	(4)	(5)
	RQCI	RQCI	RQCI	RQCI	RQCI
DIAGG	0.004***	0.004***	0.003**	0.003**	0.004**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
GRRGDP		0.003*	0.004**	0.003**	0.004**
		(0.001)	(0.002)	(0.002)	(0.002)
TELSV		-0.001	-0.001	-0.001	-0.001
		(0.002)	(0.002)	(0.002)	(0.002)
GOVADSIE			-0.006***	-0.008***	-0.008***
			(0.002)	(0.002)	(0.002)
NRUIU			0.000*	0.000*	0.000*
			(0.000)	(0.000)	(0.000)
NCSTU				-0.000	-0.000
				(0.002)	(0.002)
RFEXP				0.011***	0.009**
				(0.004)	(0.004)
RURBAN					-0.000
					(0.013)

Constant	0.056***	0.062***	0.147***	0.036	0.054
	(0.002)	(0.017)	(0.036)	(0.051)	(0.052)
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	4811	4811	4811	4811	4811
Adj.R^2	0.169	0.168	0.176	0.178	0.180

4.2 Endogeneity test

(1) Instrumental variable and system GMM

Terrain relief may indirectly affect regional DIAGG by affecting the construction cost of transportation, communication and other infrastructure. Furthermore, there may be a certain correlation between terrain relief and regional DIAGG. Since terrain relief is cross-sectional data, this paper refers to Lin and Tan (2019) and Xin et al. (2024). We construct the product of terrain relief and the annual number of fixed-line telephones in a city, and used two-stage least squares (2SLS) to eliminate possible endogeneity problems in the selection of variables in this paper. The test results are shown in columns (1) - (2) of Table 4. The Kleibergen-Papp rk LM statistic is 37.91 (p=0.00), rejecting the null hypothesis that the instrumental variables are not identifiable. The Cragg-Donald Wald F statistic is greater than the critical value at 10% level (19.93). These results show that the selected instrumental variable meets the requirements of correlation and exogeneity, and there is no weak instrumental variable problem, indicating that the selection of instrumental variable in this paper is reasonable. According to the results in column (1) of Table 4, the instrumental variable and DIAGG are significantly positive, which is consistent with the previous analysis. According to the regression results in column (2) of Table 4, the impact of DIAGG based on the instrumental variable on RQCI is significantly positive, which indicates that the regression results of this paper are still credible after eliminating the possible endogeneity problems in this paper.

In addition, considering that if there are autocorrelation and heteroscedasticity problems in the sample selection in this paper, the estimated value of 2SLS may also have bias. Therefore, this paper refers to the practice of Zhang et al. (2024) and adopts the GMM method for the test. The p value of the second-order serial correlation test result of the regression model is 0.108, which is not significant, indicating that there is no second-order serial correlation in the regression model set in this paper. According to the results in column (3), after the control variables are added, the positive promoting effect of DIAGG on RQCI is still significantly positive at the level of 1%. The reliability of the research results in this paper is further verified.

Tab. 4 – Regression results for instrumental variables and system GMM. Source: own research

VARIABLES	(1)	(2)	(3)
	First stage	Second stage	GMM
	DIAGG	RQCI	RQCI
IV	0.178***		
	(0.027)		
L.RQCI			0.700***
			(0.028)

DIAGG		0.041***	0.003*
		(0.015)	(0.002)
Constant	-1.987***	-0.474***	-0.141***
	(0.258)	(0.044)	(0.051)
Control FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj.R^2		0.514	
Kleibergen-Paap rk LM statistic	37.91***		
Cragg-Donald Wald F statistic	81.07		
AR(2) p value			0.108
Hansen test p value			0.999

(2) Heckman two-step estimation

Following Chen et al. (2014), this paper adopts the Heckman two-step estimation method to solve the endogeneity problem of sample selection. In the first stage, a dummy variable is created based on the DIAGG median (DIAGG=0.5858), with values greater than the median set to 1, and the value less than the median set to 0. Second, we use the Probit model for regression and add control variables to control the year and time, to examine the impact of DIAGG in the samples. In addition, the inverse Mill ratio (IMR) is calculated in the first stage. Thirdly, in the second stage, the IMR calculated from the first-stage regression is introduced into the original regression model as a control variable. The regression results are shown in (1) and (2) of Table 5. According to the regression in column (2) of Table 5, the influence of the Heckman two-step estimation of DIAGG on RQCI is significantly positive, which further supports Hypothesis 1. The coefficient of IMR in column 2 is significantly negative, indicating that the sample has endogeneity bias caused by selection bias. However, after adding the inverse Mills ratio, the DIAGG estimated coefficient remains significantly positive, which is consistent with the benchmark results. This result shows that the conclusion of this paper is still valid after the use of the Heckman two-stage model to correct the endogeneity problem caused by the sample selection bias, which further proves the robustness of the research results of this paper.

(3) Lagged dependent variable

To eliminate potential endogeneity in the benchmark regression results. The reverse causality that the stronger the quality competitiveness of a city, the stronger the DIAGG, should be avoided. In this paper, the explanatory variable DIAGG is lagged by one and two periods respectively, and is substituted into model (6) for testing. The test regression results are shown in columns (3) and (4) of Table 5. These test results show that L.DIAGG and L2. DIAGG are still significantly positive, with little difference in coefficients from the benchmark regression, further confirming the robustness of the results.

Tab. 5 – The results of Heckman two-step estimation with lagged explained variables. Source: own research

VARIABLES	(1)	(2)	(3)	(4)
	DIAGG_dum	RQCI	RQCI	RQCI
DIAGG		0.005***		
		(0.001)		
L.DIAGG			0.004***	
			(0.002)	
L2.DIAGG				0.004**
				(0.002)
IMR		-0.037***		
		(0.007)		
Constant	-3.109***	-0.067**	0.048	0.062
	(0.48)	(0.032)	(0.055)	(0.060)
Control FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations		4811	4528	4245
Adj.R^2			0.185	0.187

4.3 Robustness test

(1) Replace the dependent variable

To exclude the randomness of index construction, this paper selects the city's export volume (EXPORT), which best represents the city's quality competitiveness, as the explained variable for testing. In order to avoid multicollinearity, this study logarithmizes the value of urban exports, and the regression results are shown in Table 6. According to the regression results in column (1) of Table 6, the impact of DIAGG on the value of EXPORT is significantly positive at the 1% level. The results confirm the reasonableness of the indicator system, further verifying the robustness of the benchmark regression.

(2) Winsorize outliers

In the benchmark regression, the existence of outliers may lead to bias. Therefore, to eliminate the extreme values that affect the robustness of the regression results, this paper draws on the practice of Nyitrai and Virág (2019), shrinking the benchmark regression data by 1% and inserting it into model (2) for testing. It can be seen from column (2) of Table 6 that, after the outliers of the data are processed, the coefficient of DIAGG is consistent with that of the benchmark regression, which still significantly promotes the development of urban RQCI at the level of 5%, indicating that outliers do not affect the robustness of the results.

(3) Eliminate policy interference

In 2015, the State Council of China issued "Guiding Opinions on Actively Promoting the 'Internet Plus' Action," marking the beginning of the transformation of digital economic policy to the integrated application of information and communication technology and other traditional industries, and further promoting the digital development of prefecture-level cities. Therefore, in order to eliminate the policy interference, this paper refers to the practice of Wang et al. (2024), and excludes the data of 2015 and 2016 for testing. The specific regression results are shown in Table 6. According to the results in column (3) of Table 6, after excluding the samples in 2015 and 2016, the impact of DIAGG on RQCI is still significantly positive at the level of 5%, which verifies the robustness of the benchmark regression results.

Tab. 6 – Regression results of robustness test. Source: own research

	(1)	(2)	(3)
	Replace the dependent variable	Winsorize outliers	Eliminate policy interference
	EXPORT	RQCI	RQCI
DIAGG	0.002***	0.004**	0.004**
	(0.001)	(0.002)	(0.002)
Constant	0.023*	0.081	0.045
	(0.013)	(0.078)	(0.056)
Control FE	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	4811	4811	4245
Adj.R^2	0.145	0.222	0.186

4.4 Heterogeneity analysis

(1) Heterogeneity analysis of regional

This study refers to the research of Yang et al. (2020), which divides the sample data into eastern, central and western cities, and conducts group regression. The regression results are shown in the columns (1) - (3) of Table 7. The results show that the impact of DIAGG on RQCI in eastern and central cities is significantly positive, and the coefficients are 0.005 and 0.004 respectively, while the DIAGG coefficient in western China is positive but insignificant. The reason for this phenomenon may be that, as the most economically developed region in China, the development of digital industry in eastern cities started earlier and may have entered a relatively mature stage. This means that the eastern region may have made phased progress and achievements in the research and development, application and promotion of digital technology, and the scale effect and spillover effect of DIAGG have been released to a certain extent. However, for the western cities, the digital industry started late, the development level of digital industry is relatively lagging behind, and the DIAGG is still in its infancy. Therefore, DIAGG has no significant effect on RQCI. Cities in the central region are located at the junction of the east and west, and can undertake the influence of DIAGG and corresponding industrial diffusion from the eastern region. Therefore, DIAGG in the central region can rapidly improve the local industrial structure and economic level, and play a significant role in improving the RQCI.

(2) Heterogeneity analysis of resource endowments

Cities with high resource endowments are more dependent on their own resource endowments, and the impact of DIAGG on them may be weaker. According to the scope of resource-based cities determined by the policy planning of China's National Sustainable Development Plan for Resource-based Cities (2013-2020), the cities are divided into cities with high resource endowment and cities with low resource endowment, and the regression is conducted by group. The regression results are shown in the columns (4) - (5) of Table 7. To be specific, column (4) reports the regression results of cities with low resource endowment, which shows that the DIAGG coefficient is significantly positive, while the regression results of cities with high resource endowment in column (5) show that the DIAGG coefficient is positive but not significant, which is consistent with the above speculation.

(3) Heterogeneity analysis of resource endowments

The development process of China's digital economy shows remarkable phased characteristics. In 2015, The State Council promulgated the "Guiding Opinions on Actively Promoting 'Internet Plus' Actions," which established Internet plus as a national strategy for the first time, recognizinging that China's digital economy has entered the stage of large-scale development. Therefore, the impact of DIAGG on RQCI around 2015 may be related to significant heterogeneity. In this paper, the research samples were divided into "Initial Stage" (pre-2015) and "Rapid Development Stage" (post-2015) for testing using model (5) . The test results are shown in columns (6)-(7) of Table 7. The results show that the influence of DIAGG on RQCI is significantly positive at 1% level, and the coefficient is 0.006. The reason for this phenomenon may be that in the embryonic stage, the development level of digital technology is low, and the level of DIAGG is low. In this stage, the mismatch between manufacturing and producer services is weak, the intra-regional sharing effect is strong, and DIAGG has a strong promoting effect on RQCI. In the rapid development phase, the DIAGG coefficient is 0.005. It shows that in the process of the further development of DIAGG, due to the lag in the quality and scale of industrial integration, DIAGG's promotion of RQCI has gradually slowed down. The results confirm that the different levels of DIAGG have heterogeneity on regional quality competitiveness.

Tab. 7 – Regression results of heterogeneity analysis. Source: own research

	East	Central	West	Low Resource Endowment	High Resource Endowment	Initial Stage	Rapid Development Stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	RQCI	RQCI	RQCI	RQCI	RQCI	RQCI	RQCI
DIAGG	0.005*	0.004*	0.001	0.006*	0.002	0.006***	0.005*
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Constant	0.123	0.152**	0.213**	-0.289***	0.095**	-0.102***	-0.049
	(0.132)	(0.072)	(0.092)	(0.088)	(0.041)	(0.026)	(0.121)
Control FE	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	1704	1683	1424	2023	2788	2830	1981
Adj.R^2	0.202	0.351	0.190	0.163	0.308	0.377	0.333

4.5 Mechanism test

(1) Mechanism test of entrepreneurial activity

This paper uses the stepwise regression method, as outlined by Lin and Tan (2019), to test the mediating effect. Column (2) of Table 8 shows the results of industrial agglomeration's on the regional entrepreneurial activity. These results indicate a significant positive effect, consistent with the findings of Yan and Huang (2022). The test results verify Hypothesis 2a in this paper. The regression results show that DIAGG can promote the increase of regional entrepreneurial activities, and then promote the development of RQCI. The reason for this phenomenon may be that DIAGG brings about the optimal allocation of talents, technology and innovation resources within the city, supports the technology and talents of entrepreneurial activities, and continuously reduces the entrepreneurial cost, which leads to the further increase of regional entrepreneurial activity. The increase of entrepreneurial activity can enrich the urban production structure, enhance the anti-risk ability of urban production, and further promote the development of RQCI.

(2) Mechanism test of industrial synergy quality

Column (4) of Table 8 shows that DIAGG negatively impacts industrial synergy quality is significantly negative at the 1% level, indicating that it is not conducive to the integration quality of manufacturing and service industry, and verifies Hypothesis 2c in this study. When DIAGG brings technical support to the local area, the technological development level of its manufacturing industry and producer service industry will often open a large gap, which makes it difficult for producer service industry to meet the service demand of the manufacturing industry with higher technology level. These results show that attention should be paid to the development of regional producer services in the future, and policy guidance and relevant financial assistance should be given timely. We should try to get rid of the negative impact of DIAGG on industrial coordination as soon as possible, and contribute to the construction of RQCI.

(3) Mechanism test of industrial synergy depth

Column (6) of Table 8 reports that the DIAGG at the present stage is not conducive to the increase of the depth of industrial collaboration between the manufacturing industry and producer service industry, which is consistent with the above analysis and verifies hypothesis 2e in this paper. The reason for this phenomenon may be that there are large differences between manufacturing and producer services within the city in terms of industrial structure, technology level or market demand. In the process of integration, frictions and conflicts may arise, leading to waste of resources and decreased efficiency, which in turn further inhibits the development of quality competitiveness.

Tab. 8 – Results of mechanism test. Source: own research

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	RQCI	RENTACT	RQCI	INDSQ	RQCI	INDSD
DIAGG	0.004**	0.176***	0.004**	-0.015***	0.004**	-0.045*
	(0.002)	(0.051)	(0.002)	(0.006)	(0.00)	(0.02)
Constant	0.060	-2.414*	0.060	0.778***	0.060	1.702***
	(0.052)	(1.312)	(0.052)	(0.162)	(0.05)	(0.57)
Control FE	YES	YES	YES	YES	YES	YES

City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	4811	4811	4811	4811	4811	4811
Adj.R^2	0.180	0.403	0.180	0.0446	0.180	0.008

5 FURTHER ANALYSIS

To test for a nonlinear effect of DIAGG on RQCI, this paper draws on Cai and Hu (2022), introduces the quadratic term of digital industry agglomeration (DIAGG2) for testing. The specific regression results are shown in Table 9. The results show that the coefficients are all significant at the 5% level, and the coefficient is -0.003. This means that excessive DIAGG will have a negative impact on urban quality competitiveness, which verifies hypothesis . When the scale of DIAGG is too large, there may be a crowding out effect inside the city, and there may be excessive operation of infrastructure. The results in Table 9 show that the influence of DIAGG on RQCI at this stage shows an inverted U-shape, which increases first and then decreases.

Tab.9 – Results of the nonlinear effect of DIAGG. Source: own research

VARIABLES	(1)	(5)
	RQCI	RQCI
DIAGG	0.014***	0.015***
	(0.005)	(0.005)
DIAGG2	-0.003**	-0.003**
	(0.001)	(0.001)
Constant	0.052***	0.039
	(0.003)	(0.051)
Control FE	NO	YES
City FE	YES	YES
Year FE	YES	YES
Observations	4811	4811
Adj.R^2	0.172	0.184

In order to clarify the impact of different levels of DIAGG on RQCI, this paper follows Xu et al. (2021) and introduces the threshold panel model for empirical testing. First, a threshold test is conducted to determine whether there is a threshold effect in the impact of DIAGG on RQCI. The results in Table 10 indicate that the sample data exhibit a double threshold effect, confirming the presence of such an effect on the impact of DIAGG on RQCI. Second, the threshold value of the estimated value of the threshold variable, DIAGG, is shown in Table 11. Third, following model (10), this paper conducts 300 bootstrap samples to test the threshold effect. Column 1 of Table 12 show that when DIAGG exceeds the threshold value of 0.3657, the influence effect of DIAGG decreases from 0.026 to 0.006. It shows that the positive promoting effect of DIAGG on RQCI becomes slower at this stage. The reason for this phenomenon may be that the quality and depth of industrial integration in the agglomeration area is poor. The results confirm hypothesis 3.

Tab.10 – Test results of the threshold effect. Source: own research

VARIABLE	Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
DIAGG	Single	3.1873	0.0007	16.49	0.007	9.722	10.745	13.511
	Double	3.1765	0.0007	15.00	0.020	9.420	10.788	16.623
	Triple	3.1643	0.0007	17.12	0.283	27.762	41.039	64.846

Tab.11 – Estimation results of threshold values. Source: own research

VARIABLE	Model	Threshold	Lower	Uper
DIAGG	Single threshold	0.3657	0.3565	0.3733
	double threshold	2.7030	0.2664	2.7030

Tab. 12 – Test results of the threshold effect

VARIABLES	(1)
	RQCI
DIAGG<0.3657	0.026***
	(0.007)
0.3657⩽DIAGG⩽2.7030	0.006***
	(0.002)
Constant	0.015
	(0.021)
Control FE	YES
Observations	4811
Adj.R^2	0.082

6 CONCLUSIONS AND POLICY RECOMMENDATIONS

6.1 Conclusions

This paper deeply explores the internal mechanism and development path of DIAGG on RQCI. This paper creatively uses 283 cities in China from 2005 to 2021 as sample data to construct the quality competitiveness index of each city. It also discusses the impact, intermediary mechanism and nonlinear impact of DIAGG on RQCI. The empirical research of this paper finds that:

(1) DIAGG has made important contributions to the development of RQCI. Heterogeneity results show that DIAGG has a more significant effect on RQCI in eastern and central cities, pre-2015, and in cities with lower resource endowments.

(2) Regional entrepreneurial activity, industrial collaboration quality and industrial collaboration depth are the intermediary mechanisms through which DIAGG affects RQCI. Specifically, DIAGG promotes regional entrepreneurial activity, which in turn improves RQCI. DIAGG inhibits the quality and depth of industrial collaboration, which further affects the

development of RQCI. In addition, the innovation competitiveness of local governments can positively regulate the impact of DIAGG on the development of RQCI.

(3) Further analysis reveals that the influence of digita DIAGG on RQCI has non-linear and threshold effects. Specifically, both the nonlinearity and panel threshold effect test results show that the influence of DIAGG on RQCI is nonlinear. In addition, the panel threshold test results show that the promotion effect of low-level DIAGG on RQCI is more significant than that of high-level DIAGG.

6.2. Policy recommendations

Based on these research findings, this paper proposes the following policy suggestions:

(1) Formulate differentiated support strategies to promote the balanced development of DIAGG

In view of the significant positive effect of DIAGG on improving RQCI, the government should deepen its regional differential support strategy, especially in the western region and the relatively resource-poor areas. By increasing policy support and financial investment, the development gap in the digital economy across regions can be narrowed. The government should also implement targeted policies and financial incentives for these regions, focusing on upgrading and improving digital infrastructure. Additionally, local governments can flexibly use tax incentives, optimize land resource allocation, and provide financial subsidies, among other diversified incentive means to create a high-quality environment conducive to DIAGG, and accelerate the formation and development of DIAGG advantages in the central and western regions.

(2) Strengthen the integration of manufacturing and producer services

Although DIAGG positively affects RQCI, the integration between manufacturing and producer services is weakened due to the technological gap between the two. Therefore, local governments should pay special attention to promoting the deep integration of manufacturing and producer services by fostering technological collaboration and business partnerships. Specifically, governments can encourage producer services to enhance innovation activities through policy guidance and financial support. Additionally, they should guide manufacturing and producer service enterprises to collaborate in areas such as research and development, management practices, and talent training. This would improve coordination between the two sectors, promote the quality and depth of industrial integration, and further sustain growth of RQCI.

(3) Establish a dynamic monitoring and evaluation mechanism to optimize policy implementation

In view of the nonlinear influence of DIAGG on RQCI, local governments should establish a complete comprehensive evaluation system of “digital industry agglomeration - quality competitiveness” to maximize the positive promoting effect of DIAGG. Local governments should collaborate with universities, think tanks, and big data companies to develop dynamic monitoring models that include key indicators such as agglomeration density index (DI), industry correlation degree (IA), and resource mismatch coefficient (RMC). The model should support quarterly data collection, and automatically capture 12 types of administrative data such as business registration, patent declaration, and environmental monitoring through the government data platform. By monitoring the development level of DIAGG, industrial integration quality, depth and RQCI within the region in real time, the government can further optimize the implementation effect of policies according to the industrial base and development stage of different regions, such as differentiated financial support and tax incentives and other means to promote further regional development.

Although this paper adopts the panel two-way fixed effect model to test the impact of DIAGG on RQCI, there are still have some limitations. The research may not take into account for the possible impact of regional internal environmental regulation strength and energy utilization efficiency on DIAGG. In addition, the potential spatial spillover effect of DIAGG remains to be further tested in the future.

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