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Spatial distribution structure of new infrastructure and impacts of digital economy

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Abstract: With the development of 5th Generation Mobile Communication Technology (5G), industrial internet, artificial intelligence, smart manufacturing, smart construction, and other new technologies or new industries, a new infrastructure has emerged. The scale and the spatial distribution structure of new infrastructure across various regions of China from 2020 to 2022 were measured based on the official annual engineering construction project plans, and the impacts of the digital economy were analyzed by using the spatial Durbin model. The results indicate that the new infrastructure projects are mainly distributed in Eastern, Central, and Southern China. Meanwhile, the Moran's I index demonstrates a statistically significant positive spatial autocorrelation, indicating that there is a significant trend of spatial agglomeration among these new infrastructure projects. The digital economy is significantly affecting the spatial distribution of the new infrastructure. The impact of the digital economy on the new infrastructure can cross regions and has significant spatial spillover effects, which reflects the virtual characteristic of the new infrastructure and digital economy. Therefore, various regions should coordinate the digital economic development needs of local and surrounding regions to rationally plan new infrastructure projects, ensuring the supporting capacity of infrastructure while preventing over-investment.

Key words: new infrastructure; digital economy; spatial agglomeration; spatial spillover effect

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With the application of emerging digital technologies such as 5G, the industrial internet, and artificial intelligence, the form of infrastructure projects is changing[1-3]. In December 2018, China's Central Economic Work Conference proposed the concept of "new infrastructure." In 2020, the China's National Development and Reform Commission defined new infrastructure as the infrastructure system based on information networks, which includes three specific categories[4-5]: information infrastructure (5G, industrial internet, etc.), integrated infrastructure (the digital transformation of traditional infrastructure through the application of emerging technologies, such as smart cities and intelligent transportation), and innovation infrastructure (the infrastructure supporting scientific development, such as technology resources sharing platform). According to this definition, the new infrastructure is characterized by digitalization and intelligence, driven by the application of emerging digital technologies[6].

New infrastructure differs from traditional infrastructure in both physical form and service patterns. First, traditional infrastructure—such as railroads, highways, and airports—exists almost entirely in physical space. However, unlike traditional infrastructure, new infrastructure takes virtual forms and primarily exists in the network space, such as the Internet of Things, the industrial internet, and digital platforms[7]. Second, the function of infrastructure is to enable the flows of production factors[5]. Traditional infrastructure—railroads and highways—primarily serves to connect different geographic regions and facilitate the flow of labor and goods[8-10]. In contrast, the new infrastructure can provide connectivity services in network space and enable the flows of data—a new type of production factor[2, 6, 11]. Data, as a record of information, is the cornerstone for digitalization, networking, and intelligentization. The discovery and utilization of data have generated significant value-added effects across the production, distribution, circulation, and consumption processes, such as information sharing, business collaboration, and risk forecasting[12]. Currently, smart manufacturing, intelligent maintenance of urban utilities, internet-connected vehicles, internet-plus healthcare, and other digital industrial trends are increasingly driven by data[13-14]. However, traditional infrastructure cannot support data connectivity; thus, it is necessary to develop new infrastructure[12].

Existing studies have discussed the definition[1, 9], sig-

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nificance[4, 7-8], and issues of new infrastructure. To explore the development status of new infrastructure, some studies have begun to focus on its spatial distribution structure and the underlying influencing factors. Research on this issue can reveal the supply-and-demand relationship between new infrastructure and regional development and support decision-making in planning new infrastructure[15]. For example, Refs. [15-17] has analyzed the scale and spatial distribution of new infrastructure across different regions of China using data on the industrial internet, e-commerce, fixed-asset investment, and other related indicators. Refs. [15, 18] have investigated the effects of the economy, population, industrial structure, and other factors on the scale of new infrastructure.

Nonetheless, the measurements of new infrastructure in these existing studies are mainly based on relevant enterprise or industrial statistical data rather than on data from actual new infrastructure projects. Such measurement approaches indirectly reflect the scale of new infrastructure rather than providing a direct measure. Furthermore, regarding influencing factors, insufficient attention has been paid to the digital economy. New infrastructure adapts to the era of the digital economy, and various digital economy patterns—such as smart manufacturing and smart construction—have generated substantial demand for it[7, 12-13]. Therefore, the impact of the digital economy on the spatial distribution of new infrastructure should be thoroughly investigated.

In this context, this study aims to measure the scale of new infrastructure across different regions of China using statistical data from real projects and to examine its spatial distribution. This research will also empirically analyze whether and how the spatial distribution of new infrastructure is affected by the digital economy.

1 Methodology

1.1 Methods

1.1.1 Moran's I index

This study used the global and local Moran's I to analyze the spatial distribution structure of new infrastructure in China. The global Moran's I is calculated as follows[19]:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \qquad (1)$$

where n is the number of regions; w_{ij} is the element of the spatial weight matrix $\boldsymbol{W}$ (the adjacency standard is used in this study); y_i is the observation value of variable y in region i; $\bar{y}$ is the mean of variable y; S^2 is the variance of variable y. I ranges from $[-1, 1]$. $I > 0$ indicates a positive spatial correlation of variable y; that is, regions with high (low) observations are surrounded by regions with high (low) observations[19]. $I < 0$ indicates a negative spatial correlation of variable y; that is, regions with high (low) observations are surrounded by regions with low (high) observations[19]. $I = 0$ indicates the random distribution[19].

The local Moran's I is calculated as follows[19]:

$$I_i = \frac{(y_i - \bar{y})\sum_{j \neq i}^{n} w_{ij}(y_j - \bar{y})}{S^2} \qquad (2)$$

where I_i is the local Moran's I of variable y in region i. The local Moran's I can reflect the similarity of the variable y in the adjacent regions. I_i with a greater value than 0 indicates that the observation of region i is positively correlated with its neighboring regions[19].

1.1.2 Spatial Durbin model

Unlike traditional infrastructure, new infrastructure takes a virtual form and can provide services across regions. For issues related to spatial characteristics, spatial econometric models should be chosen[15]. Spatial econometric models include three categories: the spatial lag model (SAR), the spatial error model (SEM), and the spatial Durbin model (SDM)[20]. SDM can address the spatial lag of both dependent and independent variables, integrating the advantages of the first two categories of models[20]. SDM is shown as follows[1]:

$$y_i = \beta_0 + \rho \sum_{j=1}^{n} w_{ij} y_j + \beta_1 x_i + \rho_1 \sum_{j=1}^{n} w_{ij} x_j + \varepsilon \qquad (3)$$

where ρ is the spatial lag coefficient of the dependent variable; x_i is the independent variable in region i; β_1 is the influence coefficient of the independent variable; ρ_1 is the spatial lag coefficient of the independent variable. All variables take the natural logarithm.

1.2 Variables and data

1.2.1 Dependent variable: the scale of new infrastructure

This study identified new infrastructure projects by referring to official annual engineering construction project plans published by various regional governments in China, such as *Major Projects List 2021* in Jiangsu[21]. According to the definition and specific categories of new infrastructure[4-5], these projects include information infrastructure (such as 5G, the industrial internet, and artificial intelligence), digital transformation of traditional infrastructure (such as smart cities and intelligent transportation), and innovation infrastructure (such as technology resource-sharing platforms). This study used the number of these new infrastructure projects to measure the scale of new infrastructure (NI). The data sample in this study is statistical data from real NI projects. Due to data availability, this study focused on China's 31 provincial-level regions (excluding Hong Kong, Macao, and Taiwan).

The concept of NI has been evolving since it was proposed in 2018[5]. Until 2020, when the National Development and Reform Commission defined NI, arguments over its concept converged[5, 7]. Therefore, the research period runs from 2020 to 2022.

1.2.2 Independent variable: the development level of the digital economy

NI primarily supports the development of digital economic patterns, such as smart manufacturing and smart construction. Conversely, the expansion of the digital economy has generated substantial demand for NI[7, 11, 13]. Therefore, this study treated the level of development of digital economy (DE) as the core factor influencing the spatial distribution of NI. This study proposed the following hypothesis: DE has a positive relationship with the spatial distribution of NI, and the development demand of DE across regions acts as a key determinant of the scale of NI. The higher the level of regional economic digitization, the stronger the demand for NI projects.

Existing studies present varied definitions and measurement approaches for DE. This study defined the DE as the aggregate of economic activities resulting from the integration of the internet and digital technologies into the socio-economic system[22]. Following the measurement approach of Zhao et al. [23], this study used principal component analysis to measure the development level of DE based on five indicators. (1) Internet penetration is measured in terms of the number of internet users per 100 people. (2) Mobile phone penetration is measured in terms of the number of mobile phone users per 100 people. (3) The number of employees in the internet-related industry is measured in terms of the proportion of practitioners in computer services and software. (4) The output of the internet-related industry is measured in terms of the total telecommunications services per capita. (5) The development of digital financial inclusion is measured in terms of the Digital Financial Inclusion Index.

Furthermore, following existing researches[15, 18], this study set six control variables: (1) economic scale (ECO), measured by regional GDP; (2) population (POP), measured by regional total population; (3) urbanization process (UP), measured by the percentage of urban population; (4) industrial structure (IS), measured by the scale ratio of the tertiary to the secondary industry; (5) fiscal strength (FIS), measured by regional fiscal revenue; and (6) innovative human resources (RDP), measured by the scale of research and development personnel.

The government's decisions are usually based on the previous year's situation rather than the current year's; therefore, the independent and control variables are lagged by one year, taking values from 2019 to 2021 (while the dependent variable NI takes values from 2020 to 2022). This address can also avoid potential endogeneity problems arising from two-way causality[4]. Data for the independent and control variables are obtained from *China Statistical Yearbook*, *China City Statistical Yearbook*, and *Digital Finance Research Center of Peking University*.

2 Spatial Distribution Structure of NI

The scale of NI was measured using statistical data on NI projects, derived from annual engineering construction project plans published by various regional governments in China. Overall, from 2020 to 2022, China's NI projects gradually clustered in the eastern coastal areas. Meanwhile, over time, this trend becomes more obvious. To further explore the spatial agglomeration characteristics of NI and summarize its growth patterns, the 31 provincial-level regions are divided into 7 areas for statistical analysis. Fig. 1 presents the scales of NI in these areas, showing that, except for Northeastern China, the number of NI projects in the other six areas has been increasing year by year since 2020. Overall, the growth rate of NI projects in China was 84% in 2021 and 54% in 2022. This result indicates that China's NI is undergoing rapid development. Notably, the growth rate in Central China reached 415% in 2022, and the growth rates in Southern and Eastern China were also 151% and 120%, respectively, in 2021. It can be seen that China's NI projects are mainly distributed in Eastern, Central, and Southern China. The specific regions include Henan, Shandong, Guangdong, and Anhui, where the total number of NI projects exceeds 1 500. Furthermore, the total number of NI projects in Sichuan, Zhejiang, Guangxi, Jiangxi, Jiangsu, and Fujian also exceeded 500. In contrast, Northern, Northwestern, and Northeastern China have relatively fewer NI projects.

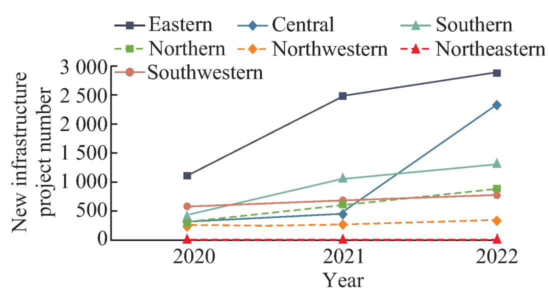

Fig. 1 Scales of NI in seven areas

Alongside statistical analysis, this study also calculated global and local Moran' I; the results are presented in Table 1. First, the global Moran' I between 2020 and 2022 is significant at the 1% level and positive. This outcome indicates a significant positive spatial correlation, suggesting that the scale of NI exhibits spatial agglomeration. Meanwhile, the global Moran' I has increased annually from 2020 to 2022, indicating that spatial agglomeration is gradually strengthening. Second, the results of local Moran' I indicate that the scale of NI in most regions shows high-high agglomeration (e. g. , Shandong, Anhui, and Fujian in Eastern China). In contrast, fewer regions show low-low agglomeration (e. g. , Jilin and Heilongjiang in Northeastern China). The results of Moran' I are consistent with the statistical results in Fig. 1; therefore, the spatial distribution of China's NI exhibits agglomeration characteristics, and spatial dependence is evident in this distribution.

Table 1 Results of global and local Moran's I

Year	Global Moran's I	Local Moran's I	
		Form	Region
2020	0.348^{***}	High-high agglomeration	Shandong, Anhui, Fujian, Henan, Guizhou, etc.
		Low-low agglomeration	Heilongjiang, Jilin, Qinghai, etc.
2021	0.366^{***}	High-high agglomeration	Shandong, Anhui, Fujian, Guangdong, Jiangxi, etc.
		Low-low agglomeration	Jilin, Heilongjiang, Xinjiang, etc.
2022	0.375^{***}	High-high agglomeration	Shandong, Henan, Anhui, Fujian, Jiangxi, etc.
		Low-low agglomeration	Jilin, Heilongjiang, Liaoning, etc.

Note: *** indicates significance at 1% level.

3 Impacts of DE

3. 1 Regression results

The spatial autocorrelation test (Moran' I) indicates that the scale of NI exhibits spatial dependence, so the SDM is appropriate. To address endogeneity, fixed effects are used. The SDMs under time-fixed, region-fixed, and double-fixed are estimated in turn and are denoted M1, M2, and M3, respectively. Table 2 presents the results of M1, M2, and M3. In Table 2, sloDE, sloECO, sloPOP, sloUP, sloIS, sloFIS, sloRDP, sloNI represent the spatial lags of DE, ECO, POP, UP, IS, FIS, RDP, NI, respectively. First, the fit of M1 is higher than those of M2 and M3, with stronger credibility (R^2 = 0. 230). This result is reasonable. Infrastructure development will be affected by macro-level policy guidance and the economic environment, leading to volatility over time[24]. The time-fixed effect can improve model performance. Meanwhile, this result aligns with Zhang et al.[15], who also found that the time-fixed model has stronger credibility in exploring the factors influencing the spatial distribution of NI. Second, the LR test is further conducted for the M1. The results of LR-SAR and LR-SEM are 84. 38% and 80. 47%, respectively, with significance at the 1% level, indicating that the SDM cannot degenerate into SAR or SEM. The results of M1 will be further discussed.

Table 2 Estimation results of SDM with fixed effects

Variable	M1	M2	M3
DE	13.750^{*}	-30.706^{**}	-21.909
ECO	-8.909^{***}	-3.290	-3.539
POP	4.821^{***}	-9.168	-12.378
UP	-6.159^{***}	36.159^{**}	33.588^{**}
IS	-0.654	-1.760	-1.510
FIS	3.191^{***}	1.764	1.942
RDP	2.069^{***}	0.855	1.020
sloDE	75.471^{***}	40.806^{**}	66.945^{***}
sloECO	-24.299^{***}	0.869	-4.217
sloPOP	12.373^{***}	84.926^{**}	88.875^{**}
sloUP	-18.376^{***}	-30.224	-10.753
sloIS	2.016	-1.684	-2.559
sloFIS	0.968	-0.635	-0.757
sloRDP	7.566^{***}	3.389^{*}	4.033^{**}
sloNI	0.373^{***}	-0.229	-0.234
R^2	0.230	0.051	0.033

Note: *** indicates significance at 1% level; ** indicates significance at 5% level; * indicates significance at 10% level.

Based on the results of M1, the spatial lag coefficient of the dependent variable NI is significant and positive, indicating the presence of spatial autocorrelation, which aligns with the results of Moran' I. To better reflect spatial spillover effects, this study estimated the direct and indirect effects of each influencing factor using a partial differential equation based on the results of M1. Table 3 presents the results of effect decomposition.

Table 3 Effect decomposition of SDM with time-fixed effect

Variable	Direct effect	Indirect effect	Total effect
DE	22.282^{***}	123.616^{***}	145.898^{***}
ECO	-11.835^{***}	-42.346^{***}	-54.181^{***}
POP	6.382^{***}	21.700^{***}	28.082^{***}
UP	-8.181^{***}	-31.706^{***}	-39.886^{***}
IS	-0.479	2.677	2.198
FIS	3.410^{***}	3.271	6.681
RDP	2.915^{***}	12.813^{***}	15.728^{***}

Note: ***indicates significance at 1% level.

This study replaces the spatial weight matrix to examine whether the scale of NI still exhibits spillover effects in other dimensions, and applies the instrumental variable method to address the endogeneity issue[25-26]. First, in addition to the adjacency weight matrix currently in use, this study also used the economic weight matrix—which is calculated from the inverse of the absolute value of the difference in GDP per capita[26]—to calculate the global Moran' I for the scale of NI. The adjacency weight matrix reflects the geographical distance among different regions, while the economic weight matrix reflects the economic distance among different regions. Table 4 presents the global Moran' I using different spatial weight matrices. The global Moran' I using an economic weight matrix is not significant, indicating that scale spillover effects among NI occur only in geographical space and that there is no correlation among regions with similar economic development. This finding is consistent with many previous studies[1, 15], which also used only the spatial weight matrix reflecting geographical distance.

Table 4 Global Moran's I using different spatial weight matrices

Year	Adjacency weight matrix	Economic weight matrix
2020	0.348***	0.002
2021	0.366***	0.037
2022	0.375***	0.026

Note: *** indicates significance at 1% level.

This study employs the shifts-share method to construct the Bartik instrumental variable, defined as the interaction between the one-period lagged DE and the national-level DE growth rate[25]. The results for the instrumental variable (MIV) are presented in Table 5. Regarding the MIV results, the F-statistic from the first-stage regression is 10.6, exceeding the empirical critical value of 10, which rules out the weak instrumental variable problem in the model[25]. The signs and statistical significance of the estimated coefficients for DE and W*DE are consistent with those of M1. The results of M1 indicate robustness and can be further discussed.

Table 5 Results of MIV

Variable	M1	MIV
DE	13.750*	13.916*
sloDE	75.471***	67.998***

Note: *** indicates significance at 1% level; *indicates significance at 10% level.

3.2 Impacts of DE

According to Table 3, the development level of the DE has a significant positive effect on the scale of NI through both direct and indirect paths. That is, the spatial distribution of NI is significantly shaped by the development of the local and surrounding digital economies.

Regarding the direct effect, the development of DE can significantly affect the scale of NI at the local level. Internet platforms, the sharing economy, smart manufacturing, and other aspects of the DE rely on data to operate; however, traditional infrastructures—such as railroads, highways, and airports—cannot connect the data. It is difficult for them to support the development of DE. NI, which has digital and networked characteristics, can solve the problem of connecting data[26]; therefore, regions with a more advanced DE plan more NI projects to meet local development needs.

Regarding the indirect effect, the DE's driving effect on NI can transcend regional boundaries. The development of DE in neighboring regions significantly affects the scale of local NI development. Specifically, the DE exerts a notable spatial spillover effect on NI, which can be broken down into two distinct paths. (1) The first path is the demand transmission driven by the cross-regional flow of data. Since data flows within network space rather than geographical space, cross-regional data flow is enabled; thus, NI does not need to be geographically co-located with the entities it supports. New locally built infrastructure projects can also support DE in neighboring regions, as the functionality of NI is not constrained by geographical boundaries[1, 27]. (2) The second path is the demand-pull effect generated by the collaboration of relevant supporting industries. Constructing NI requires coordination across supporting sectors, such as engineering, equipment operation and maintenance, and digital technologies. In the process, NI that supports DE in surrounding regions responds to the development needs of neighboring regions; however, investments in such infrastructure can still boost local industries and employment. This situation, in turn, creates an incentive for local governments to plan and develop NI. To summarize, the spatial spillover effect of the DE on NI operates through two paths: surrounding regions generate data demand → local regions provide NI support → local supporting industries expand (Fig. 2). A wealth of empirical evidence supports these paths. For example, China's Guizhou, Gansu, Ningxia, and other western regions possess advantages in natural resources pertaining to climate and energy. Such resources are conducive to the operation of data centers and computing power centers. Currently, these regions are accelerating the construction of these NI projects to meet the data storage and computing needs of

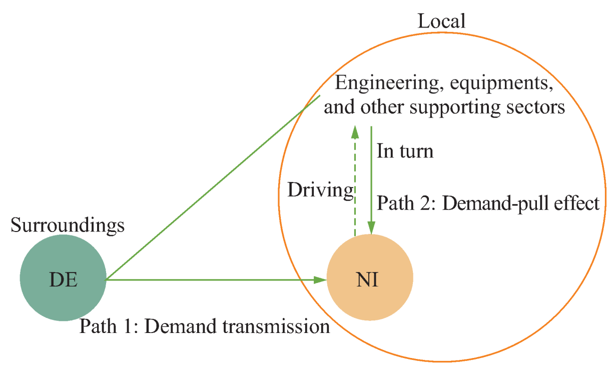

Fig. 2 Paths of spatial spillover effects

the eastern developed regions. This action responds to the cross-regional cooperative development strategy of "east data, west computing" (i. e., Path 1) and drives the development of local equipment, software, consulting, and other related industries (i. e., Path 2)[28].

3.3 Impacts of other control variables

According to the results in Table 3, regarding the control variables, first, POP and RDP have significant positive effects on the scale of NI, both directly and indirectly. The public service requirements brought by POP drive the development of local infrastructure projects (direct effect). Furthermore, in the era of DE, public service requirements are gradually being digitized[29]. E-commerce and digital governance are on the rise. These patterns can be supported by NI in non-local places, thereby driving NI planning in neighboring regions (an indirect effect). RDP is the foundation for technological advancement, thereby promoting the development of NI (direct effect). Moreover, the popularization of telecommuting in the era of DE endows such human resources with a spatial spillover effect[15, 29], which can also support the development of NI in surrounding regions (an indirect effect).

ECO and UP have significant negative effects on the scale of NI, both directly and indirectly. This outcome likely occurs because NI currently serves more as a prerequisite for regional digital transformation. Compared with developed regions, developing regions are more interested in developing NI to boost local development[9].

FIS has a significant positive direct effect on the scale of NI, but not on the indirect effect. This result is reasonable as local governments only consider their own financial situation when planning infrastructure, rather than that of other regions.

IS does not have a significant effect on the scale of NI, either directly or indirectly. This outcome likely occurs because the development of NI is still in the early stages, and its planning currently prioritizes macro-factors (such as population, economy, and urbanization) and other factors. In contrast, IS has not yet been considered[15].

3.4 Comparative analysis with existing studies

Existing studies have primarily focused on the relationships between NI and population[18], innovative human resources[15], economic scale[1], green development[4], and other socio-economic factors. In contrast, DE has been less explored. This study empirically found that the DE has a significant impact on the development of NI. Notably, the influence of DE on NI exhibits spatial spillover effects. This indirect effect reflects, in particular, the virtual feature of both DE and NI[6, 11]. Unlike traditional infrastructure, NI primarily serves as digital and virtual carriers, enabling cross-regional interaction and regional development[7]. This study also found the spatial spillover effects of other factors, such as population, innovative human resources, economic scale, and urbanization. These indirect effects have also been found in existing studies—for example, the cross-regional relationships of innovative human resources[15] and economic scale[1] with NI. The traditional and digital economies are not distinguished in these studies. In contrast, the spatial spillover effects have not been discussed within the context of digitization. In fact, it is only by examining NI within the context of digitization and networking that its characteristics can be understood and distinguished from those of traditional infrastructure[7, 12-13].

3.5 Practical implications

Effective infrastructure planning must strike a balance between over-investment and under-investment. Based on the findings, this study proposes the following policy recommendations. First, different regions should assess the current status of NI development, considering local DE demands as well as other economic and social conditions, such as population and innovative human resources, to determine the reasonable scale of NI. In regions with high concentrations of NI projects (e. g., Eastern, Central, and Southern China), efforts should be made to prevent over-investment and inefficient use of public resources. NI projects with assessed investment or resource utilization rates that are relatively low should not be permitted to continue. Conversely, in Northern, Northwestern, and Northeastern China, NI projects are relatively sparse. In these regions, local governments should avoid under-investment and infrastructure shortages. The government should support these regions in addressing their development gaps through preferential policies, such as financial subsidies and targeted funding, to prevent them from being excluded from equal participation in digital economic development due to insufficient NI, and ultimately advance digital inclusion. Second, given the virtual nature of NI, regional planning ought not merely consider local economic and social demands but also assess its potential to support neighboring regions. Furthermore, this study also serves as a global reference. Many regions are seeking to leverage NI to drive digital economic development. For example, in the U. S., many online labor platforms enable consulting professionals to conduct their work without leaving their hometowns, thereby forming the digital migration[27]. This study can help these regions understand the relationships between NI and DE, as well as the decision-making principles for their development.

4 Conclusions

(1) This study uses statistical data of real projects, providing an objective measurement of the scale of NI across China's 31 provincial-level regions (excluding

Hong Kong, Macao, and Taiwan) from 2020 to 2022. The results indicate that the number of NI projects has increased significantly across most regions of China, while NI exhibits strong spatial agglomeration.

(2) This study verifies the significant impacts of the DE on the spatial distribution of NI. Notably, a significant spatial spillover effect has also been identified. Furthermore, several other factors—such as POP, RDP, ECO, and UP—also influence the spatial distribution of NI.

(3) Due to data availability, this study primarily measures the scale of NI from a general perspective. Future research could further explore the subcategories of NI, i. e., information infrastructure, integrated infrastructure, and innovation infrastructure. Moreover, this study primarily uses the number of projects to measure the scale of NI. In the future, this study will continue to track data and collect project investment amounts to more comprehensively measure the scale of NI.

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新基建空间分布结构及数字经济影响效应

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摘要：随着5G、工业互联网、人工智能以及智能制造、智能建造等新技术、新产业的深化发展，新基建应运而生。基于各地区建设项目计划，对2020—2022年我国各地区的新基建规模进行统计，在此基础上分析新基建的空间分布结构，并利用空间杜宾模型探索其所受数字经济的影响效应。结果发现，我国新基建主要分布在华东、华中、华南等区域，莫兰指数显示其存在显著的空间正自相关性，空间集聚性明显。不同地区新基建的分布受到数字经济的显著影响，且数字经济不仅影响本地的新基建规模，其需求引导性也具有空间溢出效应，影响着异地的新基建规模，从而体现了新基建和数字经济的虚拟特征。因此，各地应统筹本地和异地的数字经济发展需求以合理规划新基建项目，确保基础设施支撑力的同时避免过度投资。

关键词：新基建；数字经济；空间集聚；空间溢出效应

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