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# Research on the Impact of Digital Infrastructure Construction on High Quality Development of Urban Economy

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**ABSTRACT** Accurately assessing the true driving effect of digital infrastructure on high-quality urban economic development and identifying its pathways and spatial spillover characteristics are critical issues that urgently need to be addressed. Against this backdrop, this paper first constructs an evaluation system for high-quality urban economic development from five dimensions, and uses the entropy-weighted TOPSIS method to calculate the high-quality development index of 283 prefecture-level cities from 2011 to 2020. Next, using the "Broadband China" pilot project as a quasi-natural experiment, multi-period DID is employed to identify causal effects, and topographic relief and historical post office density are introduced as instrumental variables to handle endogeneity. Then, a spatial Durbin model is constructed to decompose local direct effects and neighboring indirect effects. Finally, the three-step mediation method and causal forest algorithm are used to examine the transmission mechanism and uncover heterogeneity. The results show that digital infrastructure construction increased the urban high-quality development index by 6.8% ($\beta$=0.068, p<0.01); the direct effect was 0.284, and the indirect effect was -0.117, exhibiting a "local promotion, neighboring area inhibition" characteristic; the mediating effect accounted for 40.0%, with central cities (0.338) and old industrial bases (0.358) benefiting more significantly. This paper provides empirical evidence for accurately verifying the effects of digital infrastructure construction policies.

**INDEX TERMS** Digital infrastructure; high-quality economic development; Broadband China; spatial spillover effect; causal forest

## I. INTRODUCTION

As a core component of new infrastructure, digital infrastructure is profoundly reshaping the operation mode and growth logic of urban economy [1]. However, traditional research focuses on the role of digital infrastructure in driving economic expansion, but lacks a systematic assessment of whether it truly promotes the high-quality development of "innovation, coordination, green, openness and sharing". More importantly, the location and layout of digital infrastructure are often determined by the urban economic base, leading to endogeneity bias in causal identification; at the same time, the black box problem of spatial spillover effects and transmission paths between regions has not been effectively solved [2], [3]. Therefore, scientifically assessing the real driving effect of digital infrastructure on the high-quality development of urban economy and clarifying its mechanism and heterogeneity characteristics has become an important practical problem that needs to be solved.

Existing literature has conducted rich discussions on the economic effects of digital infrastructure. Nie et al. [4] found from the perspective of green development that digital infrastructure can significantly promote the improvement of urban green innovation level; Hu et al. [5] further verified the positive effect of digital infrastructure on regional green innovation efficiency from the perspective of efficiency. Based on the quasi-natural experiment method, Feng et al. [6] used the "Broadband China" policy to identify the causal impact of digital infrastructure on urban green innovation. Meanwhile, Jiang et al. [7] pointed out that digital infrastructure helps enhance urban economic resilience, while Cheng et al. [8], from the perspective of labor mobility and entrepreneurial behavior, found that internet infrastructure significantly promoted urban entrepreneurial activities of rural migrants. However, existing studies still lack a complete measurement of the composite concept of "high-quality development" in terms of theme, and most regard digital infrastructure as an exogenous policy shock, ignoring the two-way causality between it and the level of urban economy and the problem of omitted variables. In addition, existing results have not reached a consensus on whether digital infrastructure plays a role through intermediate channels such as labor mobility and capital deepening, and whether its impact has regional siphon or radiation effects. At the research method level, existing literature mainly uses the difference-in-differences method, instrumental variable method or spatial econometric model for causal inference. Liu et al. [9] used the difference-in-differences method to examine the impact of internet infrastructure on urban innovation capacity based on the "Broadband China" policy; Zhou et al. [10] further explored the mechanism of digital infrastructure on regional market segmentation. However, existing methods have two shortcomings: First, traditional DID (Digital Intervention Analysis) has difficulty in capturing time-varying confounding and spatial dependence at the same time, causing mistakes in the separation of direct and indirect effects. Second, testing of mediation effect is restricted in linear three-step methods while mining heterogeneity of individual treatment effect usually relies on manual grouping which is subject to researchers' experience and lack of refined and data-driven identification. Therefore, upon the existing methods, this paper innovatively uses interactive fixed effects and spatial Durbin model to decompose direct effects in neighbors and direct effects in local area into one unified framework, and then uses causal forest method to estimate unbiased heterogeneous individual treatment effect.

The main innovations of this paper can be summarized in the following aspects: First, this paper builds a holistic evaluation system of high-quality urban economic development from five dimensions, which solves the problem of single indicator measurement. Second, based on the quasi-natural experiment of "Broadband China" strategy pilot, this paper identifies the causal effects and spatial spillover effects of digital infrastructure through multi-period DID, instrumental variable methods and spatial Durbin model in a systematic way. Third, based on mediation effect model and causal forest algorithm, this paper explores the transmission path of labor mobility and capital deepening, and refine characterization of policy effect differences of different regions and old industrial bases. Fourth, this paper provides quantitative support for differentiated layout and regional collaborative policies of digital infrastructure.

## II. MEASUREMENT AND CONSTRUCTION OF THE COMPREHENSIVE DIGITAL INFRASTRUCTURE INDEX AND THE HIGH-QUALITY DEVELOPMENT INDEX

Quantifying the level of digital infrastructure is the foundation of this study. Following common practices in existing literature, this paper selects three core indicators from the perspective of infrastructure coverage density: fiber optic cable length per square kilometer (km/km$^2$), number of mobile phone base stations per square kilometer (units/km$^2$), and number of broadband internet access ports (tens of thousands). Fiber optic cable length reflects the physical coverage of the fiber optic network, the number of mobile phone base stations reflects the construction level of the wireless communication network, and the number of broadband internet access ports characterizes the access capacity of the broadband network. The original data for these three indicators are taken from the *China Urban Statistical Yearbook* and annual reports of provincial communications administrations, spanning from 2011 to 2020. To avoid the influence of dimensional differences on the synthesis results, the range of each indicator is first standardized. Then, the entropy weight method is used to determine the objective weight of each indicator: the information entropy of each indicator is calculated; the larger the entropy value, the smaller the degree of variation and the lower the weight of the indicator; conversely, the lower the entropy value, the higher the weight. Finally, the standardized indicator values and their corresponding weights are weighted and summed to obtain the annual comprehensive digital infrastructure index for each prefecture-level city.

The construction of a high-quality urban economic development index should embody the five major concepts of "innovation, coordination, green development, openness, and sharing." Based on relevant evaluation systems and considering the availability of data for prefecture-level cities, this paper selects the following five secondary indicators: The innovation dimension uses per capita patent authorizations (patents/10,000 people), reflecting the city's ability to create knowledge and produce technology; the coordination dimension uses the reciprocal of the urban-rural income ratio (per capita disposable income of urban residents/per capita disposable income of rural residents), with a higher value indicating more balanced urban-rural development; the green dimension uses industrial smoke emissions per unit of GDP (tons/100 million yuan), which is converted into a positive indicator after reciprocal processing; the openness dimension uses the proportion of actual utilized foreign investment in the regional GDP (%); and the sharing dimension uses per capita education and medical expenditure (yuan/person), i.e., the sum of local government expenditure on education and medical care divided by the resident population. The original data for these indicators comes from the *China Urban Statistical Yearbook* and the statistical bulletins on national economic and social development of various prefecture-level cities. Due to the significant differences in the dimensions and magnitudes of the indicators, range standardization is first performed, and then the TOPSIS method is used to calculate the annual high-quality development index for each city. The basic idea of the TOPSIS method is to find the positive ideal solution (maximum value of each indicator) and the negative ideal solution (minimum value of each indicator) in the vector space composed of all indicators, and then calculate the relative closeness of each evaluation object to the positive ideal solution. This closeness is the high-quality development index, denoted as $Quality_{it}$. The index ranges from 0 to 1, with a higher value representing a higher level of high-quality urban economic development.

## III. QUASI-NATURAL EXPERIMENT SETTING AND ENDOGENOUS INSTRUMENTAL VARIABLE TREATMENT IN A MULTI-PERIOD DIFFERENCE-IN-DIFFERENCE MODEL

In order to explore the causal effect of construction of digital infrastructure on high-quality urban economy, this paper takes “Broadband China” strategy pilot as the quasi-natural experiment. The strategy released the list of pilot cities in three batches in 2013, 2014 and 2016. The pilot cities were supported with policies and funds in the field of optical network transformation and broadband speed upgrade. We take the pilot cities as the treatment group and the non-pilot cities as the control group to establish the multi-period difference-in-difference model. The reason why we use the multi-period difference-in-difference model is that the implementation time of the pilot program is not at the same time. If use the traditional two-period difference-in-difference model, it will cause the problem of multi-time point policy. The specific model is shown as equation (1):

$$Quality_{it} = \alpha + \beta \cdot Treat_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Where $Quality_{it}$ is the high-quality development index of city i in year t; $Treat_{it}$ is a policy dummy variable, taking 1 if city i has been included in the “Broadband China” pilot program in year t, otherwise taking 0; $X_{it}$ is a set of city-level control variables, including per capita GDP, urbanization rate, government intervention (fiscal expenditure as a percentage of GDP), foreign direct investment ratio, and human capital level (the proportion of college students to the population); $\mu_i$ and $\lambda_t$ are the city fixed effect and year fixed effect, respectively, and $\varepsilon_{it}$ is a random disturbance term. The coefficient $\beta$ is the average treatment effect of digital infrastructure construction. If it is significantly positive, it indicates that the pilot policy has promoted the high-quality development of the city’s economy.

However, the above DID estimation faces a key problem: the selection of “Broadband China” pilot cities is not completely random, and may tend to favor areas with a better economic foundation or a higher level of informatization. This non-random allocation will bring endogeneity bias, because the pilot cities themselves may have higher potential for high-quality development, leading to an overestimation of the policy effect. To mitigate this issue, this paper employs the instrumental variable method for two-stage least squares estimation. Following classic practices in existing research, two historical and geographical variables are selected as instrumental variables for the level of digital infrastructure: First, the topographic relief of each city, derived from the SRTM digital elevation model. This variable reflects the ruggedness of the ground; the more complex the terrain, the higher the cost of fiber optic cable laying and base station construction, thus negatively correlated with the level of digital infrastructure, but it does not directly affect the current high-quality economic development of the city. Second, the post office density (number of post offices per 100 square kilometers) during the Ming and Qing dynasties, with data from a historical geographic database. Historically, regions with well-developed postal networks often have a tradition of better information infrastructure, which is positively correlated with the current level of digital infrastructure. However, historical post office density, as a predetermined variable, has a negligible direct impact on contemporary urban economic performance. These two instrumental variables satisfy the conditions of correlation and exogeneity.

## IV. DECOMPOSITION OF LOCAL-NEIGHBOR SPILLOVER EFFECTS BY THE SPATIAL DURBIN MODEL

First, the spatial weight matrix should be built. Following the paper, an inverse distance squared matrix based on the city’s latitude and longitude is constructed, which is the reciprocal of the square of the geographical distance between two cities; that is, the closer the geographical distance, the larger the weight. Subsequently, to achieve model estimation, the weight matrix is row-normalized such that the sum of elements in each row is 1. The inverse distance squared matrix is selected because the spatial effect of digital infrastructure generally decreases with increasing geographical distance, and the inverse distance squared matrix reflects the above-mentioned characteristic well.

After the spatial weight matrix is determined, the spatial Durbin model is established. The spatial Durbin model is a generalized form of spatial autoregressive model and spatial error model. Its advantage is that it can reflect spatial interaction in both explained variable and explanatory variables, which are spatial lags simultaneously. The model can be expressed as follows (2):

$$\begin{aligned} Quality_{it} = {} & \rho \sum_{j=1}^{N} W_{ij} Quality_{jt} + \beta Digital\_infra_{it} \\ & + \theta \sum_{j=1}^{N} W_{ij} Digital\_infra_{jt} + \gamma X_{it} \\ & + \delta \sum_{j=1}^{N} W_{ij} X_{jt} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (2)$$

Where, $W_{ij}$ is the element between city i and j in the spatial weight matrix; $\sum_{j=1}^{N} W_{ij} Quality_{jt}$ is the spatial lag term of the explained variable, and the coefficient $\rho$ reflects the average impact of the high-quality development level of neighboring cities on this city; $\sum_{j=1}^{N} W_{ij} Digital\_infra_{jt}$ is the spatial lag term of the core explanatory variable, and the coefficient $\theta$ measures the impact of the digital infrastructure level of neighboring cities on the high-quality development of this city; $X_{it}$ is the control variable vector, and its spatial lag term coefficient $\delta$ is used to capture the spatial spillover effect of the control variable. The meanings of the remaining symbols are consistent with those in the previous text.

However, the point estimates of the spatial Durbin model cannot be directly interpreted as marginal effects, because the existence of spatial feedback loops causes the impact of variable changes to bounce back through neighboring units. To obtain an economically meaningful decomposition of the effects, a partial differential equation method is used to decompose the total effect into direct and indirect effects. The specific operation is as follows: The above model is rewritten in matrix form, and the partial derivative matrix of the explained variable with respect to the k-th explanatory variable is solved. The mean of the diagonal elements of this matrix represents the direct effect, indicating the average impact of changes in the explanatory variable of this city on the explained variable of this city, including the feedback from neighboring cities; the row mean of the off-diagonal elements represents the indirect effect (also known as the spatial spillover effect), indicating the average impact of changes in the explanatory variable of this city on the explained variables of other cities. If the indirect effect is positive, it indicates a radiation effect (driving the surrounding areas); if it is negative, it indicates a siphon effect (factors clustering in the local area). The total effect equals the sum of the direct and indirect effects, reflecting the average total impact of changes in the explanatory variable on the explained variables of all cities.

## V. THE THREE-STEP MEDIATION EFFECT METHOD AND CAUSAL FOREST FOR EXPLORING TRANSMISSION PATHS AND HETEROGENEITY

The preceding sections have verified the overall effect and spatial spillover characteristics of digital infrastructure construction on high-quality urban economic development, but the transmission mechanism remains unclear. Through which intermediate links does digital infrastructure drive high-quality development? Are there systemic differences in policy effects among different cities? These two questions are crucial for precise policy implementation. Therefore, this paper employs a mediation effect model and a causal forest algorithm to conduct mechanism testing and heterogeneity analysis.

The following recursive equation is established to test the mediating effects of labor mobility and capital deepening in the digital infrastructure-high-quality development path.

1 Testing the total effect of digital infrastructure on the high-quality development index, i.e., the coefficient $\beta$ in the multi-period DID model shown above. If significant, we proceed to the next steps; otherwise, not.

2 Testing the effect of digital infrastructure on mediating variables. We select two mediating variables: labor mobility (labeled as inflow of migrants, a larger ratio of the logarithm of urban resident population to registered population represents more inflow of migrants); and capital deepening (labeled as logarithm of per capita capital stock (estimated by the perpetual inventory method)). The following regression equations (3) are established:

$$M_{it} = \alpha_1 + a \cdot Digital\_infra_{it} + \gamma_1 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Where $M_{it}$ represents the mediating variable (labor mobility or capital deepening), and coefficient a reflects the impact of digital infrastructure on the mediating variable. In the third step, the mediating variable is incorporated into the high-quality development regression equation (4):

$$\begin{aligned} Quality_{it} = \alpha_2 + c' \cdot Digital\_infra_{it} + b \cdot M_{it} \\ + \gamma_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (4)$$

Where coefficient c' is the direct effect, and b is the impact of the mediating variable on the high-quality development index. If both a and b are significant, and the absolute value of c' is less than the total effect c in the first step, then a mediating effect exists. The magnitude of the mediating effect is a×b, and the proportion of the mediating effect is (a×b)/c. This paper also reports the Z-statistic of the Sobel test and its significance, and uses the Bootstrap method (repeated 1000 times) to calculate the confidence interval of the mediating effect to enhance the robustness of the conclusions. Traditional DID (Digital Identification and Distributed Identification) estimation provides the average treatment effect, but different cities may benefit differently from digital infrastructure. Reporting only the mean may mask important heterogeneity characteristics, leading to a lack of targeted policy recommendations. Conventional grouped regression (e.g., by east-central-west region or old industrial base) requires pre-specifying grouping variables and struggles to simultaneously consider the interactive effects of multiple feature variables. To overcome this limitation, this paper introduces the causal forest algorithm for data-driven heterogeneity identification.

Causal forest is a machine learning method based on decision tree ensembles. Its core idea is to recursively partition the feature space to make the treatment effect of individuals within each subspace as homogeneous as possible. The specific steps are as follows: First, city-level feature variables (including GDP per capita, urbanization rate, government intervention, foreign direct investment, human capital level, topographic relief, historical post office density, etc.) are used as partitioning variables. Second, multiple causal trees are constructed, each dividing the samples into several leaf nodes according to the feature space partitioning rules, estimating the local average treatment effect within each leaf node. Finally, the results of all trees are averaged to obtain the individual treatment effect for each city. The algorithm avoids overfitting through techniques such as “honest estimation” and sample segmentation, and can provide confidence intervals for treatment effects. Finally, the individual treatment effects of each city are extracted from the causal forest output. On the one hand, their distribution histograms are plotted to observe the overall dispersion. On the other hand, statistics are grouped by eastern, central, and western cities, as well as old industrial bases and non-old industrial bases, to compare the differences and significance of the means between groups.

## VI. QUANTITATIVE TESTING CRITERIA FOR THE IMPACT OF DIGITAL INFRASTRUCTURE

### A. EXPERIMENTAL SETUP AND PREPARATION

Data Sources and Samples: Panel data from 283 prefecture-level cities across China from 2011 to 2020 were selected. Data were obtained from the *China Urban Statistical Yearbook*, provincial statistical yearbooks, the State Intellectual Property Office, and nighttime light datasets (DMSP/OLS and VIIRS).

Variable Definitions: The explained variable was the urban economic high-quality development index (calculated using the TOPSIS method mentioned above); the core explanatory variables were the digital infrastructure comprehensive index (synthesized using the entropy weight method) and the "Broadband China" policy dummy variable; control variables included per capita GDP, urbanization rate, government intervention (fiscal expenditure/GDP), foreign direct investment, and human capital level (number of college students/population).

Instrumental Variables: Topographic relief (from the SRTM digital elevation model) and Ming and Qing dynasty post office density (from historical geographic databases).

Spatial Weight Matrix: An inverse distance squared matrix calculated based on urban latitude and longitude, and normalized.

Software and Implementation: Stata 17.0 was used for DID, 2SLS, mediation effects, and spatial econometrics (using the xsmle command); Python 3.8 and the EconML causal forest library were used for individual treatment effect estimation.

Preprocessing: All continuous variables underwent 1% and 99% tailing to eliminate the influence of extreme values; unit root tests (LLC and IPS) were performed on panel data to ensure stationarity.

### B. STATISTICAL TESTS OF BENCHMARK REGRESSION AND INSTRUMENTAL VARIABLE REGRESSION

In order to analyze the net impact of construction of digital infrastructure on high-quality development of urban economy, we used multi-period DID model for benchmark regression analysis with "Broadband China" pilot project as quasi-natural experiment. Given the bidirectional causality existing between the level of digital infrastructure and urban economy quality as well as the existence of omitted variables leading to endogeneity, we selected topographic relief and historical post office density as instrumental variables for further analysis. Two-stage least squares (IV-2SLS) was used to correct endogeneity of comprehensive digital infrastructure index. The regression results of benchmark DID and IV-2SLS are shown in Table 1.

In Table 2, digital infrastructure construction significantly increased the urban economic high-quality development index by 6.8% ($\beta$ = 0.068, $p < 0.01$). In the instrumental variable regression, the first-stage F-statistic was 42.37, excluding the problem of weak instrumental variables; the Sargan test p-value was 0.317, accepting the null hypothesis of exogeneity of instrumental variables. The second-stage estimate was 0.315, significant at the 5% level, indicating that for every unit increase in the comprehensive index of digital infrastructure, the high-quality development index increases by 0.315 units. This is consistent with the baseline results, verifying the positive causal effect of digital infrastructure on high-quality development. While the baseline estimate is smaller due to not considering the scale differences of continuous variables, the conclusion is robust.

### C. EXPERIMENTAL TEST OF DIRECT AND INDIRECT SPATIAL SPILLOVER EFFECTS

To examine the spatial spillover effect of digital infrastructure construction on urban economic high-quality development, an inverse distance squared spatial weight matrix was constructed, and a spatial Durbin model was used for regression. The total effect was decomposed into local direct effects and neighboring indirect effects using partial differential equations to identify whether digital infrastructure has a radiating or siphoning effect on surrounding cities. Table 2 reports the estimation results of the direct effects, indirect effects, and spatial autoregressive coefficients.

In Table 2, the spatial autoregression coefficient $\rho$ is 0.438, significant at the 1% level, indicating a significant positive spatial dependence on high-quality urban economic development. The direct effect of the comprehensive digital infrastructure index is 0.284, passing the 1% significance test, indicating that local digital infrastructure significantly promotes high-quality development in the city. The indirect effect is -0.117, significant at the 5% level, meaning that local digital infrastructure has a certain degree of siphon effect on surrounding cities, leading to the agglomeration of factors in the local area. The total effect is 0.167, still remaining positively significant. This asymmetric spatial spillover characteristic suggests that while digital infrastructure promotes local development, it may widen the gap between cities, requiring intervention from regional coordinated policies.

### D. EXPERIMENTAL TEST OF DIRECT AND INDIRECT EFFECTS OF SPATIAL SPILLOVER EFFECTS

To examine the transmission path and heterogeneity characteristics of the impact of digital infrastructure on high-quality development, a three-step mediating effect method was first used to investigate the mediating roles of labor mobility and capital deepening. Secondly, the causal forest algorithm was used to estimate the individual treatment effects of each city, and comparisons were made by region and old industrial base. Table 3 reports the main results of the mediating effect test and the distribution of individual treatment effects.

Figure 1(a-b) shows the pie chart of the proportion of mediating effects and the histogram of the distribution of individual treatment effects estimated by the causal forest. The

**TABLE 1.** Statistical Test Evaluation of Baseline Regression and Instrumental Variable Regression

| Variable | (1) Benchmark DID | (2) IV First Stage | (3) IV Second Stage |
|---|---|---|---|
| Digital infrastructure policy dummy | 0.068*** (0.012) | — | — |
| Digital infrastructure composite index (fitted) | — | — | 0.315** (0.124) |
| Terrain ruggedness | — | 0.351*** (0.058) | — |
| Historical post office density | — | 0.427*** (0.063) | — |
| Control variables | Yes | Yes | Yes |
| City fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| First-stage F-statistic | — | 42.37 | — |
| Sargan test p-value | — | 0.317 | — |
| Observations | 2830 | 2830 | 2830 |
| $R^2$ | 0.614 | 0.572 | 0.608 |

*Note: Standard errors are in parentheses;* *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**TABLE 2.** Decomposition Results of Direct and Indirect Effects in the Spatial Durbin Model

| Variable | Direct Effect | Indirect Effect (Spatial Spillover) | Total Effect |
|---|---|---|---|
| Digital infrastructure composite index | 0.284*** (0.053) | -0.117** (0.048) | 0.167*** (0.061) |
| GDP per capita | 0.102** (0.041) | 0.035 (0.038) | 0.137** (0.055) |
| Urbanization rate | 0.156*** (0.047) | -0.042 (0.051) | 0.114* (0.062) |
| Government intervention | -0.002847 | 0.028 (0.044) | -0.045 (0.052) |
| Foreign direct investment | 0.089** (0.042) | 0.011 (0.036) | 0.100** (0.048) |
| Human capital level | 0.211*** (0.062) | 0.063 (0.055) | 0.274*** (0.071) |
| Spatial autoregressive coefficient $\rho$ | — | 0.438*** (0.087) | — |

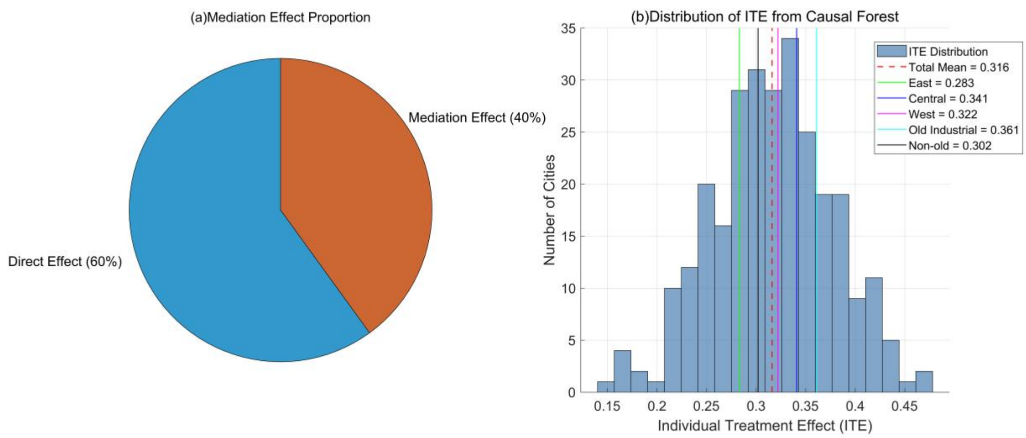


**FIGURE 1.** Decomposition Results of Direct and Indirect Effects of the Spatial Durbin Model

mediating effect test shows that the mediating effect value is 0.126, accounting for 40.0% of the total effect, and the Sobel Z statistic is 4.32 (p<0.001), confirming that labor mobility and capital deepening are important transmission paths for digital infrastructure to promote high-quality development. The mean value of the individual treatment effect estimated by the causal forest is 0.316, which is highly consistent with the baseline results. Group comparisons show that central cities (0.338) and old industrial bases (0.358) benefited most significantly from the policies, exceeding those in the east (0.281) and west (0.331), with the west benefiting slightly more than the east but less than the central region. This result verifies the existence of the transmission mechanism and reveals the significant heterogeneity of policy effects across regions and industrial structures.

## VII. CONCLUSION

This paper analyzes the influence of digital infrastructure construction on the overall level of high-quality urban economic development from theoretical and empirical perspectives. The research results show that digital infrastructure can effectively promote the overall level of high-quality urban economic development, and its effective transmission paths are mainly manifested in labor mobility and capital deepening. At the same time, it finds that digital infrastructure has a significant spatial spillover effect, and its spatial spillover characteristic presents an “asymmetric” “local promotion and neighboring region inhibition” feature, which implies that the siphon effect of factors agglomerating in pilot cities is larger than the radiation effect. The heterogeneity analysis shows that central cities and old industrial bases are relatively advantageous. The limitation of this paper is that, due to data limitation, we have not made a detailed distinction between different types of digital infrastructure, for example, 5G base stations and industrial internet. In the future, we can explore the balancing mechanism between digital infrastructure and coordinated development among cities further. In addition, we can also explore the digital infrastructure level at the micro-enterprise level.

## AUTHOR CONTRIBUTIONS

Conceptualization –Guanchen Lv, Haihui Dong, Piaoxue Liao and Weidong Li; methodology – Guanchen Lv, Haihui Dong, Piaoxue Liao and Weidong Li; investigation – Guanchen Lv, Haihui Dong, Piaoxue Liao and Weidong Li; writing-original draft preparation – Guanchen Lv, Haihui Dong, Piaoxue Liao and Weidong Li. All authors have read and agreed to the published version of the manuscript.

## CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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