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Has Information Infrastructure Construction Promoted the Optimization and Upgrading of Industrial Structure? Evidence for a Panel Data Analysis of China

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Abstract

Industrial structure optimization and upgrading driven by information infrastructure facilitates resource-efficient allocation, which is crucial for advancing China's economic development toward sustainability. This paper constructs a simplified multi-sector general equilibrium model to theoretically reveal the mechanism of information infrastructure's impact on industrial structure. Theoretical results indicate that among various factors, information infrastructure investment scale, its effect on industrial sector factor productivity, and the capital factor output elasticity of industrial sectors are three key determinants of industrial structure rationalization. Based on this, the paper uses China's provincial panel data from 2009 to 2022 and adopts the fixed effect estimation method to empirically verify the theoretical conclusions. Empirical results show that information infrastructure characteristics play a pivotal role in promoting industrial structure optimization. They exert a positive effect on the free flow of production factors across industrial sectors and efficient resource allocation. Specifically, fixed information infrastructure has a stronger impact on industrial structure rationalization than mobile information infrastructure. Neither mobile nor fixed information infrastructure exerts a significant impact on industrial structure upgrading. To fully leverage information infrastructure and its investment, further efforts are needed to strengthen their role in high-value-added industrialization and high-tech industrialization, thereby consolidating the foundation for sustainable economic development.

Keywords: information infrastructure; industrial structure; optimization and upgrading; sustainable development; resource allocation efficiency

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1. Introduction

The 2025 Chinese government work report once again explicitly calls for “vigorously promoting the construction of a modernized information infrastructure and accelerating the development of new productivity”. The information infrastructure renowned globally for its concentrated R&D investment, vibrant innovation ecosystem, and extensive application scope, constitutes a critical digital cornerstone for economic advancement [1–3]. Information infrastructure consists of two key components, namely mobile information

infrastructure and fixed information infrastructure. Mobile information infrastructure and fixed broadband infrastructure act as key material carriers of information in the digital economy, providing essential support for the evolution and application of next-generation information technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) [4,5]. China officially launched 5G commercial services in 2020 and has since achieved remarkable milestones in infrastructure deployment. By the end of 2024, the number of 5G base stations constructed in China exceeded 4.6 million. Concurrently, the number of 5G mobile users reached 1.1 billion, representing the world's largest 5G user base. Additionally, the total number of internet broadband access ports in China reached 1.2 billion. Therefore, can large-scale construction of information infrastructure promote the optimization and upgrading of industrial structure? What are the impact mechanisms? To fully leverage information infrastructure and its investment, further efforts are needed to strengthen their role in high-value-added industrialization and high-tech industrialization, thereby consolidating the foundation for economic sustainability.

Infrastructure is a crucial factor influencing industrial structure transformation, among which information infrastructure constitutes a vital category. It primarily impacts industrial structure in two dimensions: optimization and upgrading, serving as a cornerstone for sustainable economic development. From the perspective of industrial structure optimization, during the production and manufacturing process, various industries require the coordinated matching of technologies, resources, and product production to achieve efficient resource allocation, therefore realizing rationalization of the industrial structure [6]. The spillover effects, information symmetry or asymmetry associated with infrastructure in the process of industrial development can lead to overcapacity or excessive fluctuations in production capacity [7–9]. As a type of infrastructure, information infrastructure also exhibits the characteristic of spillover, serving as an important mechanism to exert influences across various sectors of the economy and society [10–12].

Most scholars have conducted research on the impact of information infrastructure on industrial structure, illuminating the particularly crucial role of information infrastructure in industrial structure adjustment in the digital information economy, particularly regarding its contribution to sustainable economic development. Jensen [13] and Vu [14] have demonstrated that information infrastructure promotes technological dissemination and innovation, reduces production costs, and stimulates an increase in demand. Yu [15] and Zhou [16] explored the link between information infrastructure investment and industrial structure transformation and upgrading, noting significant supply-side differences between information and traditional infrastructure in production technology and industrial investment sources. They emphasized that China should leverage its institutional advantages to expand new infrastructure investment. Han and Zhu [17] analyzed and indicated a significant positive correlation between information infrastructure and productivity, suggesting that the communications industry should strengthen close cooperation with vertical sectors. By constructing a game model of asymmetric competition between the digital economy and the traditional economy, Luo and Lee [18] examined the relationship between the two. The results revealed that the digital economy generates technological spillover effects on the traditional economy, which can facilitate the digital transformation and upgrading of the traditional economy. Existing studies that treat information infrastructure as an aggregate variable, this study distinguish between mobile information network infrastructure and fixed information infrastructure, verifying both promote industrial structure rationalization.

Additionally, scholars have explored how information infrastructure sustains economic effects through information network transmission. However, these scholars mainly focus on two dimensions: macroeconomic effects, such as the impacts of information network facilities on economic growth, export trade, wages and employment structure, and

microeconomic effects, including the relationships between information network facilities and entrepreneurship, operational performance and enterprise behavioral decisions. Formanc [19] revealed the positive effect of information network facilities on wages. Some studies analyzed the impact of internet development on labor productivity in the manufacturing sector. Based on a quasi-natural experiment of the “Broadband China” pilot policy, they found that information networks exert a significant productivity effect [20–23]. Using the same experiment, Koutroumpis [24] and Roller [25] also revealed that information infrastructure construction generates effects of optimizing enterprise technology structure and promoting technology diffusion. Some scholars demonstrated that the rapid development of technologies such as big data, blockchain, and artificial intelligence necessitates accelerating the construction of an information technology-centered system, therefore driving industrial structure toward the high end of the global value chain [26–28]. At the same time, improvements in communication services amid information infrastructure have enhanced the communication capabilities between sectors and industries [29–31].

In summary, although some achievements have been made in scholars on the impact of information infrastructure construction on the industrial structure from the perspective of industrial development. It is urgent to empirically reveal its role in industrial structure and clarify whether it promotes industrial structure optimization or upgrading to support economic sustainability.

The rest of the present study is arranged as follows: Section 2 outlines the analytical framework and research hypotheses. Section 3 details the econometric approaches and data sources. Section 4 of the study offers an analysis of the estimation results, with a focus on the model’s basic regression, robustness, and heterogeneous effects.

2. Materials and Methods

2.1. Industrial Structure Optimization and Upgrading

Two dimensions are commonly employed to measure the characteristics of industrial structure: namely industrial structure optimization and industrial structure upgrading. Industrial structure optimization mainly refers to the quality of structural aggregation, encompassing two key aspects: the coordination degree of the structure and the efficiency of resource allocation [32,33]. This study represents the optimization level using the industrial structure deviation degree, a metric that helps sustain balanced economic development. The calculation formula is as follows:

$$TE = \sum_{i=1}^n \left| \frac{Y_i/L_i}{Y/L} - 1 \right| = \sum_{i=1}^n \left| \frac{Y_i/Y}{L_i/L} - 1 \right|, \quad (1)$$

where TE denotes the industrial structure deviation degree, Y_i represents the output value, L_i stands for the number of employees, and n indicates the number of industrial sectors. This study mainly analyzes the industrial structure of the primary industry, secondary industry, and tertiary industry, so $n = 3$, where $i = 1, 2, 3$ correspond to the primary industry, secondary industry, and tertiary industry respectively. The primary industry mainly refers to sectors engaged in production activities directly dependent on natural resources, such as agriculture, forestry, fishery, and mining. These activities form the foundation of the human economy and provide raw materials for subsequent industries. The secondary industry encompasses sectors engaged in processing and manufacturing primary products, with typical examples including manufacturing and construction. These industries enhance the added value of raw materials through technological transformation. The tertiary industry refers to sectors that do not directly involve material

production but provide services, such as retail, education, healthcare, finance, and tourism. With economic development, the tertiary industry has gradually become the dominant force in the modern economic system.

In addition to the industrial structure deviation degree, the Theil Index is also an indicator for measuring the level of industrial structure optimization [34], and its formula is expressed as follows:

$$TL = \sum_{i=1}^n \left(\frac{Y_i}{Y}\right) \ln \left(\frac{Y_i/L_i}{Y/L}\right), \quad (2)$$

When the economy is in a steady state, $TL = 0$; the greater the deviation of the Theil Index from 0, the more irrational the industrial structure becomes.

Industrial structure upgrading refers to the changing proportional relationships among various industrial sectors, indicating the shift from the primary industry to the secondary and tertiary industries, the transformation from labor-intensive industries to capital-intensive industries and further to technology-intensive industries, as well as the transition from manufacturing low-value-added primary products to high-value-added intermediate products and final products. Generally, the level of industrial structure upgrading is reflected by the output value proportional relationships among various industries, namely the ratio of the secondary and tertiary industries [35,36], which is expressed as follows:

$$TG = \frac{Y_3}{Y_2}, \quad (3)$$

where Y_2 denotes the output value of the secondary industry, and Y_3 represents the output value of the tertiary industry. A larger value of TG indicates a higher level of industrial structure upgrading; conversely, a smaller value of TG implies a lower level of industrial structure upgrading.

2.2. The Influence Mechanism of Information Infrastructure on Industrial Structure Optimization and Upgrading

Information infrastructure serves as a critical foundation for the digitization and intelligent transformation of the economy and society. From the perspective of industrial structure, this paper conducts a theoretical analysis of the economic impacts of information infrastructure investment by constructing a simplified multi-sector General Equilibrium Model. The adoption of a multi-sector General Equilibrium model in this study is highly appropriate for exploring issues including inter-sectoral factor mobility, industrial structure transformation, and the spillover effects of infrastructure across multiple industries. Unlike single-sector models, it does not overlook inter-industrial linkages. Instead, it captures cross-industry interactions and differences in production functions and factor allocation. This choice is consistent with Zhengquan [37], reflecting methodological inheritance in related research. The model aligns with the context of information infrastructure's cross-industry empowerment. It enables precise identification of the heterogeneous impacts of information infrastructure on the primary, secondary, and tertiary industries.

Subscripts $j \in \{1, 2, 3\}$ are used to denote the three industrial sectors in the economy and society, where $j = 1$ represents the primary industry, $j = 2$ the secondary industry, and $j = 3$ the tertiary industry. It is assumed that each of the three industrial sectors is organized for production by a representative firm, with the production function given by:

$$Y_j = A_j T^{\beta_j} K_j^{\alpha_j} L_j^{1-\alpha_j}, \quad (4)$$

where Y_j denotes the output of the corresponding industrial sector, $A_j T^{\beta_j}$ represents total factor productivity (TFP), T stands for information infrastructure, T^{β_j} indicates the

promotion effect of information infrastructure on factor productivity, with β_j used to distinguish the heterogeneous promotion effects of information infrastructure on the factor productivity across different industrial sectors, K_j denotes capital, α_j represents the output elasticity of capital, L_j stands for labor, and $1 - \alpha_j$ indicates the output elasticity of labor.

2.2.1. Profit Maximization of Producers

Let P_j denote the product price of the corresponding industrial sector, R represents the capital rental rate (without a subscript, indicating that the capital rental rate is unbiased across different industrial sectors), and W_j stand for the labor wage in the corresponding industrial sector. Then, the profit maximization problem faced by the representative firm in each industrial sector is expressed as follows:

$$\max_{\{K_j, L_j\}} \pi_j(Y_j) = P_j Y_j - R K_j - W_j L_j, \quad (5)$$

The first-order conditions are:

$$\begin{cases} \frac{\partial \pi_j(Y_j)}{\partial K_j} = 0 \\ \frac{\partial \pi_j(Y_j)}{\partial L_j} = 0 \end{cases}, \quad (6)$$

The equilibrium conditions for the representative firm in each industrial sector are derived as follows:

$$\begin{cases} R K_j = \alpha_j P_j Y_j \\ W_j L_j = (1 - \alpha_j) P_j Y_j \end{cases}, \quad (7)$$

It is assumed that the production of investment goods in the economy and society is characterized by a representative investment goods producer. To simplify the model, it is assumed that starting from the current period, the investment goods producer only produces information infrastructure, adopting the Constant Elasticity of Substitution (CES) Production Function:

$$I = \left(\theta_1^{\frac{1}{\varepsilon_i}} I_1^{\frac{\varepsilon_i-1}{\varepsilon_i}} + \theta_2^{\frac{1}{\varepsilon_i}} I_2^{\frac{\varepsilon_i-1}{\varepsilon_i}} + \theta_3^{\frac{1}{\varepsilon_i}} I_3^{\frac{\varepsilon_i-1}{\varepsilon_i}} \right)^{\frac{\varepsilon_i}{\varepsilon_i-1}}, \quad (8)$$

where I denotes the quantity of investment goods (information infrastructure) produced, I_1 represents the quantity of output from the primary industry used for producing investment goods, I_2 stands for the quantity of output from the secondary industry used for producing investment goods, and I_3 indicates the quantity of output from the tertiary industry used for producing investment goods. θ_1 , θ_2 , and θ_3 are constants satisfying $\theta_1, \theta_2, \theta_3 > 0$ and $\theta_1 + \theta_2 + \theta_3 = 1$, while ε_i represents the elasticity of substitution in investment.

Let P_I denote the price of the produced investment goods. Then, the profit maximization problem faced by the representative producer of investment goods is:

$$\max_{\{I_1, I_2, I_3\}} \pi(I) = P_I I - P_1 I_1 - P_2 I_2 - P_3 I_3, \quad (9)$$

Now, the first-order conditions are:

$$\begin{cases} \frac{\partial \pi(I)}{\partial I_1} = 0 \\ \frac{\partial \pi(I)}{\partial I_2} = 0, \\ \frac{\partial \pi(I)}{\partial I_3} = 0 \end{cases} \quad (10)$$

The equilibrium conditions for the producer of investment goods (information infrastructure) are derived as follows:

$$\begin{cases} P_1 I_1 = \theta_1 P_1^{1-\varepsilon_i} P_I^{\varepsilon_i} I \\ P_2 I_2 = \theta_2 P_2^{1-\varepsilon_i} P_I^{\varepsilon_i} I, \\ P_3 I_3 = \theta_3 P_3^{1-\varepsilon_i} P_I^{\varepsilon_i} I \end{cases} \quad (11)$$

Substituting the above equation into Equation (8), there results:

$$P_I = (\theta_1 P_1^{1-\varepsilon_i} + \theta_2 P_2^{1-\varepsilon_i} + \theta_3 P_3^{1-\varepsilon_i})^{\frac{1}{1-\varepsilon_i}}, \quad (12)$$

Let μ_I denote the proportion of investment goods (information infrastructure) input sourced from the tertiary industry sector, which is defined as follows:

$$\mu_I = \frac{P_3 I_3}{P_1 I_1 + P_2 I_2 + P_3 I_3}, \quad (13)$$

Combining the above equation with Equations (11) and (12) results in the following:

$$\mu_I = \frac{\theta_3 P_3^{1-\varepsilon_i}}{P_I^{1-\varepsilon_i}}, \quad (14)$$

It is assumed that the information infrastructure investment in the current period contributes to the formation of information infrastructure in the next period. Let T' denote the information infrastructure in the next period and δ_T represent the depreciation rate of information infrastructure ($0 < \delta_T < 1$), and then:

$$T' = (1 - \delta_T)T + I, \quad (15)$$

2.2.2. Utility Maximization of Consumers

It is assumed that consumption in the economy and society is represented by a representative consumer, with the utility function taking the Constant Elasticity of Substitution (CES) form:

$$U = \left(\omega_1^{\frac{1}{\varepsilon_c}} C_1^{\frac{\varepsilon_c-1}{\varepsilon_c}} + \omega_2^{\frac{1}{\varepsilon_c}} C_2^{\frac{\varepsilon_c-1}{\varepsilon_c}} + \omega_3^{\frac{1}{\varepsilon_c}} C_3^{\frac{\varepsilon_c-1}{\varepsilon_c}} \right)^{\frac{\varepsilon_c}{\varepsilon_c-1}}, \quad (16)$$

where U denotes consumer utility, C_1 represents the quantity of output from the primary industry allocated to consumption, C_2 stands for the quantity of output from the secondary industry allocated to consumption, and C_3 indicates the quantity of output from the tertiary industry allocated to consumption. ω_1 , ω_2 and ω_3 are constants satisfying $\omega_1, \omega_2, \omega_3 > 0$ and $\omega_1 + \omega_2 + \omega_3 = 1$, while ε_c represents the elasticity of substitution in consumption.

Let Q denote the amount of money available to consumers for consumption. Then, the budget constraint faced by consumers is:

$$P_1 C_1 + P_2 C_2 + P_3 C_3 = Q, \quad (17)$$

The problem faced by consumers in pursuing utility maximization is:

$$\max_{\{C_1, C_2, C_3\}} U = \left(\omega_1^{\frac{1}{\varepsilon_c}} C_1^{\frac{\varepsilon_c-1}{\varepsilon_c}} + \omega_2^{\frac{1}{\varepsilon_c}} C_2^{\frac{\varepsilon_c-1}{\varepsilon_c}} + \omega_3^{\frac{1}{\varepsilon_c}} C_3^{\frac{\varepsilon_c-1}{\varepsilon_c}} \right)^{\frac{\varepsilon_c}{\varepsilon_c-1}}, \quad (18)$$

$$s.t. P_1 C_1 + P_2 C_2 + P_3 C_3 = Q$$

The Lagrangian function is:

$$\mathcal{L} = \left(\omega_1^{\frac{1}{\varepsilon_c}} C_1^{\frac{\varepsilon_c-1}{\varepsilon_c}} + \omega_2^{\frac{1}{\varepsilon_c}} C_2^{\frac{\varepsilon_c-1}{\varepsilon_c}} + \omega_3^{\frac{1}{\varepsilon_c}} C_3^{\frac{\varepsilon_c-1}{\varepsilon_c}} \right)^{\frac{\varepsilon_c}{\varepsilon_c-1}} + \lambda(Q - P_1 C_1 - P_2 C_2 - P_3 C_3), \quad (19)$$

The first-order conditions are:

$$\begin{cases} \frac{\partial \mathcal{L}}{\partial C_1} = 0 \\ \frac{\partial \mathcal{L}}{\partial C_2} = 0, \\ \frac{\partial \mathcal{L}}{\partial C_3} = 0 \end{cases} \quad (20)$$

Consumers satisfy the following conditions:

$$\begin{cases} P_1 C_1 = \omega_1 P_1^{1-\varepsilon_c} Q^{\varepsilon_c} U^{1-\varepsilon_c} \\ P_2 C_2 = \omega_2 P_2^{1-\varepsilon_c} Q^{\varepsilon_c} U^{1-\varepsilon_c}, \\ P_3 C_3 = \omega_3 P_3^{1-\varepsilon_c} Q^{\varepsilon_c} U^{1-\varepsilon_c} \end{cases} \quad (21)$$

Combining the above equation with Equations (16) and (17) results in the following:

$$Q = P_C U, \quad (22)$$

where

$$P_C = (\omega_1 P_1^{1-\varepsilon_c} + \omega_2 P_2^{1-\varepsilon_c} + \omega_3 P_3^{1-\varepsilon_c})^{\frac{1}{1-\varepsilon_c}},$$

Let μ_C denote the proportion of input sourced from the tertiary industry sector in consumption, which is defined as follows:

$$\mu_C = \frac{P_3 C_3}{P_1 C_1 + P_2 C_2 + P_3 C_3}, \quad (23)$$

Combining the above equation with Equations (21) and (22) results in the following:

$$\mu_C = \frac{\omega_3 P_3^{1-\varepsilon_c}}{P_C^{1-\varepsilon_c}}, \quad (24)$$

2.2.3. Market Equilibrium Condition

Based on the above discussions on production, investment, and consumption in the economy, and considering that the goods market equilibrium condition in the economy is that the output of each industrial sector is fully allocated to consumption and investment, while the factor market clearing condition is that total capital and total labor are fully allocated to production across all industrial sectors, the following holds:

$$\begin{cases} Y_j = C_j + I_j \\ K = K_1 + K_2 + K_3, \\ L = L_1 + L_2 + L_3 \end{cases} \quad (25)$$

Let s denote the investment rate, which represents the proportion of total investment in information infrastructure in the total output value of the economy and society, and is defined as follows:

$$s = \frac{P_1 I_1 + P_2 I_2 + P_3 I_3}{P_1 Y_1 + P_2 Y_2 + P_3 Y_3} \quad (26)$$

Combining the market equilibrium conditions of the goods market and producer markets, this study examines the impact of information infrastructure on industrial structure from two dimensions: the optimization and upgrading of industrial structure.

In terms of the upgrading of industrial structure, from Equations (13), (23) and (26), the following holds:

$$\begin{cases} P_3 C_3 = \mu_C (1 - s) (P_1 Y_1 + P_2 Y_2 + P_3 Y_3) \\ P_3 I_3 = \mu_I s (P_1 Y_1 + P_2 Y_2 + P_3 Y_3) \end{cases} \quad (27)$$

In general, the proportion of the output value of the tertiary industry sector in the total output value of the economy can be used to measure the level of industrial structure upgrading. From Equation (27), the following is obtained:

$$\frac{P_3 Y_3}{P_1 Y_1 + P_2 Y_2 + P_3 Y_3} = \mu_C + (\mu_I - \mu_C) s \quad (28)$$

In terms of the optimization of industrial structure, let Y'_j denote the output of the corresponding industrial sector in the next period and L'_j denote the labor of the corresponding industrial sector in the next period. Considering that this model assumes all consumer income is allocated to consumption, with no savings to form capital accumulation, the capital in the next period is thus the same as the capital in the current period. From Equations (4) and (15), the following holds:

$$\begin{cases} \ln Y_j = \ln A_j + \beta_j \ln T + \alpha_j \ln K_j + (1 - \alpha_j) \ln L_j \\ \ln Y'_j = \ln A_j + \beta_j \ln [(1 - \delta_T) T + I] + \alpha_j \ln K_j + (1 - \alpha_j) \ln L'_j \end{cases} \quad (29)$$

In general, the degree of industrial structure optimization can be measured by the matching degree between the output structure (output value share) and the employment structure (labor share). From Equation (29), the relationship between the output growth rate and labor growth rate of each industrial sector is given by:

$$\ln Y'_j - \ln Y_j = \beta_j \ln \frac{(1 - \delta_T) T + I}{T} + (1 - \alpha_j) (\ln L'_j - \ln L_j) \quad (30)$$

Furthermore, the difference between the output growth rate and labor growth rate of each industrial sector is:

$$(\ln Y'_j - \ln Y_j) - (\ln L'_j - \ln L_j) = \beta_j \ln \frac{(1 - \delta_T) T + I}{T} - \alpha_j (\ln L'_j - \ln L_j) \quad (31)$$

By constructing the model, this study clarifies the impact and mechanism of information infrastructure on the upgrading and optimization of industrial structure, and draws the following propositions:

Proposition 1. *The characteristics of information infrastructure reflect the impact of productive forces on industrial structure upgrading. This impact is linked, on one hand, to the proportion of information infrastructure investment in total economic and social output value—namely, the investment rate—and on the other hand, to disparities in the industrial composition of consumption and investment.*

Proposition 2. *The impact of information infrastructure on the optimization of industrial structure is related to the degree of influence of information infrastructure on factor productivity across*

different industrial sectors, the investment volume of information infrastructure, and the capital-output elasticity of different industrial sectors.

Based on the theoretical deductions from the simplified multi-sector general equilibrium model, two research hypotheses are proposed.

H1: Information infrastructure exerts a positive impact on industrial structure optimization.

H2: Information infrastructure has an insufficient impact on industrial structure upgrading.

3. The Model

3.1. Econometric Methods

Based on the findings of Wooldridge, this study employs the Hausman test for judgment and adopts the fixed-effects model for analysis [38]. To verify the impact of information infrastructure construction on industrial structure, the following econometric model is constructed:

$$Struct_{it} = \alpha_i + \beta_1 \ln Station_{it} + \gamma_1 \ln Pgdp_{it} + \gamma_2 Urb_{it} + \gamma_3 Grlabor_{it} + \gamma_4 Edugao_{it} + \gamma_5 Trade_{it} + \varepsilon_{it}, \quad (32)$$

$$Struct_{it} = \alpha_i + \beta_1 \ln Broadband_{it} + \gamma_1 \ln Pgdp_{it} + \gamma_2 Urb_{it} + \gamma_3 Grlabor_{it} + \gamma_4 Edugao_{it} + \gamma_5 Trade_{it} + \varepsilon_{it}, \quad (33)$$

where i denotes the region and t denotes time. $Struct_{it}$, as the dependent variable, reflects the industrial structure of region i in period t , which is measured from two dimensions: industrial structure optimization and industrial structure upgrading. Specifically, this study uses two indicators—industrial structure deviation degree (TE) and Theil Index (TL)—to measure the level of industrial structure optimization; the ratio of the tertiary industry to the secondary industry (TG) is used to measure the level of industrial structure upgrading. $Station_{it}$ and $Broadband_{it}$ are the core dependent variables. The five control variables are defined as follows: $Pgdp$ is per capita GDP, Urb is the level of urbanization, $Grlabor$ is the labor growth rate, $Edugao$ is the education level, and $Trade$ is the intensity of foreign trade. ε_{it} is the random error term.

The theoretical parameter β_j captures the heterogeneous promoting effect of information infrastructure on factor productivity across the primary, secondary, and tertiary industries ($j = 1, 2, 3$). In the empirical analysis, this parameter is operationalized by the core explanatory variables—the logarithm of mobile communication base stations ($\ln Station$) and broadband access ports ($\ln Broadband$). These two indicators directly measure the physical deployment scale of mobile and fixed information infrastructure, whose regression coefficients reflect the actual marginal impact of information infrastructure on industrial factor productivity in the empirical setting.

The econometric estimations in this study, including fixed-effects regression, robustness tests, and endogeneity tests were all conducted using Stata 17.0.

3.2. Variables

First, the number of mobile communication base stations is used as the measurement indicator for mobile information infrastructure capacity, and it serves as a core independent variable ($Station_{it}$). A mobile communication base station is a docking device for mobile terminals to access the Internet, a basic unit for achieving wireless information coverage, and a key indicator for measuring the development level of information infrastruc-

ture. The number of mobile communication base stations as the proxy for mobile information infrastructure. This aggregate measure inherently includes 5G base stations, along with 3G and 4G base stations built in previous years.

Second, the number of broadband accesses is adopted as the measurement indicator for fixed information infrastructure capacity, and it also functions as a core independent variable ($Broadband_{it}$). Broadband access is a method for realizing wired Internet access, thereby enabling broadband connection to households [39]. The number of users of fixed communication units and residents is reflected to a certain extent by the number of broadband access ports, which is an important indicator for measuring the coverage level of fixed communication information [40]. Mobile communication base stations and broadband access ports are standard proxies for information infrastructure in the literature, as they directly measure the physical deployment of network facilities.

Finally, to alleviate endogeneity bias arising from omitted variables, this study selected other factors affecting regional industrial structure upgrading as control variables, with reference to existing research outcomes. The status of economic development ($\ln Pgd_{it}$) is characterized by the logarithm of per capita GDP. The level of urbanization (Urb_{it}) is measured by the proportion of the urban population in the total population of each province. The labor growth rate ($Grlabor_{it}$) is measured by the growth rate of the population aged 15–64 (of working age) [41]. The level of human capital (Edu_{it}) is measured by proportion of the population with senior high school education or above in the population aged 6 years and over in each region. The intensity of foreign trade ($Trade_{it}$) is measured by the ratio of the total import and export value of operating units to GDP.

3.3. Data Sources

The data used in this study were gathered from various sources. Data on mobile communication base stations and broadband access ports were extracted from the China Telecommunications Statistics Yearbook Report and Annual Reports of Chinese telecommunications operators, covering the period 2009–2022. This datasets include mobile communications infrastructure, measured by the count of mobile communications base stations—encompassing 3G (e.g., WCDMA), 4G (e.g., LTE), and 5G mobile network stations. It also comprises fixed communication infrastructure, quantified as the number of broadband access ports. For individual scattered missing values in the panel data, linear interpolation was adopted to supplement the data, ensuring the continuity and comparability of time-series indicators.

Data on GDP, urban population, and import and export value were extracted from the China Statistical Yearbook. This yearbook features various GDP series. In the present study, a metric is adopted where GDP levels are built using multiple PPP benchmark years, thereby adjusting for price shifts across these benchmarks. Information on the labor force was sourced from the China Labor Statistical Yearbook, with the labor force gauged by the population aged 15 to 64 years. Table 1 presents the fundamental features of the variables:

Table 1. Descriptive Statistics of Variables.

Variables	Variable Symbols	Mean	Standard Deviation	Min.	Max.
Industrial structure deviation degree	TE	1.834	0.694	0.820	4.546
Theil Index	TL	0.215	0.130	0.017	0.662
The level of industrial structure upgrading	TG	1.200	0.669	0.500	5.169
The number of mobile communication base stations	$\ln Station$	11.520	0.944	8.433	13.540
The number of broadband accesses	$\ln Broadband$	7.037	1.083	2.879	9.052
The logarithm of per capita GDP	$\ln Pgd$	10.730	0.463	9.464	12.010
The level of urbanization	Urb	0.566	0.134	0.222	0.942
The labor growth rate	$Grlabor$	−0.009	0.026	−0.074	0.138

The level of human capital	<i>Edugao</i>	0.162	0.037	0.040	0.235
The intensity of foreign trade	<i>Trade</i>	0.260	0.274	0.011	1.324

4. Results

4.1. Basic Regression Results

Regression results were calculated using Equations (32) and (33), and they are presented in Table 2. In Columns 1 and 2 of Table 2, the dependent variable for the regression results is the industrial structure deviation degree. The core independent variables are the number of mobile communication base stations and the number of broadband access ports, with regression coefficients of -0.166 and -0.186 , respectively—both significant at the 1% statistical level.

For Columns 3 and 4, the dependent variable is the Theil Index. The regression coefficient of the core independent variable (number of mobile communication base stations) is -0.019 , significant at the 5% statistical level; the regression coefficient of the other core independent variable (number of broadband access ports) is -0.023 , significant at the 1% statistical level.

In Columns 5 and 6, the dependent variable is industrial structure upgrading. The regression coefficient of the number of mobile communication base stations (a core independent variable) is -0.190 , significant at the 1% statistical level; the regression coefficient of the number of broadband access ports (the other core independent variable) is -0.202 , also significant at the 1% statistical level.

Table 2. Basic model: effect of information infrastructure on industrial structure.

Variables	<i>TE</i> (1)	<i>TE</i> (2)	<i>TL</i> (3)	<i>TL</i> (4)	<i>TG</i> (5)	<i>TG</i> (6)
$\ln \text{Station}_{it}$	-0.166^{***} (0.042)		-0.0193^{**} (0.008)		-0.190^{***} (0.044)	
$\ln \text{Broadband}_{it}$		-0.186^{***} (0.035)		-0.023^{***} (0.006)		-0.202^{***} (0.037)
$\ln \text{Pgdp}$	-0.634^{***} (0.133)	-0.623^{***} (0.129)	-0.102^{***} (0.024)	-0.100^{***} (0.023)	0.583^{***} (0.140)	0.586^{***} (0.136)
Urb	-0.946^{**} (0.480)	-0.839^{*} (0.453)	-0.256^{***} (0.086)	-0.247^{***} (0.082)	1.913^{***} (0.507)	2.074^{***} (0.479)
Grlabor	0.552 (1.528)	-0.192 (1.508)	0.001 (0.086)	-0.101 (0.274)	0.069 (1.613)	-0.625 (1.596)
Edugao	-1.148 (1.214)	-0.477 (1.200)	0.179 (0.219)	0.272 (0.218)	-2.787^{**} (1.282)	-2.168^{*} (1.269)
Trade	-0.348^{**} (0.157)	-0.302^{*} (0.154)	-0.110^{***} (0.028)	-0.104^{***} (0.028)	-0.470^{***} (0.166)	-0.429^{***} (0.163)
Constant	11.31^{***} (1.246)	10.40^{***} (1.217)	1.673^{***} (0.224)	1.565^{***} (0.221)	-3.381^{**} (1.315)	-4.398^{***} (1.287)
Observations	372	372	372	372	372	372
Number of years	13	13	13	13	13	13
R-squared	0.532	0.549	0.551	0.560	0.286	0.310

Note: Variables with * indicate significance at the 10% level, ** at the 5% level, and *** at the 1% level; standard errors are in parentheses.

An analysis of the above calculation results indicates that information infrastructure construction can promote industrial structure optimization. Whether considering the information capacity of mobile information network infrastructure is mainly measured by the number of mobile communication base stations, or that of fixed information network infrastructure by the number of broadband access ports; and whether the dependent variable is the industrial structure deviation degree (*TE*) or the Theil Index (*TL*), the regression coefficients of information infrastructure are all negative. This suggests that information infrastructure construction can reduce the irrationality of the industrial structure.

The economic explanation for this is as follows: With the improvement of information infrastructure, the information transmission rate increases, the information carrying bandwidth expands, and the penetration into all aspects of production and life rises. This drives the interaction of information, technology, capital, and talent flows across sectors, promoting the cross-industry flow of production factors and thus facilitating more sustainable industrial structure optimization.

An additional analysis of the above calculation results reveals that while information infrastructure can promote industrial structure optimization, it does not necessarily facilitate industrial structure upgrading. When the dependent variable is the output ratio of the tertiary industry to the secondary industry, the regression coefficients of mobile communication and fixed communication are both significantly negative. This indicates that the impact of information infrastructure on industrial structure upgrading is related to the proportion of information infrastructure investment in total economic and social output value, as well as the industrial composition of consumption and investment. The improvement of information infrastructure alone cannot play a decisive role in driving industrial structure upgrading. The economic explanation for this phenomenon is as follows: Knowledge accumulation and technological progress are processes requiring long-term accumulation. China has achieved relatively high technological levels in low-end industries, but its technological capabilities in medium-to-high-end industries remain relatively weak. Although the application of communication technology can promote the transformation of low-end industrial chains to high-end ones, this transition demands a prolonged period.

Further economic explanations are provided for the finding that information infrastructure exerts a significant negative impact on industrial structure upgrading. First, regarding the sequential relationship between structural optimization and upgrading, industrial structure transformation follows a logical progression of “rationalization first, then upgrading”. Information infrastructure in China, particularly during the study period, has primarily played a role in promoting structural rationalization. It enhances information transmission efficiency and reduces information asymmetry, thereby facilitating cross-sector free flow of production factors, mitigating resource misallocation, and addressing core structural irrationalities such as output-employment structure mismatches. However, industrial structure upgrading, which involves qualitative leaps, such as shifting from labor-intensive to technology-intensive sectors and moving up the global value chain, relies on long-term accumulation of technological innovation, human capital, and high-value-added industrial agglomeration. At the current stage, the role of information infrastructure is still concentrated in laying the foundation for factor mobility, and it has not yet formed sufficient synergy with high-tech industries to drive the qualitative transformation of the industrial structure, resulting in a negative regression coefficient. Second, considering transition dynamics, the transformation of industrial structure is a long-term, path-dependent process. Before the widespread deployment of 4G/5G and the implementation of the “Broadband China” strategy, information infrastructure met basic information transmission needs, with limited capacity to support technological innovation and industrial transformation. Even in the 2014–2022 period, although infrastructure capabilities improved significantly, the time lag between digital infrastructure investment and industrial upgrading effects, coupled with rigidities in the traditional industrial system (e.g., lock-in effects of low-end production capacity), has hindered the immediate realization of upgrading dividends. Third, the rapid expansion of information infrastructure has also led to short-term overcapacity in some low-value-added digital service sectors, which to a certain extent distorts the structural upgrading trend, further contributing to the negative empirical result. Fourth, industrial structure upgrading is a complex and multi-dimensional process, jointly shaped by economic complexity (ECI), technological

intensity (OECD classification), and workforce reskilling. Economic complexity reflects the diversity and sophistication of a regional industrial system. A higher ECI helps form a synergistic ecosystem dominated by technology and knowledge-intensive sectors, laying the foundation for industrial upgrading by expanding high-value-added economic activities. Technological intensity, a core indicator distinguishing high-tech, medium-high-tech, and low-tech sectors, directly drives upgrading through the agglomeration and spillover effects of high-tech industries. These sectors not only increase the proportion of high-value-added industries but also promote the technological transformation of traditional industries. Workforce reskilling eliminates the “skill mismatch” between labor supply and the needs of technology-intensive sectors, enabling effective absorption and application of advanced technologies, thus accelerating the shift from labor-intensive to technology-intensive industrial structures. These factors interact with information infrastructure, and their development level and coordination may further affect how efficiently information infrastructure drives industrial structure upgrading.

4.2. Regression Results of Regional Heterogeneity

In terms of economic development level, industrial structure, and openness degree exist between China’s eastern coastal areas and inland regions. Information infrastructure investment presents obvious regional differences. Thus, infrastructure development levels exert distinct impacts on the industrial structure. This is of great significance for exploring core dimensions of information infrastructure construction investment. It also provides a basis for bridging regional gaps, thereby enhancing the sustainability of regional development. In accordance with the classification standards of the National Bureau of Statistics of China, the 31 provinces in China are divided into three regions: Eastern, Central, and Western China. The Eastern Region comprises 11 provinces, the Central Region includes 8 provinces, and the Western Region consists of 12 provinces.

Table 3 presents the regression results for the eastern region. Columns 1 to 4 demonstrate the impacts of information infrastructure on industrial structure optimization. Specifically, when deviation degree (TE) is used as the dependent variable in Columns 1 and 2, the regression coefficient of mobile information infrastructure is -0.051 , statistically significant at the 5% level, while that of fixed information infrastructure is -0.053 , also significant at the 5% level. For Columns 3 and 4, where Theil Index (TL) acts as the dependent variable, the coefficients of the independent variables representing mobile information network infrastructure and fixed information network infrastructure are 0.028 and 0.025 , respectively, with both significant at the 1% level. Columns 5 to 6 examine the impact of information infrastructure on industrial structure upgrading; with the level of industrial structure upgrading (TE) as the dependent variable, the regression coefficients of mobile communication and fixed communication are -0.322 and -0.333 , respectively, and both are highly significant at the 1% level. These results indicate that the development of information infrastructure in the eastern region facilitates industrial structure optimization but exerts no positive effect on industrial structure upgrading. This outcome stems from the relatively mature industrial structure of the eastern region: information infrastructure primarily enhances resource allocation efficiency within the existing industrial system, thus boosting structural optimization. In contrast, industrial structure upgrading depends more on technological innovation, industrial transformation and high-end element agglomeration, and the current development level of information infrastructure in this region has not yet formed an effective driving force for these core upgrading links, leading to the lack of a positive impact.

Table 3. Eastern Region of China: effect of information infrastructure on industrial structure.

Variables	Eastern Region of China					
	TE	TE	TL	TL	TG	TG
	(1)	(2)	(3)	(4)	(5)	(6)
ln Station _{it}	−0.051 ** (0.025)		0.028 *** (0.004)		−0.322 *** (0.109)	
ln Broadband _{it}		−0.053 ** (0.021)		0.025 *** (0.003)		−0.333 *** (0.091)
ln Pgdp	−0.537 *** (0.067)	−0.536 *** (0.064)	−0.134 *** (0.010)	−0.128 *** (0.010)	1.455 *** (0.286)	1.456 *** (0.269)
Urb	0.041 (0.239)	0.066 (0.222)	0.0716 * (0.038)	0.037 (0.035)	0.099 (1.013)	0.273 (0.930)
Grlabor	−1.828 ** (0.706)	−1.894 *** (0.701)	−0.311 *** (0.114)	−0.292 ** (0.113)	−3.52 (2.989)	−3.916 (2.937)
Edugao	1.273 (0.811)	1.201 (0.802)	0.185 (0.131)	0.186 (0.130)	11.69 *** (3.430)	11.28 *** (3.360)
Trade	−0.079 (0.069)	−0.064 (0.069)	−0.010 (0.011)	−0.013 (0.011)	−1.945 *** (0.296)	−1.858 *** (0.292)
Constant	7.539 *** (0.582)	7.313 *** (0.581)	1.159 *** (0.094)	1.268 *** (0.094)	−11.98 *** (2.463)	−13.38 *** (2.435)
Observations	132	132	132	132	132	132
Number of years	13	13	13	13	13	13
R-squared	0.701	0.707	0.808	0.812	0.568	0.584

Note: Variables with * indicate significance at the 10% level, ** at the 5% level, and *** at the 1% level; standard errors are in parentheses.

The regression results for the central region are presented in Table 4. Columns 1 and 2 take deviation degree (TE) as the dependent variable: the regression coefficient of mobile information infrastructure is −0.286, which is statistically significant at the 10% level, while the coefficient of fixed information infrastructure is insignificant. When the Theil Index (TL) serves as the dependent variable in Columns 3 and 4, neither the coefficient of mobile information infrastructure nor that of fixed information infrastructure is statistically significant. Columns 5 to 6 explore the impact of information infrastructure on industrial structure upgrading; with TG as the dependent variable, the regression coefficients of mobile information network infrastructure and fixed information infrastructure are 0.321 and 0.311, respectively, both highly significant at the 1% level.

The underlying economic explanation for the results is that the development of information infrastructure exerts no significant impact on industrial structure optimization but has a prominent positive effect on industrial structure upgrading in the central region. This phenomenon may be attributed to the stage-specific characteristics of industrial development in the central region: the region is in a critical period of industrial transformation, where information infrastructure mainly provides technical support and factor connection channels for the upgrading of traditional industries and the cultivation of emerging industries, thereby effectively promoting industrial structure upgrading. However, due to the unbalanced allocation of regional resources and the relatively fragmented industrial layout, the role of information infrastructure in optimizing the rationality of the existing industrial structure has not been fully exerted, resulting in insignificant regression results.

Table 4. Central Region of China: effect of information infrastructure on industrial structure.

Variables	Central Region of China					
	TE	TE	TL	TL	TG	TG
	(1)	(2)	(3)	(4)	(5)	(6)
ln Station _{it}	−0.286 * (0.165)		−0.057 (0.034)		0.321 *** (0.094)	

ln Broadband _{it}		0.157 (0.152)		0.020 (0.032)		0.311 *** (0.084)
ln Pgdp	0.885 *** (0.211)	0.694 *** (0.222)	0.146 *** (0.044)	0.114 ** (0.047)	−0.830 *** (0.120)	−0.887 *** (0.123)
Urb	0.692 (0.923)	2.421 *** (0.736)	−0.114 (0.195)	0.198 (0.156)	4.211 *** (0.526)	3.733 *** (0.409)
Grlabor	−3.597 (2.420)	−3.218 (2.482)	−0.210 (0.512)	−0.162 (0.526)	−0.625 (1.380)	0.154 (1.381)
Edugao	3.637 *** (1.335)	3.750 *** (1.414)	1.088 *** (0.282)	1.077 *** (0.300)	−0.786 (0.761)	0.580 (0.787)
Trade	−0.319 (1.009)	0.656 (0.968)	−0.181 (0.213)	−0.004 (0.205)	−2.799 *** (0.575)	−3.073 *** (0.539)
Constant	−5.219 * (2.739)	−8.670 *** (2.268)	−0.761 (0.579)	−1.410 *** (0.481)	4.119 ** (1.562)	6.261 *** (1.261)
Observations	96	96	96	96	96	96
Number of years	13	13	13	13	13	13
R-squared	0.406	0.390	0.370	0.350	0.717	0.723

Note: Variables with * indicate significance at the 10% level, ** at the 5% level, and *** at the 1% level; standard errors are in parentheses.

The regression results for the western region are displayed in Table 5. Across Columns 1 to 4, neither the regression coefficient of mobile information infrastructure nor that of fixed information infrastructure is statistically significant. As for Columns 5 to 6, the coefficient of mobile information infrastructure remains insignificant, while the coefficient of fixed information infrastructure is −0.038, which is statistically significant at the 10% level. The underlying economic explanations for the widespread insignificant coefficients may be as follows: the western region has a relatively backward level of information infrastructure construction, with insufficient coverage and low quality, leading to weak transmission efficiency of its role in industrial development and thus failing to form a statistically significant impact.

Table 5. Western Region of China: effect of information infrastructure on industrial structure.

Variables	Western Region of China					
	TE	TE	TL	TL	TG	TG
	(1)	(2)	(3)	(4)	(5)	(6)
ln Station _{it}	0.028 (0.068)		−0.002 (0.010)		−0.036 (0.022)	
ln Broadband _{it}		−0.024 (0.062)		−0.009 (0.009)		−0.038 * (0.020)
ln Pgdp	−1.214 *** (0.312)	−1.262 *** (0.313)	−0.171 *** (0.049)	−0.178 *** (0.049)	−0.248 ** (0.104)	−0.257 ** (0.104)
Urb	−0.934 (1.194)	−0.941 (1.193)	−0.213 (0.189)	−0.203 (0.189)	−0.829 ** (0.397)	−0.765 * (0.395)
Grlabor	1.185 (3.396)	0.481 (3.408)	−0.070 (0.539)	−0.168 (0.539)	−0.456 (1.129)	−0.563 (1.128)
Edugao	4.152 (2.775)	4.894 * (2.818)	1.447 *** (0.440)	1.558 *** (0.445)	−1.500 (0.923)	−1.341 (0.933)
Trade	−2.008 *** (0.758)	−1.836 ** (0.775)	−0.584 *** (0.120)	−0.555 *** (0.122)	0.593 ** (0.252)	0.648 ** (0.257)
Constant	14.970 *** (3.161)	15.810 *** (3.036)	2.127 *** (0.501)	2.204 *** (0.480)	4.527 *** (1.051)	4.404 *** (1.005)
Observations	144	144	144	144	144	144
Number of years	13	13	13	13	13	13
R-squared	0.318	0.318	0.362	0.367	0.503	0.507

Note: Variables with * indicate significance at the 10% level, ** at the 5% level, and *** at the 1% level; standard errors are in parentheses.

4.3. Regression Results of the Development Phases of Information Infrastructure

To verify the impact of information infrastructure development on optimization and upgrading of industrial structure, this study constructs period-specific dummy variables for 2009–2013 and 2014–2022. The 2009–2013 period corresponds to China’s 3G information infrastructure construction era, which improved voice and data transmission speeds to meet basic mobile internet needs. The 2014–2022 period saw the construction of 4G and 5G networks, delivering higher-speed data capabilities, significantly enhancing upload/download speeds, and facilitating the growth of mobile payments and short video applications. Meanwhile, China’s “Broadband China” strategy was launched in 2014, with broadband infrastructure supporting the development of high-tech industries such as the Internet of Things (IoT) and cloud computing.

The regression results for 2009–2013 are presented in Table 6. Columns 1 to 4 examine information infrastructure’s impact on industrial structure optimization. In Columns 1 and 2, with the deviation degree (TE) as the dependent variable, mobile information infrastructure has a regression coefficient of −0.152 significant at the 5% level, while fixed information infrastructure’s coefficient is −0.170 significant at the 1% level. Columns 3 and 4 use the Theil Index (TL) as the dependent variable: mobile information infrastructure’s coefficient is statistically insignificant, but fixed information infrastructure’s coefficient of −0.020 is significant at the 1% level. Columns 5 to 6 focus on industrial structure upgrading, with the level of industrial structure upgrading (TG) as the dependent variable. Mobile information infrastructure’s coefficient is −0.153 and fixed information infrastructure’s is −0.168, both significant at the 1% level.

Table 6. Effect of Information Infrastructure on Industrial Structure (2009–2013).

Variables	2009–2013					
	TE	TE	TL	TL	TG	TG
	(1)	(2)	(3)	(4)	(5)	(6)
ln Station _{it}	−0.152 ** (0.064)		−0.018 (0.011)		−0.153 *** (0.055)	
ln Broadband _{it}		−0.170 *** (0.053)		−0.020 ** (0.009)		−0.168 *** (0.045)
ln Pgdp	−1.412 *** (0.261)	−1.386 *** (0.254)	−0.205 *** (0.048)	−0.201 *** (0.047)	0.513 ** (0.224)	0.535 ** (0.217)
Urb	1.404 (0.888)	1.567 * (0.848)	0.104 (0.164)	0.122 (0.158)	1.279 * (0.762)	1.450 ** (0.725)
Grlabor	0.477 (2.108)	−0.289 (2.098)	−0.086 (0.390)	−0.183 (0.391)	3.321 * (1.809)	2.594 (1.794)
Edugao	−4.552 ** (1.915)	−4.057 ** (1.895)	−0.350 (0.354)	−0.287 (0.353)	−3.637 ** (1.644)	−3.168 * (1.620)
Trade	−0.175 (0.220)	−0.143 (0.217)	−0.092 ** (0.040)	−0.088 ** (0.040)	−0.328 * (0.189)	−0.298 (0.186)
Constant	18.320 *** (2.308)	17.310 *** (2.301)	2.603 *** (0.427)	2.480 *** (0.429)	−2.736 (1.982)	−3.735 * (1.968)
Observations	155	155	155	155	155	155
Number of years	5	5	5	5	5	5
R-squared	0.613	0.625	0.594	0.599	0.289	0.317

Note: Variables with * indicate significance at the 10% level, ** at the 5% level, and *** at the 1% level; standard errors are in parentheses.

The above results show information infrastructure promoted industrial structure optimization but not upgrading during 2009–2013. Economically, this reflects the stage-specific nature of 3G-era infrastructure, which improved basic information transmission efficiency to reduce cross-sector resource misallocation and boost rationalization. However,

the period's traditional sector-dominated industrial base and insufficient integration between information infrastructure and high-tech industries also prevented qualitative industrial upgrading.

The regression results for the 2014–2022 period are presented in Table 7. Columns 1 and 2 use the deviation degree (TE) as the dependent variable. The coefficient of mobile information infrastructure is −0.157 and is significant at the 1% level. The coefficient of fixed information infrastructure is −0.183 and is also significant at the 1% level. Columns 3 and 4 adopt the Theil Index (TL) as the dependent variable. The coefficient of mobile information infrastructure is −0.018 and is significant at the 10% level. The coefficient of fixed information infrastructure is −0.023 and is significant at the 1% level. Columns 5 and 6 use the level of industrial structure upgrading (TG) as the dependent variable. The coefficient of mobile information infrastructure is −0.218 and the coefficient of fixed information infrastructure is −0.225, both significant at the 1% level. These results show that the coefficients for both mobile and fixed information infrastructure are larger in magnitude and more significant than those in the 2009–2013 period.

Table 7. Effect of Information Infrastructure on Industrial Structure (2014–2022).

Variables	2014–2022					
	TE	TE	TL	TL	TG	TG
	(1)	(2)	(3)	(4)	(5)	(6)
ln Station _{it}	−0.157 *** (0.053)		−0.018 * (0.009)		−0.218 *** (0.068)	
ln Broadband _{it}		−0.183 *** (0.044)		−0.023 *** (0.008)		−0.225 *** (0.057)
ln Pgdp	−0.289 ** (0.145)	−0.283 ** (0.140)	−0.057 ** (0.026)	−0.055 ** (0.025)	0.695 *** (0.187)	0.686 *** (0.182)
Urb	−1.733 *** (0.550)	−1.715 *** (0.514)	−0.388 *** (0.099)	−0.393 *** (0.093)	2.067 *** (0.708)	2.199 *** (0.667)
Grlabor	3.587 (2.720)	2.337 (2.692)	0.412 (0.492)	0.230 (0.491)	−2.652 (3.498)	−3.878 (3.493)
Edugao	1.624 (1.502)	2.388 (1.479)	0.591 ** (0.272)	0.709 *** (0.270)	−1.249 (1.932)	−0.596 (1.919)
Trade	−0.584 *** (0.218)	−0.537 ** (0.214)	−0.137 *** (0.039)	−0.130 *** (0.039)	−0.695 ** (0.281)	−0.651 ** (0.277)
Constant	7.667 *** (1.441)	6.923 *** (1.384)	1.206 *** (0.260)	1.119 *** (0.252)	−4.507 ** (1.854)	−5.548 *** (1.796)
Observations	217	217	217	217	217	217
Number of years	9	9	9	9	9	9
R-squared	0.495	0.518	0.537	0.549	0.319	0.337

Note: Variables with * indicate significance at the 10% level, ** at the 5% level, and *** at the 1% level; standard errors are in parentheses.

The results indicates that information infrastructure exerted a stronger promoting effect on industrial structure optimization during 2014–2022. The economic explanation lies in the widespread deployment of 4G and 5G networks, which improved data transmission speeds and accelerated the diffusion of digital technologies into traditional industries. In addition, the implementation of China's "Broadband China" strategy in 2014 expanded infrastructure coverage and quality, strengthened integration with high-tech industries such as the Internet of Things and cloud computing, and thus enhanced the role of information infrastructure in driving industrial structure optimization.

4.4. Robustness Test

To verify the reliability of the model estimation results, a robustness test was conducted using the variable replacement method. The number of mobile communication and fixed communication users were adopted as independent variables to replace the

number of mobile communication base stations and broadband access ports mentioned earlier, with the regression results presented in Table 8. Additionally, the business revenues of mobile communication and fixed communication were used as independent variables to substitute for the number of mobile communication base stations and broadband access ports respectively, and the corresponding regression results are shown in Table 9. The regression analysis results indicate that different indicators reflecting communication and information capabilities still yield significant and similar outcomes. Specifically, both mobile communication information and fixed communication information play a facilitating role in industrial structure optimization measured by the industrial structure deviation degree and Theil Index, but they fail to enhance the industrial structure upgrading level.

Table 8. Robustness test—alternative variables: the number of mobile communication and fixed communication users.

Variables	TE (1)	TE (2)	TL (3)	TL (4)	TG (5)	TG (6)
ln mobile users _{it}	−0.143 *** (0.039)		−0.014 ** (0.007)		−0.191 *** (0.041)	
ln broadband users _{it}		−0.180 *** (0.033)		−0.021 *** (0.006)		−0.224 *** (0.035)
ln Pgdp	−0.677 *** (0.131)	−0.618 *** (0.129)	−0.109 *** (0.024)	−0.100 *** (0.024)	0.550 *** (0.137)	0.616 *** (0.134)
Urb	−0.762 (0.469)	−0.962 ** (0.459)	−0.227 *** (0.085)	−0.258 *** (0.084)	2.034 *** (0.491)	1.828 *** (0.478)
Grlabor	0.431 (1.551)	−0.016 (1.499)	0.015 (0.279)	−0.066 (0.273)	−0.408 (1.623)	−0.804 (1.561)
Edugao	−1.047 (1.238)	−0.173 (1.220)	0.164 (0.223)	0.294 (0.222)	−2.349 * (1.296)	−1.412 * (1.271)
Trade	−0.348 ** (0.157)	−0.303 * (0.154)	−0.111 *** (0.029)	−0.105 *** (0.028)	−0.442 *** (0.165)	−0.403 *** (0.160)
Constant	10.91 *** (1.243)	10.21 *** (1.219)	1.624 *** (0.224)	1.545 *** (0.222)	−3.816 ** (1.301)	−4.697 *** (1.269)
Observations	372	372	372	372	372	372
R-squared	0.529	0.549	0.548	0.558	0.293	0.331

Note: Variables with * indicate significance at the 10% level, ** at the 5% level, and *** at the 1% level; standard errors are in parentheses.

Table 9. Robustness test—alternative variables: telecommunications business revenue.

Variables	TE (1)	TE (2)	TL (3)	TL (4)	TG (5)	TG (6)
ln mobile service income _{it}	−0.156 *** (0.043)		−0.018 ** (0.008)		−0.147 *** (0.046)	
ln broadband service income _{it}		−0.167 *** (0.043)		−0.022 *** (0.008)		−0.083 *** (0.046)
ln Pgdp	−0.614 *** (0.136)	−0.583 *** (0.137)	−0.100 *** (0.024)	−0.094 *** (0.025)	0.575 *** (0.144)	0.522 *** (0.148)
Urb	−0.880 * (0.481)	−0.647 (0.460)	−0.249 *** (0.086)	−0.226 *** (0.083)	2.114 *** (0.512)	2.496 *** (0.496)
Grlabor	0.625 (1.540)	0.360 (1.545)	0.007 (0.276)	−0.044 (0.277)	0.408 (1.639)	1.052 (1.667)
Edugao	−1.154 (1.232)	−1.398 (1.220)	0.181 (0.221)	0.167 (0.215)	−3.123 *** (1.311)	−3.950 *** (1.291)
Trade	−0.320 ** (0.160)	−0.269 * (0.162)	−0.107 *** (0.029)	−0.098 *** (0.029)	−0.468 *** (0.170)	−0.505 *** (0.175)
Constant	11.42 *** (1.257)	10.97 *** (1.240)	1.688 *** (0.226)	1.636 *** (0.223)	−3.380 ** (1.337)	−3.898 *** (1.338)
Observations	372	372	372	372	372	372
R-squared	0.528	0.531	0.549	0.553	0.268	0.252

Note: Variables with * indicate significance at the 10% level, ** at the 5% level, and *** at the 1% level; standard errors are in parentheses.

A potential bidirectional causality may exist between information infrastructure and industrial structure changes [42]. To address this endogeneity concern, the instrumental variable (IV) approach is employed for endogeneity testing [43]. Following the methodology for endogeneity tests, the telecom operators' market share is selected as the instrumental variable for the number of mobile communication base stations and the number of broadband accesses respectively [44,45], with the regression results reported in Table 10. Telecom operators' market share in China is mainly determined by historical licensing policies, regional infrastructure layout plans, and early-stage network coverage investments—factors that are exogenous to the short-term optimization and upgrading of local industrial structures. Specifically, the approval of telecom operation licenses and the planning of network construction are dominated by national and provincial regulatory authorities, with little direct correlation to the dynamic changes in regional industrial structure. This ensures that the IV does not affect the dependent variable through unobserved confounding factors, satisfying the exclusion restriction. From the regression outputs in Columns 1, 3, and 5 of Table 10, it can be observed that the instrumental variable is strongly correlated with the independent variable the number of mobile communication base stations, and the null hypothesis of “weak instrumental variables” is rejected. Thus, the telecom operator market share is a valid instrumental variable for the number of mobile communication base stations. For the number of broadband accesses, the p-value of the instrumental variable is 0.000, which is statistically significant at the 1% level, indicating a strong correlation between the instrumental variable and this independent variable. Additionally, the first-stage F-statistic is 30.87, which exceeds the critical value of 10, leading to the rejection of the null hypothesis of “weak instrumental variables”. Therefore, the telecom operator market share is also an appropriate instrumental variable for the number of broadband accesses.

Table 10. Endogeneity test: instrumental variable—telecom operator market share.

Variables	<i>TE</i> (1)	<i>TE</i> (2)	<i>TL</i> (3)	<i>TL</i> (4)	<i>TG</i> (5)	<i>TG</i> (6)
ln Station _{it}	−0.677 *** (0.321)		−0.084 ** (0.053)		−0.377 *** (0.288)	
ln Broadband _{it}		−0.436 ** (0.181)		−0.054 *** (0.032)		−0.243 *** (0.178)
ln Pgdp	−0.223 (0.301)	−0.430 ** (0.195)	−0.050 (0.050)	−0.076 ** (0.034)	0.733 *** (0.270)	0.618 *** (0.192)
Urb	−3.005 ** (1.401)	−1.588 ** (0.721)	−0.515 ** (0.231)	−0.340 *** (0.126)	1.161 (1.258)	1.950 *** (0.710)
Grlabor	−4.570 (3.671)	−3.410 (2.801)	−0.644 (0.605)	−0.500 (0.490)	−1.804 (3.296)	−1.157 (2.756)
Edugao	3.784 (3.389)	2.562 (2.512)	0.800 (0.559)	0.649 (0.439)	−0.984 (3.043)	−1.665 (2.472)
Trade	0.006 (0.290)	−0.088 (0.225)	−0.066 (0.048)	−0.077 ** (0.039)	−0.372 (0.260)	−0.394 * (0.221)
Constant	12.95 *** (1.818)	9.899 *** (1.358)	1.880 *** (0.300)	1.503 *** (0.237)	−2.778 * (1.632)	−4.481 *** (1.336)
Instrumental variable p-value	0.004	0.000	0.004	0.000	0.004	0.000
First-stage F-statistic	21.4	30.87	21.4	30.87	21.4	30.87
Observations	372	372	372	372	372	372

Note: Variables with * indicate significance at the 10% level, ** at the 5% level, and *** at the 1% level; standard errors are in parentheses.

5. Conclusions and Discussion

This study explores the impact mechanism of information infrastructure on industrial structure changes through both theoretical deduction and empirical testing. It concludes that information infrastructure serves as a critical pathway to sustain high-quality industrial transformation.

By constructing and solving a simplified multi-sector general equilibrium model, this study reveals the impact mechanism of information infrastructure on the industrial structure at the theoretical level. Theoretical analysis results indicate three key factors significantly impact industrial structure optimization: information infrastructure's heterogeneous influence on factor productivity across industrial sectors, its investment volume, and the capital factor output elasticity of various sectors. Additionally, the proportion of information infrastructure investment in total economic and social output, along with differences in industrial composition between consumption and investment, constrain industrial structure upgrading.

On this basis, this study employs provincial panel data from 2009 to 2022 and adopts a fixed effects model to conduct benchmark regression analysis of various factors. The robustness test and endogeneity test are passed, further verifying the theoretical conclusions at the empirical level. The results indicate the following: First, in terms of industrial structure optimization, the development of both mobile information infrastructure and fixed broadband infrastructure can promote industrial structure optimization, exerting positive effects on the full flow of production factors among various industrial sectors and the efficient allocation of resources. Moreover, the impact of fixed information infrastructure on industrial structure optimization is slightly greater than that of mobile information infrastructure. Second, regarding industrial structure upgrading, neither mobile information infrastructure nor fixed information infrastructure has a significant impact on industrial structure upgrading. This suggests that current construction and investment in information infrastructure need further strengthening to support the transition toward a sustainable, high-value-added, and high-tech industrial structure.

Synthesizing the above conclusions, it can be seen that the construction of information infrastructure is an important means to promote the industrial structure optimization in China, exerting positive effects on the flow of production factors among various sectors and the efficient allocation of resources. However, its impact on industrial structure upgrading is not significant. Therefore, it is necessary to strengthen the key supporting role of information infrastructure, vigorously promote the in-depth integration of information infrastructure with industries, and continuously expand application scenarios. Efforts should be made to enhance the new empowerment of information infrastructure to traditional and emerging industries, enabling mobile communication technologies and fixed communication information technologies to be more rapidly integrated into various industries. For regions with a mature industrial base, the focus should be on leveraging mobile and fixed information infrastructure to facilitate the integration of emerging technologies with high-end manufacturing and producer services. For regions with relatively backward infrastructure, priority should be given to basic fixed broadband and advanced mobile information infrastructure coverage in key industrial zones, with a focus on supporting the transition of resource-based industries to high-value-added segments, such as deep processing of mineral resources and green energy technology development.

Additionally, the supporting role of communication technology application industries should be fully exerted to promote extensive industry collaboration and connection in relevant vertical industries, construct a cross-industry collaborative communication technology application ecosystem, and comprehensively improve the ability of information infrastructure to empower industrial transformation and upgrading.

This study also has two limitations: First, the multi-sector General Equilibrium model has inherent limitations tied to its core assumptions. These assumptions include perfect competition, no transaction costs, perfect factor mobility, and the absence of household savings. Such settings deviate from real economic conditions. Specifically, this study assumes perfect inter-sectoral capital mobility. This assumption is inconsistent with the existing segmentation in China's factor markets. As a result, the model may overestimate the efficiency of cross-industry capital allocation. Second, there may be complex influencing factors between information infrastructure construction and industrial structure changes. In addition to the variables considered in this study, there are other factors that exert important impacts on innovative development and industrial structure, such as the level of marketization, government intervention, and even social and humanistic factors like cultural differences. Future research should explore these factors more comprehensively to provide a stronger foundation for sustainable industrial development.

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References

1. Wan, J.; Xie, Q.; Fan, X. The impact of transportation and information infrastructure on urban productivity: Evidence from 256 cities in China. *Struct. Change Econ. Dyn.* **2024**, *68*, 384–392.
2. Hulten, C.R.; Bennathan, E.; Srinivasan, S. Infrastructure, externalities and economic development: A study of the Indian manufacturing industry. *World Bank Econ. Rev.* **2006**, *20*, 291–308.
3. Li, Y.; Ma, X.; Liu, Y.; Zhong, F. Can China's New Infrastructure Promote Urban–Rural Integrated Development? Evidence from 31 Chinese Provinces. *Buildings* **2024**, *14*, 3978. <https://doi.org/10.3390/buildings14123978>.
4. Gao, Y.; Chen, N. How Information Infrastructure Construction Drives Rural Inclusive Green Growth in China: The Mediating Role of Labor Mobility. *Sustainability* **2025**, *17*, 10500. <https://doi.org/10.3390/su172310500>.
5. David, O.O. Nexus between telecommunications infrastructures, economic growth and development in Africa: Panel vector autoregression (P-VAR) analysis. *Telecommun. Policy* **2019**, *43*, 101–116.
6. Wu, W.; Ji, Z.; Liang, H. The Impact of New infrastructure Construction on Optimization and Upgrading of Industrial Structure. *Buildings* **2023**, *13*, 2580. <https://doi.org/10.3390/buildings13102580>.

7. D'Amico, E.; Belitski, M.; Braga, A.; Savoie, R. Enhancing knowledge spillover of innovation through artificial intelligence: An empirical investigation. *J. Technol. Transf.* **2025**, 1–29. <https://doi.org/10.1007/s10961-025-10217-7>.
8. Gu, T.; Zhang, P.; Zhang, X. Spatio-temporal Evolution Characteristics and Driving Mechanism of the New Infrastructure Construction Development Potential in China. *Chin. Geogr. Sci.* **2021**, 31, 646–658.
9. Thompson, H.G.; Garbacz, C. Economic impacts of mobile versus fixed broadband. *Telecommun. Policy* **2011**, 35, 999–1009.
10. Wei, B.; Zhao, C.; Cai, W.; Chen, B.; Lu, Y. The entrepreneurial effect of digital infrastructure development: Micro evidence from China. *Inf. Technol. Dev.* **2025**, 31, 604–634.
11. Meng, J.; Zhu, Y.; Han, Y. Can 'new' infrastructure become an engine of growth for the Chinese economy? *J. Chin. Econ. Bus. Stud.* **2022**, 21, 341–362.
12. Cheong, T.S.; Wu, Y. The Impacts of Structural Transformation and Industrial Upgrading on Regional Inequality in China. *China Econ. Rev.* **2014**, 31, 339–350.
13. Jensen, R. The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector. *Q. J. Econ.* **2007**, 122, 879–924.
14. Vu, K.M. ICT as a source of economic growth in the information age: Empirical evidence from the 1996–2005 period. *Telecommun. Policy* **2011**, 35, 357–372.
15. Yu, H.J.; Sun, H.Y.; Chen, M.B. The Evolution of Industrial Structure for Marine Economic Growth in China: An Empirical Study on the Effects of Rationalization and Optimization. *J. Coast. Res.* **2021**, 37, 1042–1052.
16. Zhou, Q.; Li, Z. The Impact of Industrial Structure Upgrades on the Urban–Rural Income Gap: Evidence from China's Provincial Panel Data. *Growth Change* **2021**, 52, 1761–1782.
17. Han, D.; Zhu, Y.; Diao, Y.; Liu, M.; Shi, Z. The Impact of New Digital Infrastructure Construction on Substantive Green Innovation. *Manag. Decis. Econ.* **2024**, 45, 4072–4083.
18. Luo, K.; Lee, C.C.; Zeng, M.L.; Hu, W.H. How does the development of digital economy in central cities promote the coordinated development of regions? Evidence from 19 urban agglomerations in China. *Technol. Soc.* **2024**, 78, 102674. <https://doi.org/10.1016/j.techsoc.2024.102674>.
19. Forman, C.; Goldfarb, A.; Greenstein, S. The internet and local wages: A puzzle. *Am. Econ. Rev.* **2012**, 102, 556–575.
20. Weeks, K.; Safa, M.; Zamiran, S. The Productivity–Safety Nexus: The Impact of Human Factors on Operational Efficiency in Construction Projects. *Buildings* **2026**, 16, 87. <https://doi.org/10.3390/buildings16010087>.
21. Deng, Y.; Li, K.; Hu, W.; Zhang, L.; Gao, Y. Formation of human-machine trust in smart construction: Influencing factors and mechanisms. *Buildings* **2025**, 15, 2332.
22. Girmay, G.H. Information telecommunications technology and economic growth in Sub-Saharan Africa: A panel data approach. *Telecommun. Policy* **2019**, 43, 88–99.
23. Zou, W.; Pan, M. Does the Construction of Network Infrastructure Reduce Environmental Pollution? Evidence from a Quasi-Natural Experiment in “Broadband China”. *Environ. Sci. Pollut. Res.* **2022**, 30, 242–258.
24. Koutroumpis, P. The economic impact of broadband on growth: A simultaneous approach. *Telecommun. Policy* **2009**, 33, 471–485.
25. Roller, L.; Waverman, L. Telecommunications infrastructure and economic development: A simultaneous approach. *Am. Econ. Rev.* **2001**, 91, 909–923.
26. Shi, X.; Liu, Y.; Zhang, D.; Li, R.; Qiao, Y.; Opoku, A.; Cui, C. Influencing Factors of Human Errors in Metro Construction Based on Structural Equation Modeling (SEM). *Buildings* **2022**, 12, 1498. <https://doi.org/10.3390/buildings12101498>.
27. Harald, E.; Peter, G.; Jonathan, H.; Xuan, L.; Edward, L. How important are mobile broadband networks for the global economic development? *Inf. Econ. Policy* **2018**, 45, 16–29.
28. Gereffi, G. International Trade and Industrial Upgrading in the Apparel Commodity Chain. *J. Int. Econ.* **1999**, 48, 37–70.
29. Wang, S.; Sun, X.; Cong, X.; Gao, Y. Input Efficiency Measurement and Improvement Strategies of New Infrastructure under High-Quality Development. *System* **2023**, 11, 243.
30. Yang, Y.; Su, F.; Zhang, X. Network infrastructure construction and inter-counties collaborative innovation in China with center-periphery effect. *Habitat Int.* **2025**, 163, 103483.
31. Pradhan, R.P.; Arvin, M.B.; Bahmani, S.; Norman, N.R. Telecommunications Infrastructure and Economic Growth: Comparative Policy Analysis for the G-20 Developed and Developing Countries. *J. Comp. Policy Anal. Res. Pract.* **2014**, 16, 401–423.
32. Zhang, P.; Wang, J.; Li, M.; Fan, X. Research on the mechanism of information infrastructure affecting industrial structure upgrading. *Sci. Rep.* **2022**, 12, 19962.
33. Zhang, E.; Fan, L. Study on the “Quality Effect” of New Infrastructure Construction. *Front. Bus. Econ. Manag.* **2022**, 9, 82–89.

34. Wang, F.; Wu, M.; Du, X. Does Industrial Upgrading Improve Eco-Efficiency? Evidence from China's Industrial Sector. *Energy Econ.* **2023**, *124*, 106774.
35. El-Gohary, K.M.; Aziz, R.F. Factors influencing construction labor productivity in Egypt. *J. Manag. Eng.* **2014**, *30*, 1–9.
36. Hu, L.; Yuan, W.; Jiang, J.; Ma, T.; Zhu, S. Asymmetric Effects of Industrial Structure Rationalization on Carbon Emissions: Evidence from Thirty Chinese Provinces. *J. Clean. Prod.* **2023**, *428*, 139347.
37. Guo, Z.Q.; Zhang, X.P.; Ding, Y. A Forecasting Analysis on China's Energy Use and Carbon Emissions Based on A Dynamic Computable General Equilibrium Model. *Emerg. Mark. Financ. Trade* **2021**, *3*, 727–739.
38. Wooldridge, J.M. *Econometric Analysis of Cross Section and Panel Data*; Massachusetts Institute of Technology Press: Cambridge, MA, USA, 2002; pp. 67–72.
39. Johnson, L. Who builds Shanghai's fiber-optic network? Thinking urban infrastructure through migrant construction labor. *Environ. Plan. A Econ. Space* **2023**, *55*, 795–809.
40. Rahman, H.U.; Ali, G.; Zaman, U. Role of ICT Investment and Diffusion in the Economic Growth: A Threshold Approach for the Empirical Evidence from Pakistan. *Int. J. Financ. Stud.* **2021**, *9*, 14–25.
41. Maestas, N.; Kathleen, J.M.; David, P. The Effect of Population Aging on Economic Growth, the Labor Force and Productivity. *Am. Econ. J.-Macroecon* **2023**, *15*, 306–332.
42. Ding, L.; Haynes, K.E.; Liu, Y. Telecommunications infrastructure and regional income convergence in China: Panel data approaches. *Reg. Sci.* **2008**, *42*, 843–861.
43. Staiger, D.; Stock, J.H. Instrumental variables regression with weak instruments. *Econometrica* **1997**, *65*, 557–586.
44. Shao, X.; Ma, X.; Fan, F. Network infrastructure, digital technology innovation and enterprise performance: Evidence from Chinese listed companies. *Appl. Econ.* **2025**, 1–15. <https://doi.org/10.1080/00036846.2025.2487715>.
45. Li, M.; Xu, Y. The Impact of Computing Infrastructure Construction on Innovation in Manufacturing Enterprises: Evidence from a Quasi-Natural Experiment Based on the Establishment of China's National Supercomputing Centers. *Sustainability* **2025**, *17*, 8858. <https://doi.org/10.3390/su17198858>.

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