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The Impact of Digital Infrastructure on China's Green Total Factor Productivity: A Quasi-Natural Experiment Based on the “Broadband China” Pilot Policy

Xudong Hu [a], Sen Wang [a, *], Jinpei Cao [a], Pu Hao [a]

[a] *School of Economics and Management, Xinjiang University, Urumqi, China*

ABSTRACT

The digital economy has emerged as a crucial driving force for promoting China’s green transformation in the new development phase. The “Broadband China” initiative, a key policy aimed at fostering the digital economy, plays a significant role in enhancing green total factor productivity (GTFP). This paper, based on the "Broadband China" policy and panel data from 283 prefecture-level cities from 2009 to 2022, constructs a theoretical model and employs a multi-period difference-in-differences (DID) method to systematically analyze the impact of digital infrastructure development on urban green total factor productivity (GTFP) and its underlying mechanisms. The findings reveal that the “Broadband China” policy has significantly improved GTFP in pilot cities, with stronger effects observed in economically developed regions and large- to medium-sized cities. Mechanism analysis indicates that technological innovation, industrial structure optimization, and energy conservation and emission reduction are the main pathways through which digital infrastructure promotes the improvement of green total factor productivity (GTFP). The regional heterogeneity analysis reveals that policy effects are more significant in eastern regions and large or medium-sized cities, whereas the effects are relatively weaker in central and western regions and smaller cities. Robustness checks further validate the reliability of the research conclusions. Additionally, this study reveals the critical role of digital infrastructure development in enhancing green total factor productivity and promoting high-quality economic development from both theoretical and empirical perspectives. It provides valuable insights for optimizing digital infrastructure investment strategies and formulating regional development policies.

KEYWORDS

Digital Infrastructure; Green Total Factor Productivity; Technological Innovation; Industrial Structure Upgrading; Energy Conservation and Emission Reduction; “Broadband China” Strategy

* Corresponding author: Sen Wang
E-mail address: 15903215735@163.com

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1. Introduction

As China progresses towards a high-quality development phase, enhancing Green Total Factor Productivity (GTFP) has become a central task for driving economic growth and achieving sustainable development (Fu, L., Zhang, S., & Guo, S., 2024). Under the traditional economic growth model, extensive development that heavily relies on resource consumption and environmental pollution has revealed its limitations, with resource and environmental constraints becoming increasingly evident (Feng, C., Huang, J. B., & Wang, M., 2018). Data indicates that China's global ranking in the Environmental Performance Index (EPI) remains low, highlighting the urgent need to shift towards innovation-driven growth, improve resource utilization efficiency, and achieve harmonious economic and environmental development (Yang, J., Li, L., Liang, Y., Wu, J., Wang, Z., Zhong, Q., & Liang, S., 2022).

Against this backdrop, new infrastructure development, particularly the digital infrastructure-driven digital transformation, has emerged as a critical tool for promoting green economic development. President Xi Jinping has repeatedly emphasized that accelerating the construction of new digital infrastructure is a vital strategic measure for seizing opportunities brought about by the new technological revolution and industrial transformation. Digital infrastructure can effectively optimize resource allocation, reduce information costs, and enhance GTFP (Lee, C. C., & Lee, C. C., 2022). As one of the core strategies for digital infrastructure development, the "Broadband China" policy has significantly enhanced network coverage and transmission efficiency on a large scale, providing critical support for China's economic and social transformation and advancing the achievement of sustainable development goals. The further development of digital infrastructure has substantially reduced information costs and resource waste, optimized resource allocation, and promoted the efficient use of resources. Moreover, the continuous improvement of digital infrastructure has driven green technological innovation, improved industrial structures, and made significant contributions to sustainable development.

Theoretically, the role of digital infrastructure in improving productivity has received widespread attention in academic research. However, existing studies have primarily focused on the effects of digital infrastructure on traditional Total Factor Productivity (TFP), with limited exploration of its combined economic and environmental effects on Green TFP. This paper contributes to the literature by analyzing the mechanisms through which digital infrastructure drives technological innovation, industrial structure upgrading, and energy conservation and emission reduction, thereby expanding the theoretical framework of digital infrastructure within the context of high-quality development.

From a practical perspective, China's "Broadband China" strategy has achieved significant success in recent years, facilitating economic green transformation and high-quality development. However, due to regional disparities in economic foundations and resource endowments, the policy's effects vary significantly across regions. In particular, its potential impact in small and medium-sized cities, as well as less-developed areas, has yet to be fully explored.

The implementation of the "Broadband China" strategy provides an excellent policy background and quasi-natural experimental setting for analyzing the economic effects of digital infrastructure. Since the advent of the information era, broadband network development has profoundly impacted Chinese residents' lives, firms' production processes, and broader socio-economic activities. Amid a shift in economic growth drivers, industries are increasingly adopting rational, efficient, sustainable, and green development principles. Advanced digital technologies play a foundational role in this process by unleashing new growth momentum and providing fresh impetus for improving GTFP and achieving economic growth in the short and long term.

Nevertheless, empirical research on the impact of digital infrastructure on urban GTFP remains limited, particularly studies based on quasi-natural experiments that enable causal inference. Therefore, this paper leverages the "Broadband China" pilot policy as a quasi-natural experimental treatment variable to investigate the effects of digital infrastructure development on urban GTFP. Urban GTFP refers to the efficiency of achieving economic growth while accounting for resource consumption and environmental pollution. This paper hypothesizes that digital infrastructure can influence urban GTFP levels and trends through pathways such as technological innovation, industrial structure optimization, and energy conservation and emission reduction. The primary objective of this study is to analyze the causal effects and underlying mechanisms of the "Broadband China" pilot policy on urban GTFP, thereby providing theoretical insights and empirical evidence for the formulation and refinement of relevant policies.

2. Literature Review

Digital infrastructure, as a core driving force of modern economic development, not only enhances production efficiency but also plays a crucial role in promoting the green economic transition. Early studies defined digital infrastructure as a shared platform for both technological and non-technological outcomes, emphasizing its universal support for economic activities (Hanseth, O., Monteiro, E., & Hatling, M., 1996; Färe, R., Grosskopf, S., Norris, M., et al., 1994). In recent years, the concept of digital infrastructure has expanded to include network development, platform management, and the cultivation of digital technology talent (Henfridsson, O., & Bygstad, B., 2013). International research indicates that digital infrastructure significantly reduces transaction costs and provides critical support for economic growth, particularly in less-developed regions (Norton, S. W., 1992; Katz, M. L., 1994). Chinese scholars have also highlighted that digital infrastructure promotes regional economic equilibrium by optimizing resource allocation and facilitating industrial agglomeration effects (Chang, K., Zhang, H., & Li, B., 2024).

Regarding the relationship between digital infrastructure and environmental benefits, the academic community holds two main perspectives. On the one hand, the construction and operation of digital infrastructure require substantial energy inputs, which may exacerbate pollution emissions (Tang, K., & Yang, G., 2023). On the other hand, the development of digital technologies accelerates knowledge sharing and technology diffusion among firms, driving the transition from high-energy to low-energy consumption models (Ren, S., Hao, Y., Xu, L., Wu, H., & Ba, N., 2021).

In recent years, the relationship between digital infrastructure and Green Total Factor Productivity (GTFP) has become a focal point of research. Existing studies suggest that digital infrastructure significantly enhances GTFP by fostering technological innovation and optimizing industrial structure (Hao, X., Li, Y., Ren, S., Wu, H., & Hao, Y., 2023). Some scholars have found that new infrastructure, represented by the internet, has a positive effect on urban GTFP in China (Wu, L., & Zhang, Z., 2020). Furthermore, digital infrastructure also drives green development in surrounding areas through spatial spillover effects (Hong, M., Tian, M., & Wang, J., 2023).

This paper makes three primary contributions to the existing literature. First, using a dataset of Chinese prefecture-level cities, this study empirically examines the impact of digital infrastructure development on urban GTFP. This analysis addresses the current research gap and provides robust data support for maximizing the green empowerment effect of digital infrastructure in China. Second, building on the existing literature, this study investigates the mechanisms through which digital infrastructure affects GTFP, focusing on technological progress, industrial upgrading, and energy conservation and emission reduction. Third, recognizing the heterogeneity in economic development, technological innovation capacity, and industrial structure across cities, this paper further explores the differential impacts of digital infrastructure development on GTFP across cities with varying characteristics.

3. Theoretical Framework and Research Hypotheses

Based on existing literature and economic logic, this paper posits that digital infrastructure enhances urban Green Total Factor Productivity (GTFP) through mechanisms such as technological innovation, industrial structure upgrading, and energy conservation and emission reduction.

3.1. Direct Impact of Digital Infrastructure on Green Total Factor Productivity

The construction of digital infrastructure improves network accessibility and coverage, providing critical technological and informational support for economic activities. This significantly enhances resource allocation efficiency and economic performance (Lyu, Y., Wang, W., Wu, Y., & Zhang, J., 2023). In the process of economic digital transformation, digital infrastructure reduces information circulation costs and mitigates market information asymmetry, thereby increasing transaction efficiency and production quality (Borgman, C. L., 2010). Additionally, the widespread adoption of digital infrastructure enhances corporate transparency and societal oversight, encouraging firms to prioritize corporate social responsibility and contribute to green economic development.

Existing studies suggest that digital infrastructure not only improves traditional Total Factor Productivity (TFP) but also indirectly boosts GTFP by promoting green technological innovation and energy conservation and emission reduction (Lee, C. C., He, Z. W., & Yuan, Z., 2023). It can be seen that digital infrastructure improves resource allocation efficiency, reduces information asymmetry, and promotes green total factor productivity (GTFP).

Hypothesis 1: Digital infrastructure enhances urban green total factor productivity.

3.2. The Role of Technological Innovation in Enhancing Green Total Factor Productivity

Digital infrastructure development supports technological innovation, particularly in the area of green technology research and dissemination (Du, Z. Y., & Wang, Q., 2024). Under the "Broadband China" policy, improved digital infrastructure significantly enhances access to technological innovation for researchers and firms. This broadens knowledge sources, increases innovation diversity, and accelerates the development and application of green technologies (Hao, X., Wang, X., Wu, H., & Hao, Y., 2023).

Technological innovation directly enhances GTFP by improving resource allocation efficiency and reducing environmental pollution. Through network platforms and big data technologies, firms and research institutions can efficiently access frontier knowledge, expand innovation pathways, and accelerate the adoption of green technologies. Advanced digital platforms such as cloud computing, the Internet of Things (IoT), and artificial intelligence (AI) provide firms with efficient resource management tools, enabling them to optimize production processes, minimize resource waste, and reduce energy consumption.

Furthermore, digital infrastructure fosters knowledge diffusion and technological spillovers across regions, enabling faster dissemination of innovation outcomes and accelerating GTFP growth (Kirschning, R., & Mrożewski, M., 2024).

Hypothesis 2: Digital infrastructure indirectly enhances green total factor productivity by promoting technological innovation.

3.3. Industrial Structure Upgrading and Green Total Factor Productivity

Digital infrastructure significantly enhances GTFP by promoting the transformation of traditional industries and supporting the growth of emerging industries. In traditional industries, the application of digital technologies improves resource allocation efficiency, reduces resource consumption and pollution emissions in high-energy industries, and facilitates green transformation (Zhu, L., Luo, J., Dong, Q., Zhao, Y., Wang, Y., & Wang, Y., 2021). Meanwhile, digital technologies enable large-scale and precise production, improving operational efficiency and reducing costs (Li, W., Wang, S., & Deng, X., 2024).

In emerging industries, digital infrastructure drives the development of green economies, smart manufacturing, and resource recycling systems, supporting the shift to a low-carbon economy. Digital platforms and technological collaboration enable information sharing and production coordination across industrial chains, further optimizing the industrial structure. Firms, as key agents of industrial upgrading, benefit from the connectivity and information-sharing features of digital technologies, reducing transaction costs and improving production efficiency.

By optimizing value chains and promoting clean production, digital infrastructure provides firms with strong support for achieving green development. Overall, industrial structure optimization significantly enhances GTFP, laying the foundation for achieving high-quality green economic development (Zhang, Y., & Dilanchiev, A., 2022).

Hypothesis 3: Digital infrastructure indirectly enhances green total factor productivity by promoting industrial structure optimization.

3.4. Energy Conservation and Emission Reduction as a Pathway to GTFP

Digital infrastructure positively impacts GTFP by improving energy efficiency and reducing pollution emissions (Wu, H., Hao, Y., Ren, S., Yang, X., & Xie, G., 2021). By providing efficient tools for firms and society, digital infrastructure enhances resource utilization efficiency, minimizes waste, and accelerates the adoption of energy-saving and emission-reduction technologies.

At different levels, digital infrastructure demonstrates its energy-saving effects among households, firms, and industries (Teng, S. Y., Touš, M., Leong, W. D., How, B. S., Lam, H. L., & Máša, V., 2021). For households, activities such as online shopping, remote work, and online education reduce commuting and transportation energy consumption. Firms leverage information technologies to optimize production processes and organizational efficiency, effectively reducing power and water resource consumption. At the industry level, digital technologies optimize resource allocation and promote industrial upgrading, facilitating the emergence of low-energy, high-efficiency industries such as IoT and cloud computing.

Through the pathway of energy conservation and emission reduction, digital infrastructure not only enables efficient resource utilization but also serves as a key driver for enhancing GTFP (Liu, Y., Yang, Y., Li, H., & Zhong, K., 2022).

Hypothesis 4: Digital infrastructure indirectly enhances green total factor productivity by improving energy efficiency and reducing pollutant emissions.

4. Research Design

4.1. Policy Background

In 2013, the State Council released the "Broadband China" Strategy and Implementation Plan, which explicitly positioned broadband network infrastructure as a strategic public infrastructure for national development. The policy aims to accelerate the construction of broadband infrastructure, improve network access speeds, reduce internet costs, and promote the innovation and development of broadband applications and services, thereby advancing the process of social informatization. Through the "Broadband China" policy, the government not only sought to leverage information infrastructure development to drive economic growth and technological innovation but also aimed to facilitate the digital transformation of social services through widespread internet access. This was intended to provide urban and rural residents with more convenient public services, improve quality of life, and enhance overall social welfare.

To implement the "Broadband China" policy, the Ministry of Industry and Information Technology (MIIT), in collaboration with the National Development and Reform Commission (NDRC), issued a notification titled "Notice on the Establishment of 'Broadband China' Pilot Cities (City Clusters)". Between 2014 and 2016, MIIT selected 117 cities in three batches to serve as pilot cities for the "Broadband China" policy. These pilot cities were systematically planned and targeted for improvements in broadband coverage, capability enhancement, application development, and industrial growth. A partial list of these pilot cities is shown in Table 1.

Table 1. Partial List of “Broadband China” Pilot Cities.

Batch/Year	Pilot Cities List
First Batch (2014)	Beijing, Shanghai, Chang-Zhu-Tan Urban Agglomeration, ... Guiyang, Chengdu (41 cities)
Second Batch (2015)	Yangzhou, Hefei, Panjin, ... Lanzhou, Zhangye (38 cities)
Third Batch (2016)	Shenyang, Ji’an, Baotou, ... Nyingchi, Weinan (38 cities)

Source: Ministry of Industry and Information Technology of the People's Republic of China

At the same time, the implementation of the "Broadband China" strategy aligns with China’s green development philosophy. The nationwide construction of high-speed and widely accessible broadband networks not only fosters the development of green technologies, such as smart cities and intelligent transportation systems, but also encourages enterprises to conserve energy and reduce emissions, promoting the efficient use of resources. This creates a synergy between economic growth and environmental protection. By vigorously advancing information infrastructure, China aspires to build a more inclusive, green, and sustainable future. The implementation of this policy plays a crucial role in advancing China’s economic transformation and upgrading, as well as achieving sustainable development.

4.2. Model Specification

In recent years, the Difference-in-Differences method has been widely used in studies evaluating policy effects. It is based on a randomized experiment or natural experiment, focusing on the impact generated before and after the experiment. DID is a commonly used policy evaluation tool that estimates the causal effect of a policy by comparing the differences between the treatment group and the control group before and after the policy implementation. The multi-period DID method extends the traditional DID model to scenarios with multiple time points and groups, making it suitable for analyzing the long-term and dynamic effects of policies. In this study, the phased implementation of the "Broadband China" policy provides an ideal quasi-natural experimental background for applying the multi-period DID method, allowing us to track the dynamic changes before and after the policy implementation. This study adopts the progressive DID model inspired by other scholars (Wang, Q., Xu, W., Huang, Y., & Yang, J. 2022; Jin, X., Ma, B., & Zhang, H. 2023). The group dummy variable (Group) is set by assigning a value of 1 to cities participating in the "Broadband China" pilot and 0 to others. The policy time dummy variable (Time) is set by designating the year of policy implementation and subsequent years as 1, and all other years as 0. Thus, the progressive DID model with two-way fixed effects is structured as follows:

$$GTFP_{it} = \alpha_0 + \alpha_1 Time_{it} \times Group_{it} + \sum \gamma_j X_{it} + \mu_i + \nu_t + \lambda_{it} \quad (1)$$

Here, GTFPit represents the dependent variable, the total factor productivity growth rate of city i in year t; Time×Group indicates the "Broadband China" pilot policy, serving as a proxy for infrastructure development, with its coefficient α_1 reflecting the policy's effectiveness. X represents a set of control variables, μ_i denotes individual fixed effects, λ_{it} represents the random error term, and ν_t denotes time fixed effects, effectively controlling for differences between pilot and non-pilot cities, as well as time trends.

4.3. Variable Selection

This study considers 283 prefecture-level cities in mainland China from 2009 to 2022, constructing panel data with relevant indicators.

4.3.1. Dependent Variable

Green Total Factor Productivity (GTFP) is calculated using the SBM Directional Distance Function combined with the GML Index. A higher index indicates enhanced green total factor productivity, suggesting stronger synergistic capabilities of urban economic development and pollution reduction. Inputs for GTFP measurement include capital input, labor input, and energy input, with capital input represented by the capital stock of each city. The capital stock is calculated using the perpetual inventory method: $K_{it}=I_{it}/P_{it}+(1-\delta)K_i(t-1)$, where K_{it}、 I_{it} and P_{it} represent the capital stock, capital inflow, and price index of fixed asset investment for each city in each period, respectively (Berlemann, M., & Wesselhöft, J. E. 2014). Assuming initial capital stock for each city as 10% of the fixed asset investment in 2008 and a depreciation rate δ of 9.6%, the base year capital stock for each city is calculated.

Outputs for GTFP measurement include desired and undesired outputs. Desired outputs are measured using actual GDP of each city, whereas undesired outputs include industrial wastewater discharge, industrial sulfur dioxide emissions, and industrial dust emissions.

4.3.2. Core Explanatory Variable

The "Broadband China" pilot policy is represented as a dummy variable, PolicyPolicyPolicy, with a value of 1 assigned to pilot cities in the year of policy implementation and thereafter, and 0 otherwise. Cities involved in multiple batches are treated according to their first inclusion.

4.3.3. Control Variables

Economic development level (lnPgdp), measured by the logarithm of actual per capita GDP to gauge urban economic development. Developed regions typically have more accumulated social wealth, enriching their capacity in capital, technology, and labor, thereby aiding in enhancing local green total factor productivity.

Foreign capital utilization (Fdi), represented by the ratio of actual used foreign capital to regional GDP, with foreign capital amounts converted to RMB using the annual average exchange rate.

Human capital (Hum), measured by the ratio of university students to the total population at the end of the year.

Fiscal intervention (Gover), measured by the ratio of fiscal expenditure to GDP, reflecting the extent of government intervention.

Industrial structure (Indu), represented by the proportion of the secondary and tertiary industries' added value to GDP.

Environmental regulation (Envir), indicated by the number of employees in water resources, environmental, and public facilities management industries, reflecting governmental focus on environmental construction.

4.4. Data Sources and Descriptive Statistics

Given the availability of data and the implementation timeline of the "Broadband China" pilot policy, this study utilizes balanced panel data from 280 prefecture-level cities in China spanning 2009 to 2022 as the research sample, with relevant indicators selected to construct the panel dataset. All data primarily come from publicly available sources, including the China Urban Statistical Yearbook, China Environmental Statistical Yearbook, China Fiscal Statistical Yearbook, China Educational Statistical Yearbook, various provincial and municipal statistical yearbooks, the EPS database, and the CSMAR database. For missing values, linear interpolation was employed to ensure data completeness and consistency. The sample selection was based on the following considerations. The time span covers both the pre- and post-implementation periods of the "Broadband China" policy, providing sufficient temporal dimensions for policy evaluation. This is shown in Table 2, The data at the prefecture-level city scale have broad coverage, effectively reflecting the policy's impacts across different regions and city types. During the data cleaning process, cities with significant data deficiencies were excluded, ensuring that the analytical sample is both representative and scientifically robust.

Table 2. Descriptive Statistics of Variables.

Variable	Variable Name	Sample Size	Mean	Std. Dev.	Min	Max
GTFP	Green Total Factor Productivity	3920	0.339	0.131	0.0970	1
Policy	Broadband China City Pilot	3920	0.220	0.414	0	1
lnpgdp	Economic Development Level	3920	10.70	0.631	4.595	13.06
fdi	Foreign Capital Utilization	3920	0.017	0.020	-0.005	0.340
hum	Human Capital	3920	0.020	0.025	-0.001	0.150
gover	Fiscal Intervention	3920	4.963	2.333	-2.850	23.12
indu	Industrial Structure	3920	0.877	0.080	0.501	1.013
envir	Environmental Regulation	3920	790.988	229.420	2.400	1594.600

5. Empirical Results Analysis

5.1. Baseline Regression Results

Based on the above analysis, this study constructs the Broadband China pilot policy as a quasi-natural experiment and employs the Difference-in-Differences (DID) method to empirically examine the impact of digital infrastructure construction on the Green Total Factor Productivity (GTFP) of Chinese cities.

Given the potential multicollinearity between per capita GDP and other control variables, a stepwise regression approach is used to analyze the baseline model's empirical results. Table 3 summarizes the baseline regression results based on the econometric model.

Table 3. Baseline Regression Results of the Impact of Broadband China Pilot Policy on Green Total Factor Productivity.

Variables	(1) GTFP	(2) GTFP	(3) GTFP	(4) GTFP	(5) GTFP
Policy	0.061***	0.020***	0.023***	0.023***	0.024***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
lnPgdp			0.032***	0.012	0.012*
			(0.007)	(0.008)	(0.008)
Fdi			-0.178***	-0.183*	-0.186*
			(0.096)	(0.096)	(0.096)
Hum			-0.935**	-0.926***	-0.914***
			(0.250)	(0.249)	(0.249)
Gover			-0.004***	-0.004***	-0.004***
			(0.001)	(0.001)	(0.001)
Indu				0.351***	0.358***
				(0.068)	(0.068)
Envir					-0.011
					(0.003)
Constant	0.326***	0.335***	0.035	-0.057	-0.052
	(0.002)	(0.001)	(0.075)	(0.077)	(0.077)
Observations	3,920	3,920	3,920	3,920	3,920
R^2	0.654	0.692	0.696	0.698	0.699
City Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes	Yes
r2_a	0.628	0.667	0.671	0.673	0.674
F	210.6	16.97	13.57	15.84	13.96

The results in column (2) demonstrate that the Broadband China pilot policy has a significant positive effect on GTFP, after controlling for year and city fixed effects. After gradually including additional control variables, the estimated coefficients of the Policy variable in columns (3) to (5) remain positive and statistically significant at the 1% level, with a stable magnitude ranging between 0.023 and 0.024.

These findings indicate that the Broadband China pilot policy significantly improves the GTFP of pilot cities, confirming the positive effects of the policy. The coefficient of the policy dummy variable directly reflects the direct impact of digital infrastructure on green total factor productivity. Using the DID model, this study measures the difference in GTFP changes between the "Broadband China" policy pilot cities and non-pilot cities before and after policy implementation, thereby verifying whether digital infrastructure directly influences GTFP by improving resource allocation efficiency and reducing information asymmetry. This suggests that as an early attempt at digital infrastructure construction, the Broadband China pilot policy has not only improved the level of digital infrastructure development over the years but also made a meaningful contribution to promoting green and high-quality economic development.

5.2. Parallel Trend Test

The parallel trend test is a necessary condition for identifying the policy treatment effect, as satisfying the parallel trend assumption is the core premise of using a multi-period Difference-in-Differences (DID) model. The applicability of the DID method relies on the parallel trend assumption, which requires that, prior to policy implementation, the outcome variables of the treatment group and the control group exhibit similar trends over time. This study employs the Event Study Approach to test the parallel trend assumption. The results indicate that the green total factor productivity (GTFP) trends of the treatment group and the control group were consistent before the implementation of the policy, confirming the validity of the multi-period DID model. Furthermore, the dynamic effects during different periods after the policy implementation demonstrate that the "Broadband China" policy significantly boosted GTFP in pilot cities over the long term, with the policy effects showing a gradually cumulative pattern. Thus, If the treatment group and the control group exhibit the same time trends prior to the implementation of the Broadband China pilot policy, then the statistical significance of the Policy variable can be attributed to the policy itself. Conversely, significant results might reflect the impact of unobserved external shocks.

In this study, the parallel trend assumption requires that, prior to the implementation of the Broadband China policy, the treated and control cities exhibit similar trends in Green Total Factor Productivity (GTFP). To test whether the baseline regression satisfies the parallel trend assumption, this paper follows the research frameworks of Ren et al. (2019) and McGavock (2021) and employs the Event Study Approach to examine the assumption and the dynamic effects of the policy. Using 2009 as the baseline year, we advance and lag the policy implementation period, and the model is specified as follows:

$$GTFP_{it} = \alpha_0 + \sum_{q=-4}^{q=8} \beta_q DID_q + \alpha_c X_{it} + \sigma_i + \delta_t + \varepsilon_{it} \tag{2}$$

Specifically, we set the fourth year before the implementation of the Broadband China policy (Pre4) as the reference period and construct dummy variables for the four years before the policy (Pre4, Pre3, Pre2, Pre1), the year of policy implementation (Current), and eight years after the policy (Post1, Post2, ..., Post8). These dummies are interacted with the policy treatment variable (Policy). To avoid multicollinearity, Pre5 is excluded as the baseline group in the regression analysis. Table 4 presents the regression results for the parallel trend test, while Figure 1 illustrates the dynamic policy effects with a 95% confidence interval.

The regression results show that the estimated coefficients of the interaction terms for the years prior to the policy implementation (Pre4, Pre3, Pre2, Pre1) are not statistically significant, with values close to zero. This confirms that, prior to the policy, the treated and control cities exhibited similar growth trends in GTFP, thereby validating the parallel trend assumption underlying the multi-period DID model.

Meanwhile, the estimated dynamic effects shown in Figure 1 reveal that the positive effect of the Broadband China policy on GTFP begins to emerge in the year of implementation (Current). In the first year after implementation (Post1), the policy's impact coefficient is 0.018, which is statistically significant at the 5% level. By the second year (Post2), the coefficient remains significant at 0.017. The policy effect strengthens in the fourth and fifth years (Post4 and Post5), with coefficients increasing to 0.025 and 0.028, respectively, and significance levels improving to 1%. It is evident that the green total factor productivity (GTFP) of pilot cities experienced significant growth after the policy implementation in 2013, showing a gradually cumulative trend and reaching its peak during the third to fifth years following the policy implementation. In contrast, the GTFP growth of non-pilot cities was relatively moderate. This indicates that the "Broadband China" policy has had a significant impact on enhancing GTFP in pilot cities, with the long-term effects of the policy primarily achieved through the optimization of digital infrastructure and the promotion of green technologies. This cumulative positive effect over time suggests that the Broadband China policy has a substantial long-term impact on promoting digital infrastructure construction and green technology adoption.

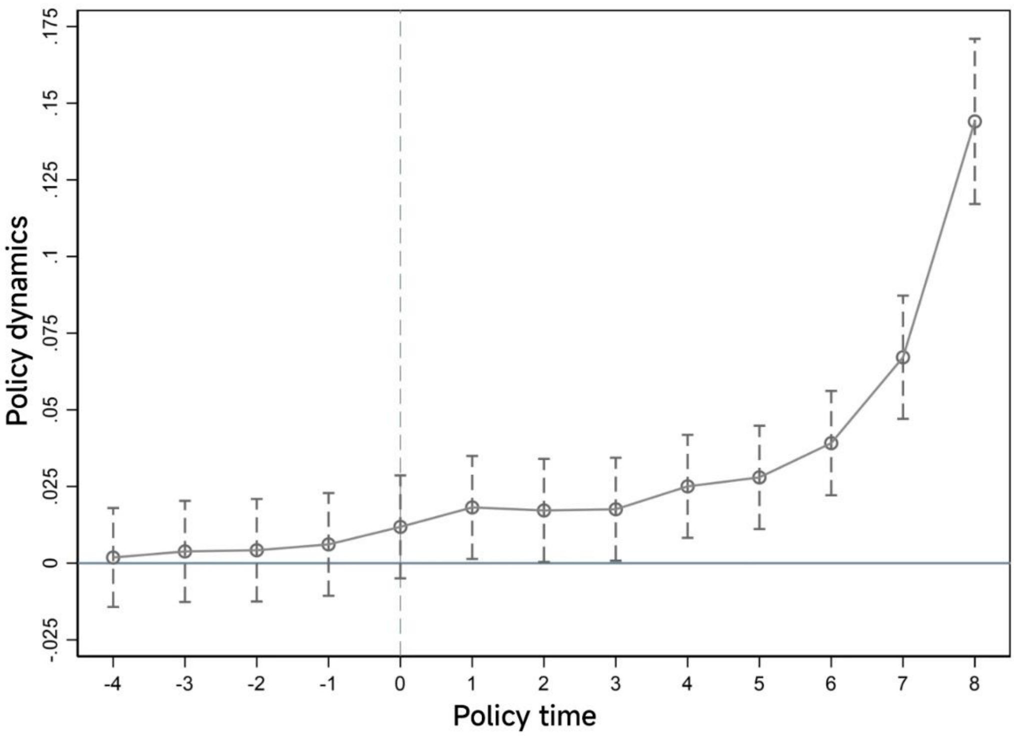

Figure 1. Multi-Period Dynamic Effects of the Broadband China Policy.

In summary, the results of the parallel trend test further confirm the validity of the multi-period DID model and the robustness of the study’s conclusions. The findings demonstrate that the Broadband China policy effectively enhances GTFP in pilot cities through continuous optimization of digital infrastructure and the promotion of green technological innovation. The consistent trend between the two sample groups prior to policy implementation further validates the applicability of the DID model and strengthens the causal interpretability of the study's results. The gradual accumulation of policy effects highlights the critical role of digital infrastructure in driving green economic development and provides valuable theoretical and empirical insights for future policy formulation.

Table 4. Results of the Parallel Trend Test.

Variable	GTFP	Variable	GTFP
Pre4	0.002	Post1	0.018**
	(0.008)		(0.009)
Pre3	0.004	Post2	0.017**
	(0.008)		(0.009)
Pre2	0.004	Post3	0.018**
	(0.009)		(0.009)
Pre1	0.006	Post4	0.025***
	(0.009)		(0.009)
Current	0.012	Post5	0.028***
	(0.009)		(0.009)
Constant		-0.014	
		(0.064)	
Observations		3920	
R^2		0.709	

5.3. Robustness Tests

5.3.1. Placebo Test

To ensure the reliability of the evaluation of the Broadband China pilot policy's effect on Green Total Factor Productivity (GTFP), this study employs the placebo test to address potential endogeneity issues. Specifically, to verify the randomness of the results and eliminate the interference of unobserved factors, we randomly generate false policy intervention timing for the control cities, conduct multiple simulations, and repeat the Difference-in-Differences (DID) estimation.

Through 500 simulations, we calculate the estimated policy effect and its corresponding p-values for each simulation to test the randomness of the policy effect.

As shown in Figure 2, the red line represents the kernel density estimation curve of the coefficients for the core explanatory variable, while the blue dots display the distribution of p-values across the simulations. The results indicate that the kernel density curve is highly concentrated around zero, suggesting that, under the randomly generated false policy intervention timing, the estimated policy effects do not exhibit systematic deviations. This further confirms that the baseline regression results are not coincidental.

Moreover, the distribution of blue dots shows that most simulated results have high p-values, failing to pass the significance test. This further validates the assumption that, under random policy intervention timing, the policy effect is insignificant. In contrast, by comparing the actual policy intervention effect with the simulated distribution, the estimated actual policy effect significantly deviates from zero and falls within the right tail of the kernel density curve, far exceeding the range of randomly simulated estimates.

These findings reject the null hypothesis of the placebo test, which assumes no effect of the policy on GTFP. Specifically, the significance of the actual policy intervention effect indicates that the Broadband China policy indeed optimizes information infrastructure and promotes green technological innovation, significantly enhancing the GTFP of pilot cities.

The results of the placebo test further confirm the robustness and reliability of this study. By effectively controlling for unobservable factors through random simulations, the estimated policy effect is shown to have a high degree of credibility. Combined with other robustness tests, it can be further inferred that the Broadband China pilot policy not only has significant green development effects but also demonstrates strong robustness in addressing model endogeneity. This provides important support for causal inference regarding the policy effect and offers meaningful insights for related research.

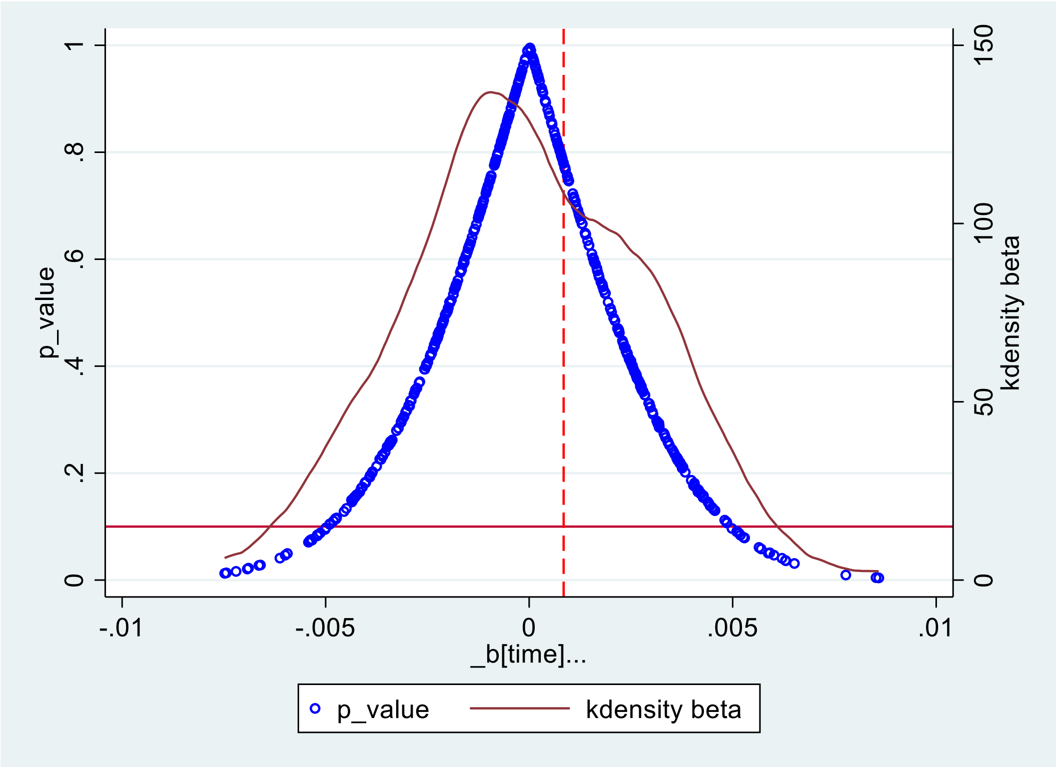

Figure 2. Placebo Test.

5.3.2. Propensity Score Matching and DID (PSM-DID) Test

To ensure the robustness of the research findings and the credibility of causal inference, this study conducted multidimensional robustness checks on the estimated policy effects. Regarding propensity score matching, the selection of pilot cities during the policy implementation process might have been influenced by factors such as local economic development levels and infrastructure conditions, potentially leading to selection bias. To address this, the study applied the PSM method to match the treatment group and the control group, ensuring that the two groups shared similar characteristics before policy implementation. Subsequently, the matched sample data were used to reapply the Difference-in-Differences method for further estimation. The Difference-in-Differences model assumes that the selection of treated and control group members is completely random. However, under China's current socio-economic system, the central government considers foundational conditions, development characteristics, and representativeness when selecting Broadband China pilot cities. Therefore, there are objective initial differences between pilot and non-pilot cities. To mitigate the "selection bias" caused by these differences, this study uses the Propensity Score Matching (PSM) method to match pilot and non-pilot cities based on observable variables. This avoids errors caused by cities with distinctive characteristics entering the control group. After constructing the control group successfully, we re-estimate the effect using the DID method. Notably, as the Broadband China pilot cities were established in multiple periods, this study follows Lu's approach and uses a year-by-year matching method to match control samples for the treatment group.

Following this approach, we first select covariates related to the outcome variable (GTFP) and treatment variable (Policy). Referring to Fu Jingyan's method, we treat control variables as covariates, including economic development level (ln Pgdp), foreign direct investment (Fdi), human capital (Hum), fiscal intervention (Gover), industrial structure (Indu), and environmental regulation (Envir). Next, we use the Logit model to calculate the propensity scores for pilot and non-pilot cities. Table 5 presents the Logit model results, showing that the selected covariates significantly influence whether a city is chosen as a Broadband China pilot city. This effectively reduced the estimation bias caused by initial differences between pilot and non-pilot cities, thereby enhancing the credibility of the policy effect estimation. The results indicate that the policy effect estimates based on the matched samples are consistent with the baseline regression results, further validating the robustness of the study's conclusions.

Table 5. Logit Model Estimation Results.

Variable	Coefficient	Z-statistic	P-value
lnPgdp	1.7611	15.27	0.000
Fdi	-6.7862	-2.85	0.004
Hum	12.1219	6.89	0.000
Gover	0.0547	3.09	0.002
Indu	0.9188	1.00	0.317
envir	0.0033	-1.65	0.098
constant	-21.4606	-20.85	0.000
Prob>chi2=0.0000			

Next, we perform one-to-one nearest-neighbor matching for pilot and non-pilot cities and test for balance before and after matching. The results in Table 6 show that after matching, failing to reject the null hypothesis, which indicates no systematic differences. Additionally, the absolute standardized bias for all covariates after matching is less than 10%, and the bias for most variables is significantly reduced. Before matching, significant differences existed between the treatment and control groups, such as the standardized bias for ln Pgdp, which reached 117.6%, with a P-value of 0.000. After matching, the P-values for all covariates exceed 0.1, indicating that the differences between the treatment and control groups are no longer significant.

Table 6. Comparison of Variables Before and After Matching.

Variable	Matching	Mean		Std. Bias (%)	T-Statistic	
		Treated	Control		T-value	P-value
lnPgdp	Unmatched	11.201	10.554	117.6	29.31	0.000
	Matched	11.071	11.079	-1.6	-0.33	0.740
Fdi	Unmatched	0.01986	0.01675	14.8	4.11	0.000
	Matched	0.02003	0.0191	4.4	0.78	0.436
Hum	Unmatched	0.03501	0.01527	72.6	21.93	0.000
	Matched	0.02674	0.02887	-7.8	-1.44	0.149
Gover	Unmatched	5.7138	4.7516	38.8	10.85	0.000
	Matched	5.7114	5.665	1.9	0.34	0.736
Indu	Unmatched	0.92354	0.86345	85.5	20.53	0.000
	Matched	0.91243	0.91	3.5	0.74	0.460
envir	Unmatched	794.19	790.09	1.8	0.46	0.643
	Matched	791.87	800.74	-4.0	-0.75	0.454

Figure 3 visually illustrates the changes in standardized bias before and after matching. The black dots represent the standardized bias before matching, while the cross symbols indicate the bias after matching. After matching, the standardized biases for all covariates shrink significantly, approaching the vertical line (standardized bias = 0), further demonstrating that the initial condition differences between the treatment and control groups are significantly reduced.

Following the matching process, we re-conduct the DID analysis on the matched sample. The results show that the estimated policy effect remains consistent with the baseline regression results: the Broadband China policy continues to have a significant positive effect on GTFP. This suggests that although there were initial differences between pilot and non-pilot cities, the PSM method effectively controls for selection bias, providing further verification and robustness support for the causal inference of the policy effect.

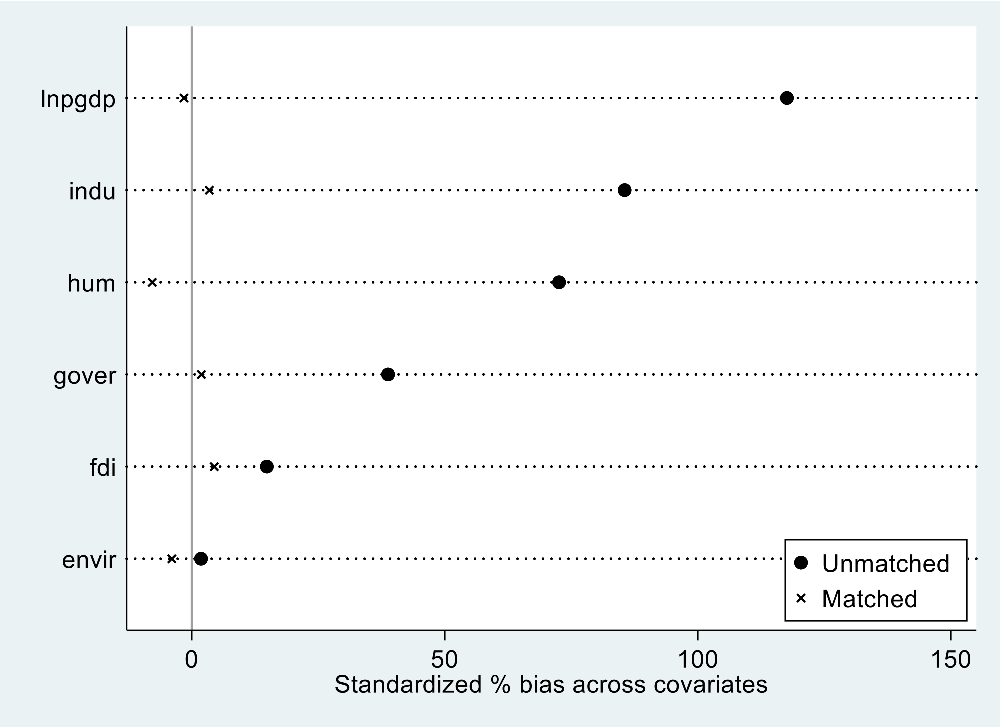

Figure 3. Standardized Bias of Covariates Before and After Matching.

5.3.3. Controlling for Other Policy Effects

To promote high-quality economic growth and address severe environmental pollution, the Chinese government has introduced a series of policies aimed at enhancing green productivity. Policies such as low-carbon city pilots, smart city initiatives, and National E-Commerce Demonstration Cities (NEDC) may have influenced Green Total Factor Productivity (GTFP) through different channels during the sample period. To avoid bias in the baseline estimation caused by cities being affected by these policies, this study focuses on the three major pilot policies that could impact the development of the digital economy and green productivity during the sample period:(1)Smart City Initiatives: Smart cities are defined as cities that integrate smart development, ecological considerations, and low-carbon principles.(2)Low-Carbon City Pilot Policy: The low-carbon city pilot policy helps to reduce carbon emissions and promotes green economic growth through green technological progress.(3)National E-Commerce Demonstration Cities (NEDC): The establishment of NEDCs enhances urban competitiveness and affects GTFP through industrial upgrading effects, non-productive cost reduction effects, and green innovation incentives. Furthermore, NEDCs promote green economic development by reducing pollutant emissions (Jiang et al., 2021).

To exclude the impact of these other pilot policies during the implementation of the Broadband China policy, this study incorporates dummy variables for these policies into the baseline regression. The revised regression equation is as follows:

$$GTFP_{it} = \alpha_0 + \alpha_1 Policy_{it} + \alpha_{01} Policy01_{it} + \alpha_{02} Policy02_{it} + \alpha_{03} Policy03_{it} + \alpha_c X_{it} + \sigma_i + \delta_t + \varepsilon_{it} \qquad (3)$$

In Equation (3), Policy01it, Policy02it, and Policy03it represent the Difference-in-Differences (DID) estimators for the Smart City Initiative, the Low-Carbon City Pilot Policy, and the National E-Commerce Demonstration Cities (NEDC), respectively. Specifically, if city I becomes a Smart City in year t, then Policy01it = 1 for year t and all subsequent years; otherwise, it is zero. Policy02it and Policy03it follow the same logic.

The regression results are presented in Table 7. Column (4) shows the regression results after including all policy impact variables. The results indicate that regardless of whether individual policy variables are controlled step-by-step or all are included simultaneously, the coefficient of Policy remains significantly positive. Furthermore, the magnitude of the coefficient does not change significantly compared to the baseline regression. This finding suggests that other concurrent or related policies have not affected the positive impact of the Broadband China policy on urban Green Total Factor Productivity (GTFP). Therefore, the results are robust.

Table 7. Controlling for the Effects of Concurrent Policies.

Variables	(1) GTFP	(2) GTFP	(3) GTFP	(4) GTFP
Policy	0.023***	0.025***	0.018***	0.018***
	(0.005)	(0.005)	(0.005)	(0.005)
Policy01	0.007			0.003
(Smart City Initiative)	(0.005)			(0.005)
Policy02		-0.014***		-0.019***
(Low-Carbon City Pilot)		(0.005)		(0.005)
Policy03			0.030***	0.034***
(E-Commerce Demonstration)			(0.006)	(0.006)
Constant	-0.048	-0.058	-0.066	-0.073
	(0.077)	(0.077)	(0.077)	(0.077)
Control Variables	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,920	3,920	3,920	3,920
Cities	282	282	282	282
R^2	0.699	0.699	0.701	0.702

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

5.3.4. Additional Robustness Tests

To ensure the robustness of the research conclusions, this study conducts a series of tests from multiple dimensions, including alternative variables, sample adjustments, and controlling for fixed effects.

Alternative Variable Analysis: To reduce potential bias caused by the measurement of Green Total Factor Productivity (GTFP), two alternative approaches are employed. First, considering that the original undesirable outputs mainly include "three wastes emissions" (waste gas, water, and solid emissions), which may not fully reflect the environmental costs of urban economic activities, CO_2 emissions are introduced as a new undesirable output to reconstruct the GTFP indicator. Second, CO_2 emissions are used individually as the sole undesirable output to focus on the impact of carbon emissions on green production efficiency.

This is shown in Table 8, the results show that the coefficient of the core explanatory variable Policy ranges between 0.016 and 0.030 ($p<0.01$), as shown in Table 8, and its significance and direction remaining unchanged. This confirms that the policy's positive effect on GTFP is robust under alternative indicators.

Excluding Specific Samples: To avoid potential bias caused by municipalities with special resource allocations and administrative status, Beijing, Tianjin, Shanghai, and Chongqing are excluded from the sample. The results indicate that the coefficient of Policy is 0.020 ($p<0.01$), consistent with the baseline results, validating the general applicability of the conclusions.

Excluding COVID-19 Years: To control for the disruptions caused by the COVID-19 pandemic on urban economic activities, data from 2020 to 2021 are excluded. The regression results show that the coefficient of Policy remains 0.020 ($p<0.01$), suggesting that the pandemic did not significantly affect the estimation of the policy effect.

Controlling for Provincial Heterogeneity: To account for heterogeneity across provinces, province fixed effects and province-year interaction fixed effects are introduced into the regression model. The results indicate that the coefficient of Policy is 0.023 ($p<0.01$), with the significance and magnitude consistent with the baseline results. This demonstrates that the policy effect is not influenced by potential macro-level systemic factors.

Re-Excluding COVID-19 Years: Considering the severe disruptions to urban economic and social activities during the pandemic, this study further confirms the robustness of the results by re-excluding data from 2020 and 2021. The re-estimation shows that the coefficient of Policy remains 0.020 ($p<0.01$), with no changes in significance levels. This further demonstrates that specific economic disturbances during the pandemic did not bias the estimated policy effects of the Broadband China initiative.

Table 8. Additional Robustness Tests.

Variables	(1) Alternative Variable 1	(2) Alternative Variable 2	(3) Excluding Municipalities	(4) Controlling for Province Fixed Effects	(5) Excluding COVID-19 Years
Policy	0.016***	0.030***	0.020***	0.023***	0.020***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.089	0.326***	-0.054	-0.055	-0.151*
	(0.086)	(0.082)	(0.076)	(0.077)	(0.082)
Control Variables	YES	YES	YES	YES	YES
Observations	3,920	3,920	3,864	3,920	3,080
R^2	0.671	0.732	0.698	0.700	0.745
Province Effects	NO	NO	NO	YES	NO
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Adjusted R^2	0.644	0.710	0.673	0.675	0.718
F-Statistic	10.84	11.61	12.06	14.03	9.252

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Through the aforementioned multidimensional robustness checks, the conclusions of this study have been fully validated. Whether by using the PSM-DID method to control for policy selection bias or by employing alternative variables, sample adjustments, and parallel trend tests to account for potential confounding factors, the results consistently show that the "Broadband China" policy has significantly promoted green total factor productivity (GTFP) in pilot cities. Moreover, the conclusions demonstrate strong robustness.

6. Further Analysis on the Impact of Digital Infrastructure on Green Total Factor Productivity Growth

6.1. Mediating Mechanism Test

To further analyze the indirect effects of digital infrastructure on green total factor productivity (GTFP) through technological innovation, industrial structure optimization, and energy conservation and emission reduction, this study constructs a mediation effect model. In this framework, technological innovation, industrial structure optimization, and energy conservation and emission reduction are included as mediating variables. To test the mechanisms through which the Broadband China policy influences Green Total Factor Productivity (GTFP), the study constructs a mediation effect model. Using panel data from 283 cities in China from 2009 to 2022, we explore the influence of digital infrastructure on GTFP through these mediating pathways.The mediating effect model is specified as follows:

$$Med_{it} = \beta_0 + \beta_1 Time_{it} \times Group_{it} + \beta_i X_{it} + \mu_i + \nu_t + \lambda_{it} \tag{4}$$

$$GTFP_{it} = \gamma_0 + \gamma_1 Time_{it} \times Group_{it} + \gamma_2 Med_{it} + \gamma_i \mathrm{X}_{it} + \mu_i + \nu_t + \lambda_{it} \tag{5}$$

Where Medit represents the mediating variables, including technological innovation, industrial structure upgrading, and energy conservation and emission reduction.

6.1.1. Results for Technological Innovation

The first and second columns examine the direct effect of the Broadband China policy on GTFP and its effect on technological innovation. We can see from Table 9, results show that the Broadband China policy has a significant positive impact on GTFP (coefficient = 0.024, p<0.01), indicating that digital infrastructure construction directly enhances GTFP. Moreover, in column (3), the policy significantly improves technological innovation capacity (coefficient = 0.524, p<0.01). This result validates the hypothesis proposed in the theoretical analysis, confirming how digital infrastructure indirectly enhances GTFP by promoting green technology research and development, as well as knowledge diffusion, thereby improving technological innovation capacity. The "Broadband China" policy has driven the development and application of green technologies, providing significant momentum for urban green development.

Table 9. Results of the Mechanism Analysis.

VARIABLES	(1) GTFP	(2) Technological Innovation	(3) GTFP	(4) Industrial Structure	(5) GTFP	(6) Energy Conservation
time	0.024***	0.524***	0.024***	0.006***	0.024***	0.364***
	(0.005)	(0.052)	(0.005)	(0.002)	(0.005)	(0.049)
					0.012	-0.294***
					(0.008)	(0.080)
lnpgdp	0.012	-0.155*	0.012	-0.037***	-0.186*	-4.974***
	(0.008)	(0.085)	(0.008)	(0.004)	(0.096)	(0.964)
fdi	-0.186*	-5.227***	-0.186*	0.195***	-0.914***	6.158**
	(0.096)	(1.020)	(0.096)	(0.042)	(0.249)	(2.499)
hum	-0.914***	-10.097***	-0.914***	0.067	-0.004***	-0.048***
	(0.249)	(2.646)	(0.249)	(0.110)	(0.001)	(0.010)
gover	-0.004***	-0.072***	-0.004***	0.000	0.358***	0.444
	(0.001)	(0.010)	(0.001)	(0.000)	(0.068)	(0.683)
indu	0.358***	0.242	0.358***	0.954***	-0.000	0.000
	(0.068)	(0.723)	(0.068)	(0.030)	(0.000)	(0.000)
envir	-0.000	-0.000	-0.000	0.000***	-0.052	4.228***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.077)	(0.773)
Constant	-0.052	2.304***	-0.052	1.823***		
	(0.077)	(0.818)	(0.077)	(0.034)	3,920	3,920
					0.699	0.870
Observations	3,920	3,920	3,920	3,920	YES	YES
R-squared	0.699	0.655	0.699	0.953	YES	YES
Firm FE	YES	YES	YES	YES	0.674	0.859
Year FE	YES	YES	YES	YES	13.96	21.34
r2_a	0.674	0.627	0.674	0.949		
F	13.96	29.23	13.96	168.1		

*Standard errors in parenthese, *** p<0.01, ** p<0.05, * p<0.1*

6.1.2. Results for Industrial Structure Upgrading

In the analysis of the influencing mechanism of the industrial upgrading pathway, this study examines whether digital infrastructure indirectly enhances green total factor productivity (GTFP) by driving the green transformation of traditional industries and the development of emerging industries, thereby achieving industrial structure upgrading. The empirical results reveal the impact of the "Broadband China" policy on industrial structure upgrading and its subsequent effect on GTFP. The third and fourth columns focus on the industrial upgrading pathway. Results show that the Broadband China policy has a significant direct impact on GTFP (coefficient = 0.024, p<0.01) while also significantly promoting industrial structure optimization (coefficient = 0.006, p<0.01). This indicates that digital infrastructure contributes to GTFP indirectly by facilitating industrial structure upgrading.

6.1.3. Results for Energy Conservation and Emission Reduction

The preceding analysis on the mechanism of the energy conservation and emission reduction pathway examines how digital infrastructure indirectly enhances green total factor productivity (GTFP) by optimizing energy efficiency and reducing pollutant emissions, thereby promoting energy conservation and emission reduction. Results demonstrate that the Broadband China policy significantly enhances energy efficiency and reduces emissions (coefficient = 0.364, $p<0.01$). At the same time, energy conservation and emission reduction significantly promote GTFP (coefficient = 0.024, $p<0.01$). This confirms the indirect effect of digital infrastructure in improving resource efficiency, fostering green production, and enhancing environmental quality.

6.2. Heterogeneity Analysis

6.2.1. Urban Regional Heterogeneity

Columns (1) to (5) in table 10 below present the regression results for the eastern, central, and western regions, as well as for coastal and non-coastal cities within the eastern region. The coefficients of the core explanatory variable Policy exhibit significant variation across regions, specifically as follows:

In the eastern region, the effect of the policy on green total factor productivity (GTFP) is the most significant, with the coefficient of the Policy variable being 0.045 ($p < 0.01$). This result indicates that the Broadband China policy has had the most prominent effect on improving GTFP in the eastern region. This may be closely related to the region’s well-developed digital infrastructure, higher level of economic development, and strong technological innovation capacity. The digitalization efforts in the eastern region benefit from comprehensive supporting infrastructure and industrial backing, enabling digital technologies to be integrated into economic production and daily life more rapidly, thereby significantly improving green production efficiency.

In the central region, the coefficient of the Policy variable is 0.004, which does not pass the significance test. This suggests that the Broadband China policy has had no significant impact in the central region. This outcome may reflect the central region's relative deficiencies in economic development, digital infrastructure, and technological innovation compared to the eastern region. The diffusion of digital technology and the adoption of green production methods in the central region may require a longer time horizon or stronger policy support to yield noticeable effects.

In the western region, the coefficient of the Policy variable is 0.014 ($p < 0.1$), indicating a limited but positive effect of the policy on GTFP. This result may be attributed to the higher proportion of resource-intensive industries in the western region, which provides a weaker foundation for green transformation. Although the policy’s role in economic restructuring and technological innovation has not yet fully manifested, its effects have started to emerge.

When further subdividing the eastern region into coastal and non-coastal cities, it is observed that the policy effect is more significant in eastern coastal cities, where the coefficient of the Policy variable is 0.036 ($p < 0.01$). In contrast, in non-coastal cities, the policy effect is still positive but weaker, with a coefficient of 0.013 ($p < 0.05$). This result suggests that coastal cities, due to their higher levels of openness, more advanced information infrastructure, and stronger marketization, are able to more quickly translate the policy into productivity gains. This is mainly attributed to the higher level of economic development, more advanced digital infrastructure, and stronger capacity for green technology application in the eastern region. Enterprises and local governments in the eastern region demonstrate higher responsiveness to policies, enabling them to more quickly translate digital infrastructure into productivity gains and environmental benefits. Additionally, the higher policy implementation efficiency and degree of marketization in the eastern region further amplify the policy effects. In contrast, while non-eastern coastal cities also benefit from the policy implementation, the relatively lower baseline levels of informatization and green technology application result in a comparatively weaker impact of the policy.

Table 10. Heterogeneity Analysis Based on Different Urban Regions.

VARIABLES	(1) Eastern	(2) Central	(3) Western	(4) Coastal Eastern Cities	(5) Non-Coastal Eastern Cities
Policy	0.045***	0.004	0.014*	0.036***	0.013**
	(0.009)	(0.007)	(0.007)	(0.009)	(0.006)
lnpgdp	0.020	0.027	0.050***	0.033**	0.013
	(0.016)	(0.019)	(0.010)	(0.016)	(0.009)
fdi	-0.157	0.186	-0.395*	-0.012	-0.125
	(0.153)	(0.139)	(0.229)	(0.186)	(0.111)
hum	-2.801***	0.615*	0.545	-3.155***	0.467
	(0.519)	(0.362)	(0.334)	(0.461)	(0.285)
gover	-0.001	-0.005***	-0.005***	-0.001	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
indu	0.524***	0.165	0.268***	0.086	0.403***
	(0.134)	(0.131)	(0.089)	(0.159)	(0.072)
envir	-0.000***	0.000	0.000**	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.166	-0.133	-0.468***	0.042	-0.148*
	(0.154)	(0.162)	(0.108)	(0.172)	(0.083)
Observations	1,680	1,120	1,120	1,568	2,352
R-squared	0.665	0.689	0.709	0.670	0.709
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
r2_a	0.635	0.659	0.681	0.639	0.684
F	15.13	3.438	9.661	11.27	11.05

*Standard errors in parenthese, *** p<0.01, ** p<0.05, * p<0.1*

6.2.2. Heterogeneity in City Size

According to the Notice on the Classification Standards for Urban Sizes issued by the State Council (Document No. 51 [2014]), cities are categorized based on the resident population in their administrative districts. Cities with a population ≥1 million are classified as large, very large, or mega cities, while those with a population <1 million are considered small cities. This study employs group regression analysis to explore the heterogeneity in the impact of the Broadband China policy on green total factor productivity (GTFP) across cities of different sizes.

Columns (1) and (2) in Table 11 show the regression results for large and small cities, respectively. The results reveal significant differences in the policy's effects based on city size:

In large cities, the coefficient of the core explanatory variable Policy is 0.017 ($p < 0.05$), indicating that the Broadband China policy significantly promotes GTFP in large cities. Large cities generally possess more developed information infrastructure, greater human capital accumulation, and stronger technological innovation capabilities, which allow policy effects to materialize quickly. Furthermore, the high industrial concentration in large cities means that the demand for and application of green technologies are relatively mature, further enhancing the policy's role in promoting green productivity.

In small cities, the coefficient of Policy is 0.008, but it is not statistically significant. This suggests that the policy's impact in small cities is not notable. Small cities are characterized by underdeveloped information infrastructure, a traditional economic structure, and slower diffusion of green technologies. As a result, the policy effects may take longer to fully materialize. Additionally, limitations in technological capacity, capital investment, and industrial chain collaboration in small cities may further weaken the short-term impacts of the policy.

Table 11. Heterogeneity Analysis Based on City Size.

VARIABLES	(1) Large/Mega Cities	(2) Small Cities
Policy	0.017**	0.008
	(0.008)	(0.007)
lnpgdp	0.012	0.025***
	(0.015)	(0.010)
fdi	0.056	-0.434***
	(0.138)	(0.132)
hum	-1.237***	-0.664
	(0.307)	(0.426)
gover	-0.007***	-0.001
	(0.002)	(0.001)
indu	0.182	0.338***
	(0.195)	(0.073)
envir	-0.000***	-0.000
	(0.000)	(0.000)
Constant	0.196	-0.209**
	(0.178)	(0.088)
Observations	1,372	2,548
R-squared	0.728	0.663
Firm FE	YES	YES
Year FE	YES	YES
r2_a	0.703	0.634
F	7.221	9.515

*Standard errors in parenthese, *** p<0.01, ** p<0.05, * p<0.1*

6.2.3. Heterogeneity in Environmental Regulation Intensity

Key environmental protection cities are primarily identified based on the national 11th Five-Year Plan for Environmental Protection. These cities include 113 cities such as Beijing, Tianjin, Shanghai, and Chongqing, and encompass 27 provincial capitals (e.g., Taiyuan, Kunming, Hohhot, Guiyang), 5 sub-provincial cities, and 77 other cities such as Dalian, Qingdao, Ningbo, Xiamen, Shenzhen, and Handan.

The selection of these key cities is based on their regional or national importance for environmental protection, with a focus on addressing atmospheric and water quality issues in the cities and their surrounding areas. Policy directions include strengthening industrial pollution control, urban wastewater treatment, and solid waste management, while improving air and water quality benchmarks.

In recent policies, adjustments have been made to prioritize 82 cities for atmospheric pollution control, covering regions such as Beijing-Tianjin-Hebei and its surroundings, the Yangtze River Delta, and the Fenwei Plain. Cities that achieve stable compliance with PM2.5 standards are removed, while cities with worsening air quality (e.g., southern Shandong and central-southern Henan) are added. The overall objective of these key environmental protection cities is to improve environmental quality through strengthened local governance, driving sustainable economic development in the region.

We can see this from Table 12, regression results show that in key environmental protection cities, the coefficient of Policy is 0.031 ($p < 0.01$), suggesting that the Broadband China policy significantly promotes GTFP. This highlights that the stricter environmental regulation intensity in these cities enables faster transformation of information infrastructure into green productivity. Enhanced regulatory requirements encourage firms and governments to invest more resources in energy saving, emission reduction, green technological innovation, and industrial structure optimization, amplifying the policy's positive effects.

In non-key environmental protection cities, the coefficient of Policy is -0.004, and it is not statistically significant. This suggests that the policy does not have a notable effect on GTFP in these cities. Weaker environmental regulations in non-key cities lead to limited incentives for green technology adoption and environmental investments. Additionally, their reliance on high-pollution and high-energy-consuming industries makes it challenging to achieve green transformation through information infrastructure in the short term.

Table 12. Heterogeneity Analysis Based on Environmental Regulation Intensity.

	(1)	(2)
VARIABLES	Key Environmental Cities	Non-Key Environmental Cities
Policy	0.031***	-0.004
	(0.008)	(0.007)
lnpgdp	0.038**	0.003
	(0.015)	(0.009)
fdi	0.087	-0.252**
	(0.201)	(0.105)
hum	-0.950***	-1.911***
	(0.308)	(0.464)
gover	-0.008***	-0.000
	(0.001)	(0.001)
indu	0.385**	0.439***
	(0.178)	(0.072)
envir	-0.000	-0.000
	(0.000)	(0.000)
Constant	-0.309*	-0.050
	(0.180)	(0.085)
Observations	1,512	2,408
R-squared	0.729	0.669
Firm FE	YES	YES
Year FE	YES	YES
r2_a	0.704	0.641
F	10.83	10.62

*Standard errors in parenthese, *** p<0.01, ** p<0.05, * p<0.1*

7. Conclusions and Policy Recommendations

7.1. Main Conclusions

This study, conducted within the context of the "Broadband China" policy implementation, explores the impact and mechanisms of digital infrastructure development on the green total factor productivity (GTFP) of Chinese cities through both theoretical analysis and empirical research. The findings reveal that the implementation of the "Broadband China" policy has significantly improved GTFP in pilot cities. This enhancement effect is statistically significant and robust. Empirical results indicate that digital infrastructure enhances urban economic green efficiency by optimizing resource allocation, promoting green technological innovation, and facilitating industrial upgrading.

Theoretical analysis uncovers that the core mechanisms through which the "Broadband China" policy influences GTFP include the following: by reducing information flow costs and improving network coverage efficiency, digital infrastructure significantly enhances overall resource utilization efficiency; by promoting technological innovation, especially the research, development, and dissemination of green technologies, the policy fosters the green transformation of traditional industries; and by establishing open and collaborative information networks, the policy achieves regional economic integration, further amplifying GTFP improvements.

The study also highlights notable regional and scale heterogeneities in the policy's impact. At the regional level, the policy effects are particularly pronounced in the more developed eastern regions, while the central and western regions exhibit relatively weaker impacts due to lagging digital infrastructure. At the scale level, large and medium-sized cities experience greater improvements in GTFP compared to smaller cities, owing to more significant resource agglomeration and technology diffusion effects.

Dynamic policy effect analysis indicates that the "Broadband China" policy has significant long-term and cumulative impacts on GTFP. During the initial phase of implementation, the effects are mainly driven by digital infrastructure improvement and resource optimization. As digitalization progresses, the policy's role in fostering green technological innovation and industrial upgrading becomes increasingly prominent. This highlights that digital infrastructure delivers enduring growth dividends and serves as a strategic foundation for urban green economic transformation.

Overall, this study systematically reveals the critical role of the "Broadband China" policy in promoting urban green development and high-quality economic growth from both theoretical and empirical perspectives, offering new insights into the relationship between digital infrastructure and green total factor productivity.

7.2. Policy Recommendations

Based on the findings of this study, the "Broadband China" policy has played a significant role in improving green total factor productivity (GTFP), providing new perspectives and practical insights into the application of digital infrastructure in driving economic green transformation. The following are specific recommendations:

7.2.1. Optimize the Regional Allocation of Digital Infrastructure Resources

The study finds that the effects of the "Broadband China" policy are significantly greater in the eastern regions compared to the central and western regions, reflecting an imbalance in the regional allocation of digital infrastructure resources. To bridge the regional digital divide, policymakers should increase fiscal support for the central and western regions as well as small and medium-sized cities, promoting a more balanced distribution of infrastructure. Establishing dedicated fiscal subsidies to support digital infrastructure construction in the central and western regions is essential to enhance network coverage and transmission quality. Additionally, efforts should be made to strengthen the cultivation and attraction of talent in digital economy-related fields in underdeveloped areas, providing the intellectual foundation necessary for digital transformation.

7.2.2. Strengthen Policy Incentives for Green Technology Innovation

The government should establish dedicated funds to support green technology research and development, creating a comprehensive support system that spans the entire process from technological innovation to industrialization. To further enhance the green empowerment effects of digital infrastructure, policymakers should provide stronger support for the research and promotion of green technologies. Specifically, a green technology special fund should be created to encourage enterprises and research institutions to engage in R&D in areas such as low-carbon technologies, pollution control, and energy-saving equipment. Additionally, tax incentive policies should be implemented to provide tax reductions or exemptions for enterprises that adopt green technologies, motivating them to actively utilize digital tools to promote green production.

7.2.3. Promote the Digital and Green Transformation of Traditional Industries

Policymakers should actively promote the green transformation of traditional industries and the digital development of emerging industries. In the industrial sector, policy incentives and financial subsidies should be used to encourage energy-intensive industries to intensify their efforts in technological upgrading, leveraging digital technologies to improve production efficiency, reduce energy consumption, and lower pollutant emissions. In the service sector, efforts should focus on integrating digital technologies with green principles to achieve sustainable development. This can be accomplished through initiatives such as smart logistics and green consumption, which aim to foster the green transformation of the service industry.

7.2.4. Promote the Deep Integration of the Digital Economy and the Green Economy

The "Broadband China" policy should serve as an opportunity to fully explore the potential of the digital economy in driving green transformation. Cities should be encouraged to explore new pathways for the coordinated development of digitization and greening, such as smart city construction, low-carbon transportation networks, and intelligent energy management.

By implementing these measures, the comprehensive effects of the "Broadband China" policy can be further strengthened, fostering the synergistic development of digitalization and green transformation. This will inject strong momentum into China's sustainable development and high-quality economic growth.

7.3. Future Research Directions and Prospects

Based on the findings of this study, future research can be expanded in several directions. One promising area is to actively explore the multidimensional impacts of digital infrastructure. Beyond its economic and environmental benefits, digital infrastructure may have profound effects on society, culture, and governance. Key questions for future research could include how digital infrastructure facilitates smart city construction and enhances urban governance efficiency, as well as whether digital infrastructure might lead to new social challenges, such as issues related to privacy protection and cybersecurity risks.

Another important direction is to expand the research scope to other countries or regions. The universality of digital infrastructure provides critical support for the global green economic transition. Evaluating the green economic effects and applicability of digital infrastructure development in Belt and Road Initiative countries and other developing nations would offer valuable insights. These studies could explore how digital infrastructure contributes to green economic transformation in different contexts.

Additionally, comparative research on the implementation of digital strategies across various countries and regions could provide a deeper understanding of policy differences and their outcomes. Such studies would summarize experiences and lessons learned at different stages of development, offering diverse references and practical guidance for advancing global green transformation efforts.

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Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

Author contributions

Xudong Hu: Conceptualization, Methodology, Supervision, Formal analysis, Writing - review & editing. Sen Wang: Software, Visualization, Funding acquisition, Writing - original draft, Writing - review & editing, Formal analysis. Jinpei Cao: Conceptualization, Methodology. Pu Hao: Writing - review & editing.

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