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Toward carbon neutrality: The impact of the opening of high-speed rail on urban green total factor energy efficiency in China

Lan Yu[1]*, Chunheng Fu[1], Ting Yu[2], and Yuntao Wei[3]

[1]Department of International Trade, School of Economics and Management, Zhejiang Sci-Tech University, Hangzhou, Zhejiang, China

[2]Department of Administrative Management, School of Politics and Public Administration, Soochow University, Suzhou, Jiangsu, China

[3]School of Fashion Design and Engineering, Zhejiang Sci Tech University, Hangzhou, Zhejiang, China

***Corresponding author:**
Lan Yu
(yulan@zstu.edu.cn)

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Abstract

As a key low-carbon-oriented transport infrastructure, the opening of high-speed rail (HSR) has been widely recognized as a critical enabler to support China's national carbon peaking and carbon neutrality strategic targets. This study employs the dynamic network slacks-based measure (DNSBM) framework to estimate urban green total factor energy efficiency (GTFEE), accounting for both internal production linkages and cross-period production inertia. Our causal identification based on the time-varying staggered difference-in-differences (DID) model revealed that HSR opening exerts a significant positive impact on urban GTFEE, and this core conclusion remained consistent across several robustness checks, including propensity score matching DID estimation, counterfactual placebo test, exclusion of concurrent policy shocks, and alternative measurement of core variables. Heterogeneity tests further indicated that the GTFEE improvement effect of HSR opening is particularly pronounced in three subgroups: smart-city pilot cities, high-innovation-level cities, and cities with advanced industrial structures. Mediating mechanism analysis verified that HSR opening promotes urban low-carbon transformation through three core transmission paths: stimulating economic agglomeration, driving industrial structure optimization, and enhancing green innovation capacity. Furthermore, the Goodman–Bacon decomposition test for heterogeneous treatment effects confirmed that the potential estimation bias of staggered DID is negligible in this study, further supporting the reliability of our baseline estimation results.

Keywords: High-speed railway; Dynamic network slacks-based measure model; Green total factor energy efficiency; Carbon neutrality; Low-carbon transformation

1. Introduction

China's decades-long, high-growth model, marked by high energy consumption and pollution, has propelled its economic take-off but also made it the world's largest energy consumer and industrial polluter. Against this backdrop, improving green total factor energy efficiency (GTFEE) has emerged as a core policy priority to support China's low-carbon transition and high-quality development, covering industrial upgrading, energy structure optimization, and overall production efficiency enhancement.

As a low-carbon transport infrastructure with the lowest per capita energy consumption, high-speed rail (HSR) has been increasingly recognized as a critical enabler for green development.[1] Existing studies have demonstrated that HSR can not only directly reduce transport-related carbon emissions by replacing high-emission passenger transport modes[2] but also indirectly drive regional low-carbon transformation through factor reallocation, technological innovation, and industrial structure adjustment. Against the background of the "eight vertical and eight horizontal" HSR network construction proposed in the 2016 Medium and Long-Term Railway Network Plan, the current study attempts to answer two core questions: Can HSR opening significantly improve urban GTFEE? If the effect exists, what are the underlying transmission mechanisms?

Compared with existing studies, we make three marginal contributions: First, we employed a time-varying staggered difference-in-differences (DID) model to identify the causal effect of HSR on GTFEE, providing new evidence for evaluating the environmental benefits of transport infrastructure. Second, we adopted the dynamic network slacks-based measure (DNSBM) model (Section A1), incorporating inter-sector link variables and inter-temporal carry-over variables to measure urban GTFEE, thereby improving the accuracy of efficiency measurement compared with traditional static methods. Third, we used the Goodman–Bacon decomposition to address potential estimation bias in staggered DID settings, ensuring the robustness of causal identification.

2. Literature review

2.1. Environmental and efficiency effects of high-speed rail opening

Existing research shows that, on the one hand, the HSR opening can promote regional coordinated development[3-8] and improve social fixed asset investment and overall national welfare.[9-11] On the other hand, there may be a negative siphon effect.[12] As a core low-carbon transport infrastructure, the environmental effects of HSR operation have become a research hotspot in transportation and environmental economics in recent years. Compared with traditional road and air transport, HSR has inherent advantages of lower carbon intensity per passenger turnover and higher energy efficiency,[13] and its large-scale adoption has been shown to significantly reduce emissions of conventional air pollutants and CO_2.[14] Song *et al.*[1] found that the proportion of railway passenger transport is significantly positively correlated with regional ecological efficiency, directly verifying the environmental dividend of HSR development. Dalkic *et al.*,[2] based on Turkish HSR data, also confirmed that HSR reduces fossil energy consumption and thus curbs regional carbon emissions. From the perspective of indirect mechanisms, existing studies have explored two core paths for HSR to affect urban environmental performance: First, the factor flow effect brought by HSR can reduce the cost of cross-regional innovation cooperation, driving enterprises to improve their energy conservation and emission reduction technology levels and achieve cleaner production.[15] Second, HSR can promote the agglomeration of low-carbon tertiary industries, optimize the regional industrial structure, and reduce overall energy consumption intensity.[16,17]

2.2. Measurement and driving factors of green total factor energy efficiency

Green total factor energy efficiency is the core explanatory variable in this study, and its scientific measurement is the premise of accurate causal identification. Early GTFEE measurement studies mostly used static data envelopment analysis (DEA) models, such as the Charnes–Cooper–Rhodes and Banker–Charnes–Cooper models, which only consider expected outputs and ignore undesirable outputs such as pollutant emissions, leading to substantial estimation bias.[18] To address this limitation, Tone[19] proposed the non-radial slacks-based model–DEA model incorporating undesirable outputs, which has become the mainstream method for GTFEE measurement in recent years. However, these static measurement methods still have obvious limitations: they are usually constructed under the assumption that input–output correlation remains unchanged during the investigation period, thereby ignoring the dynamic inter-temporal correlation of input factors (e.g., capital stock carry-over) and the internal network connections among production activities across sectors. The DNSBM model can effectively address this problem by introducing link variables to characterize inter-sector connections and carry-over variables to characterize inter-temporal factor transmission, but its application in urban-level GTFEE measurement remains very limited. In terms of the driving factors of GTFEE, existing studies have confirmed that green technology innovation,[20-23] environmental regulatory policies,[24,25] industrial structure upgrading, and transportation infrastructure are core factors affecting urban GTFEE levels.[26-31]

2.3. Intersectional research gaps between high-speed rail and green total factor energy efficiency

Sorting through existing literature, it can be seen that three key research gaps remain to be filled, directly corresponding to the marginal contributions of this study:

First, although existing studies have separately discussed the environmental effects of HSR opening and the driving factors of GTFEE, few studies have included the two into a unified causal identification framework. The net effect and internal transmission mechanisms of HSR opening on urban GTFEE are still unclear. Second, the application of dynamic GTFEE measurement methods that account for both intra-urban production linkages and inter-temporal factor carry-over remains limited, which may lead to bias in the evaluation of HSR's efficiency-improvement effect. Third, existing relevant studies mostly use traditional staggered DID models for causal identification, without accounting for potential estimation bias caused by heterogeneous treatment effects in multi-period policy settings. In addition, the heterogeneous impact of HSR opening on GTFEE of different types of cities has not been fully explored. This study aims to systematically address the three research gaps outlined above.

3. Theoretical analysis and research hypotheses

3.1. Overall effect of high-speed rail opening on urban green total factor energy efficiency

As a disruptive upgrade to the modern transportation system, HSR opening fundamentally breaks the administrative and spatial barriers to cross-regional factor flows.[32,33] From the perspective of input–output efficiency matching: On the one hand, HSR directly reduces the energy consumption intensity of the transport sector by replacing high-emission road and air passenger transport, and alleviates urban road congestion to reduce additional carbon emissions from vehicle idling, which directly reduces the undesirable output of the urban production system. On the other hand, HSR improves the cross-regional allocation efficiency of high-end factors such as talent, research and development (R&D) capital, and green technologies, thereby optimizing the input structure of the urban production system and improving the expected output level per unit of energy input.[34,35] Based on the above analysis, we proposed the first research hypothesis:

Hypothesis 1: HSR opening has a significant positive promotion effect on urban GTFEE.

3.2. Mediating mechanisms of high-speed rail affecting green total factor energy efficiency

3.2.1. Economic agglomeration mediating channel

The time–space compression effect brought by HSR opening attracts enterprises, capital, and labor to agglomerate in cities along the line, generating a significant scale effect in economic activities. For the DNSBM-measured GTFEE, this agglomeration effect improves efficiency from two aspects: First, the spatial concentration of production entities optimizes upstream and downstream industrial linkages, reduces resource waste caused by information asymmetry, and directly improves the energy efficiency of the material production sector. Second, the concentration of industrial enterprises reduces the cost of environmental supervision for local governments, and the unified environmental supervision standard will urge enterprises to reduce illegal pollution discharge, thus reducing the undesirable carry-over output of the urban system.

3.2.2. Industrial structure optimization mediating channel

High-speed rail opening significantly increases cross-city passenger flow and drives the agglomeration of high-value-added tertiary industries (producer services, high-end commercial services, etc.) with low pollution-emission intensity.[36] This structural change is directly aligned with the inter-sector labor link variable in our DNSBM model: the flow of labor from high-energy-consumption secondary industries to low-energy-consumption tertiary industries optimizes the cross-sector allocation of the core link variable, reduces the overall energy consumption intensity of the urban industrial system, and thus improves GTFEE.

3.2.3. Innovation-driven mediating channel

The convenient HSR transportation network reduces the communication costs of cross-regional innovation cooperation and accelerates the spillover of green technology and low-carbon management experience. These effects directly act on the R&D innovation sector in our DNSBM framework: the increase of innovation output (invention patents, green technologies, etc.) not only improves the expected output of the R&D sector but also penetrates the material production sector to promote the application of energy-saving technologies, thus realizing the overall improvement of GTFEE across departments. Based on the above analysis of the three mediating mechanisms, we proposed the second research hypothesis:

Hypothesis 2: HSR opening improves urban GTFEE through three mediating channels: economic agglomeration effect, industrial structure optimization effect, and innovation-driven effect.

4. Model construction, variable selection, and data source

4.1. Model construction

Building on the aforementioned theoretical mechanism analysis, this study adopted the staggered DID model as the baseline empirical method to accurately identify the net policy effect of HSR opening on GTFEE.

$$GTFEE_{it} = \alpha + \beta HSR_{it} + \eta X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (1)$$

For the baseline econometric model (**Equation 1**), the subscript i denotes the prefecture-level city in the research sample, and the subscript t corresponds to the observation year. The explanatory variable $GTFEE_{it}$ measures the GTFEE level for city i in year t, and is estimated by the DNSBM model incorporating non-expected outputs. The core explanatory variable HSR_{it} is a dummy variable that characterizes the HSR operation status of city i. The estimated coefficient β captures the average causal treatment effect of HSR opening on urban GTFEE. To alleviate omitted-variable bias caused by observable confounding factors, we included a set of control variables X_{it} in the model, specifically covering economic development level, urbanization rate, foreign direct investment, local government fiscal expenditure scale, and urban total factor productivity. To further eliminate the interference of unobservable time-invariant city characteristics and common macro-shocks that affect all cities in the same year, we also controlled for the city fixed effect μ_i and the year fixed effect φ_t in the model. ε_{it} is the idiosyncratic error term, which is clustered at the city level to adjust for potential heteroskedasticity and serial correlation within the same city, satisfying the classical econometric assumptions.

4.2. Variable definition and measurement

4.2.1. Explainatory variable: Green total factor energy efficiency

This study adopted the DNSBM model to calculate the urban GTFEE. This model integrates multi-sector input–output indicators, inter-temporal carry-over variables, and inter-sector free link variables into a unified evaluation framework to obtain more accurate dynamic efficiency measurement results. The specific indicator systems are shown in Figure 1. We developed two parallel modules in the DNSBM model framework: the material production sector and the R&D innovation sector. For the material production sector, total urban energy consumption is selected as the core input, and actual GDP, adjusted by the price deflator (base year 2000), is the desired output. For the R&D innovation sector, local government annual science and technology expenditure is used as an innovation input, and the number of invention patents granted in the current year is used as an innovation output. For cross-sector connection rules, the total urban labor force is treated as a free-link variable connecting the two sectors to characterize the free allocation of human resources between production and innovation activities. For inter-temporal carry-over variables capturing the cross-period lag effect of production factors, we divided them into two categories: (i) Desirable free carry-over variable: urban fixed capital stock, calculated by the perpetual inventory method with 2000 as the base period; and (ii) Undesirable bad carry-over variable: industrial CO_2 emissions and PM2.5 concentration. For special indicator processing, since prefecture-level CO_2 emission statistics are not publicly available in China, we estimated CO_2 emissions using calibrated nightlight data and a top-down inversion method. For PM2.5 data, in view of the lack of historical monitoring data before 2013, we integrated National Aeronautics and Space Administration (NASA) satellite remote sensing data and national ground monitoring data into a two-stage spatial statistical model for correction, and matched the results with China's prefecture-level administrative vector boundaries through ArcGIS software (10.8, Environmental Systems Research Institute, United States of America) to obtain accurate annual average PM2.5 concentration data for each sample city. Based on the above input, output, carry-over and link variables, we substituted all data into the DNSBM model to calculate the GTFEE for 265 prefecture-level and above cities in China during the study period.

4.2.2. Core independent variable: Urban high-speed rail operation

As a landmark upgrade of China's intercity transportation

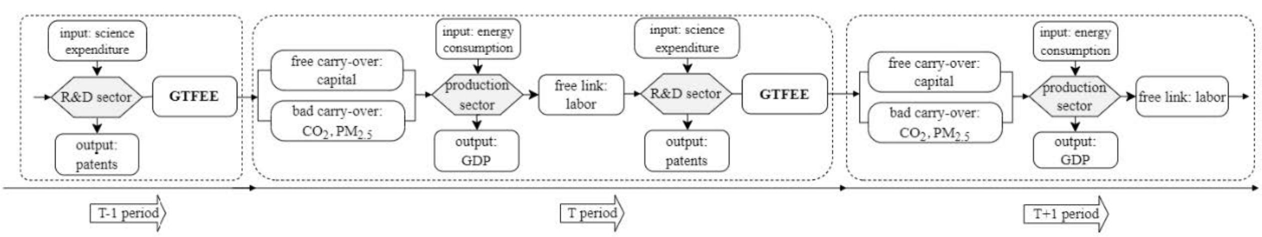

Figure 1. Inter-temporal dynamic change process of urban green total factor energy efficiency (GTFEE)
Abbreviations: GDP: Gross domestic product; R&D: Research and development.

infrastructure system, the operation of HSR was selected as the core policy shock variable in this study. Following the standard setting of staggered DID models, we defined this variable as a time-varying dummy variable: for sample city *i*, if its first HSR line was officially put into operation in year *t*, the variable HSR_{it} is assigned a value of 1 in year *t* and all subsequent years; otherwise, it is assigned a value of 0.

4.2.3. Control variables

To alleviate the potential estimation bias caused by observable confounding factors, we selected five city-level characteristic variables as controls in the baseline regression, with specific definitions as follows:

(i) Urban economic development level (*Gdp*): Measured by the natural logarithm of the city's actual per capita gross domestic product (GDP), which is adjusted by the provincial consumer price index (base year 2000) to eliminate the interference of price fluctuations.

(ii) Urbanization rate (*Urbanrate*): Calculated as the proportion of non-agricultural registered population in the total registered population of the city at the end of the statistical year.

(iii) Foreign direct investment intensity (*Fdi*): Measured by the proportion of the city's annual actual utilized foreign direct investment in the city's GDP of the same year.

(iv) Government fiscal expenditure scale (*Gov*): Measured by the natural logarithm of the local government's annual general public budget expenditure.

(v) Urban labor productivity (*Pro*): Calculated as the ratio of the city's annual actual GDP to the total number of employed persons at the end of the year, reflecting the per-capita output level of the city's labor force.

4.3 Data sources and descriptive statistics

All data were collected from three official authoritative sources: First, the HSR opening date data of each city were manually sorted from the official announcements of the National Railway Administration, the annual *China Railway Statistical Yearbook*, and special bulletins on railway passenger and freight transport, and cross-checked with public authoritative information such as the 12306 official platform to ensure data accuracy. Second, city-level macroeconomic data, including GDP, urbanization rate, fiscal expenditure, and other control variables, were sourced from the *China City Statistical Yearbook* over the sample period, with a small number of missing values filled by linear interpolation. Third, the energy consumption data required for GTFEE calculation were obtained from the annual *China Energy Statistical Yearbook*. The descriptive statistics for all core variables are shown in Table 1.

5. Results and discussion

5.1. Baseline regression results

This study adopted the time-varying staggered DID framework, with city- and year-fixed effects, to empirically identify the net causal effect of HSR opening on urban GTFEE. The specific baseline regression outputs are summarized in Table 2. Column (1) presents the estimation result, including only the core explanatory variable and two-way fixed effects (TWFEs), without adding any control variables. The coefficient for the *HSR* dummy variable was significantly positive at the 1% level, preliminarily confirming that HSR opening can effectively promote improvements in urban GTFEE. Columns (2–6) report the regression results as control variables are gradually added, while retaining the TWFEs specification. The results

Table 1. Descriptive statistics of variables

Variable	Obs.	Mean	SD	Min.	Max.
Green total factor energy efficiency	5,035	0.2759	0.4470	0	1
Urban economic development level	5,035	10.0730	0.8464	4.5951	13.0557
Urbanization rate	5,035	0.4131	0.2255	0.0381	1
Foreign direct investment	5,035	11.3165	2.0918	2.4932	16.8742
Government financial expenditure	5,035	13.4190	1.2480	8.3603	18.2405
Urban productivity	5,035	12.3044	0.7215	8.7073	14.4988

Abbreviation: Obs.: Observation.

Table 2. Benchmark regression results

Variable	GTFEE					
	(1)	(2)	(3)	(4)	(5)	(6)
HSR	0.0119* (0.0066)	0.0120* (0.0066)	0.0116* (0.0065)	0.0115* (0.0065)	0.0149** (0.0061)	0.0154** (0.0062)
Gdp		0.0004 (0.0081)	−0.0002 (0.0082)	0.0006 (0.0082)	0.0088 (0.0085)	0.0052 (0.0083)
Urbanrate			0.0181 (0.0203)	0.0183 (0.0203)	0.0212 (0.0199)	0.0244 (0.0198)
Fdi				−0.0013 (0.0015)	0.0003 (0.0014)	0.0001 (0.0014)
Gov					−0.0535*** (0.0055)	−0.0541*** (0.0054)
Pro						0.0098 (0.0069)
_cons	0.1402*** (0.0018)	0.1364* (0.0816)	0.1403*** (0.0018)	0.1417* (0.0819)	0.7562*** (0.1043)	0.6807*** (0.1230)
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
n	5,035	5,035	5,035	5,035	5,035	5,035
R^2	0.539	0.539	0.539	0.539	0.570	0.570

Notes: Values in parentheses are heteroskedasticity-robust standard errors clustered at the city level. Column (1) includes only the core explanatory variable and two-way fixed effects. Columns (2–6) report the regression results as control variables are gradually added, while retaining the two-way fixed effects specification. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Abbreviations: FE: Fixed effect; GTFEE: Green total factor energy efficiency.

showed that the estimated coefficient of the *HSR* dummy variable remained significantly positive at the 5% level or higher, and the coefficient magnitude remained relatively stable, indicating that the promotion effect of HSR opening on GTFEE is not affected by the inclusion of confounding factors. Overall, the baseline regression results consistently support the core conclusion that HSR opening has a significant positive effect on improving urban GTFEE, thereby verifying the validity of our Hypothesis 1.

5.2. Parallel trend test

The core precondition for the validity of the staggered DID estimation framework is that the treatment group and control group satisfy the parallel trends assumption before policy implementation, to ensure that the estimated net policy effect is not confounded by pre-existing divergent trends between the two groups. Specifically, before the opening of HSR, the trend in GTFEE should remain largely consistent across cities that later opened HSR (the treatment group) and those that did not open HSR during the sample period (the control group). To verify whether this assumption holds, we adopted the event study method to dynamically test the temporal heterogeneity of HSR opening's impact on urban GTFEE and, accordingly, to judge the validity of the parallel trend hypothesis. We took the year immediately before HSR opening (d_1) as the reference base period, where d_k (k = −4, −3, −2, −1, 0, 1, 2, 3, 4, 5) denotes the dummy variable for the k-th year relative to the year of HSR opening.

The parallel trend test results are shown in Figure 2, where the solid line connecting the point estimates reflects the dynamic marginal effect of HSR opening on GTFEE, and the upper and lower dashed lines represent the 90% confidence intervals of the estimated coefficients. It can be seen from Figure 2 that the estimated coefficients of the relative time dummy variables before HSR opening fluctuated around 0, and none of them were statistically significant at the 10% level, indicating that there is no significant systematic difference in the GTFEE changing trend between the treatment group and the control group before HSR opening. Therefore, the parallel trend assumption required for DID estimation was satisfied in this study.

Furthermore, following the approach of Biasi and Sarsons,[37] we conducted a parallel trend sensitivity analysis of the GTFEE enhancement effect of urban HSR opening by calculating the maximum deviation degree of parallel trends (Mbar; defined as 1 × standard error) and the corresponding confidence intervals for the processed point estimates. Figure 3 shows the parallel trend sensitivity test results for the treatment effect of the policy implementation year under constraints on relative deviation degree and smoothness. It can be observed that, regardless of the constraints, there are confidence intervals that do not include zero values, indicating that the impact of HSR opening on promoting urban GTFEE improvement is robust.

5.3. Robustness test

5.3.1. Propensity score matching–difference-in-differences test

To mitigate self-selection bias caused by inherent differences between HSR-opened cities and non-HSR-opened cities, and to further improve the robustness of the estimation results, we used the propensity score matching–DID method for re-estimation. Specifically, we first treated all the aforementioned city-level control variables as matching covariates and used the nearest-neighbor matching method with a 1:1 ratio to pair the treatment group and control group. Then, we re-estimated the net effect of HSR opening on GTFEE using the staggered DID model based on the successfully matched samples. The regression results are reported in Columns (1–2) of Table 3. The coefficient of HSR remained significantly positive regardless of whether control variables were added, consistent with the baseline regression conclusion.

To rule out potential bias caused by the subjective setting of matching ratios, we further adjusted the nearest-neighbor matching ratio to 1:3 for re-matching and regression estimation, with the results presented in Columns (3–4). The coefficient for the core explanatory variable, HSR, remained significantly positive at the 5% level. On this basis, we also replaced the nearest-neighbor matching method with the kernel matching

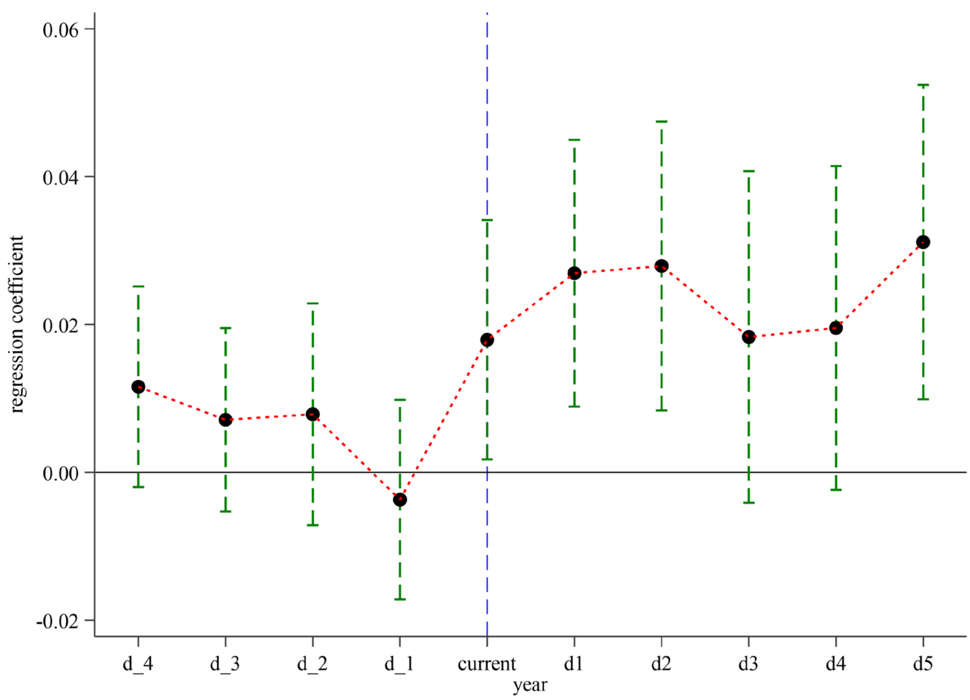

Figure 2. Results of the parallel trend test

method to reconstruct the counterfactual control group for robustness testing, and the corresponding estimation results are reported in Columns (5–6). Across the three specifications above, the estimated coefficients for HSR remained consistently positive, fully verifying that the core conclusion of this study is not affected by the choice of propensity score matching methods and is robust.

5.3.2. Counterfactual placebo test

To rule out the potential confounding effects of unobserved time-varying city-level characteristics and random estimation errors on the baseline findings, we designed a counterfactual placebo test by artificially shifting the timing of HSR opening. Specifically, for each city in the treatment group, we respectively advanced its actual first HSR operation year by 1, 2, 3, and 4 years to construct four sets of pseudo-policy shock dummy variables, and generated the corresponding interaction terms between these pseudo-dummy variables and the treatment group indicator. These constructed pseudo-interaction terms

Table 3. Robustness test I

Variable	GTFEE					
	PSM-DID 1:1		PSM-DID 1:3		Nuclear radius matching	
	(1)	(2)	(3)	(4)	(5)	(6)
HSR	0.0141** (0.0067)	0.0172*** (0.0064)	0.0123* (0.0066)	0.0156** (0.0062)	0.0125* (0.0065)	0.0158** (0.0061)
_cons	0.1416*** (0.0020)	0.6999*** (0.1243)	0.1403*** (0.0018)	0.6760*** (0.1264)	0.1361*** (0.0017)	0.6852*** (0.1285)
Control variables	N	Y	N	Y	N	Y
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
n	4,743	4,743	4,970	4,970	4,683	4,683
R^2	0.540	0.571	0.539	0.570	0.529	0.562

Notes: Values in parentheses are heteroskedasticity-robust standard errors clustered at the city level. Columns (1, 3, 5) are without control variables, while Columns (2, 4, 6) are with control variables. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.
Abbreviations: DID: Difference-in-differences; FE: Fixed effect; GTFEE: Green total factor energy efficiency; PSM: Propensity score matching.

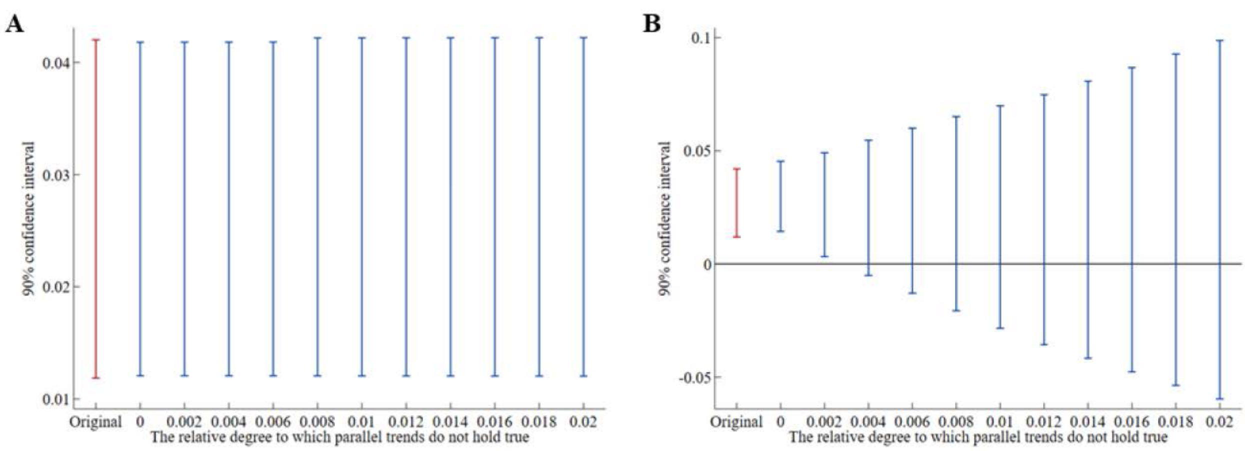

Figure 3. Sensitivity tests of the parallel trend hypothesis under (A) the constraint of relative deviation degree, and (B) smoothness constraint

were then included in the baseline TWFEs model for re-estimation. The estimation results of the placebo test are shown in Columns (1–4) of Table 4. The coefficients of the pseudo-*HSR* variables were not statistically significant at the conventional 10% level, showing a pattern completely different from the significant positive promotion effect captured in the benchmark specification. This result confirms that the positive effect of HSR opening on urban GTFEE is not driven by pre-existing divergent time trends or other unobserved systematic confounding factors, further supporting the robustness of the core conclusion.

Table 4. Robustness test II

Variables	GTFEE			
	(1)	(2)	(3)	(4)
HSR	0.0005 (0.0061)	−0.0050 (0.0056)	−0.0045 (0.0053)	0.0014 (0.0064)
_cons	0.7100*** (0.1237)	0.7078*** (0.1234)	0.7079*** (0.1238)	0.7102*** (0.1237)
Control variables	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
n	5035	5035	5035	5035
R^2	0.569	0.569	0.569	0.569

Notes: Values in parentheses are heteroskedasticity-robust standard errors clustered at the city level. Columns (1–4) indicate advanced high-speed rail (HSR) operation by 1, 2, 3, and 4 years, respectively. ***$p <$ 0.01.
Abbreviations: FE: Fixed effect; GTFEE: Green total factor energy efficiency.

We further conducted permutation tests to distinguish the statistical significance and random variability of the estimated results. Among them, the null hypothesis was that the opening of HSR has no significant impact on urban GTFEE, and the policy implementation time and experimental group subjects were reset based on the randomization method. We randomly assigned the implementation timing of pilot policies to various prefecture-level cities and established experimental groups in each policy pilot city. Drawing on the research method of Liu and Lu,[38] an indirect placebo test was conducted. The estimation coefficient $\hat{\beta}$ of HSR can be expressed as:

$$\hat{\beta} = \beta + \gamma \frac{cov(post \times treat, \varepsilon \mid C)}{var(post \times treat \mid C)} \tag{2}$$

where C represents a series of control variables and fixed effects included in the baseline regression, γ is used to capture the potential impact of unobservable factors on urban GTFEE, and $\hat{\beta}$ is an unbiased estimator when and only when $\gamma = 0$. Due to the inability to directly verify whether γ is equal to 0, indirect placebo testing was used to randomize the implementation time and subjects of the pilot policy, resulting in false estimates of $\hat{\beta}$. At this point, the actual policy treatment effect is 0. If the estimated $\hat{\beta}$ is also 0, it can be inferred that $\gamma = 0$, and the estimated result is unbiased. Using a Monte Carlo simulation, the above process was repeated 500 times and 500 distributions were plotted, as shown in Figure 4. From the distribution chart of the estimated coefficient $\hat{\beta}$ and the p-value reported in Figure 4, it can be seen that $\hat{\beta}$ followed a normal distribution centered at 0, and the true estimated coefficient values were clearly outliers, indicating that the virtual processing effect constructed in this study does not exist. Therefore, the regression results in the previous section were not caused by unobservable accidental factors, which is in line with placebo testing expectations, and the benchmark conclusion remains robust.

5.3.3. Endogeneity test

To address potential endogeneity issues, we first used the Heckman two-stage model to test for sample self-selection bias. Specifically, in the first stage of regression, the Probit model was used to calculate the inverse Mills ratio (*imr*) by taking whether the city becomes a location for HSR opening as the dependent variable, and incorporating it back into the second stage regression equation to address potential sample selection bias in the benchmark model. According to the empirical test results of the Heckman model shown in Column (1) of Table 5, it can be seen that the estimation coefficient of HSR was still positively significant; that is, after controlling for sample selection bias, the positive impact of HSR opening on promoting urban GTFEE improvement is still significant.

Secondly, to address potential reverse causality, we used the average slope for each city as an instrumental variable for HSR opening. The cost of building HSR in areas with steep terrain is often higher than in areas with lower terrain. Geographical slopes are an important factor affecting the cost of HSR construction and meet the relevant requirements. Besides, geographic slope is a natural condition unaffected by human factors and cannot directly affect the GTFEE level of the region, thus meeting the exogenous condition. It is cross-sectional data that needs to be multiplied by the time trend term to form panel data.

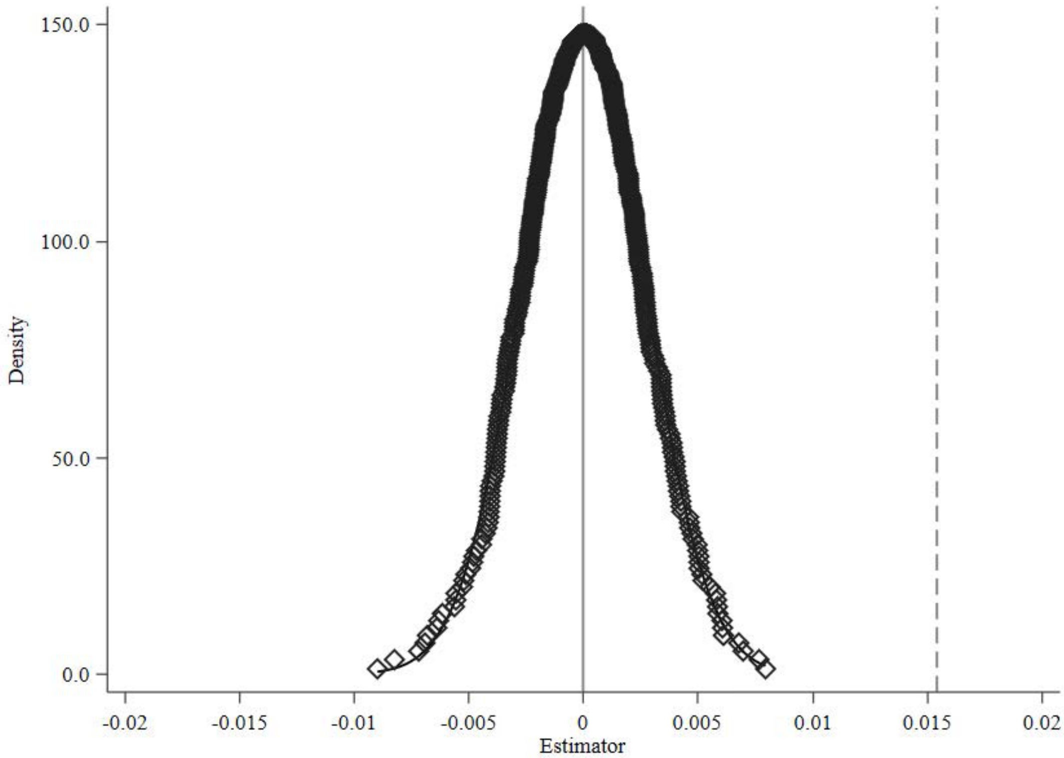

Figure 4. Permutation tests

At the same time, considering the consistency of variable directions, the reciprocal of the average geographic slope was taken and multiplied, and the resulting value was used as an instrumental variable for the HSR. The two-stage least squares (2SLS) method was used for estimation, and the instrumental-variable results are shown in Columns (2–3) of Table 5. The results of the first stage showed that the instrumental variable (*IV*) coefficient was significantly positive and passed the non-identification test and weak-identification test. The results of the second stage show that the HSR coefficient remained significantly positive, indicating that HSR opening significantly improves urban GTFEE.

5.3.4. Excluding concurrent policy interference

Urban GTFEE is likely to be simultaneously affected by a series of energy conservation and environmental governance policies implemented during the sample period. To address this concern, we manually identified major national policies and exogenous shocks that may affect urban energy efficiency during the sample period, and controlled for them one by one in the regression. The policies included are as follows:

(i) New energy vehicle industry subsidy pilot: Since 2009, the Ministry of Finance has jointly launched a financial incentive policy for the new energy vehicle industry with relevant departments, providing fiscal support for R&D, production and end-user consumption of new energy vehicles. This policy will promote the optimization of the urban passenger transport structure and industrial green transformation, thus affecting the GTFEE levels of pilot cities.

(ii) Comprehensive demonstration pilot of energy conservation and emission reduction fiscal policies: In 2011, the Ministry of Finance and the National Development and Reform Commission launched this pilot policy, focusing on supporting key projects including industrial energy efficiency transformation, renewable energy application and urban low-carbon infrastructure construction, which directly promotes the low-carbon transformation process of pilot cities.

(iii) Construction of national high-tech industrial development zones: High-tech zones gather a large number of technology-intensive enterprises and R&D institutions, which can effectively promote industry–university–research collaborative innovation and the agglomeration of green technology industries, thus boosting the development of the urban low-carbon economy.

(iv) Low-carbon city pilot policy: The National

Development and Reform Commission launched the first batch of low-carbon province and city pilot projects in 2010. This policy encourages pilot cities to independently explore differentiated low-carbon development paths, thereby significantly enhancing their motivation to pursue low-carbon technology innovation and to accelerate the low-carbon transformation process.

(iv) 2008 global financial crisis shock: The crisis led to a sharp tightening of the external financing environment for enterprises, especially for cities with a high degree of opening up. When enterprises face strong financing constraints, they usually cut high-uncertainty R&D investments first, which can inhibit the development of low-carbon technologies and thus negatively impact GTFEE improvement.[39]

Table 5. Robustness test III

Dependent variable	*GTFEE*	*HSR*	*GTFEE*
	(1)	(2)	(3)
HSR	0.0150** (0.0062)		0.0629*** (0.0163)
IV		0.0038*** (0.0012)	
imr	0.0559 (0.0483)		
_cons	0.5953*** (0.1463)	1.5667*** (0.5291)	0.5257*** (0.0753)
Control variables	Y	Y	Y
City FE	Y	Y	Y
Year FE	Y	Y	Y
Non-identification test			310.106 (<0.01)[a]
Weak identification test			311.563 (16.38)[b]
n	5,035	5,016	5,016
R^2	0.5444	0.6263	0.5573

Notes: Values in parentheses are heteroskedasticity-robust standard errors clustered at the city level. [a] The corresponding p-value. [b] The critical values at the 10% level. Column (1): Heckman model; Columns (2–3): Two-stage least squares model. $^{**}p < 0.05$, $^{***}p < 0.01$.
Abbreviations: FE: Fixed effect; GTFEE: Green total factor energy efficiency; HSR: High-speed rail.

To control for the confounding effects of the concurrent events above, we constructed corresponding time-varying dummy variables for each policy or shock. For a specific event, if city *i* was affected by the event in year *t*, the corresponding dummy variable was assigned 1; otherwise, 0. We added these dummy variables individually to the baseline regression model for re-estimation, with the results reported in Table 6. After controlling for all the above concurrent interference factors, the estimated coefficient for *HSR* remained significantly positive at the 5% level or higher. This indicates that the promotion effect of HSR opening on urban GTFEE is not disturbed by other concurrent policies or exogenous shocks, and the core conclusion remains robust.

5.3.5. Additional robustness checks

We further conducted a series of supplementary robustness tests across three dimensions: adjustment of the model estimation method, replacement of the measurement of the core explanatory variable, and elimination of extreme-value interference, to ensure the stability of the core conclusion. First, considering that the measured value of urban GTFEE was distributed in the range [0,1], which is a typical left- and right-censored limited dependent variable, the baseline fixed-effect model may be biased due to the truncated distribution of the explanatory variable. To address this concern, we adopted the two-limit panel Tobit model as an alternative estimation method to re-estimate the baseline specification. The regression result is reported in Column (1) in Table 7; it is consistent with the baseline conclusion. Second, we adjusted the measurement setting for GTFEE in the re-estimation: we replaced the original constant returns-to-scale assumption with a variable returns-to-scale assumption in the DNSBM efficiency measurement framework and recalculated the urban GTFEE accordingly. The regression result based on the re-measured GTFEE is shown in Column (2), where the promotion effect of HSR opening on GTFEE remained statistically significant. Furthermore, we adjusted the indicator composition of undesirable carry-over variables in the DNSBM model: we retained only CO_2 and CO_2 and $PM_{2.5}$ concentrations as the bad carry-over indicators, and recalculated GTFEE under the constant-returns-to-scale assumption for regression analysis. The results are presented in Columns (3–4), and the estimated HSR coefficient remained significantly positive. To mitigate the interference of extreme outliers in GTFEE on baseline estimation results, we adopted two outlier-processing methods: bilateral winsorization and bilateral truncation on the GTFEE variable at the 5th and 95th percentiles, respectively, and then re-ran the baseline regression. The results, shown in Columns (5–6), consistently confirm that HSR opening significantly improves urban GTFEE. Considering that the estimation results of the event study

Table 6. Robustness test IV

Variable	GTFEE				
	(1)	(2)	(3)	(4)	(5)
HSR	0.0155** (0.0060)	0.0151** (0.0062)	0.0153** (0.0062)	0.0153** (0.0062)	0.0125** (0.0060)
*HSR*dum*	−0.0019 (0.0162)	0.0087 (0.0108)	0.0099* (0.0059)	0.0039 (0.0099)	0.0536*** (0.0125)
_cons	0.6817*** (0.1243)	0.6816*** (0.1235)	0.6858*** (0.1231)	0.6796*** (0.1231)	0.6032*** (0.1216)
Control variables	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
n	5,035	5,035	5,035	5,035	5,035
R^2	0.570	0.570	0.571	0.570	0.576

Notes: Values in parentheses are heteroskedasticity-robust standard errors clustered at the city level. Column definitions: (1) Controlling for new energy vehicle subsidy pilot policy; (2) Controlling for energy conservation and emission reduction fiscal pilot policy; (3) Controlling for national high-tech zone construction policy; (4) Controlling for low-carbon city pilot policy; and (5) Controlling for 2008 financial crisis shock. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Abbreviations: FE: Fixed effect; GTFEE: Green total factor energy efficiency.

Table 7. Other robustness tests

Variable	GTFEE						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HSR	0.0154*** (0.0062)	0.0184*** (0.0056)	0.0182*** (0.0062)	0.0121* (0.0065)	0.0140*** (0.0047)	0.0134*** (0.0044)	0.0181*** (0.0065)
_cons	0.9391*** (0.1342)	0.5557*** (0.1146)	0.6339*** (0.1299)	0.3722*** (0.1200)	0.6275*** (0.1037)	0.6379*** (0.0992)	0.9873*** (0.1681)
Control variables	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
n	5,035	5,035	5,035	4,240	5,035	4,535	3,051
R^2	-	0.530	0.510	0.580	0.598	0.553	0.587

Notes: Values in parentheses are heteroskedasticity-robust standard errors clustered at the city level. Column definitions: (1) Two-limit panel Tobit model estimation, addressing the truncated distribution of GTFEE; (2) GTFEE recalculated under variable returns-to-scale assumption; (3) GTFEE recalculated with only CO_2 as undesirable output; (4) GTFEE recalculated with only CO_2 and PM2.5 as undesirable outputs; (5) GTFEE Winsorized at the 5th and 95th percentiles to exclude outliers; (6) GTFEE truncated at the 5th and 95th percentiles to exclude outliers; and (7) Robustness test with adjusted event study window width. $^*p < 0.10$, $^{***}p < 0.01$.
Abbreviations: FE: Fixed effect; GTFEE: Green total factor energy efficiency.

method are sensitive to the selection of event windows, this study again selected the three phases after the opening of the urban HSR as the window width for robustness testing. The empirical results are shown in Column (7), indicating that the opening of HSR still has a significant effect on improving urban GTFEE.

5.4. Heterogeneity analysis

5.4.1. Pilot policies for smart cities

We first conducted the test based on the smart city pilot policy attribute. The smart city pilot policy launched in 2012 in China promotes the deep application of digital technology and an intelligent governance model in urban operation, improves urban governance efficiency and green technology innovation investment, and provides a technical and institutional foundation for low-carbon transformation. We divided the research samples into smart-city pilot cities and non-pilot cities to conduct group regression and examine the heterogeneous impact of HSR opening on GTFEE. The estimation results are shown in Table 8. The promotion effect of HSR opening on GTFEE was significantly positive in the smart-city pilot cities, and the estimated coefficient was not significant in the non-pilot cities. The inherent logic of this heterogeneity lies in that smart-city construction empowers environmental governance efficiency through digital technology and builds a collaborative innovation platform for industry–university–research, providing sufficient capital, talent, and policy support for low-carbon technology R&D and achievement transformation. The factor flow convenience brought by HSR opening can further amplify this policy dividend, making the low-carbon promotion effect of HSR more prominent in pilot cities. During the construction of smart cities, active cooperation with enterprises and social parties ensures the supply of capital and knowledge required for urban low-carbon development, further strengthening the positive promoting effect of HSR opening on GTFEE improvement in the smart-city pilot cities.

5.4.2. Urban innovation activity

The development of urban GTFEE is closely related to technology, talent, funding, and other factors, and an active level of urban innovation can accelerate the emergence of new technologies. Therefore, we divided the level of urban innovation into two groups: low-innovation-level cities and high-innovation-level cities. The heterogeneity test results are shown in Table 8, where the estimated HSR coefficient was significantly positive only in high-innovation-level cities. In areas with higher levels of urban innovation, rapid technological iteration is already a characteristic, further strengthened by the opening of HSR. Green technology innovation enterprises can grow rapidly with the help of regional innovation infrastructure, thereby enhancing the urban GTFEE.

5.4.3. Differences in initial industrial structure

The higher the degree of upgrading of the urban industrial structure, the more solid the local foundation of the digital industry, and the easier it is to attract a concentration of clean industry and digital high-end talent, which, in turn, affects the net effect of urban HSR opening. Based on this, we measured the advanced level of local industrial structure by calculating the industrial structure hierarchy coefficient for each city and further dividing it into two groups: cities with low levels of industrial structure and cities with high levels of industrial structure. The heterogeneity test results, as shown in Table 8, demonstrated that the estimated coefficient of HSR was significantly positive only in cities with high levels of industrial structure. The possible reason is that cities with advanced industrial structures provide a more complete introduction, foundation, and application scenarios for the agglomeration of clean industries and the research and development of low-carbon technologies, thereby making the promotion of GTFEE by the opening of HSR more significant in the sample of cities with higher industrial structure levels.

5.5. Transmission mechanism test

5.5.1. Measurement of mechanism variables

Several measurements of mechanism variables were performed:

(i) Economic agglomeration level: We selected output density as the proxy variable, which can both reflect the economic output scale per unit geographical space and accurately capture the agglomeration intensity of urban economic activities. Specifically, this indicator was calculated as the ratio of the total added value of non-agricultural industries to the built-up area of the prefecture-level city.
(ii) Industrial structure upgrading: This variable measures the dynamic evolution process of the urban industrial system from a primary and secondary industry-dominated structure to a high value-added tertiary industry-dominated structure. In this study, the measure was the proportion of the tertiary industry's added value in the city's annual GDP.
(iii) Urban innovation level: We adopted the urban innovation index released in the 2017 *China Urban and Industrial Innovation Capacity Report*[40] as the proxy variable. This index comprehensively covers invention patents, utility model patents, and design patents, and assigns different weights according to the actual industrialization value of each patent, thereby

Table 8. Heterogeneity analysis

Variable	GTFEE					
	Smart-city pilot cities	Non-smart-city pilot cities	High-innovation-level cities	Low-innovation-level cities	Cities with high levels of industrial structure	Cities with low levels of industrial structure
HSR	0.0203** (0.0079)	0.0087 (0.0102)	0.0185** (0.0079)	0.0074 (0.0077)	0.0219*** (0.0080)	0.0107 (0.0081)
_con	0.4277** (0.1777)	0.9468*** (0.1653)	0.6483*** (0.1997)	0.8303*** (0.1386)	0.8930*** (0.1836)	0.6825*** (0.1660)
Control variables	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
p-value for the inter-group difference coefficient	0.080		0.050		0.050	
n	2,869	2,166	1,672	3,363	1,672	3,363
R^2	0.602	0.505	0.496	0.591	0.438	0.611

Notes: Values in parentheses are heteroskedasticity-robust standard errors clustered at the city level. The p-value for the inter-group difference coefficient was calculated using Fisher's combination test. $^{**}p < 0.05$, $^{***}p < 0.01$.
Abbreviations: FE: Fixed effect; GTFEE: Green total factor energy efficiency.

more accurately reflecting the actual innovation output level of prefecture-level cities.

5.5.2. Sobel–Goodman mediation tests

The empirical test results based on the Sobel–Goodman mediation effect are shown in Table 9. Column (1) indicates that the opening of urban HSR can significantly improve urban GTFEE. Column (2) demonstrated that HSR opening significantly promoted economic agglomeration (*Scale*) at the 1% level, confirming that the change of the mediating variable is driven by the policy shock. In Column (3), economic agglomeration had a significant positive impact on GTFEE at the 1% level, indicating that economic agglomeration significantly promotes urban low-carbon transformation. After controlling for economic agglomeration, the HSR coefficient decreased from 0.0153 to 0.0121, and the Sobel–Goodman test confirmed that the indirect effect was significant at the 1% level. The mediating effect of economic agglomeration accounted for 21.00% of the total effect of HSR on GTFEE, indicating that economic agglomeration is an important transmission channel for HSR to promote urban low-carbon transformation.

Column (4) shows that the HSR opening significantly promoted industrial structure (*Ind*) upgrading at the 1% level. The result in Column (5) shows that the industrial structure upgrading had a significant positive impact on urban GTFEE. After controlling for industrial structure upgrading, the HSR coefficient decreased to 0.0149, and the Sobel–Goodman test confirmed that the indirect effect was marginally significant at the 10% level. The mediating effect of industrial structure upgrading accounted for 2.88% of the total effect, indicating that industrial structure upgrading is another transmission channel for HSR to promote GTFEE.

The empirical results in Column (6) demonstrate that the HSR opening significantly promoted urban technological innovation (*Innov*) at the 1% level. According to the results in Column (7), technological innovation had a significant positive impact on urban GTFEE at the 1% level. After controlling for technological innovation, the HSR coefficient decreased to 0.0135, and the Sobel–Goodman test confirmed that the indirect effect was significant at the 1% level. The mediating effect of technological innovation accounted for 29.7% of the total effect, making it the most important transmission channel for HSR to promote urban GTFEE.

Table 9. Sobel–Goodman mediation test

Variable	GTFEE	Scale	GTFEE	Ind	GTFEE	Innov	GTFEE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HSR	0.0154** (0.0062)	0.3840*** (0.0497)	0.0121*** (0.0041)	0.3822*** (0.1025)	0.0149*** (0.0062)	0.3168*** (0.0200)	0.0135*** (0.0046)
Scale			0.0084*** (0.0012)				
Ind					0.0012*** (0.0006)		
Innov							0.0180*** (0.0035)
_cons	0.6807*** (0.1230)	3.0996*** (1.0132)	0.8146*** (0.0837)	14.9887*** (2.0908)	0.7787*** (0.0832)	7.7342*** (0.4229)	0.7019*** (0.0982)
Control variables	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Sobel			0.0032*** (5.1840)[a]		0.0004* (1.7470)[a]		0.0057*** (4.8390)[a]
Goodman−1 (Aroian)			0.0032*** (5.1600)[a]		0.0004* (1.7000)[a]		0.0057*** (4.8310)[a]
Indirect effect			0.0032*** (5.1837)[a]		0.00304* (1.7468)[a]		0.0057*** (4.8392)[a]
Proportion of the total effect that is mediated			21.00%		2.88%		29.72%
n	5,035	5,033	5,033	5,033	5,033	4,240	4,240
R^2	0.570	0.661	0.575	0.384	0.571	0.898	0.626

Notes: Values in parentheses are heteroskedasticity-robust standard errors clustered at the city level. [a] The corresponding z value. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Abbreviations: FE: Fixed effect; GTFEE: Green total factor energy efficiency.

5.6. Extended analysis: heterogeneous treatment effect test

This study employed the time-varying staggered DID framework to identify the causal effect of HSR opening on urban GTFEE. However, recent econometric studies have identified a non-negligible estimation bias in the staggered DID setting, namely heterogeneous treatment effects over time.[41,42] Specifically, when the policy implementation timing varies across units, the traditional TWFE estimator for staggered DID is essentially a weighted average of the estimation coefficients across all possible 2 × 2 DID comparison groups. Among these combinations, some comparisons treat earlier-treated units as the control group for later-treated units, which are referred to as “bad control groups” in existing methodological studies. If the policy effect presents dynamic heterogeneity with increasing treatment duration, such invalid comparisons will lead to biased TWFE estimates.

To examine whether the baseline estimation in this study is affected by heterogeneous treatment effect bias, we used the Goodman–Bacon decomposition method to decompose the TWFE estimations from the baseline model and calculated the average treatment effect and the corresponding weight for each 2 × 2 DID combination across different control group categories. The specific decomposition results are reported in Table 10. The average treatment effect estimated using “never-treated units” as the control group was 0.0108, and the average treatment effect estimated using “later-treated units” as the control group was 0.0130. These two types of “good control group” comparisons accounted for 98.16% of the total weight of all 2 × 2 DID combinations, and their estimated values were very close to the baseline TWFE estimate of 0.0154, indicating that most of the causal variations identified in the baseline regression come from valid comparison settings. In contrast, the average treatment effect estimated using "earlier-treated units" as the control group was 0.2007, but this invalid comparison accounted for only 1.84% of the total weight, with negligible impact on the overall weighted average treatment effect.

Table 10. Goodman–Bacon decomposition

2 × 2-DID control group type	ATE	Weight (%)
Never received the treatment	0.0108	49.66
Received the treatment later	0.0130	48.50
Received the treatment earlier	0.2007	1.84

Abbreviations: ATE: Average treatment effect; DID: Difference-in-differences.

To visually present the decomposition results, we plotted the coefficient size and corresponding weight of each 2 × 2 DID combination in Figure 5. The vertical axis represents the estimated coefficient of each 2 × 2 DID group, the horizontal axis represents the weight of each 2 × 2 DID coefficient in the overall TWFE estimator, and the horizontal dashed line refers to the weighted average of all 2 × 2 DID coefficients, that is, the baseline TWFE estimation result. As shown in the figure, the points corresponding to the "bad control group" comparisons are all located in the far-left area with extremely low weight, confirming that their contribution to the overall estimation is negligible. Moreover, the estimated coefficient for the "bad control group" was also positive, consistent with the baseline estimate's sign, further excluding the risk of sign bias from heterogeneous treatment effects. Overall, the Goodman–Bacon decomposition results indicate that the heterogeneous treatment effect problem is not severe in this study, and the baseline TWFE estimates are not affected by the staggered DID estimation bias, further verifying the robustness of the core conclusion that HSR opening significantly improves urban GTFEE.

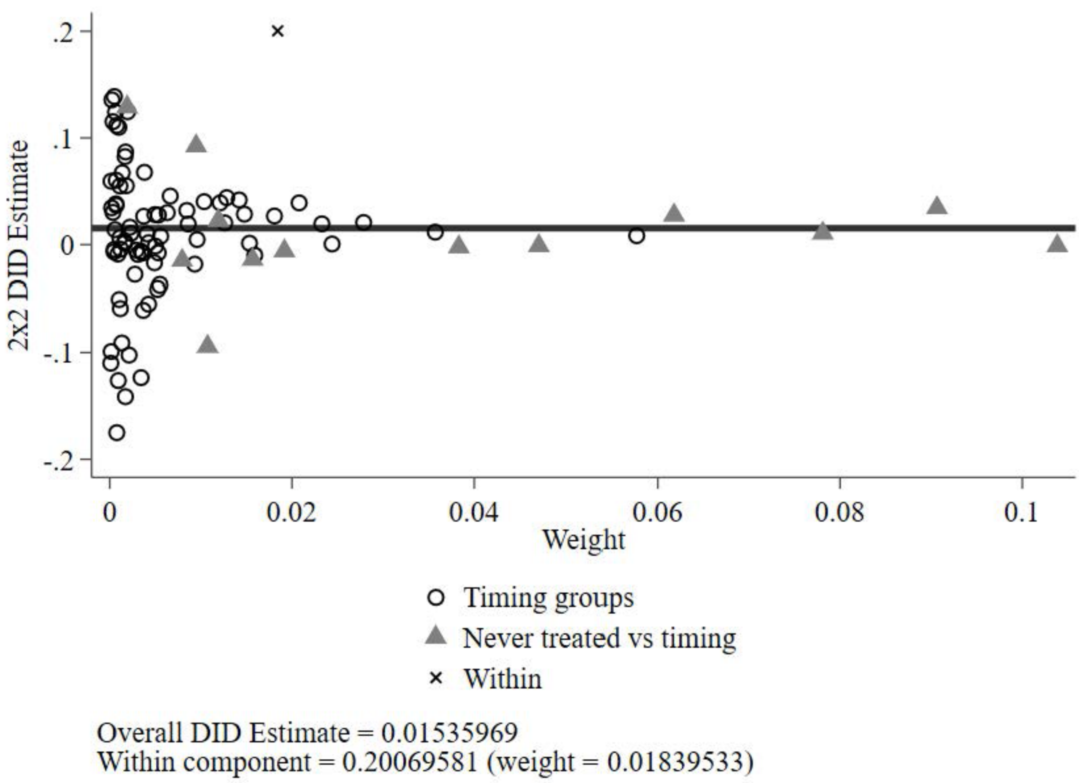

Figure 5. Goodman–Bacon decomposition results
Abbreviation: DID: Difference-in-differences.

6. Conclusion

The expansion of China's HSR network is a core policy instrument to support urban low-carbon transition and the national "double carbon" strategic targets. This study constructs a theoretical framework for the impact of HSR opening on urban GTFEE, clarifying three transmission mechanisms: economic agglomeration, industrial structure upgrading, and green innovation driving. We measured GTFEE using the DNSBM model incorporating inter-temporal link and carry-over variables, and adopted a time-varying staggered DID model for causal identification. The core findings are fourfold: (i) HSR opening exerts a significant positive effect on urban GTFEE, which remains robust after a series of tests; (ii) Heterogeneity analysis shows the promotion effect is more prominent in smart-city pilot cities, high-innovation-level cities, and cities with high levels of industrial structures; (iii) Mechanism tests confirm the validity of the three proposed transmission paths; and (iv) Goodman–Bacon decomposition shows the potential estimation bias of staggered DID is negligible, further supporting the robustness of baseline conclusions.

These findings provide three targeted policy implications: First, implement region-specific HSR construction policies and coordinate green industry guidance, innovation subsidies, and environmental assessment tools tailored to local resource endowments to unlock the green dividends of transport infrastructure. Second, take the HSR opening as an opportunity to guide the agglomeration of high-end manufacturing, producer services, and green technology enterprises along HSR routes, and to build cross-city green technology collaborative innovation platforms to accelerate low-carbon technology spillover and industrial upgrading. Third, optimize the overall HSR network layout, increase investment in underdeveloped regions with high low-carbon transformation potential, remove administrative barriers to cross-regional factor flows, and promote deeper integration of smart-city construction and HSR operation to achieve coordinated regional GTFEE improvement.

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Conflict of interest

The authors declare they have no competing interests.

Author contributions

Conceptualization: Lan Yu, Chunheng Fu
Formal analysis: Lan Yu, Chunheng Fu, Ting Yu
Methodology: Lan Yu, Ting Yu
Writing–original draft: Chunheng Fu, Ting Yu, Yuntao Wei
Writing–review & editing: Lan Yu, Chunheng Fu, Ting Yu, Yuntao Wei

Availability of data

Data may be obtained from the corresponding author upon reasonable request.

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Appendix

A1. The mathematical formula of the dynamic network slacks-based measure model

For the dynamic network slacks-based measure (DNSBM) model employed in this study, we assume a total of n decision-making units (DMUs), each corresponding to a prefecture-level city in our sample. Each DMU contains K internal sectors (sub-DMUs), and the analysis covers T time periods. In each period, assuming that the number of input and output factors in department k is m_k and r_k, respectively, representing the connecting variables between department k and department h, and the number of connecting variables is $L_{kh}\left(l=1,\ldots,L_{kh}\right)$, $z_{jk_l}^{(t,t+1)}$ representing the cross-period correlation of input factors in department k from the previous period to the current period and even the next period, where the number of cross-period variables is L_k. The production, research, and development activities of various sectors within the economy and neighboring economies across different periods are linked through connecting and inter-temporal variables.

We construct a balanced panel covering T periods for efficiency estimation. Consistent with our theoretical framework, each DMU is set to include two parallel sectors: a material production sector and a research and development (R&D) innovation sector. For the material production sector, we include total urban energy consumption as a current-period input indicator and real gross domestic product (GDP) as the desirable output indicator. Capital stock is set as a free carry-over variable, given its ambiguous and lagged impact on energy efficiency and pollution abatement. Undesirable by-products of production (including CO_2 and SO_2 emissions) are set as bad carry-over variables, as these pollutants are long-lasting and cannot be naturally degraded in the short term. For the R&D innovation sector, annual local government science and technology expenditure is set as the input indicator, and the total number of invention patents granted is set as the desirable output indicator. Total urban employment is set as a free-link variable that can be allocated freely between the material production and R&D innovation sectors.

We define x_{ijk}^t as the i-th input factor of sector k in DMU_j in period t; y_{rjk}^t as the r-th output factor of sector k in DMU_j in period t; $z_{j(kh)_l}^t$ as the link variable flowing from sector k to sector h in DMU_j in period t; and $z_{jk_l}^{(t,t+1)}$ as the carry-over variable of sector k in DMU_j transmitted from period t to period t+1, where L_k denotes the number of carry-over variables in sector k. The production possibility set $P^t=\left\{\left(X_k^t,Y_k^t,Z_{(kh)}^t,Z_{i_k}^{(t,t+1)}\right)\right\}\left(t=1,\ldots,T\right)$ is defined as follows:

$$x_k^t \geq \sum_{j=1}^{n} x_{jk}^t \lambda_{jk}^t,\left(\forall k;\forall t\right) \tag{A1}$$

$$y_k^t \leq \sum_{j=1}^{n} y_k^t \lambda_{jk}^t,\left(\forall k;\forall t\right) \tag{A2}$$

$$z_{(kh)}^t = \sum_{j=1}^{n} z_{j(kh)}^t \lambda_{jk}^t,\left(\forall\left(kh\right);\forall t\right) \tag{A3}$$

$$z_{(kh)}^t = \sum_{j=1}^{n} z_{j(kh)}^t \lambda_{jh}^t,\left(\forall\left(kh\right);\forall t\right) \tag{A4}$$

$$z_{l_k}^{(t,t+1)} = \sum_{j=1}^{n} z_{jl_k}^{(t,t+1)} \lambda_{jk}^t,\left(\forall l_k;\forall k;t=1,\ldots,T-1\right) \tag{A5}$$

$$z_{l_k}^{(t,t+1)} = \sum_{j=1}^{n} z_{jl_k}^{(t,t+1)} \lambda_{jk}^{t+1},\left(\forall l_k;\forall k;t=1,\ldots,T-1\right) \tag{A6}$$

$$\sum_{j=1}^{n} \lambda_{jk}^t = 1,\left(\forall k;\forall t\right);\lambda_{jk}^t \geq 0,\left(\forall j;\forall k;\forall t\right) \tag{A7}$$

where λ_{jk}^t denotes the weight vector for sector k of DMU_j in period t. For the target DMU_o under evaluation, the production constraints can be specified as:

$$x_{ok}^t = X_k^t \lambda_k^t + s_{ko}^{t-},\left(\forall k;\forall t\right) \tag{A8}$$

$$y_{ok}^t = Y_k^t \lambda_k^t - s_{ko}^{t+}, (\forall k; \forall t) \tag{A9}$$

$$e\lambda_k^t = 1(\forall k, \forall t) \tag{A10}$$

$$\lambda_k^t \geq 0, s_{ko}^{t-} \geq 0, s_{ko}^{t+} \geq 0, (\forall k; \forall t) \tag{A11}$$

where $X_k^t = \left(X_{1k}^t, \ldots, X_{nk}^t\right)$ and $Y_k^t = \left(Y_{1k}^t, \ldots, Y_{nk}^t\right)$ denote the input and output matrices, respectively; s_{ko}^{t-} and s_{ko}^{t+} denote the input slack (representing redundant inputs) and output slack (representing insufficient outputs) for DMU_o, respectively.

The setting of link variables and carry-over variables is the core feature of the DNSBM model. For free link variables that can be optimally allocated across sectors, the linkage constraint is specified as:

$$Z_{(kh)free}^t \lambda_h^t = Z_{(kh)free}^t \lambda_k^t \left(\forall (k,h) free, \forall t\right) \tag{A12}$$

In **Equation A12**, $Z_{(kh)free}^t = \left(z_{1(kh)free}^t, \ldots, z_{n(kh)free}^t\right) \in R^{L_{(kh)free} \times n}$ The values of link variables can be freely adjusted according to the optimal allocation of cross-sector factors. The corresponding slack constraint for free-link variables is:

$$z_{o(kh)free}^t = Z_{(kh)free}^t \lambda_k^t + s_{o(kh)free}^t \tag{A13}$$

where $s_{o(kh)free}^t \in R^{L_{kh}}$ denotes the slack of the free link variable between sector k and sector h for DMU_o. For carry-over variables transmitting across adjacent periods, the inter-temporal constraint is specified as:

$$\sum_{j=1}^{n} z_{jk_l\alpha}^{(t,t+1)} \lambda_{jk}^t = \sum_{j=1}^{n} z_{jk_l\alpha}^{(t,t+1)} \lambda_{jk}^{t+1} \left(\forall k, \forall k_l, t = 1, \ldots, T-1\right) \tag{A14}$$

In **Equation A14**, α represents two types of carry-over output relationships: bad and free. This constraint makes the economic activities in period t closely linked to those in period $t + 1$. For various carry-over variables, the production constraints are:

$$z_{ok_lbad}^{(t,t+1)} = \sum_{j=1}^{n} z_{jk_lbad}^{(t,t+1)} \lambda_{jk}^t + s_{ok_lbad}^{(t,t+1)} \left(k_l = 1, \ldots, nbad_k; k = 1, \ldots, K; t = 1, \ldots, T\right) \tag{A15}$$

$$z_{ok_lfree}^{(t,t+1)} = \sum_{j=1}^{n} z_{jk_lfree}^{(t,t+1)} \lambda_{jk}^t + s_{ok_lfree}^{(t,t+1)} \left(k_l = 1, \ldots, nfree_k; k = 1, \ldots, K; t = 1, \ldots, T\right) \tag{A16}$$

where $s_{ok_lbad}^{(t,t+1)}$ and $s_{ok_lfree}^{(t,t+1)}$ denote the slack of bad carry-over variables and free carry-over variables, respectively; $nbad_k$ and $nfree_k$ denote the number of bad carry-over variables and free carry-over variables in sector k, respectively. The definitions of core notations in the DNSBM model are summarized in Table A1.

We adopt the non-radial efficiency estimation framework (combining input-oriented and output-oriented adjustments) to calculate GTFEE. The overall efficiency of DMU_o is estimated by solving the following optimization problem:

$$\theta_o^* = min \frac{\sum_{t=1}^{T} W^t \{\sum_{k=1}^{K} w^k [1 - \frac{1}{m_k + linkfree_k + nbad_k} (\sum_{i=1}^{m_k} \frac{s_{iok}^{t-}}{x_{iok}^t} + \sum_{(kh)_l=1}^{linkfree_k} \frac{s_{o(kh)_l free}^t}{z_{o(kh)_l free}^t} + \sum_{k_l=1}^{nbad_k} \frac{s_{ok_lbad}^{(t,t+1)}}{z_{ok_lbad}^{(t,t+1)}})]\}}{\sum_{t=1}^{T} W^t \left\{\sum_{k=1}^{K} w^k \left[1 + \frac{1}{r_k + nfree_k} \left(\sum_{r=1}^{r_k} \frac{s_{rok}^{t+}}{y_{rok}^t} + \sum_{k_l=1}^{nfree_k} \frac{s_{ok_lfree}^{(t,t+1)}}{z_{ok_lfree}^{(t,t+1)}}\right)\right]\right\}} \tag{A17}$$

where W^t denotes the weight of period t, and w^k denotes the weight of sector k, satisfying $\sum_{t=1}^{T} W^t = 1$, $\sum_{k=1}^{K} w^k = 1$, $W^t \geq 0$, $w^k \geq 0$. The period-specific efficiency and sector-specific efficiency can be further derived as:

$$\tau_o^{t*} = \frac{\sum_{k=1}^{K} w^k \left[1 - \frac{1}{m_k + linkfree_k + nbad_k} \left(\sum_{i=1}^{m_k} \frac{s_{iok}^{t-}}{x_{iok}^t} + \sum_{(kh)_l=1}^{linkfree_k} \frac{s_{o(kh)_l free}^t}{z_{o(kh)_l free}^t} + \sum_{k_l=1}^{nbad_k} \frac{s_{ok_lbad}^{(t,t+1)}}{z_{ok_lbad}^{(t,t+1)}}\right)\right]}{\sum_{k=1}^{K} w^k \left[1 + \frac{1}{r_k + nfree_k} \left(\sum_{r=1}^{r_k} \frac{s_{rok}^{t+}}{y_{rok}^t} + \sum_{k_l=1}^{nfree_k} \frac{s_{ok_lfree}^{(t,t+1)}}{z_{ok_lfree}^{(t,t+1)}}\right)\right]}, (t = 1, \ldots, T) \tag{A18}$$

$$\delta_{ok}^{*}=\frac{\sum_{t=1}^{T}W^{t}\left[1-\frac{1}{m_k+linkfree_k+nbad_k}\left(\sum_{i=1}^{m_k}\frac{s_{iok}^{t-}}{x_{iok}^{t}}+\sum_{(kh)_l=1}^{linkfree_k}\frac{s_{o(kh)_l\,free}^{t}}{z_{o(kh)_l\,free}^{t}}+\sum_{k_l=1}^{nbad_k}\frac{s_{ok_lbad}^{(t,t+1)}}{z_{ok_lbad}^{(t,t+1)}}\right)\right]}{\sum_{t=1}^{T}W^{t}\left[1+\frac{1}{r_k+nfree_k}\left(\sum_{r=1}^{r_k}\frac{s_{rok}^{t+}}{y_{rok}^{t}}+\sum_{k_l=1}^{nfree_k}\frac{s_{ok_l\,free}^{(t,t+1)}}{z_{ok_l\,free}^{(t,t+1)}}\right)\right]},(k=1,...,K) \tag{A19}$$

Based on **Equations A17–A19**, by solving the optimal set, the non-radial optimal efficiency is defined as:

$$\rho_{ok}^{t*}=min\frac{1-\frac{1}{m_k+linkfree_k+nbad_k}\left(\sum_{i=1}^{m_k}\frac{s_{iok}^{t-}}{x_{iok}^{t}}+\sum_{(kh)_l=1}^{linkfree_k}\frac{s_{o(kh)_l\,free}^{t}}{z_{o(kh)_l\,free}^{t}}+\sum_{k_l=1}^{nbad_k}\frac{s_{ok_lbad}^{(t,t+1)}}{z_{ok_lbad}^{(t,t+1)}}\right)}{1+\frac{1}{r_k+nfree_k}\left(\sum_{r=1}^{r_k}\frac{s_{rok}^{t+}}{y_{rok}^{t}}+\sum_{k_l=1}^{nfree_k}\frac{s_{ok_l\,free}^{(t,t+1)}}{z_{ok_l\,free}^{(t,t+1)}}\right)},(k=1,...,K;t=1,...,T) \tag{A20}$$

If the optimal solution satisfies $\rho_{ok}^{t*}=1$, the DMU is deemed overall efficient under the non-radial framework, with all slacks equal to $s_{iok}^{t-}=0$, $s_{rok}^{t+}=0$, $s_{o(kh)_l\,free}^{t}=0$, $s_{ok_lbad}^{(t,t+1)}=0$, $s_{ok_l\,free}^{(t,t+1)}=0$. Similarly, if $\rho_{o}^{t*}=1$, the DMU is efficient in period *t*; if $\rho_{ok}^{*}=1$, the DMU is efficient in sector *k*. An overall efficient DMU is necessarily efficient in all periods and all sectors.

Table A1. Symbols and meanings of the dynamic network slacks-based measure model

Variable Category	Notation	Definition
Input variable	x_{ijk}^{t}	*i*-th input of sector *k* in DMU_j in period *t*
Output variable	y_{ijk}^{t}	*r*-th input of sector *k* in DMU_j in period *t*
Link variable	$z_{j(kh)l}^{t}$	link variable from sector *k* to sector *h* in DMU_j in period *t*
Carry-over variable	$z_{jkl}^{(t,t+1)}$	carry-over variable of sector *k* in DMU_j from period *t* to *t*+1
Weight	λ_{jk}^{t}	weight of sector k in DMU_j in period t
Input slack	s_{iok}^{t-}	*i*-th input slack of sector k in DMU_o in period *t*
Output slack	s_{rok}^{t+}	*r*-th output slack of sector *k* in DMU_o in period t
Link slack	$s_{o(kh)_l\alpha}^{t}$	slack of link variable between sector k and *h* in DMU_o in period *t*
Carry-over slack	$s_{ok_l\alpha}^{(t,t+1)}$	slack of carry-over variable of sector *k* from period *t* to *t* + 1