MOVING TOWARD SUSTAINABLE DEVELOPMENT: INFLUENCE OF HIGH-SPEED RAIL DEVELOPMENT ON THE URBAN-RURAL INCOME GAP FROM A LAND FACTOR PERSPECTIVE IN CHINA

SHI, H. Y.[1] – NAM, E.-Y.[2*]

[1]*Guizhou Communications Polytechnic University, Guiyang 551400, China*
(e-mail: 1202290068@jxufe.edu.cn)

[2]*Department of Global Trade, Dongguk University-Seoul, Seoul 04620, South Korea*

**Corresponding author*
e-mail: nanyinying@dgu.ac.kr; phone: +82-2-2260-3262

(Received 7th Sep 2025; accepted 23rd Dec 2025)

Abstract. While extensive research links the transportation infrastructure to reductions in the urban–rural income gap (URIG) in support of Sustainable Development Goal 10 (reduced inequalities), little attention has been paid to the underlying mechanisms related to land (e.g., land green use efficiency and land value). Using 3843 observations across 283 Chinese cities from 2008 to 2023, this study treats high-speed rail (HSR) openings as a quasi-natural experiment and employs a staggered difference-in-differences method to both estimate the effect of HSR development on the URIG and identify the role of land-related factors in the mechanism. Results showed that HSR development significantly narrows the URIG, primarily by improving land green use efficiency and raising land value. The effect is more pronounced in non-central cities and regions with greater HSR service accessibility (i.e., stronger intercity connectivity). These findings enrich the theory at the intersection of transportation, applied ecology, and environmental governance and provide useful insights for political decision-making.
Keywords: *transport infrastructure, regional inequality, land green use efficiency, land value, sustainability*

Introduction

Income inequality, a critical social issue, has drawn widespread attention from scholars, governments, and the public (Wei, 2015; Wei et al., 2017). In recent decades, income inequality, particularly the urban–rural income gap (URIG), has intensified in developing countries (Breau, 2015), posing a challenge to the global Sustainable Development Goals. Although China has achieved extraordinary economic growth over four decades of reform and opening-up, structural imbalances persist, with the URIG remaining a major concern. Data from China's National Bureau of Statistics (2023) indicate that the disposable income of urban residents is 2.39 times that of rural residents,[1] while the World Bank reports that this ratio in developed countries is below 1.5.[2]

According to the literature, the factors affecting the URIG can be classified as endogenous and exogenous. Endogenous factors are primarily related to economic growth, such as urban expansion (Zhong et al., 2022), urbanization (Su et al., 2015; Yuan et al., 2020), digital economy or digital technologies (Jiang and Jin, 2024; Shen et al., 2025; Wang et al., 2023b; Xia et al., 2024; Yin and Choi, 2022), and financial development (Liu et al., 2025; Wang et al., 2023a; Xu and Wang, 2023; Zheng et al.,

[1] https://www.stats.gov.cn/sj/zxfb/202401/t20240116_1946622.html.
[2] https://data.worldbank.org.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

2025). Exogenous factors include natural disasters (Cheng et al., 2025; Lin and Wang, 2024) and government policy interventions, such as energy transitions (Gao et al., 2023), rural revitalization (Tan et al., 2025), and poverty alleviation programs (Tang et al., 2022; Zhou et al., 2023). In addition to these key factors, transportation infrastructure development is frequently cited as an important explanation for the URIG (Li et al., 2023; Lu et al., 2022; Sun et al., 2025), with high-speed rail (HSR) development being a notable example (Jia et al., 2024; Liu and Lin, 2025). China's exploration of HSR began in the 1990s, building experience through quasi-HSR upgrades on the Guangzhou–Shenzhen line and speed-increase pilots on major corridors. The Qinhuangdao–Shenyang Passenger Line, which opened in 2003 with a design speed of 250 km/h, served as a pivotal quasi-HSR experiment. The Beijing–Tianjin Intercity Railway, launched in 2008 with a 350 km/h design speed, marked the formal start of China's HSR era. Since then, the network has expanded rapidly. Given this, we plot *Figure 1* to depict the spatial distribution of China's HSR network.

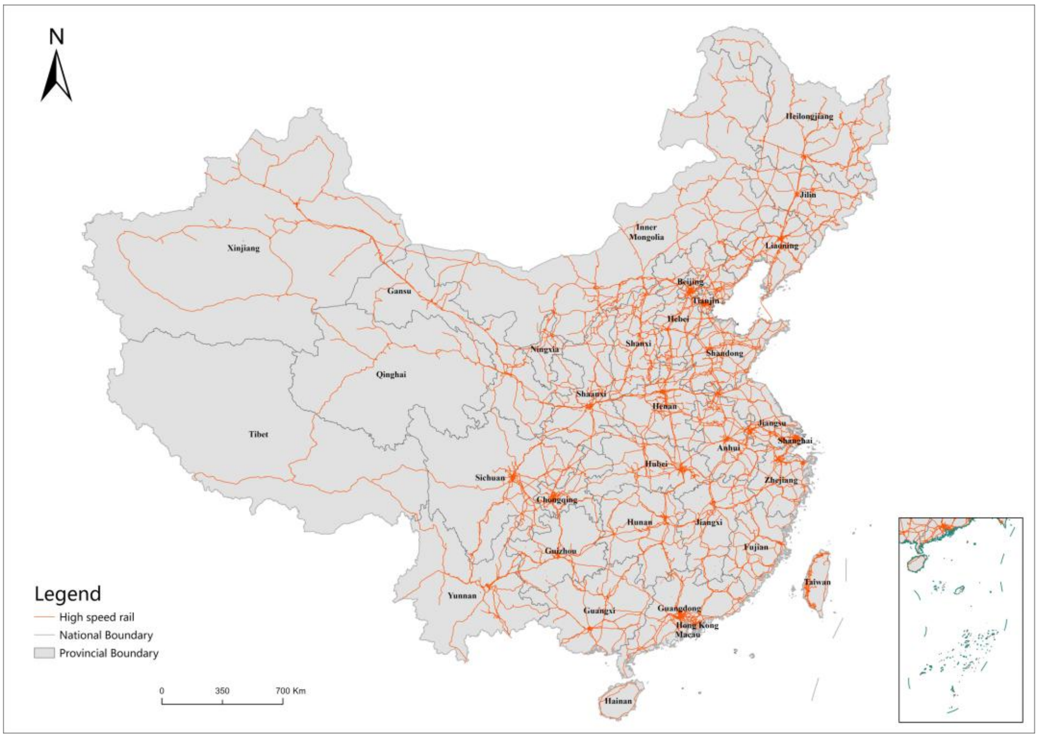

***Figure 1.** Spatial distribution of the high-speed rail network. Data sourced from the China State Railway Group and processed by the authors using OpenQGIS (www.openstreetmap.org)*

As China's HSR expanded, its definitions and technical standards were progressively clarified. The National Railway Administration's Code for Design of High-Speed Railway defines HSR as newly built, standard-gauge passenger-dedicated lines designed for 250–350 km/h and operated with electric multiple unit trains.[3] In addition, to support an integrated transport network, the National Development and Reform Commission's Medium- and Long-Term Railway Network Plan broadens its scope: Lines operating at 200 km/h or above—including upgraded legacy corridors—are

[3] https://www.doc88.com/p-91173405929498.html.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

incorporated into the HSR network to accommodate regional transport needs and heterogeneous development levels.[4]

However, the impact of HSR development on the URIG remains contested. Some scholars argue that the introduction of HSR development has reduced the URIG (Jin et al., 2024; Li and Zhang, 2024; Liu and Lin, 2025; Wang et al., 2024). Others hold the opposite view, suggesting that HSR development exacerbates the URIG (Jia et al., 2024; Sun et al., 2023; Xu and Zhu, 2024; Yoo et al., 2024). These disagreements motivate the key research question (RQ) of this study:

RQ1: Does HSR development narrow the URIG?

Additionally, prior work largely agrees that HSR affects the URIG through human capital (Kong et al., 2024; Sun et al., 2023; Xu and Zhu, 2024), employment structure (Di Matteo and Cardinale, 2023; Li and Zhang, 2024), industrial upgrading (Jin et al., 2024; Liu and Lin, 2025), travel accessibility (Li et al., 2023; Wang et al., 2024), and financial capital (Liu and Lin, 2025; Xu and Zhu, 2024). Yet, land-based mechanisms remain underexplored. In fact, HSR construction reshapes urban land use (Chen et al., 2021; Wenner and Thierstein, 2022). It converts agricultural land to urban uses (Yu et al., 2022), reallocates land resources (Lu and Li, 2025; Niu et al., 2021), and shifts land value (Jiao et al., 2025; Okamoto and Sato, 2021; Wu et al., 2024). For example, Yoo et al. (2024) show that, from 2000 to 2019, Japan's HSR raised urban land prices by 39.38% and lowered rural land prices by 21.13%. Despite this evidence, the literature has not identified how land-use and land-value changes mediate the HSR–URIG link. Particularly, China's rapid buildout of transport infrastructure—exemplified by the 2008 opening of the Beijing–Tianjin Intercity HSR—marked a major milestone that substantially reshaped the country's land structure. This leads to the second RQ of this study:

RQ2: Do land factors (e.g., land green use efficiency and land value) play a critical role in the effect of HSR development on the URIG?

The RQs above remain unanswered and warrant further empirical inquiry. To address this gap, we utilize panel data from 283 Chinese cities from 2008 to 2023 and apply a staggered difference-in-differences (DID) approach, leveraging the "HSR opening" in China as a quasi-natural experiment. The substantial cross-city variation in the "HSR opening" years provides a unique identification mechanism for this method design. Within this framework, we first investigated the direct influence of HSR development on the URIG. We find that HSR development could really narrow the URIG. Specifically, a 1% increase in HSR development reduces the URIG by 0.4%. These results remain robust after a battery of checks. Second, focusing on land-related mechanisms, we test whether land green use efficiency and land value mediate this relationship. We show that HSR development significantly improves land green use efficiency and raises land value in HSR-served cities, thereby narrowing the URIG. Third, we further document heterogeneity by city type and HSR service accessibility. The URIG-reducing effect of HSR is stronger in cities with non-central and higher HSR service accessibility.

This study makes three key contributions: First, it explores how changes in land green use efficiency and land value driven by HSR development influence the URIG, contributing new insights to the applied ecology field. Unlike prior studies that focus on industrial upgrading (Jin et al., 2024; Liu and Lin, 2025), human capital spillovers (Kong et al., 2024; Sun et al., 2023; Xu and Zhu, 2024), and financial capital (Liu and Lin, 2025;

[4] https://www.ndrc.gov.cn/fggz/zcssfz/zcgh/201607/W020190910670620449319.pdf.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

Xu and Zhu, 2024) as mechanisms linking HSR development and the URIG, this study innovatively examines the role of land-related factors.

Second, we introduce a context-driven innovative perspective, focusing on heterogeneity by city type (core vs. non-core) and regional HSR service accessibility, to inform differentiated HSR investment strategies. This perspective departs from prior studies that examine heterogeneity across China's eastern, central, and western regions (Sun et al., 2023), across city tiers (Liu and Lin, 2025; Sun et al., 2023), or across industries (Jin et al., 2024; Zhang et al., 2022).

Third, our methodology delivers credible evidence to resolve debates in the literature. We employ a staggered DID method and conduct extensive robustness checks, with a focus on treatment-effect heterogeneity in staggered DID. Cities with HSR openings at different times may receive varying weights, potentially biasing the results. As De Chaisemartin and D'Haultfoeuille (2020) note, this method essentially builds a two-way fixed-effects (TWFE) model to estimate the average treatment effect. We test for heterogeneous treatment effects in the staggered DID and add a suite of validations: parallel-trends tests, placebo tests using simulated HSR opening dates, exclusion of special samples, and an alternative dependent variable. All results consistently show that HSR development narrows the URIG, ensuring robustness and reliability.

The remainder of the paper is structured as follows. The Theory and Hypotheses section lays out the conceptual framework and research expectations. The methodology section explains the data sources, variable declaration, and empirical model. The Results and Discussion section analyzes and discusses the empirical findings. The Conclusion and Policy Recommendations section summarizes the study and offers policy advice.

Theory and hypotheses

HSR development and URIG

Transportation systems profoundly affect income distribution by transforming the economic geography and influencing outcomes (Li and DaCosta, 2013). Prior studies examine these impacts extensively (Huang et al., 2020; Lu et al., 2022). HSR, as one of the fastest-growing transportation modes, can offer speed, punctuality, and comfort, facilitating more efficient connections between cities and playing an increasingly vital role in intercity transportation. China has constructed the largest HSR network in the world over the past decade. Its high speed and density have generated a profound time-space compression effect, transforming spatial accessibility and urban transportation. This has enhanced the movement of people, commodities, and information, boosting the economic power of regions along HSR routes and accelerating economic integration (Zheng et al., 2019; Zheng and Kahn, 2013). Consequently, the association between HSR development and the URIG has garnered substantial research attention. For instance, studies find that HSR alleviates regional inequality by improving accessibility in underdeveloped areas (Li et al., 2023; Wang et al., 2024). Compared to air transportation, HSR connects more cities along its routes, enhancing the accessibility of local and surrounding areas. One characteristic of HSR development in China is the location of HSR stations, with most stations constructed in urban–rural fringe areas. This choice is driven by two factors: first, building stations in relatively remote areas reduces development costs; second, with rapid urbanization and ongoing city expansion, constructing HSR stations in suburban areas promotes urban growth. The establishment of HSR stations creates jobs in suburban regions that link rural and urban economies,

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

positively impacting residents' wages (Liu and Yang, 2023). This raises rural workers' income from urban jobs, narrowing the URIG. Similarly, Li and Zhang (2024) find that HSR introduces additional job options for rural inhabitants, indirectly reducing urban–rural disparities. Thus, to directly answer RQ1, we propose the following hypothesis:

H1. HSR development narrows the URIG.

HSR development, land green use efficiency, and URIG

HSR stations often anchor new urban nodes, triggering spatial reconfiguration and land-use redesign in adjacent areas (Gong and Li, 2022; Lu and Li, 2025; Wenner and Thierstein, 2022). Planners commonly rezone these precincts for commercial, residential, or mixed uses (Yu et al., 2022). These reallocations do more than intensify development; they optimize the structure, function, and environmental performance of urban land. By creating well-connected public spaces and infrastructure, they lower transaction and coordination costs; support effective fiscal decentralization; and strengthen the legitimacy, efficiency, and equity of green land-use and public land strategies (Yilmaz and Bilim, 2024).

Critically, HSR-induced restructuring raises land-use density where appropriate and channels development toward transit-proximate areas. This, in turn, enables the conversion and ecological upgrading of underutilized or low-productivity parcels into parks, green corridors, and other ecosystem-serving spaces. Such measures enhance land green use efficiency by delivering more economic and social output per unit of land and energy while reducing environmental externalities. Previous empirical evidence shows that HSR operations increase urban land-use intensity by roughly 4.4%, and upgraded HSR stations generate stronger green land-use gains than newly built ones (Niu et al., 2021). Cross-country evidence in Europe shows that stations nearer to urban cores and better integrated with public transit see larger improvements in land green use efficiency (Wenner and Thierstein, 2022). Similarly, opening of an HSR line in California shifted the surrounding land toward higher-value, transit-compatible uses, improving land green use efficiency (Wang et al., 2017).

Improvements in land green use efficiency propagate through local and regional economies. Higher-density, mixed-use, and transit-accessible environments raise commercial activity and housing demand, attracting private investment to HSR-adjacent districts (Haoran et al., 2022). These gains extend these effects into suburbs and nearby rural areas, facilitating the coordinated integration and ecological restoration of rural land resources (Yin et al., 2020). This integrated development links rural residents to urban labor markets, broadens employment choices, and supports diversification of rural economies (Li and Zhang, 2024). As rural incomes rise and regional consumption and investment deepen, the URIG narrows. Thus, to explore the land green use efficiency mechanism posed in RQ2, we posit the following hypothesis:

H2. HSR development narrows the URIG by improving land green use efficiency.

HSR development, land value, and URIG

Opening of HSR not only enhances a city's locational attractiveness but also triggers significant fluctuations in land prices along its routes. The "siphoning effect" is a key mechanism by which HSR networks influence land prices (Wu et al., 2024). For example, Yoo et al. (2024) observe that HSR expansion increased urban land prices by 39.38%. Similarly, Huang and Du (2021) demonstrate that HSR positively impacts land prices, with stronger effects observed in cities with higher population density, greater reductions in travel time, and more pronounced spatial fragmentation. Okamoto and Sato (2021) also confirm this through their study on the Kyushu Shinkansen in Japan, which shows that metropolitan areas benefited from HSR, experiencing significant land price increases. HSR stations are often located in suburban areas in China, acting as hubs for new urban development (Diao et al., 2017). Local governments actively attract HSR investment and develop new districts around stations, aiming to sell land at higher prices and increase land transfer revenue (Chang and Murakami, 2019). HSR stations maximize the geographic and time accessibility of these areas and influence real estate developers who are willing to pay a premium to acquire land in proximity to HSR stations (Chen and Haynes, 2015). Moreover, previously remote or inaccessible rural areas benefit directly from improved accessibility after HSR station construction. This increases the use value and commercial potential of rural land, enabling farmers to earn higher incomes by selling or leasing their land (Chang et al., 2022), thereby balancing income levels between urban and rural regions. Accordingly, to investigate the land-value mechanism in RQ2, we propose the following hypothesis:

H3. HSR development narrows the URIG by raising land value.

Methodology

Empirical model

Baseline model

To test H1, we use “HSR opening” as an exogenous policy shock in a quasi-natural experiment. This technique is justified by the staggered schedule of HSR openings across Chinese cities, which lacked a uniform starting point. Among the eight sampled prefecture-level cities—including Shenyang, Hefei, and Nanjing—were the first to open HSR lines in 2008. Since then, the HSR network has rapidly expanded. In other words, HSR openings in China occurred incrementally on an annual basis. *Figure 2* describes the changes in the length of China’s HSR network from 2008 to 2023. Specifically, the total length of HSR lines increased from 1043.5 km in 2008 to 64163.281 km in 2023, reflecting an average annual growth of more than 3900 km. The most notable surge occurred after 2013, when the network length surpassed 20,000 km and continued to accelerate.

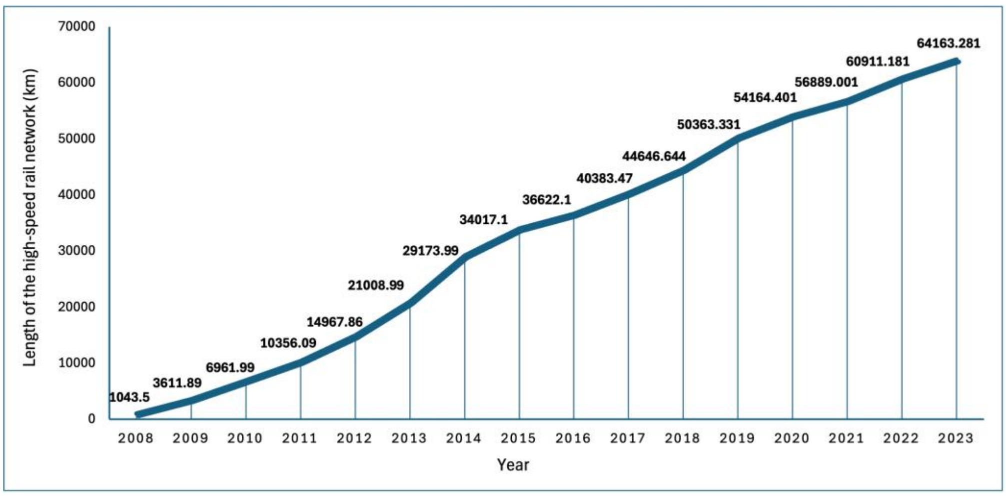

Figure 2. *Changes in the length of the high-speed rail network in China from 2008 to 2023. Data sourced from China State Railway Group by the authors*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

Furthermore, HSR construction was part of a national strategic plan, beyond the control of local governments (Wang et al., 2019). This unique data structure allows us to consider HSR openings as a “quasi-natural experiment.” Following Qing et al. (2025) and Jin et al. (2022), we use a staggered-DID method, fundamentally a TWFE model (*Eq. 1*), to ascertain the causal impact of HSR development on the URIG.

$$URIG_{ct} = \alpha + \beta DID_{ct} + \lambda Controls_{ct} + \sum Year + \sum City + \varepsilon_{ct} \qquad \text{(Eq.1)}$$

where c denotes the city and t signifies the year. $URIG$ is the core dependent variable that quantifies the income gap between urban and rural regions. DID is the key independent variable, a dummy for HSR opening. If a prefecture-level city has an HSR station, it is considered to have HSR access and assigned a value of 1, categorizing it as the treatment group. Cities without HSR access are classified as the control group and assigned a value of 0. β is the primary interest coefficient. $Controls$ represents a set of control variables. ε denotes the random error component, whereas α signifies the constant term. $Year$ and $City$ represent year and city fixed effects, respectively, which absorb the time- and location-specific heterogeneity and together constitute the TWFE structure of our staggered-DID estimator. In addition, to address heteroskedasticity and potential autocorrelation within cities across time, we apply cluster-robust standard errors at the city level.

Mediation model for mechanism analysis

To test H2 and H3, we follow the approach of Qing et al. (2024): we replace the dependent variable in *Equation 1* with the mechanism variable ($Mechanism_{ct}$) and employ the mediation model (*Eq. 2*) to examine the mechanisms, including land green use efficiency and land value:

$$Mechanism_{ct} = \alpha + \beta DID_{ct} + \lambda Controls_{ct} + \sum Year + \sum City + \varepsilon_{ct} \qquad \text{(Eq.2)}$$

where $Mechanism_{ct}$ includes land green use efficiency and land value. All other variables follow the definitions in *Equation 1*.

Variables declaration

Independent variable: HSR development

Following Jin et al. (2022), we treat “HSR opening” as an exogenous policy shock and measure the core independent variable—HSR development—using a dummy variable approach, denoted as HSR_DID. The assignment of values to the DID variable is as follows: Cities are coded 1 in the treatment year of the first HSR opening and in all subsequent years; cities without an opening are coded 0 as controls. Classification of whether a city has HSR access is based on the earliest year of HSR operation in that city.[5] If the HSR line opened before July of a given year, it is considered operational for that year. If it opened after July, it is considered operational starting the following year.[6] *Figure 3* shows the trend of the proportions of cities marked as HSR or non-HSR. The

[5] If any county (district or city) under a city has an HSR station, the city is considered to have HSR access.
[6] For example, the Wuhan-Guangzhou HSR opened in December 2009. We classify cities along this route with HSR access for the first time as having opened HSR in 2010.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

number of cities with HSR service (blue bars) rises sharply and persistently, increasing from 34 in 2008 to 270 in 2023. Conversely, the number of cities without HSR (orange bars) declines markedly and continuously, falling from 249 in 2008 to 13 in 2023. These patterns indicate that China's HSR network now covers the vast majority of sample cities. Additionally, the crossover—when HSR cities outnumber non-HSR cities—occurs in 2014, marking a pivotal year in the network's expansion.

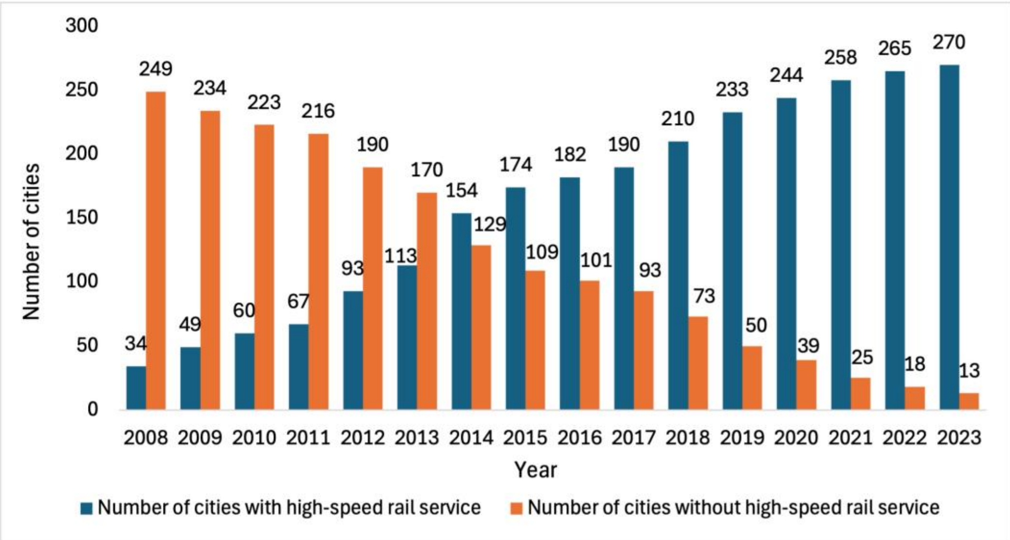

Figure 3. *Trend of the proportions of the cities marked as high-speed-rail or non- high-speed-rail cities. Data sourced from the China State Railway Group by the authors*

Dependent variable: URIG

Scholars often measure the URIG using indicators such as the Gini coefficient (Molero-Simarro, 2017), urban–rural disposable income ratio (Yang, 2023), and Theil index (Fang et al., 2023; Tang et al., 2022). Among these, the Theil index, introduced by econometrician Theil in 1967, is a widely used measure to assess income disparities (or economic inequality) between individuals or regions. Its calculation is based on income ranking or population classification, comparing disparities between any two income intervals. The Theil index captures absolute changes in both urban–rural income and population, offering significant advantages (Schneider, 2021). Consequently, in accordance with Wang et al. (2024), we employ the Theil index to assess the URIG, as detailed in *Equation 3*:

$$Theil_{it} = \sum_{j=1}^{n} \frac{P_{jit}}{P_{it}} ln\left(\frac{P_{jit}}{P_{it}} / \frac{Z_{jit}}{Z_{it}}\right) \quad \text{(Eq.3)}$$

where t reflects the year, and i denotes the region. The Theil index, denoted as $Theil$, shows that a larger value signifies a greater level of URIG. $n = 2$, and $j = 1,2$ represents urban and rural regions, respectively. P_{jit} denotes the disposable income of urban inhabitants ($j = 1$) or rural people ($j = 2$) in region i during year t. P_{it} denotes the aggregate disposable income, including urban and rural, in region i for year t. Z_{jit} denotes the number of urban or rural inhabitants ($j = 1, j = 2$) in region i during year t, whereas Z_{it} signifies the aggregate urban and rural population in region i during year t.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

Moreover, we plot *Figure 4* to visualize the trends in the heterogeneity between the rural and urban income gap (based on the Theil index) across sample cities from 2008 to 2023. Overall, both the treatment and control groups exhibit a declining URIG, yet clear between-group heterogeneity persists: the gap in the treatment group remains consistently lower than in the control group. This trend suggests that macroeconomic conditions or policies may have curbed the expansion of urban–rural inequality, providing visual support for our subsequent assessment of HSR openings' effects on the URIG.

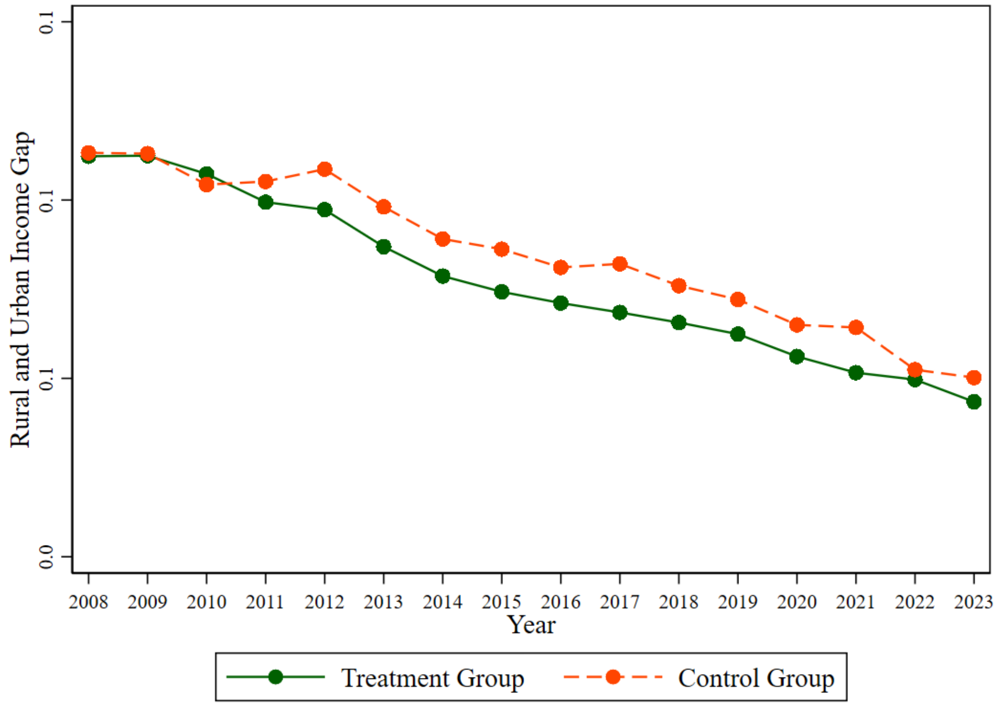

Figure 4. *The trends in the heterogeneity between the rural and urban income gap*

Mechanism variables

(1) Land green use efficiency ($Land\_efficiency$). Land green use efficiency represents the association between inputs—land, capital, and labor—and outputs, including economic, social, and ecological benefits under specific production conditions. Its core is to maximize target outputs with minimal input and the lowest pollution costs (Ferreira and Féres, 2020). First, based on data availability and representativeness, and following Li et al. (2025), Qian and Luo (2024), and Zhang et al. (2024), this study develops an evaluation index system for land green use efficiency (see *Appendix*). Inputs include land, capital, and labor, while outputs cover desirable and undesirable outcomes. Specifically, land input is measured by urban construction land area, and capital input is determined by the perpetual inventory technique to transform fixed asset investment into capital stock. Labor input refers to employees in secondary and tertiary industries. Desirable outputs are proxied by the gross domestic product, while undesirable outputs are measured by urban carbon emissions and energy consumption, respectively. To reduce biases and outliers, all indicator data are transformed logarithmically.

Second, following Zhang et al. (2024), we use the super-efficient slacks-based measure (SBM) model to measure land green use efficiency, denoted as $Land\_efficiency$. The

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

non-radial, non-oriented SBM method, introduced by Tone (2001), addresses input excess and output shortfalls. Unlike traditional radial models, it not only incorporates proportional radial improvements between decision-making units (DMUs) and frontier target values but also addresses slack and non-radial improvement issues, providing strong efficiency discrimination (Hao et al., 2022). The SBM technique addresses the efficiency overestimation issue inherent in standard radial data envelopment analysis (DEA) models—including the Banker, Charnes, and Cooper; Charnes Cooper, and Rhodes; and basic directional distance function models—by considering slack variables. Therefore, the super-efficiency SBM-DEA model resolves the ranking issue among efficient DMUs in traditional DEA. It differentiates DMUs with efficiency scores greater than 1 and yields a more precise measure of land green use efficiency. The computation follows *Equations 4* and *5*:

$$\rho = min \frac{1-\frac{1}{m}\times\sum_{i=1}^{m}\frac{s_i^-}{X_0}}{1+\frac{1}{S1+S2}\times\left(\sum_{r=1}^{S_1}\frac{s_r^g}{Y_{y_{r0}}^g}+\sum_{k=1}^{S_2}\frac{s_k^b}{Y_k^b}\right)} \ (i = 1,2,\dots,m; r = 1,2,\dots,S_1; k = 1,2,\dots,S_2) \quad \text{(Eq.4)}$$

$$\text{Subject to} \begin{cases} X_0 = X \times \lambda + S^- \\ Y_0^g = Y^g \times \lambda - S^g \\ Y_0^b = Y^b \times \lambda + S^b \\ S^- \geq 0, S^g \geq 0, S^b \geq 0 \\ i = 1,2,\dots,m; r = 1,2,\dots,S_1; k = 1,2,\dots,S_2 \end{cases} \quad \text{(Eq.5)}$$

where ρ denotes each city's land-use efficiency, while m is the number of input indicators. S_1 and S_2 represent the quantities of desired and undesired output indicators, respectively. S^- and X_i denote input slacks and input variables, respectively. S_r^g and Y_r^g represent shortfalls in desired outputs and corresponding desired output variables, while S_k^b and Y_k^b indicate excesses in non-desired outputs and their associated variables, respectively. λ is the weight vector. X_0, Y_0^g, and Y_0^b are the actual values of input, desired-output, and non-desired-output variables for the DMUs, respectively. Additionally, X, Y^g, and S^g denote the estimated inputs, desired outputs, and undesired outputs required by the DMUs, respectively. S^-, S^g, and S^b are the observed input slacks, desired-output shortfalls, and undesired-output excesses for the DMUs, respectively.

(2) Land value ($Land\_value$). We follow the methodology of Huang and Du (2021) and use the logarithm of land transfer fees as a proxy for land value. Land transfer fees refer to payments collected by the government when granting land-use rights to developers. These fees reflect the market value of land, influenced by factors such as supply and demand, land location, availability, and expected usage. The level of land transfer fees directly indicates the economic value of the land and the market's assessment of specific parcels. Compared to other land value measurement methods, land transfer fees are typically recorded and published by local governments during public market transactions, such as on the China's Land Market website (http://www.landchina.com/). This makes the data easily accessible, highly reliable, and standardized.

Control variables

Beyond the focus on HSR development, numerous factors may contribute to widening or narrowing the URIG. Following Sun et al. (2023), we include several city-level control

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

variables: city size ($size$), economic development level ($lnpgdp$), industrial structure ($struct$), openness level ($open$), financial development (fin), urbanization level (urban), unemployment rate ($unemploy$), and government intervention (gov). *Table 1* summarizes the measurements of all variables.

Table 1. *Description of variables*

Variables	Name	Symbol	Description	Data sources
Independent	High-speed rail (HSR) development	HSR_DID	Cities are coded 1 in the treatment year of the first HSR opening and all subsequent years; cities without an opening are coded 0 as controls	Official website of the China State Railway Group (http://www.china-railway.com.cn/), National Railway Administration announcements, news reports (http://www.nra.gov.cn/), and the 12306 website (https://www.12306.cn/index/)
Dependent	Urban-rural income gap	$URIG$	Refer to *Equation 3*	*China Urban Statistical Yearbook (2009–2024)*, *China Rural Statistical Yearbook (2009–2024)*, and *Statistical Communique on National Economic and Social Development (2009–2024)*
Mechanisms	Land green use efficiency	$Land\_efficiency$	It is measured by the super-efficient slacks-based measure model	*Urban and Rural Construction Statistical Yearbook (2009–2024)*, *China Statistical Yearbook (2009–2024)*, *China Energy Statistical Yearbook (2009–2024)*, and Emissions Database for Global Atmospheric Research
	Land value	$Land\_value$	$Ln(land\ transfer\ fees)$	China Land Market Network (https://www.landchina.com), *China Land and Resources Statistical Yearbook (2009–2024)*, *China Land and Resources Yearbook (2009–2024)*, and official websites of various prefecture-level cities
Controls	City size	$size$	$Ln(urban\ registered\ population)$	*China Urban Statistical Yearbook (2009–2024)* and the National Bureau of Statistics
	Economic development level	$lnpgdp$	$Ln(per\ capita\ gross\ domestic\ product)$	
	Industrial structure	$Instruct$	$\frac{\text{Added value of the tertiary industry}}{\text{Added value of the second industry}}$	
	Openness level	$open$	$\frac{Actual\ foreign\ direct\ investment}{Regional\ gross\ domestic\ product}$	
	Financial development	fin	$\frac{Loan\ balances\ of\ financial\ institutions}{Gross\ domestic\ product}$	
	Urbanization level	$urban$	$\frac{Non-agricultural\ population}{Registered\ population}$	
	Unemployment rate	$unemploy$	$\frac{Unemployed\ urban\ population}{Total\ population}$	
	Government intervention	gov	$\frac{Local\ fiscal\ general\ budget\ expenditure}{Regional\ gross\ domestic\ product}$	

Samples and data sources

We ascertain the causal impact of HSR development on the URIG, based on a panel dataset of 3,843 observations from 283 cities in China spanning 2008 to 2023. Cities with

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

substantial missing data within this time frame are excluded. Data on the URIG are sourced from the *China Urban Statistical Yearbook (2009–2024)*, *China Rural Statistical Yearbook (2009–2024)*, and *Statistical Communique on National Economic and Social Development (2009–2024)*. HSR data are collected from the official website of the China State Railway Group,[7] National Railway Administration announcements, news reports,[8] and the 12306 website.[9] Data on land green use efficiency are derived from the *Urban and Rural Construction Statistical Yearbook (2009–2024)*, *China Statistical Yearbook (2009–2024)*, *China Energy Statistical Yearbook (2009–2024)*, and Emissions Database for Global Atmospheric Research. Land value data are compiled from the *China Land Market Network* (https://www.landchina.com), *China Land and Resources Statistical Yearbook (2009–2024)*, *China Land and Resources Yearbook (2009–2024)*, and official websites of various prefecture-level cities. Control variables are extracted from the *China Urban Statistical Yearbook (2009–2024)* and National Bureau of Statistics. Missing data for certain cities are supplemented using interpolation. *Table 2* reports the descriptive statistics.

Table 2. *Descriptive statistics*

Variables	Obs	Mean	SD	Min	p25	p50	p75	Max
URIG	3843	0.077	0.046	0.006	0.044	0.067	0.102	0.234
HSR_DID	3843	0.578	0.494	0	0	1	1	1
size	3843	5.909	0.654	3.991	5.528	5.941	6.375	7.238
lnpgdp	3843	10.66	0.734	9.022	10.16	10.61	11.13	12.47
struct	3843	1.042	0.549	0.300	0.681	0.915	1.235	3.443
open	3843	0.002	0.003	0	0	0.002	0.004	0.012
fin	3843	2.519	1.187	0.929	1.671	2.221	3.030	6.752
urban	3843	0.390	0.207	0.105	0.234	0.335	0.505	0.991
unemploy	3843	3.096	0.807	1.200	2.490	3.130	3.710	5.020
gov	3843	0.192	0.093	0.070	0.129	0.168	0.227	0.600

Results and discussion

Baseline regression

We use a sequential regression to evaluate HSR's impact on the URIG, with findings displayed in *Table 3*. Column (1), without controls and fixed effects, yields a large negative effect of HSR development on the URIG (coefficient = -0.043, $p < 0.01$). Adding city and year fixed effects in Column (2) retains a significant negative impact of HSR_DID on $URIG$ (coefficient = -0.005, $p < 0.01$). Column (3), with controls but no fixed effects, again yields a strong negative effect of HSR_DID on $URIG$ (coefficient = -0.019, $p < 0.01$). Column (4), with both controls and fixed effects, confirms a negative persistence of this effect at the 1% significance level. Specifically, a 1% rise in HSR_DID lowers $URIG$ by 0.4% (coefficient = -0.004, $p < 0.01$). Thus, overall, HSR development robustly narrows the URIG, supporting H1. Our findings align with Chen et al. (2023) and Li et al. (2020), who show that HSR reduces county-level economic disparities and narrows China's URIG,

[7] http://www.china-railway.com.cn/.
[8] http://www.nra.gov.cn/.
[9] https://www.12306.cn/index/.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

respectively. By contrast, our results diverge from Sun et al. (2023), who, using panel data of 285 prefecture-level cities from 2004 to 2018, report that HSR opening widens the URIG. This discrepancy likely reflects the dynamic, stage-dependent nature of HSR effects. The window of Sun et al. (2023) ends in 2018 and thus primarily captures early agglomeration effects that can temporarily widen gaps between core cities and surrounding areas. By extending the sample to 2023, we observe HSR network maturation, bringing a stronger economic boost, especially in rural economies, thus narrowing the URIG.

Table 3. *Baseline regression*

Variables	(1)	(2)	(3)	(4)
	URIG	**URIG**	**URIG**	**URIG**
HSR_DID	-0.043*** (-12.46)	-0.005*** (-2.90)	-0.019*** (-6.57)	-0.004*** (-2.77)
size			0.006** (2.02)	0.022** (2.35)
lnpgdp			-0.022*** (-7.50)	-0.024*** (-5.37)
struct			-0.011** (-2.44)	-0.003 (-1.31)
open			-0.998** (-2.31)	-1.655*** (-4.86)
fin			0.003* (1.82)	0.001 (1.05)
urban			-0.059*** (-6.02)	0.030*** (2.96)
unemploy			0.001 (0.34)	0.001 (1.57)
gov			0.052** (2.13)	-0.054*** (-3.28)
Constant	0.102*** (27.21)	0.080*** (84.51)	0.310*** (7.76)	0.198** (2.48)
Observations	3843	3843	3843	3843
R-squared	0.206	0.914	0.534	0.924
City FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Robust t-statistics in parentheses. FE: fixed effects

Robustness checks

We performed multiple robustness checks to validate the baseline estimates of the effect of HSR development on the URIG.

Parallel trend test

The parallel trend test is conducted to validate the DID method. *Figure 5* presents the test results, where the horizontal axis indicates policy times, with “current” marking the policy's start in 2008 and estimated coefficients of interventions on the vertical axis. For the pre-policy period (pre_5 to pre_1), the estimated coefficients follow oscillatory behavior around the zero line, where the confidence intervals span zero. The result suggests no statistically significant difference in the behavior before treatment between the treated and control groups. Second, at the point of policy implementation (current), there is no abrupt deviation in the trend, further validating the absence of pre-treatment biases. Third, after the policy implementation (post_1 to post_5), the confidence intervals do not overlap with zero for most observations, and the estimated coefficients become increasingly negative, indicating a reduction in the URIG. Moreover, the trend becomes more pronounced over time, implying that the influence of HSR development accumulates. Thus, the results support the robustness of the DID method by validating the parallel trend assumption.

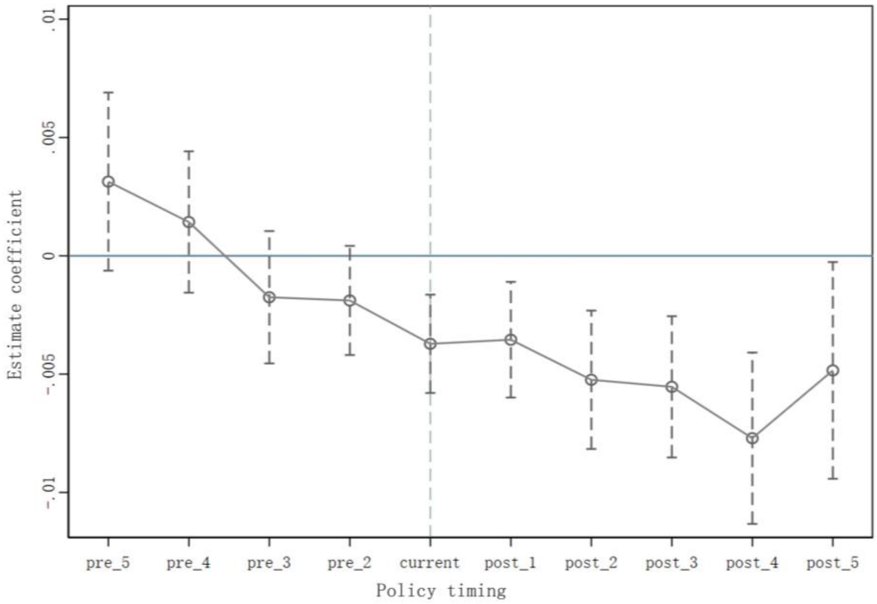

Figure 5. *Parallel trend test. (Because the first pre-treatment period serves as the baseline group, we omit data for the pre_1 period)*

Staggered DID treatment effect

Staggered adoption of "HSR opening" across cities and timeframes is typically analyzed using a TWFE model. However, due to variations in policy adoption timing, the TWFE model often employs a weighted 2×2 sample estimation approach (Goodman-Bacon, 2021), which can introduce bias. Specifically, when previously treated units act as controls for subsequently treated units, it can result in skewed estimates (Callaway and Sant'Anna, 2021; De Chaisemartin and D'Haultfœuille, 2020). To address this, we apply the weighted group-time average treatment effect on the treated (ATT) methodology introduced by Callaway and Sant'Anna (2021), which accounts for treatment heterogeneity across groups and periods. *Table 4* presents an ATT coefficient of -0.175, indicating that HSR development reduces the URIG by 17.5% on average. This impact is statistically significant at the 5% level ($p < 0.05$) with a z-statistic of -2.25, providing strong evidence that the observed reduction is improbable to be coincidental. These findings confirm the robustness and reliability of our conclusion that HSR development significantly narrows the URIG.

Table 4. *Staggered DID treatment effect*

Variables	**(1)** **URIG**
ATT	-0.175** (-2.25)
Observations	1869
City FE	YES
Year FE	YES

*** p < 0.01, ** p < 0.05, * p < 0.1; z-statistics in parentheses. ATT: average treatment effect on the treated; FE: fixed effects

Placebo test

Narrowing of the URIG after HSR opening may stem from other factors such as unanticipated or unobservable influences coinciding with HSR development. To control for this, we also conduct a placebo test to provide additional evidence. This test tackles two key issues of (1) if we have selected random treatments and controls and (2) whether omitted variables in the baseline regression cause endogeneity. If the HSR variable's coefficient becomes smaller or insignificant in the placebo test, the main results are robust. *Figure 6* presents the placebo test results. The horizontal axis shows the placebo treatment effect estimates, whereas the vertical axis displays their p-values and kernel density. The blue dots represent p-values for the placebo estimates, with most values exceeding conventional significance thresholds (e.g., 0.05 or 0.1, marked by the red dashed line). The red kernel density curve peaks near zero, indicating that placebo treatments produce no significant effects. These findings strengthen the reliability and truth of our conclusions.

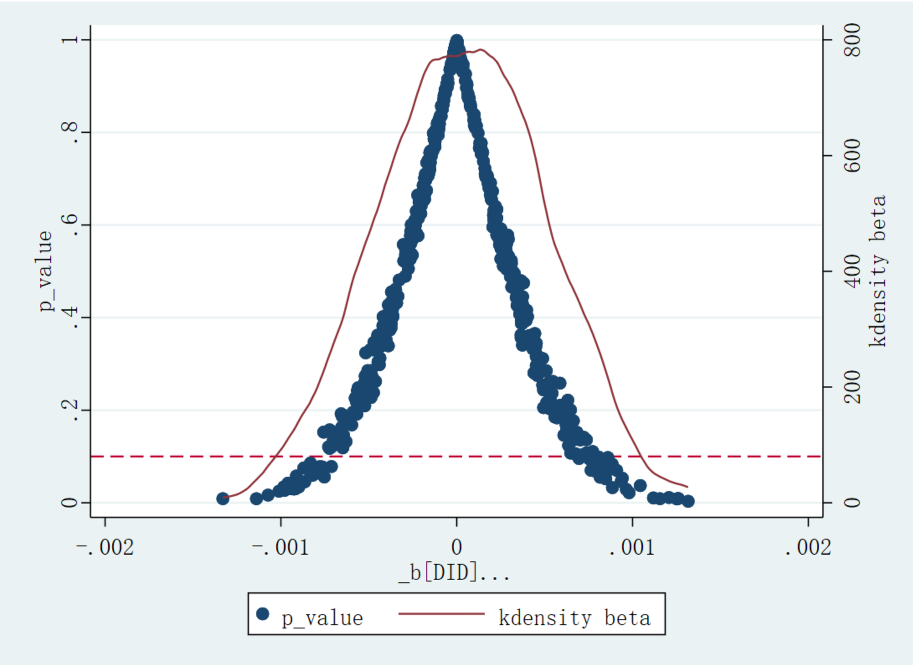

Figure 6. *Placebo test*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

Alternative dependent variable

We perform a sensitivity test by replacing the dependent variable. Building on Zhong et al. (2022), we measure the URIG (marked as "gap") as the ratio of urban to rural per capita disposable income. This metric is common in the literature and straightforward to compute (Yuan et al., 2022). Information of cities is extracted from the *China City Statistical Yearbook (2009-2024), Provincial Statistical Yearbooks (2009-2024)* and *Statistical Bulletins (2009-2024)*. We interpolate missing values for some years using a linear method. Column (1) of *Table 5* reveals a significant, negative connection between the HSR_DID and $URIG$, with a significance level of 5% (coefficient = -0.038, $p < 0.05$). The evidence suggests that HSR development decreases the URIG, thereby verifying our main findings.

Table 5. *Further robustness checks*

Variables	Alternative dependent variable	Sample excluding municipalities
	-1	-2
	gap	URIG
HSR_DID	-0.038**	-0.004**
	(-2.07)	(-2.38)
size	-0.08	0.023**
	(-0.72)	-2.37
lnpgdp	-0.236***	-0.023***
	(-4.87)	(-5.25)
struct	-0.023	-0.004
	(-0.81)	(-1.61)
open	-19.580***	-1.677***
	(-4.18)	(-4.70)
fin	0.027*	0.001
	-1.89	-1.15
urban	0.231**	0.031***
	-2.05	-3.09
unemploy	0.012	0.001
	-1.4	-1.55
gov	-0.874***	-0.052***
	(-4.25)	(-3.19)
Constant	5.417***	0.192**
	-5.7	-2.41
Observations	3840	3779
R-squared	0.923	0.924
City FE	YES	YES
Year FE	YES	YES

This table is consistent with the footnote below *Table 3*

Excluding municipalities samples

China's municipalities are better than some cities in terms of economics, urbanization, population, and quality, which could impact the study's accuracy. Following Sun et al.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

(2023), we modify the sample by excluding four municipalities—Beijing, Tianjin, Shanghai, and Chongqing. We then perform regression analysis to verify the results' reliability. As shown in Column (2) of *Table 5,* removing these municipalities leaves the HSR effect as negative and significant at the 5% level (coefficient = −0.004, $p < 0.05$). This implies that HSR opening reduces the URIG. These results remain coherent with our baseline results.

Endogeneity tests

To address the self-selection bias, we follow Ma et al. (2024) and implement DID combined with propensity score matching (PSM). All control variables are entered as covariates. We use 1:1 nearest-neighbor matching to pair treated cities with comparable controls. *Figure 7* shows the PSM distribution. The majority of observations fall within the common support range. In the mid-to-high range (roughly 0.35–0.95), the green and red bars are dense, indicating strong overlap across groups and permitting reliable matches.

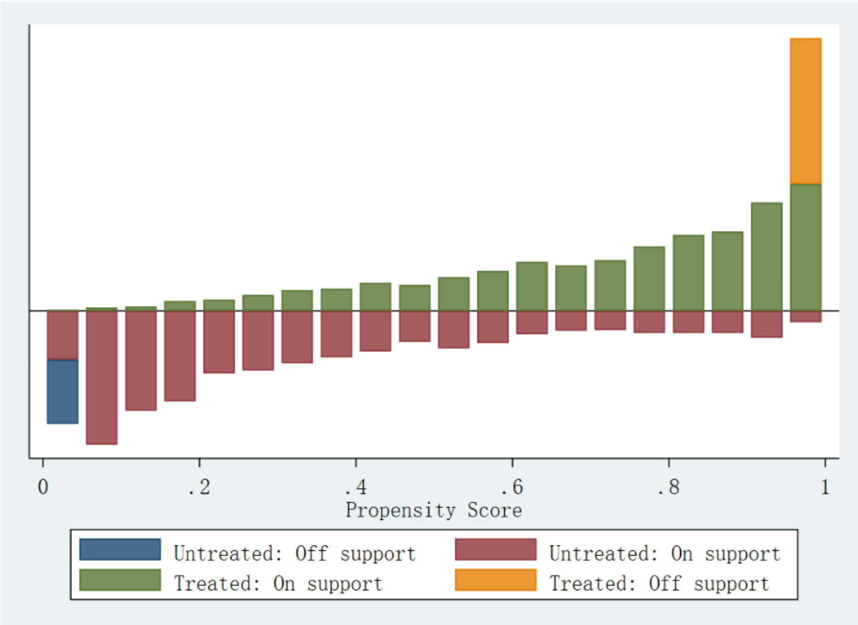

Figure 7. *Sample distribution following propensity score matching. X-axis (propensity score): The likelihood of treatment, that is, a city's predicted probability of receiving the intervention (opening its first high-speed rail line) given the covariates, ranging from 0 to 1. Y-axis (bar height/direction): Relative number of observations within each propensity-score bin and their group status*

Second, we assess balance in the matched sample. *Figure 8* presents covariate differences before and after matching. Before matching, most covariates show large, mixed-sign biases, signaling substantial gaps between the treated and control groups. After matching, all covariate biases contract around zero (mostly within ± 10%), showing that PSM markedly improves comparability and achieves good balance.

Finally, we re-run the baseline model. *Table 6* confirms a negative HSR–URIG correlation at the 10% significance level, consistent with the baseline estimates, confirming robustness and credibility.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

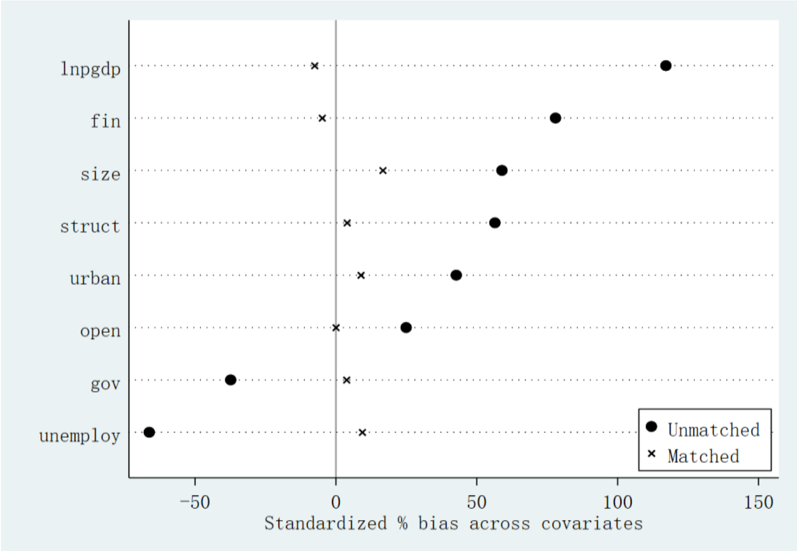

Figure 8. *Covariate balance outcomes*

Table 6. *Endogenous test: propensity score matching approach*

Variables	(1) URIG
HSR_DID	-0.002* (-1.43)
size	0.013 (0.87)
lnpgdp	-0.019*** (-3.77)
struct	-0.005* (-1.72)
open	-1.457*** (-4.15)
fin	0.000 (0.17)
urban	0.025 (1.63)
unemploy	0.000 (0.07)
gov	-0.021 (-1.37)
Constant	0.211** (1.98)
Observations	1591
R-squared	0.935
City FE	YES
Year FE	YES

This table is consistent with the footnote below *Table 3*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

Mechanism analysis

To probe how HSR influences URIG, we analyze the roles of two mechanisms: land green use efficiency and land value.

First, we test whether land green use efficiency mediates the HSR–URIG link. Column (1) of *Table 7* shows a positive HSR_DID effect on $Land\_efficiency$ (coefficient = 0.004, $p < 0.05$). The evidence suggests that HSR improves land green use efficiency, thereby narrowing the URIG. This finding aligns with H2 and resonates with prior studies that highlight the land green use restructuring effects of HSR. For instance, Niu et al. (2021) and Wenner and Thierstein (2022) emphasize that HSR stations—particularly those well-integrated with urban transit networks—can catalyze greener, more efficient land development around transport nodes. Our analysis extends this line of inquiry by empirically linking such land green use efficiency gains to broader socioeconomic outcomes, specifically reduction of the URIG. This underscores the role of HSR as not only a transport improvement but also a potential catalyst for sustainable land restructuring that benefits both urban and surrounding rural area.

Table 7. *Mechanisms analysis: land green use efficiency and land value*

Variables	-1	-2
	Land_efficiency	**Land_value**
HSR_DID	0.004**	0.124**
	-2.28	-2.3
size	-0.016	1.391***
	(-1.48)	-4.1
lnpgdp	0.004	1.435***
	-0.64	-8.45
struct	0.003	-0.068
	-0.91	(-0.79)
open	-0.797*	25.895**
	(-1.87)	-2.02
fin	0	-0.001
	(-0.08)	(-0.02)
urban	-0.004	0.015
	(-0.32)	-0.05
unemploy	-0.001	-0.009
	(-0.99)	(-0.30)
gov	-0.003	2.187***
	(-0.18)	-3.14
Constant	0.939***	-10.848***
	-8.27	(-3.39)
Observations	3619	3843
R-squared	0.823	0.871
City FE	YES	YES
Year FE	YES	YES

This table is consistent with the footnote below *Table 3*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

Second, we investigate whether land value serves as a mediator between HSR expansion and the URIG. As reported in Column (2) of *Table 7,* we find that it has a robust positive effect on land value equal to 0.124 at the 5% significance level. This suggests that HSR-induced appreciation in land value represents a significant pathway through which transport infrastructure can contribute to narrowing the URIG, thereby supporting H3. Our finding is consistent with prior literature documenting that HSR expansion exerts a positive effect on land value (Huang and Du, 2021; Okamoto and Sato, 2021; Yoo et al., 2014). By situating this mechanism within the context of the URIG, our analysis extends the conventional discourse on transport economics. Specifically, rising land values in connected areas can increase local government revenue through land finance, potentially enabling greater fiscal transfers or public investments in rural infrastructure and social services (Chen et al., 2023). Furthermore, appreciation of rural land near HSR nodes may enhance the asset wealth of rural households, helping reduce the wealth-based dimension of the urban-rural divide. This linkage underscores the multifaceted role of HSR, which operates through not only economic channels such as labor mobility and capital factors (Sun et al., 2023) but also land value effects.

Heterogeneity analysis

We conduct two heterogeneity analyses to gain deeper insights into how HSR development affects the URIG. These analyses focus on the differences in city type and HSR service accessibility (i.e., travel convenience to other cities).

First, the heterogeneity analysis is based on city type. Prior research suggests that the effects of HSR development on URIG exhibit spatial and temporal heterogeneity (Gong and Li, 2022; Lu et al., 2021; Niu et al., 2021). Therefore, we consider city type as a contextual factor to further supplement the analysis of how HSR development impacts the URIG. Following Zheng and Sun (2025), we classify four municipalities, sub-provincial cities, and provincial capitals as central (code = 1); all other cities are non-central (code = 0). Column (1) of *Table 8* reports an insignificant HSR_DID estimate, indicating that HSR development exerts little influence on the URIG in central cities. Column (2) shows the results for non-central cities. Here, HSR development reduces the URIG: the HSR_DID coefficient is negative and significant at the 10% level (coefficient = −0.003, $p < 0.1$). This finding indicates that in non-central cities, HSR development has a greater effect on narrowing the URIG. This finding aligns with the theoretical expectation that HSR tends to produce more pronounced equalizing effects in non-core regions (Li and Zhang, 2024). Central cities generally possess advanced infrastructure, diversified industrial structures, and well-developed innovation ecosystems, which may diminish the marginal impact of additional transport connectivity (Zhang and Wu, 2022). In contrast, non-central cities—often characterized by relatively limited access to markets and resources—experience more substantial gains from HSR through improved mobility, talent inflow, and investment attraction, thereby fostering rural–urban integration and narrowing the income gap (Sun et al., 2023). Our results thus corroborate and extend the view that the transport infrastructure can serve as a leveling tool for lagging regions, particularly outside major urban cores.

Second, the heterogeneity analysis is based on regional HSR service accessibility. Existing studies suggest that transportation accessibility significantly influences the URIG within Chinese cities (Jia et al., 2024; Li et al., 2023). Therefore, we further examine whether the influence of HSR development on narrowing of the URIG varies with regional HSR service accessibility. As the distribution of HSR stations within a

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

region reflects its service accessibility, we use it as a proxy for regional HSR accessibility. We employ the second quartile of HSR stations as the dividing point (i.e., the dataset's median). We split cities into high- and low-accessibility groups and report the results in in *Table 9*. In high-accessibility cities, the HSR_DID estimate in column (1) is negative and significant at the 1% level (coefficient = −0.008, $p < 0.01$), indicating a stronger URIG reduction where HSR service is more accessible. In low-accessibility cities, the HSR_DID coefficient in column (2) is insignificant, implying a limited narrowing effect. This finding aligns with the theoretical perspective that accessibility amplifies the network effects of transport infrastructure. Regions with dense HSR connections experience stronger integration of urban and rural economic systems, facilitating efficient flows of labor, goods, and rural entrepreneurship (Li et al., 2025; Lyu et al., 2025), leading to a more pronounced reduction in the URIG. By contrast, in areas with limited HSR accessibility, network effects remain underdeveloped, constraining the potential for cross-regional spillovers (Li et al., 2025). Our results thus reinforce the view that the transport infrastructure's equality outcomes are not uniform but are contingent on the broader connectivity context.

Table 8. *Heterogeneity analysis: city type*

Variables	**Central cities**	**Non central cities**
	-1	**-2**
	URIG	**URIG**
HSR_DID	-0.005	-0.003*
	(-0.92)	(-1.88)
size	-0.019	0.017
	(-0.79)	-1.4
lnpgdp	-0.028*	-0.026***
	(-1.97)	(-5.60)
struct	0	-0.006**
	(-0.02)	(-2.28)
open	-0.239	-1.930***
	(-0.44)	(-4.80)
fin	-0.004	0.001
	(-1.14)	-0.8
urban	-0.002	0.030***
	(-0.08)	-2.78
unemploy	0	0.001
	-0.06	-1.27
gov	-0.023	-0.047***
	(-0.39)	(-3.02)
Constant	0.514*	0.263***
	-1.95	-2.95
Observations	497	3323
R-squared	0.858	0.927
City FE	YES	YES
Year FE	YES	YES

This table is consistent with the footnote below *Table 3*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

Table 9. *Heterogeneity analysis: accessibility of high-speed rail services*

Variables	**High-accessibility cities**	**Low-accessibility cities**
	-1	**-2**
	URIG	**URIG**
HSR_DID	-0.008***	-0.001
	(-3.78)	(-0.59)
size	0.023**	-0.003
	-2.48	(-0.22)
lnpgdp	-0.031***	0.003
	(-6.91)	-0.49
struct	-0.003	-0.001
	(-0.80)	(-0.38)
open	-1.510***	-0.873**
	(-4.37)	(-2.22)
fin	0.001	0.002
	-0.76	-1.21
urban	0.019*	0.024**
	-1.71	-2.59
unemploy	0.002	-0.002*
	-1.65	(-1.80)
gov	-0.068***	-0.002
	(-3.31)	(-0.13)
Constant	0.281***	0.053
	-3.35	-0.61
Observations	2860	983
R-squared	0.94	0.966
City FE	YES	YES
Year FE	YES	YES

This table is consistent with the footnote below *Table 3*

Moreover, we further examine how the accessibility of HSR impacts the volume of passenger and freight traffic. We use annual city-level passenger volume (labeled as $Passenger$) and freight volume (labeled as $Freight$) as dependent variables, our HSR accessibility indicator (labeled as $Accessibility$) as an independent variable, and a set of city controls; we then re-estimate the regression. Results are reported in *Table 10*. Column (1) shows that HSR accessibility has a positive effect on passenger volume (coefficient = 0.355, $p < 0.01$). Column (2) yields an interesting find: although the effect on total freight volume is statistically significant, its economic magnitude is negligible (the coefficient is near zero). This divergence indicates a pronounced passenger bias in HSR's effect on narrowing the URIG. In other words, the gap likely narrows not by lowering logistics costs or directly boosting goods flows, but through the passengers, facilitating cross-urban-rural labor movements and the spread of consumption or entrepreneurial opportunities. Hence, we suggest that HSR accessibility primarily operates through its impact on passenger volume, thereby driving the evolution of the URIG.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

Table 10. *The impact of HSR accessibility on the volume of passenger and freight traffic*

Variables	-1	-2
	Passenger	**Freight**
Accessibility	0.355*** -2.75	0.000*** -6.26
size	20.036*** -3.14	0 -0.69
lnpgdp	2.197 -1.12	-0.001*** (-5.29)
struct	-1.743* (-1.77)	0 -0.5
open	-465.880*** (-2.98)	-0.019** (-2.10)
fin	-0.782* (-1.69)	0 (-0.29)
urban	8.505 -1.47	0.001*** -2.76
unemploy	-0.197 (-0.78)	0 -0.44
gov	-2.333 (-0.65)	-0.001 (-0.95)
Constant	-133.546*** (-2.84)	0.008*** -2.76
Observations	3682	3683
R-squared	0.852	0.956
City FE	YES	YES
Year FE	YES	YES

This table is consistent with the footnote below *Table 3*

Conclusions and policy recommendations

Conclusions

Reducing the URIG is a key pathway to Sustainable Development Goals 10 (Reduced Inequalities) and a foundation for a fairer, more inclusive society. We exploit the rollout of China's HSR as a quasi-natural experiment and use panel data for 283 cities from 2008 to 2023 with a staggered DID method to assess whether—and through which channels—HSR development alleviates the URIG. The main findings are as follows:

(i) URIG benefits greatly from HSR development. More specifically, a 1% increase in HSR development leads to a reduction in URIG by 0.4%. This finding remains very robust to a variety of tests, such as tests for alternative dependent variables, placebo tests, handling of staggered DID heterogeneity effects, and exclusion of special samples from municipalities.

(ii) HSR development narrows the URIG by improving land green use efficiency and raising land value.

(iii) The effect of HSR development on the URIG is context-dependent. The attenuation is stronger in cities with non-central and high HSR service accessibility. Also, HSR accessibility primarily operates through its impact on passenger volume.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

Policy recommendations

Our results have substantial consequences for those who make policy decisions, including governments and urban planners.

(i) Policy recommendations at the government level: First, governments should continue to increase investment in HSR infrastructure, particularly in regions that are not central. This includes developing new lines and improving existing ones. For instance, governments should prioritize connecting economically weaker rural areas with major cities through HSR. Second, while expanding HSR infrastructure, governments should design and implement more effective land-use policies to enhance land green use efficiency and value, especially around HSR stations. For example, revising land transfer policies to ensure fair distribution of land transfer revenues is essential. We should pay special attention to ensuring that the growth in land value benefits rural areas, thereby narrowing the URIG.

(ii) Policy recommendations for urban planners: First, urban planners should develop integrated urban development and transportation plans centered around HSR stations. For instance, implementing smart transportation systems can enhance the efficiency of high-speed transport networks, effectively improving connectivity between cities and the surrounding rural areas. This improved connectivity not only increases mobility but also facilitates the rapid flow of goods, services, and information. As a result, it drives economic development and creates employment opportunities in rural regions, thereby narrowing the URIG. Second, urban planners should tighten green land-use planning and oversight and promote mixed-use development—such as parks, green corridors, housing, commerce, and recreational amenities—especially along HSR corridors. Such mixes will increase spatial proximity of economic activities and foster joint agglomeration of the economy and ecological environment, helping narrow the URIG while preserving ecological quality.

Limitations and future research

Some limitations endure and should be tackled in future research. First, our analysis is anchored in China's context and tests whether—and how—HSR development influences the URIG. Given cross-country institutional differences, future studies should benchmark these results against evidence from advanced economies and other emerging markets to strengthen external validity. Second, while we use panel data to estimate HSR's impact on URIG, we do not fully assess spatial spillovers or threshold effects. Future research should employ finer spatial designs (e.g., a spatial Durbin model) to examine these dynamics and trace how HSR's effects on the URIG vary across space and under changing policy and technological conditions.

REFERENCES

[1] Breau, S. (2015): Rising inequality in Canada: a regional perspective. – Applied Geography 61: 58-69. https://doi.org/10.1016/j.apgeog.2014.11.010.

[2] Callaway, B., Sant'Anna, P. H. (2021): Difference-in-differences with multiple time periods. – Journal of Econometrics 225(2): 200-230. https://doi.org/10.1016/j.jeconom.2020.12.001.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

[3] Chang, Z., Murakami, J. (2019): Transferring land-use rights with transportation infrastructure extensions. – Journal of Transport and Land Use 12(1): 1-19. https://www.jstor.org/stable/26911256.
[4] Chang, Z., Zheng, L., Yang, T., Long, F. (2022): High-speed rail, new town development, and the spatial mismatch of land leases in China. – Land Use Policy 115: 106014. https://doi.org/10.1016/j.landusepol.2022.106014.
[5] Chen, M., Liu, X., Xiong, X., Wu, J. (2023): Has the opening of high-speed rail narrowed the inter-county economic gap? The perspective of China's state-designated poor counties. – International Review of Economics & Finance 88: 1-13. https://doi.org/10.1016/j.iref.2023.05.004.
[6] Chen, Z., Haynes, K. E. (2015): Impact of high speed rail on housing values: an observation from the Beijing–Shanghai line. – Journal of Transport Geography 43: 91-100. https://doi.org/10.1016/j.jtrangeo.2015.01.012.
[7] Chen, Z., Zhou, Y., Haynes, K. E. (2021): Change in land use structure in urban China: Does the development of high-speed rail make a difference? – Land Use Policy 111: 104962. https://doi.org/10.1016/j.landusepol.2020.104962.
[8] Cheng, L., Wang, C., Mi, Z. (2025): Narrowing urban-rural income gap and mitigating air pollution: Synergy or trade-off? – Cities 163: 106020. https://doi.org/10.1016/j.cities.2025.106020.
[9] De Chaisemartin, C., D'Haultfoeuille, X. (2020): Two-way fixed effects estimators with heterogeneous treatment effects. – American Economic Review 110(9): 2964-2996. https://doi.org/10.1257/aer.20181169.
[10] Di Matteo, D., Cardinale, B. (2023): Impact of high-speed rail on income inequalities in Italy. – Journal of Transport Geography 111: 103652.
[11] https://doi.org/10.1016/j.jtrangeo.2023.103652.
[12] Diao, M., Zhu, Y., Zhu, J. (2017): Intra-city access to inter-city transport nodes: the implications of high-speed-rail station locations for the urban development of Chinese cities. – Urban Studies 54(10): 2249-2267. https://doi.org/10.1177/0042098016646686.
[13] Fang, K., Mao, M., Tian, C., Chen, J., Wang, W., Tan, R. (2023): Exploring the impact of emissions trading schemes on income inequality between urban and rural areas. – Journal of Environmental Management 329: 117067. https://doi.org/10.1016/j.jenvman.2022.117067.
[14] Ferreira, M. D. P., Féres, J. G. (2020): Farm size and land use efficiency in the Brazilian Amazon. – Land Use Policy 99: 104901. https://doi.org/10.1016/j.landusepol.2020.104901.
[15] Gao, S., Zhou, P., Zhang, H. (2023): Does energy transition help narrow the urban-rural income gap? Evidence from China. – Energy Policy 182: 113759. https://doi.org/10.1016/j.enpol.2023.113759.
[16] Gong, W., Li, V. J. (2022): The territorial impact of high-speed rail on urban land development. – Cities 125: 103581. https://doi.org/10.1016/j.cities.2022.103581.
[17] Goodman-Bacon, A. (2021): Difference-in-differences with variation in treatment timing. – Journal of Econometrics 225(2): 254-277. https://doi.org/10.1016/j.jeconom.2021.03.014.
[18] Hao, Z., Ye, D., Hui, W., Zenglin, H., Hongye, W. (2022): An empirical analysis of tourism eco-efficiency in ecological protection priority areas based on the DPSIR-SBM model: a case study of the Yellow River Basin, China. – Ecological Informatics 70: 101720. https://doi.org/10.1016/j.ecoinf.2022.101720.
[19] Haoran, Y., Cong, W., Youyang, Y. (2022): The spatial structure evolution of China's high-speed rail network and its impacts on real estate investment. – Applied Spatial Analysis and Policy 15(1): 49-69. https://doi.org/10.1007/s12061-021-09390-7.
[20] Huang, Z., Du, X. (2021): How does high-speed rail affect land value? Evidence from China. – Land Use Policy 101: 105068. https://doi.org/10.1016/j.landusepol.2020.105068.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

[21] Huang, Z., Xu, H., Li, J., Luo, N. (2020): Has highway construction narrowed the urban–rural income gap? Evidence from Chinese cities. – Papers in Regional Science 99(3): 705-723. https://doi.org/10.1111/pirs.12504.
[22] Jia, Y., Wang, Y., Li, P., Gao, S. (2024): Economic communication: the influence of high-speed rail on urban-rural income inequality in China. – Social Indicators Research 174(1): 47-73. https://doi.org/10.1007/s11205-024-03375-y.
[23] Jiang, C., Jin, B. (2024): Does the development of digital economy infrastructure reduce the urban-rural income gap? Theoretical experience and empirical data from China. – Kybernetes 53(2): 600-619. https://doi.org/10.1108/K-12-2022-1744.
[24] Jiao, J., An, R., Du, D., Zhu, M. (2025): Non-linear and heterogeneous relationship between proximity to high-speed rail stations and land value in China: analysis using XGBoost-SHAP modelling. – Transportation Research Part A: Policy and Practice 196: 104486. https://doi.org/10.1016/j.tra.2025.104486.
[25] Jin, M., Gu, R., Li, K. X., Shi, W., Xiao, Y. (2024): Heterogeneous impacts of the high-speed railway network on urban–rural income disparity: spatiotemporal evidence from Yangtze River Delta of China. – Transportation research part A: policy and practice 183: 104050. https://doi.org/10.1016/j.tra.2024.104050.
[26] Jin, M., Shi, W., Liu, Y., Xu, X., Li, K. X. (2022): Heterogeneous impact of high speed railway on income distribution: a case study in China. – Socio-Economic Planning Sciences 79: 101128. https://doi.org/10.1016/j.seps.2021.101128.
[27] Kong, G., Liu, L., Kong, D., Zhang, J. (2024): High-speed rails, labor mobility and within-Firm pay gap. – Emerging Markets Finance and Trade 60(5): 1018-1034. https://doi.org/10.1080/1540496X.2023.2266115.
[28] Li, K., Zhang, X. (2024): Does high-speed railway promote horizontal equity within and between cities? Evidence from China. – Land Use Policy 144: 107217. https://doi.org/10.1016/j.landusepol.2024.107217.
[29] Li, L., Zhou, H., Chen, Y., Liu, B., Shen, Y., Zheng, M. (2023): Investigating the influence of transport accessibility on urban–rural income gaps. – Applied Economics 56(59): 8650-8665. https://doi.org/10.1080/00036846.2023.2293088.
[30] Li, W., Wang, X., Hilmola, O. P. (2020): Does high-speed railway influence convergence of urban-rural income gap in China? – Sustainability 12(10): 4236. https://doi.org/10.3390/su12104236.
[31] Li, X., Wang, C., Huang, C. (2025): Does the opening of high-speed rail give rise to the birth of enterprises in peripheral areas: evidence from county-level cities in China? – Review of Development Economics. https://doi.org/10.1111/rode.70027.
[32] Li, Y., DaCosta, M. N. (2013): Transportation and income inequality in China: 1978-2007. – Transportation Research Part A: Policy and Practice 55: 56-71. https://doi.org/10.1016/j.tra.2013.08.006.
[33] Li, Y., Li, B., Chen, J., Zhang, Y., Hu, Y., Li, C. (2025): Data-driven green transformation: how public data openness fuels urban land use eco-efficiency in Chinese cities. – Land 14(5): 990. https://doi.org/10.3390/land14050990.
[34] Lin, B., Wang, Y. (2024): How does the natural disasters affect urban-rural income gap? Empirical evidence from China. – Energy 295: 131067. https://doi.org/10.1016/j.energy.2024.131067.
[35] Liu, J., Yang, H. (2023): Income allocation and distribution along with high-speed rail development in China. – Transportation Research Part A: Policy and Practice 175: 103767. https://doi.org/10.1016/j.tra.2023.103767.
[36] Liu, T. Y., Lin, Y. (2025): Is the high-speed railway network narrowing the urban–rural income gap? – Applied Spatial Analysis and Policy 18(1): 20. https://doi.org/10.1007/s12061-024-09622-6.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

[37] Liu, X., Sun, R., Hu, H., Chen, D., Fu, Q. (2025): A study of the impact of informal finance on the urban-rural income gap—evidence from China. – Emerging Markets Finance and Trade 61(4): 1083-1094. https://doi.org/10.1080/1540496X.2024.2399525.

[38] Lu, H., Zhao, P., Hu, H., Zeng, L., Wu, K. S., Lv, D. (2022): Transport infrastructure and urban-rural income disparity: a municipal-level analysis in China. – Journal of Transport Geography 99: 103292. https://doi.org/10.1016/j.jtrangeo.2022.103292.

[39] Lu, J., Li, H. (2025): Can high-speed rail improve agricultural land use in China's counties? From the perspective of dynamic network two-stage model. – Land Use Policy 148: 107403. https://doi.org/10.1016/j.landusepol.2024.107403.

[40] Lu, X., Tang, Y., Ke, S. (2021): Does the construction and operation of high-speed rail improve urban land use efficiency? Evidence from China. – Land 10(3): 303. https://doi.org/10.3390/land10030303.

[41] Lyu, S., Sun, T., Sun, X. (2025): The effect of high-speed railway connections on economic development in China's peripheral cities: a perspective of innovation capacity. – Transport Policy 171: 1-17. https://doi.org/10.1016/j.tranpol.2025.05.018.

[42] Ma, J., Li, Q., Zhao, Q., Liou, J., Li, C. (2024): From bytes to green: the impact of supply chain digitization on corporate green innovation. – Energy Economics 139: 107942. https://doi.org/10.1016/j.eneco.2024.107942.

[43] Molero-Simarro, R. (2017): Inequality in China revisited. The effect of functional distribution of income on urban top incomes, the urban-rural gap and the Gini index, 1978-2015. – China Economic Review 42: 101-117. https://doi.org/10.1016/j.chieco.2016.11.006.

[44] Niu, F., Xin, Z., Sun, D. (2021): Urban land use effects of high-speed railway network in China: a spatial spillover perspective. – Land Use Policy 105: 105417. https://doi.org/10.1016/j.landusepol.2021.105417.

[45] Okamoto, C., Sato, Y. (2021): Impacts of high-speed rail construction on land prices in urban agglomerations: evidence from Kyushu in Japan. – Journal of Asian Economics 76: 101364. https://doi.org/10.1016/j.asieco.2021.101364.

[46] Qian, Q., Luo, S. (2024): The dilemma of land green use efficiency in resource-based cities: a perspective based on digital transformation. – Frontiers in Environmental Science 12: 1339928. https://doi.org/10.3389/fenvs.2024.1339928.

[47] Qing, L., Li, P., Dagestani, A. A., Woo, C., Zhong, K. (2024): Does climate change exposure impact on corporate finance and energy performance? Unraveling the moderating role of CEOs' green experience. – Journal of Cleaner Production 461: 142653. https://doi.org/10.1016/j.jclepro.2024.142653.

[48] Qing, L., Shen, P., Nam, E. Y., Ma, X. (2025): Does supply chain digitalization improve corporate energy performance? A quasi-natural experiment from Chinese supply chain innovation and application pilot policy. – Energy Economics 108567. https://doi.org/10.1016/j.eneco.2025.108567.

[49] Schneider, M. (2021): The discovery of the Gini coefficient: was the Lorenz curve the catalyst? – History of Political Economy 53(1): 115-141. https://doi.org/10.1215/00182702-8816637.

[50] Shen, C., Wu, X., Shi, L., Wan, Y., Hao, Z., Ding, J., Wen, Q. (2025): How does the digital economy affect the urban–rural income gap? Evidence from Chinese cities. – Habitat International 157: 103327. https://doi.org/10.1016/j.habitatint.2025.103327.

[51] Su, C. W., Liu, T. Y., Chang, H. L., Jiang, X. Z. (2015): Is urbanization narrowing the urban-rural income gap? A cross-regional study of China. – Habitat International 48: 79-86. https://doi.org/10.1016/j.habitatint.2015.03.002.

[52] Sun, D., Zhao, X., Zhang, G., Chen, P. (2023): Impact of the introduction of high-speed rail on the income gap between urban and rural residents. – PloS ONE 18(11): e0292105. https://doi.org/10.1371/journal.pone.0292105.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

[53] Sun, S. L., Jia, P., Qi, J., Guo, C. (2025): Shaping opportunity structures: how transport infrastructure fuels social ventures and reduces income inequality. – Entrepreneurship & Regional Development 1-24. https://doi.org/10.1080/08985626.2024.2444895.
[54] Tan, X., Kamaruddin, R. B., Hu, S., Peng, L., Que, Y., Cai, W. (2025): Rural revitalization and urban-rural income gap: a perspective from land transfer scale. – Finance Research Letters 107705. https://doi.org/10.1016/j.frl.2025.107705.
[55] Tang, J., Gong, J., Ma, W. (2022): Narrowing urban–rural income gap in China: the role of the targeted poverty alleviation program. – Economic Analysis and Policy 75: 74-90. https://doi.org/10.1016/j.eap.2022.05.004.
[56] Theil, H. (1967): Economics and Information Theory. – North Holland, Amsterdam.
[57] Tone, K. (2001): A slacks-based measure of efficiency in data envelopment analysis. – European Journal of Operational Research 130(3): 498-509. https://doi.org/10.1016/S0377-2217(99)00407-5.
[58] Wang, C. H., Chen, N., Chan, S. L. (2017): A gravity model integrating high-speed rail and seismic-hazard mitigation through land-use planning: application to California development. – Habitat International 62: 51-61. https://doi.org/10.1016/j.habitatint.2017.02.009.
[59] Wang, F., Wei, X., Liu, J., He, L., Gao, M. (2019): Impact of high-speed rail on population mobility and urbanisation: a case study on Yangtze River Delta urban agglomeration, China. – Transportation Research Part A: Policy and Practice 127: 99-114. https://doi.org/10.1016/j.tra.2019.06.018.
[60] Wang, L. M., Wu, X. L., Chu, N. C. (2023a): Financial development, technological innovation and urban-rural income gap: time series evidence from China. – PloS ONE 18(2): e0279246. https://doi.org/10.1371/journal.pone.0279246.
[61] Wang, M., Yin, Z., Pang, S., Li, Z. (2023b): Does Internet development affect urban-rural income gap in China? An empirical investigation at provincial level. – Information Development 39(1): 107-122. https://doi.org/10.1177/02666669211035484.
[62] Wang, Z., Zheng, X., Wang, Y., Bi, G. (2024): A multidimensional investigation on spatiotemporal characteristics and influencing factors of China's urban-rural income gap (URIG) since the 21st century. – Cities 148: 104920. https://doi.org/10.1016/j.cities.2024.104920.
[63] Wei, Y. D. (2015): Spatiality of regional inequality. – Applied Geography 61: 1-10. https://doi.org/10.1016/j.apgeog.2015.03.013.
[64] Wei, Y. D., Li, H., Yue, W. (2017): Urban land expansion and regional inequality in transitional China. – Landscape and Urban Planning 163: 17-31. https://doi.org/10.1016/j.landurbplan.2017.02.019.
[65] Wenner, F., Thierstein, A. (2022): High speed rail as urban generator? An analysis of land use change around European stations. – European Planning Studies 30(2): 227-250. https://doi.org/10.1080/09654313.2021.1946485.
[66] Wu, G., Liu, T., Hu, Z. (2024): Land price dynamics in response to high-speed rail network characteristics: an empirical analysis. – Research in Transportation Business & Management 56: 101184. https://doi.org/10.1016/j.rtbm.2024.101184.
[67] Xia, H., Yu, H., Wang, S., Yang, H. (2024): Digital economy and the urban–rural income gap: impact, mechanisms, and spatial heterogeneity. – Journal of Innovation & Knowledge 9(3): 100505. https://doi.org/10.1016/j.jik.2024.100505.
[68] Xu, Y., Wang, Y. (2023): Has financial development made income more equal?—From the perspective of regional development imbalance. – International Review of Financial Analysis 90: 102870. https://doi.org/10.1016/j.irfa.2023.102870.
[69] Xu, Y., Zhu, S. (2024): Transport infrastructure, intra-regional inequality and urban-rural divide: evidence from China's high-speed rail construction. – International Regional Science Review 47(3): 378-406. https://doi.org/10.1177/01600176231177672.
[70] Yang, D. (2023): Income growth, income uncertainty, and urban–rural household savings rate in China. – Regional Science and Urban Economics 99: 103855.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

https://doi.org/10.1016/j.regsciurbeco.2022.103855.
[71] Yilmaz, A., Bilim, N. S. (2024): The role of land values in land policies: the case of Turkish land readjustment. – Land Use Policy 144: 107244. https://doi.org/10.1016/j.landusepol.2024.107244.
[72] Yin, Q., Hu, J., Sun, Z., Xu, D., Ntim-Amo, G., Tang, H. (2020): Assessing the viability of vacant farmhouse market in China: a case study in Sichuan. – Land 9(11): 467. https://doi.org/10.3390/land9110467.
[73] Yin, Z. H., Choi, C. H. (2022): Does e-commerce narrow the urban–rural income gap? Evidence from Chinese provinces. – Internet Research 32(4): 1427-1452. https://doi.org/10.1108/INTR-04-2021-0227.
[74] Yoo, S., Kumagai, J., Sho, K., Managi, S. (2024): Impact of high-speed railway on gentrification and regional inequality in Japan. – Transportation Research Part D: Transport and Environment 134: 104346. https://doi.org/10.1016/j.trd.2024.104346.
[75] Yu, M., Chen, Z., Long, Y., Mansury, Y. (2022): Urbanization, land conversion, and arable land in Chinese cities: the ripple effects of high-speed rail. – Applied Geography 146: 102756. https://doi.org/10.1016/j.apgeog.2022.102756.
[76] Yuan, Y., Wang, M., Zhu, Y., Huang, X., Xiong, X. (2020): Urbanization's effects on the urban-rural income gap in China: a meta-regression analysis. – Land Use Policy 99: 104995. https://doi.org/10.1016/j.landusepol.2020.104995.
[77] Zhang, H., Song, Y., Zhang, M., Duan, Y. (2024): Land use efficiency and energy transition in Chinese cities: a cluster-frontier super-efficiency SBM-based analytical approach. – Energy 304: 132049. https://doi.org/10.1016/j.energy.2024.132049.
[78] Zhang, H., Wu, D. (2022): The impact of transport infrastructure on rural industrial integration: spatial spillover effects and spatio-temporal heterogeneity. – Land 11(7): 1116. https://doi.org/10.3390/land11071116.
[79] Zhang, M. T., Yu, F., Zhong, C. B., Tang, Y. H. (2022): Influence of high-speed railway network on individual income: evidence from China's microeconomic data. – Transportation Letters 14(8): 874-887. https://doi.org/10.1080/19427867.2021.1952043.
[80] Zheng, F., Chen, S., Wang, X. (2025): How the impact and mechanisms of digital financial inclusion on agricultural carbon emission intensity: new evidence from a double machine learning model. – Frontiers in Environmental Science 13: 1549623. https://doi.org/10.3389/fenvs.2025.1549623.
[81] Zheng, L., Long, F., Chang, Z., Ye, J. (2019): Ghost town or city of hope? The spatial spillover effects of high-speed railway stations in China. – Transport Policy 81: 230-241. https://doi.org/10.1016/j.tranpol.2019.07.005.
[82] Zheng, S., Kahn, M. E. (2013): China's bullet trains facilitate market integration and mitigate the cost of megacity growth. – Proceedings of the National Academy of Sciences 110(14): E1248-E1253. https://doi.org/10.1073/pnas.1209247110.
[83] Zheng, T., Sun, B. (2025): The impact of city-county amalgamations on small administrative units: evidence from land transfer in China. – Local Government Studies 1-26. https://doi.org/10.1080/03003930.2025.2552196.
[84] Zhong, S., Wang, M., Zhu, Y., Chen, Z., Huang, X. (2022): Urban expansion and the urban–rural income gap: empirical evidence from China. – Cities 129: 103831. https://doi.org/10.1016/j.cities.2022.103831.
[85] Zhou, Y., Liu, Z., Wang, H., Cheng, G. (2023): Targeted poverty alleviation narrowed China's urban-rural income gap: a theoretical and empirical analysis. – Applied Geography 157: 103000. https://doi.org/10.1016/j.apgeog.2023.103000.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452

APPENDIX

Specific input–output indicators of land green use efficiency

Primary indicator	Secondary indicator	Indicator description	Unit	Data source
Input	Land input	$Ln(Urban\ construction\ area)$	km^2	*Urban and Rural Construction Statistical Yearbook (2009-2024)*
	Capital input	Ln(Fixed capital stock of the municipal	10,000 RMB	*China Statistical Yearbook (2009-2024)*
	Labor input	Ln(Number of employees in secondary	10,000 people	
		Ln (Number of employees in tertiary in		
Output	Desired output	$Ln\ (Gross\ domestic\ product)$	Billion RMB	
	Non-desired output	Ln(Carbon emissions)	10,000 tons	Emissions Database for Global Atmospheric Research
		$Ln(Enegy$ consumptions)		*China Energy Statistical Yearbook (2009-2024)*

APPLIED ECOLOGY AND ENVIRONMENTAL RESEARCH 24(1):1423-1452.
http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_14231452