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Evaluating high-speed rail's impact on regional tourism performance

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Abstract

Purpose – This study explores the impacts of high-speed rail (HSR) on regional tourism performance. This study aims to identify short-term shocks, medium-term causal effects and long-term dynamic trends and analyze heterogeneous influences across cities with different scales and resource endowments.

Design/methodology/approach – Based on 2005–2023 panel data of Chinese prefecture-level cities, this research adopts the Synthetic Control Method, instrumental variable difference-in-differences and a Bayesian dynamic panel model for multi-angle empirical analysis and conducts multi-dimensional heterogeneity tests.

Findings – HSR significantly boosts tourism gross domestic product, employment and revenue with cumulative lag effects. Its impacts are stronger in large and tourism-intensive cities. Regional disparities exist across geographic areas and urban development levels.

Social implications – The findings support differentiated HSR and tourism policies. It helps balance regional development, promote decent jobs, advance sustainable tourism and ecological governance and align with inclusive growth goals.

Originality/value – This integrated multi-method framework addresses endogeneity and uncertainty. It enriches policy evaluation methods for transport infrastructure and provides references for tourism development worldwide.

Keywords High-speed rail, Regional tourism performance, Causal inference, Bayesian dynamic modeling, Policy evaluation

Paper type Research paper

Introduction

Transportation infrastructure plays a key role in economic growth by reducing spatial distance, improving resource allocation and strengthening regional connectivity (Yao et al., 2022). High-speed rail (HSR), a major form of large-scale transport infrastructure, has expanded rapidly worldwide, especially in China (Wang et al., 2023a). China's growing HSR network has reshaped intercity economic relations and provides a suitable setting for examining how HSR affects regional industrial structures and consumption patterns (Wang et al., 2023b). Management research also shows that public-sector policy performance increasingly depends on information technology, knowledge networks and decision-making under uncertainty (Seo et al., 2025; Cabrilo et al., 2024).

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Existing studies have examined the effects of HSR on urban economies, real estate and employment, yet evidence of its specific impact on tourism remains limited. Tourism relies heavily on transport accessibility, but many studies treat HSR as a general transport improvement and fail to isolate its effects on the tourism economy (Shu et al., 2023). In addition, HSR research has paid insufficient attention to regional resilience, digital capabilities and knowledge structures, although these factors affect policy performance and regional recovery amid external shocks (Fan et al., 2024; Tsai, 2022). Some studies find that HSR promotes tourism flows, but their identification strategies often rely on panel regressions or difference-in-differences (DID) models that do not fully address policy endogeneity (Li et al., 2023). Therefore, the tourism effects of HSR remain exposed to identification bias and measurement limitations.

This study applies the "transportation accessibility → tourism development → regional performance" framework. HSR reduces travel time, strengthens intercity links, improves perceived accessibility and increases demand for tourism services such as lodging and dining. These changes can further expand tourism output, employment and income. To examine this mechanism, this study uses panel data on Chinese prefecture-level cities from 2005 to 2023 and constructs a multi-method identification framework. The synthetic control method (SCM) captures short-term policy shocks, instrumental variable DID (IV-DID) estimates average treatment effects (ATE) while addressing endogeneity and a Bayesian dynamic panel model traces medium- and long-term policy effects. The data set includes tourism-related gross domestic product (GDP), employment and per capita tourism expenditure before and after HSR operation.

This study contributes to spatial policy evaluation by integrating SCM, IV-DID and a Bayesian dynamic panel model within a triangular identification strategy. The framework incorporates policy timing, spatial distribution and dynamic responses, thereby improving the reliability and explanatory power of infrastructure policy assessment. It also provides evidence for research on regional development, tourism planning and transportation externalities.

Literature review

Using a panel data model, Zhou et al. (2022) found that HSR significantly enhanced GDP growth in cities along its route, particularly in regions with strong economic foundations. Li & Terason (2023), in their study on the impact of China's railway network on urban development, identified that railway improvements contributed to increased industrial output and population growth in cities. In the real estate sector, Di Ruocco & D'Auria (2024), using a spatial autoregressive model, revealed that HSR operations drove significant increases in housing prices in metropolitan suburbs, forming a "commuter economic zone" effect. Additionally, Wang et al. (2023c) highlighted that HSR strengthened the core cities' capacity to attract surrounding resources. An increasing number of empirical studies are exploring how HSR systems can reshape tourism demand. For example, Jou & Chen (2020) found a positive correlation between the development of HSR and tourism growth, as it shortened travel time and improved transportation convenience. Overall, while existing studies have extensively validated the macroeconomic benefits of HSR infrastructure, industry-specific research remains insufficient, particularly for the service sector, which is characterized by consumption-driven growth.

In contrast, research on the relationship between HSR and the tourism economy remains in its early stages and exhibits methodological limitations. Di Matteo (2023), using data from most Chinese provinces and a traditional fixed-effects model, found that HSR significantly increased domestic tourist numbers. However, the study did not effectively control for variations in tourism resources on the results (Di Matteo, 2023). Boto-García et al. (2025) used the DID method to evaluate the impact of HSR on tourism revenue. Although their study established a causal relationship, it failed to address the endogeneity of HSR route selection (Boto-García et al., 2025). Gallo & La Rocca (2022), using a spatial Durbin model, identified tourism spillover effects from HSR to adjacent regions, providing preliminary insights into spatial interconnectivity mechanisms. However, their study did not incorporate a dynamic perspective, limiting its ability to capture the long-term effects of HSR policies (Gallo & La Rocca, 2022). Moreover, most existing research relies on coarse-grained data, primarily at the provincial or national level, making it difficult to capture micro-level differences at the city or prefectural level (Shi et al., 2022; Zhao et al., 2022). In summary, although empirical studies on the relationship between HSR and tourism are gradually increasing, most remain within static, linear analytical frameworks and lack sufficient exploration of long-term, heterogeneous and multi-channel effects.

In addition to concerns about tourism and consumption, recent tourism research emphasizes how urban space and responsible tourism practices affect destination performance. In the case of urban blocks, Liang et al. (2025) pointed out that "responsible tourism scenes" could affect tourists' perceptions and behavioral patterns, thereby affecting the quality and sustainability of tourism performance (Liang et al., 2025). This viewpoint suggests that HSR accessibility impacts the tourism industry in terms of the number of tourists and in how local scenery and governance affect the effectiveness of tourism development.

From a management perspective, recent research emphasizes that performance in turbulent environments depends on external shocks and the dynamic capabilities of decision-makers. Gomes et al. (2025) found that dynamic management capabilities could enable organizations to perceive, grasp and reconfigure resources under uncertainty, thereby improving overall performance. However, most HSR tourism research rarely incorporates this capacity and performance-oriented framework, leading to a lack of understanding of how regional governance and adaptability affect the economic benefits of large-scale transportation infrastructure.

The literature on the resilience of emerging tourism destinations emphasizes that performance during shocks depends on adaptability and innovation dynamics. Della Corte et al. (2021) pointed out that resilience assessment and performance indicators of tourist destinations still require further research and called for the construction of a comprehensive framework that links infrastructure, innovation and resilience (Della Corte et al., 2021). This further emphasizes the necessity of adopting a dynamic and uncertain approach when evaluating the long-term performance impact of HSR expansion on the regional tourism economy.

Compared with existing studies, this study extended the scope of data, methodology and temporal coverage. At the data level, prefecture-level city panel data were combined with nighttime light data to identify regional differences at a finer spatial scale. At the methodological level, the study integrated the synthetic control method, the IV-DID approach and the Bayesian dynamic panel model to address endogeneity, short-term shocks and long-term dynamic effects simultaneously. In terms of temporal coverage, the sample spanned from 2005 to 2023, enabling the analysis of cumulative policy effects across different stages of China's HSR network expansion.

Identification strategy design: a multi-method framework for evaluating spatial policy effects

Traditional infrastructure policy studies often rely on a single DID model or regression design, which can be affected by endogeneity, spatial spillovers and delayed responses. To strengthen causal identification, this study adopts a three-pronged strategy that combines cross-sectional matching, instrumental–variable estimation and dynamic modeling. The empirical pathway is "HSR launch → improved accessibility → expanded tourism demand → enhanced regional economic performance." This logic is grounded in urban resilience, transportation accessibility and the tourism multiplier effect. Prior studies show that transport connectivity strengthens urban resilience to shocks (Snower & Wilson, 2025), improves access to regional activities and services (Hamza et al., 2025) and amplifies employment and output through tourism consumption linkages (Martínez-García & Cámara, 2022; Roldan, 2022).

Data sources and variable definitions

This study constructs a multidimensional, multi-time-point empirical data set using regional panel data from China spanning 2005–2023. The data set covers all 31 provincial-level administrative regions and their respective prefecture-level cities, enabling a dynamic assessment of how HSR operations affect regional tourism economies across different areas.

The data sources are as follows:

- The *China Statistical Yearbook* (www.stats.gov.cn/sj/ndsj/) provides official statistics on tourism-related GDP, tourism sector employment and total retail sales of consumer goods. This serves as the primary source for measuring regional tourism economic activity.
- The National Railway Administration (www.nra.gov.cn/) publishes HSR operation timelines and station distribution data, which are used to determine the timing and status of HSR access in different regions and to construct both treatment and control groups for policy evaluation.
- Nighttime light remote sensing data from the *National Polar-orbiting Partnership–Visible Infrared Imaging Radiometer Suite* (www.ngdc.noaa.gov/eog/download.html) is used to measure regional economic activity intensity. This serves as a key proxy for tourism economic dynamism, helping to mitigate the limitations of conventional statistical indicators, which often have lower frequency and coarser granularity.

Based on the research objectives, this study defines the following variable framework:

- Key dependent variables:
  - Tourism-related GDP (unit: 100m RMB), which reflects the direct economic output of the tourism industry within a region.
  - Tourism sector employment (unit: 10,000 persons) is used to assess the impact of HSR expansion on the regional labor market.
  - Tourism revenue growth rate captures the annual growth trend of the regional tourism economy.
  - Per capita tourism expenditure measures tourists' spending capacity and the tourism sector's efficiency in generating revenue.
- Key independent variable:
  - A binary HSR operation status variable, assigned a value of 1 if a city had HSR access in a given year and 0 otherwise (including years prior to HSR operation and non-HSR regions). Additionally, a year since the HSR operation variable was introduced to capture the cumulative impact of HSR over time, supporting the construction of dynamic models.
- Control variables:
  - Per capita GDP (unit: RMB), representing the overall economic development level of a region.
  - Population density (unit: persons/km^2) measures the concentration of labor and consumer populations.

Infrastructure investment level (unit: 100m RMB) is sourced from fixed asset investment data for transportation and municipal infrastructure, controlling for differences in regional development capacity. All monetary indicators are adjusted to constant prices using the GDP deflator to eliminate the effects of inflation. Continuous variables are log-transformed to mitigate the influence of extreme values and enhance model stability.

To improve causal inference validity and ensure robust estimation results, this study integrates multiple empirical identification methods into a comprehensive analytical framework, as illustrated in Figure 1.

Based on Figure 1, this framework sequentially uses the SCM, the IV-DID method and the Bayesian dynamic panel model to identify short-term shocks, control for endogeneity bias and evaluate long-term trends and uncertainties, thereby providing a multidimensional analysis of HSR's economic effects.

Synthetic control method

For each city i where HSR becomes operational, let T_0 denote the number of pre-treatment observation periods, with HSR commencing in year T_0+1. SCM constructs a weighted synthetic counterpart for city i by selecting a set of untreated cities $j = 1, 2, \ldots J$ (i.e. the control group) from the donor pool and assigning them weights w_j, as expressed in equation (1):

$$Y_{it}^{SC} = \sum_{j=1}^{J} w_j Y_{jt}, \sum_{j=1}^{J} w_j = 1, w_j \geq 0 \tag{1}$$

where Y_{it}^{SC} represents the predicted tourism economic indicator for city i in year t based on the synthetic counterpart.

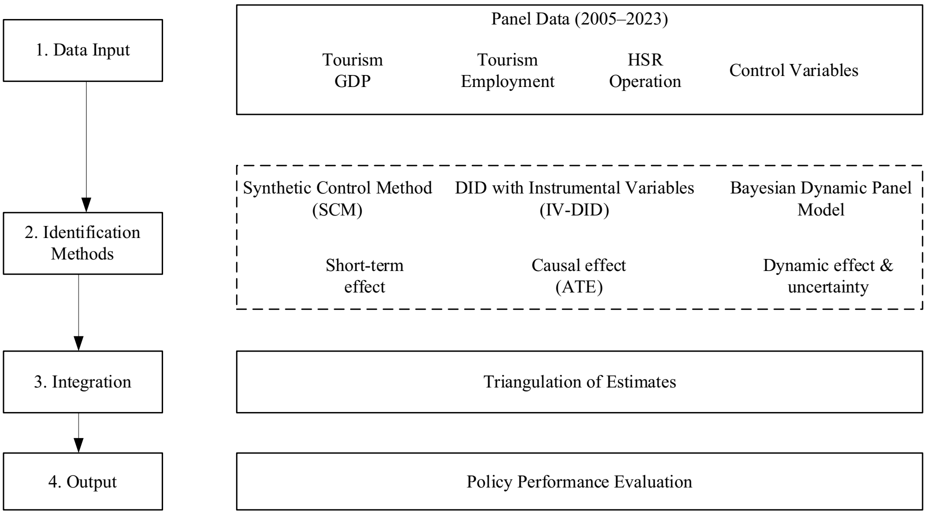

Figure 1. Empirical strategy and identification workflow

Note(s): The figure illustrates the multi-method empirical strategy. SCM identifies short-term effects, IV-DID estimates causal impacts while addressing endogeneity and the Bayesian model captures dynamic trajectories and uncertainty

The optimal weights w_j are determined by minimizing the distance between observed characteristics in the pre-treatment period ($t = 1, \ldots, T_0$). To enhance comparability, this study selects the following key matching indicators:

- *Population size*: Reflecting the tourism market base.
- *Baseline tourism-related GDP*: Controlling for initial tourism development levels.
- *Share of the tertiary sector in GDP*: Representing the economic structure's support for tourism activities.
- *Per capita GDP and infrastructure investment*: Controlling for differences in economic and construction conditions.

The optimization objective is to minimize the pre-treatment mean squared error (MSE) (Guan & Hu, 2023; Zhang et al., 2022), as formulated in equation (2):

$$\min_{w} \sum_{t=1}^{T_0} \left(Y_{it}\text{-}Y_{it}^{SC}\right)^2 \tag{2}$$

Once the optimal weight vector w^* is determined, the treatment effect of HSR operation is estimated as shown in equation (3):

$$\alpha_{it}=Y_{it}-Y_{it}^{SC}, \text{for } t>T_0 \tag{3}$$

where α_{it} represents the estimated net effect of HSR operation on city i in year t.

Given the asynchronous expansion of China's HSR network (Hu & Xu, 2022), the SCM estimation follows a staggered event-study logic. Each treated city is matched to a synthetic control group based on its HSR opening year, and city-level effects are then averaged to obtain the overall treatment pattern. Robustness is checked by excluding cities with large pre-treatment matching errors and by conducting placebo tests using pseudo-HSR opening years.

Instrumental variable difference-in-differences

To further estimate the ATE of HSR operation on regional tourism economies and address endogeneity concerns arising from non-random HSR placement, this study uses a multi-period DID model (Abdelati, 2024) and introduces an external IV for two-stage estimation.

HSR deployment is not random – it is influenced by unobservable factors such as local government preferences and regional economic potential. As a result, the treatment variable D_{it} may be correlated with the error term ε_{it}, violating the independence assumption required for valid DID estimation. This introduces significant endogeneity risks.

To address this issue, two IVs are introduced: HSR planning density (Z_{1it}): This variable captures the number of planned HSR routes and connection points in a city, as recorded in national planning documents published by the National Development and Reform Commission and China Railway Corporation. While it is highly correlated with actual HSR deployment, it does not directly affect short-term tourism economic outcomes. HSR operation status of neighboring cities (Z_{2it}): This is defined as the proportion of adjacent cities with HSR services. It captures the spatial spillover effects of rail network expansion. The variable influences local HSR development through regional infrastructure coordination but does not directly impact tourism indicators.

These IVs satisfy both relevance and exclusion restrictions, making them suitable for estimation via two-stage least squares (Russell et al., 2024; Nokkaew et al., 2024). To reduce the risk that the IV reflects pre-existing economic expectations associated with HSR construction, this study further conducts validity and exclusion restriction tests for the instrument. The tests focus on three aspects. First, it examines the correlation between HSR planning density and actual HSR operational status to assess whether the instrument has sufficient explanatory power. Second, it tests whether HSR planning density directly affects tourism economic trends prior to HSR operation. If the instrument significantly explains tourism revenue, tourism employment or tourism-related GDP before policy implementation, its exclusion restriction would be weakened. Third, the IV model is re-estimated after controlling for pre-trends in tourism growth, city fixed effects and year fixed effects to examine the robustness of the results.

The first-stage regression is formulated in equation (4):

$$D_{it} = \pi_1 Z_{1it} + \pi_2 Z_{2it} + \mathbf{X}_{it}^{'}\delta + \mu_i + \lambda_t + \eta_{it} \tag{4}$$

where D_{it} is a dummy variable indicating HSR operation. If region i has HSR service in year t, then $D_{it} = 1$; otherwise, $D_{it} = 0$. The vector $\mathbf{X}_{it}^{'}$ represents control variables (e.g. per capita GDP, population density, infrastructure investment). μ_i and λ_t denote region and time fixed effects, respectively, while η_{it} is the error term.

The second-stage regression is given in equation (5):

$$Y_{it} = \beta \cdot \widehat{D}_{it} + \mathbf{X}_{it}^{'}\gamma + \mu_i + \lambda_t + \varepsilon_{it} \tag{5}$$

where Y_{it} represents the dependent variable for region i in year t (such as tourism-related GDP or tourism employment), and $\widehat{D}_{it}$ is the predicted probability of HSR operation obtained from the first-stage regression.

This study adopts a staggered DID design to account for differences in HSR opening years. Model validity is assessed through parallel-trend tests, first-stage F-statistics for IV relevance, robustness checks using alternative trends and treatment windows and city-level clustered standard errors.

Bayesian dynamic panel data model

To identify the dynamic evolution of tourism economic effects following the opening of HSR, this study constructs a Bayesian dynamic panel data model. The model incorporates a lagged dependent variable into the explanatory structure to capture the temporal dependence of policy effects (Chen et al., 2023). It also controls for city fixed effects, year fixed effects and a set of city-level covariates, thereby reducing potential biases from omitted variables in long-term estimates (Fang et al., 2024; Sudan, 2022; Lertpusit & Suvakanta, 2023).

The baseline specification is defined as follows:

$$Y_{it} = \rho Y_{i,t-1} + \beta HSR_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{6}$$

where Y_{it} denotes the tourism economic indicator of city i in year t, including tourism revenue growth, per capita tourism expenditure, or tourism-related GDP. $Y_{i,t-1}$ is the first-order lag of the dependent variable, capturing persistence in tourism activity. HSR_{it} represents the HSR operation status. X_{it} is a vector of control variables, including per capita GDP, population density, infrastructure investment and night-time light intensity. μ_i and λ_t denote city and year fixed effects, respectively and ε_{it} is the idiosyncratic error term.

Further model details are provided in Appendix.

Research results on high-speed rail and regional tourism growth

Descriptive statistics and sample structure

Table 1 reports descriptive statistics for the main variables. The sample covers Chinese prefecture-level cities from 2005 to 2023 and is divided into treatment and control groups according to HSR access. Monetary variables are deflated to constant prices using the GDP deflator, and continuous variables are log-transformed in the econometric analysis.

Table 1 shows substantial cross-city heterogeneity in tourism-related economic indicators, with relatively large standard deviations, indicating pronounced regional disparities in development levels. The mean value of the HSR variable is 0.42, suggesting that approximately 40% of the sampled cities are integrated into the HSR network. The distribution of HSR operational years is highly dispersed, reflecting the phased expansion of HSR construction.

The sample composition is presented in Table 2. The sizes of the treatment and control groups are broadly comparable, indicating a relatively balanced sample structure and supporting credible counterfactual comparisons. The distribution of HSR opening years is shown in Table 3, revealing a clear staged expansion pattern in HSR construction and providing a suitable empirical foundation for multi-period policy evaluation.

Table 1. Descriptive statistics of key variables

Variable	Unit	Observations	Mean	SD	Min.	Max.
Tourism-related GDP	100m CNY	4,560	312.4	285.7	18.5	1,842.30
Tourism employment	10,000 persons	4,560	26.8	19.6	2.1	112.4
Tourism revenue growth rate	%	4,560	8.7	5.3	−6.4	24.8
Per capita tourism consumption	CNY	4,560	1,245	432	380	2,860
High-speed rail operation status	0/1	4,560	0.42	0.49	0	1
Years since HSR opening	years	4,560	3.6	4.2	0	15
Per capita GDP	CNY	4,560	68,300	32,500	12,400	198,000
Population density	persons/km^2	4,560	427	356	18	2,980
Infrastructure investment	100m CNY	4,560	215.6	180.3	12.8	1,120.50
Night-time light intensity	DN value	4,560	32.7	21.4	3.2	78.5

Table 2. Sample structure of cities

Group	No. of cities	City-Year observations	Share (%)
Treatment group	118	2,422	49.17
Control group	122	2,318	50.83
Total	240	4,560	100

Table 3. Distribution of high-speed rail opening years

Stage	Period	Newly added cities	Cumulative cities
Initial stage	2005–2010	17	17
Expansion stage	2011–2015	44	61
Acceleration stage	2016–2020	45	106
Extension stage	2021–2023	12	118

Synthetic control method estimation results

To assess the short-term impact of HSR operation on regional tourism economies, this study constructs synthetic control groups for each HSR city and extracts the net effect over the two years before and after operation. Five cities – Wuhan, Zhengzhou, Hefei, Jinan and Nanchang – are selected as case studies based on the following characteristics: Strategic importance in China's HSR network, Significant tourism industry development potential and Availability of high-quality pre-treatment data.

To assess the short-term economic impact of HSR openings, Table 4 compares tourism economic trends of selected cities with their synthetic controls before and after HSR launch. The results reveal clear structural increases in GDP and consumption in treated cities, confirming that HSR acts as an exogenous shock that boosts tourism.

Table 4 shows that, within two years after HSR operation, the tourism-related GDP of the five representative cities significantly exceeded that of their synthetic control groups, with an average increase of 11.2%. Wuhan recorded the highest increase at 13.1%. As a core pillar of the tourism economy, the service sector also experienced an average growth of 6.8% during the same period. This indicates that HSR operation has driven the expansion of tertiary industries. The growth has been particularly evident in accommodation, catering and entertainment. Regarding per capita tourism expenditure, all cities saw an increase, with an average rise of 145.7 CNY. Wuhan and Jinan saw the largest increases, both exceeding 150 CNY, suggesting that improved transportation accessibility has enhanced tourists' spending. The MSE for all cities remained below 0.025, demonstrating that the synthetic control groups closely resembled the actual cities before HSR operation, thereby enhancing the credibility of policy effect identification. Overall, the SCM results clearly reveal the short-term multidimensional benefits of HSR operation, including boosting tourism output, expanding the service sector and increasing tourists' spending power.

Instrumental variable difference-in-differences results

To validate the effectiveness of the IVs and mitigate the risk that they capture pre-existing economic expectations before HSR operation, this study further conducts correlation, pre-trend and overidentification tests. The results are reported in Table 5.

According to Table 5, both HSR planning density and HSR adoption rate in neighboring cities are significantly correlated with the actual HSR operational status. The first-stage joint *F*-statistic is 24.7, exceeding the conventional threshold of 10, indicating that the weak instrument problem is not a concern. In the pre-trend test covering the three years prior to HSR opening, HSR planning density has no statistically significant effect on tourism revenue

Table 4. Comparison of tourism economic indicators between HSR cities and synthetic control groups (average change two years after operation)

City	Tourism-related GDP growth (%)	Service industry growth (%)	Per capita tourism consumption growth (yuan)	MSE (previous matching error)
Wuhan	13.1	7.2	168.5	0.014
Zhengzhou	11.7	6.5	145.3	0.019
Hefei	10.9	6.1	132.4	0.021
Jinan	12.4	6.9	158.2	0.017
Nanchang	9.8	5.4	123.9	0.02
Average	11.2	6.8	145.7	0.0182

Table 5. Validity and exclusion restriction tests of instrumental variables

Test type	Dependent variable	Key variable	Coefficient	SE	*p*-value
First-stage relevance test	HSR operation status	HSR planning density	0.286	0.041	<0.001
First-stage relevance test	HSR operation status	Neighboring city HSR adoption rate	0.194	0.052	0.001
Weak instrument test	HSR operation status	Joint instruments	F = 24.7	–	<0.001
Pre-trend test	Tourism revenue growth (pre-3 years)	HSR planning density	0.013	0.018	0.468
Pre-trend test	Tourism employment growth (pre-3 years)	HSR planning density	0.009	0.015	0.551
Pre-trend test	Tourism-related GDP growth (pre-3 years)	HSR planning density	0.016	0.021	0.439
Overidentification test	Second-stage residuals	Instrument set	Hansen J = 1.82	–	0.402
Robustness check (excluding high-growth cities)	Tourism employment growth	IV-DID	7.6	1.93	0.044
Robustness check (with city linear trends)	Tourism employment growth	IV-DID	7.9	1.91	0.042

growth, tourism employment growth or tourism-related GDP growth, suggesting that the instrument does not directly capture pre-existing tourism trends.

The Hansen overidentification test fails to reject the null hypothesis of instrument exogeneity, supporting the validity of the exclusion restriction. Furthermore, after excluding cities with rapid pre-treatment tourism growth and adding city-specific linear trends, the IV-DID estimates remain statistically significant. This indicates that the IV specification is robust.

To strengthen the identification of HSR policy effects and control for endogeneity bias, this study employs multiple models to estimate and compare its impact on tourism employment. The models include basic ordinary least squares (OLS), fixed effects models, traditional DID, IV-DID and two extended versions of the IV model.

To ensure robust causal inference, Table 6 compares the impact of HSR on tourism employment growth across five models. The IV model consistently reports stronger effects, suggesting that traditional models may underestimate HSR's role in boosting employment.

As shown in Table 6, the estimated policy effect becomes more stable and pronounced as the model identification strength increases. The OLS model produces a positive estimate; however, as it does not control for time-invariant heterogeneity, the results lack explanatory power. After accounting for city and year fixed effects, the fixed effects model estimates the employment effect at 4.5%, though potential endogeneity remains unresolved. The traditional DID model indicates a positive impact of HSR operation on tourism employment growth (+5.4%), but its statistical significance is relatively weak ($p = 0.072$). The main IV-DID model, incorporating "HSR planning density" and "neighboring city HSR operation rate" as IV, estimates the effect at 8.1%, reaching the 5% significance level. The IV-DID model with city-specific trend interactions further confirms the robustness of the estimation, yielding an employment growth estimate of 7.9%. A model incorporating a one-period lag variable assesses the persistence of the HSR effect, revealing that the delayed response remains significant (+7.5%, $p = 0.047$).

Employment in the accommodation and catering sectors shows a consistently upward trend across all models. Significant growth is observed in the IV models, with increases ranging from

Table 6. Multi-model estimation results of HSR operation on tourism employment (dependent variable: tourism-related employment growth rate)

Model type	Overall tourism employment growth (%)	Accommodation and catering employment growth (%)	SE	*p*-value
Model 1: OLS without fixed effects	3.2	1.8	2.01	0.186
Model 2: Panel fixed effects	4.5	2.1	1.77	0.098
Model 3: DID	5.4	2.7	1.83	0.072
Model 4: DID with city linear trend	6.1	3.3	1.74	0.054
Model 5: IV-DID baseline model	8.1	4.3	1.96	0.038
Model 6: IV-DID with city linear trend	7.9	4.1	1.91	0.042
Model 7: IV-DID with one-period lagged treatment	7.5	3.8	1.87	0.047

Note(s): The dependent variable is the tourism-related employment growth rate. IV-DID denotes DID with instrumental variables. The lagged treatment variable refers to the one-period lag of HSR operation status. Standard errors are clustered at the city level

4.1% to 4.3%. This highlights HSR operations' direct stimulus for service sector job creation. These findings further validate that: 1. Failing to control for endogeneity may lead to an underestimation of policy effects. 2. The impact of HSR construction on employment is not only significant but also structurally concentrated in tourism-related service sectors.

Bayesian dynamic model prediction results

To evaluate the cumulative impact of HSR operations on regional tourism economies over the medium to long-term, this study uses a Bayesian dynamic panel data model. The model is used to predict the tourism revenue growth trajectory over five years following HSR operation. This model effectively captures the time dependence of the dependent variable and uses posterior simulations to obtain confidence intervals for parameter estimates, revealing the dynamic evolution of policy effects. The estimated annual tourism revenue growth rate and the corresponding 95% posterior credible interval for the first five years after HSR operation are shown in Figure 2.

In Figure 2, tourism revenue shows positive growth in the first year following HSR operation (+1.4%). The effect then increases year by year, with the average annual growth rate reaching 3.2% in the fifth year after operation. The posterior confidence interval stabilizes and converges (95% CI: [2.5%, 3.9%]), indicating that the economic effects of HSR operation are cumulative and time-delayed, rather than a one-time shock. This progressive trend is often explained in infrastructure policy research by mechanisms such as improvements in service supply capacity and enhanced tourism network externalities. Although this study does not model the specific mechanisms, the results align with theoretical predictions.

Further heterogeneity analysis shows that cities with more developed infrastructure exhibit more significant effects after HSR operation. Figure 3 shows tourism revenue five years after HSR openings for cities of different sizes and resource endowments. The results reveal that mega-cities and resource-rich cities gain more significantly. This confirms the location-based mechanism linking infrastructure, attractiveness and performance. Specifically, Hangzhou and Suzhou are classified as "first-tier cities," Zhengzhou and Jinan as "new first-tier/second-tier cities" and Lanzhou and Nanning as "mid-western third-tier cities."

Figure 3 illustrates the heterogeneous effects of HSR operation across different city categories. First-tier cities exhibit the highest estimated growth rate, at approximately 4.35%,

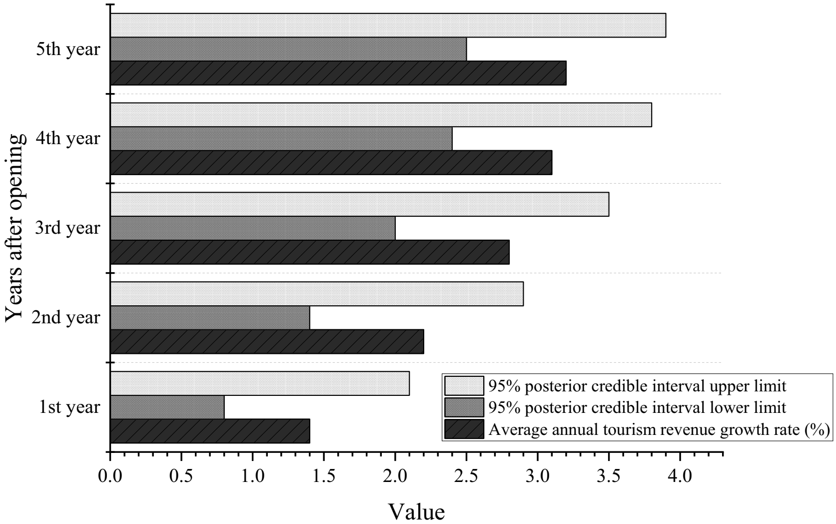

Figure 2. Dynamic effects of HSR on tourism revenue growth
Note(s): The figure shows posterior mean estimates and 95% credible intervals over five years after HSR operation

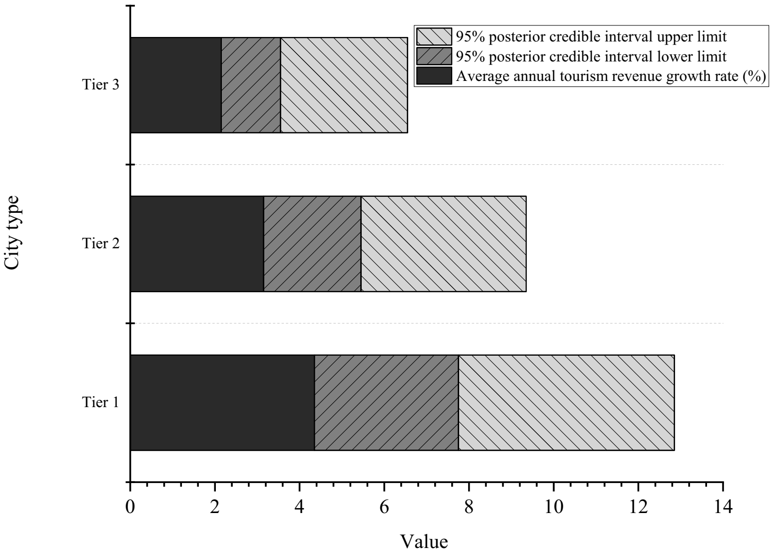

Figure 3. Heterogeneous effects of HSR on tourism revenue growth by city type
Note(s): Bars represent average annual tourism revenue growth five years after HSR operation. Error bars denote 95% posterior credible intervals

followed by second-tier cities at 3.15% and third-tier cities at around 2.15%. The confidence intervals indicate that the differences between these city groups are statistically significant. This pattern suggests that cities with stronger economic foundations and more developed tourism capacity are more equipped to translate improved transport accessibility into sustained income growth, whereas smaller or less developed cities require a longer adjustment period to fully gain the benefits of HSR connectivity.

To assess differences in predictive performance for forecasting tourism revenue growth, this study calculated model fit metrics, including root mean squared error (RMSE) and mean absolute error (MAE). As shown in Table 7, the Bayesian dynamic panel model consistently outperformed the other models both in-sample and out-of-sample, demonstrating its effectiveness in identifying medium- to long-term policy effects.

As shown in Table 7, the Bayesian dynamic panel model achieves the lowest RMSE and MAE across all metrics, demonstrating superior predictive accuracy and robustness. In-sample, its RMSE of 1.73 and MAE of 1.42 are substantially lower than those of OLS (RMSE = 3.22) and DID with IV (RMSE = 2.31), highlighting its strength in capturing the dynamic evolution of policy effects. Out-of-sample predictions remain stable, with an RMSE of 1.94 – significantly better than OLS (3.67) and fixed effects models (3.02) – indicating a stronger ability to extrapolate future policy impacts. This advantage mainly derives from the Bayesian approach’s capacity to incorporate prior information and dynamically update parameter estimates, effectively detecting structural changes and uncertainties in time series data. Overall, the Bayesian dynamic panel model not only fits current data well but also generalizes better, making it an ideal tool for identifying the medium- and long-term economic effects of transportation infrastructure policies.

Heterogeneity analysis

To further explore the heterogeneous impacts of the HSR operation policy on regional tourism economies, this study conducts heterogeneity analysis based on three dimensions: city size, initial tourism resource intensity and natural geographical regions. This helps identify systematic differences in policy effects between different types of cities. City size is classified according to the “*Notice on Adjusting the Standards for City Size Classification*” (State Council [2014] No. 51). Cities are divided into super-large cities, megacities, large cities (Type I/II), medium cities and small cities (Type I/II) based on urban population size. For analysis convenience, the cities are grouped into two categories. The first group is the large city group, which includes cities with a resident population of over 1 million (i.e. Type II large cities and above). The second group is the medium-small city group, which includes cities with a resident population under 1 million. Tourism resource intensity is categorized based on the average proportion of tourism revenue to GDP over the three years preceding HSR

Table 7. Model fit performance comparison

Model type	RMSE (in-sample)	MAE (in-sample)	RMSE (out-of-sample)	MAE (out-of-sample)
OLS	3.22	2.8	3.67	3.01
Fixed effects (FE)	2.85	2.33	3.02	2.61
DID	2.48	2.12	2.77	2.38
IV-DID	2.31	1.95	2.53	2.17
Bayesian dynamic panel	1.73	1.42	1.94	1.65

operation, as follows: high resource group (tourism revenue-to-GDP ratio >6%) and low resource group (tourism revenue-to-GDP ratio ≤6%).

Regional classification follows the natural geographical division standards published by the People's Republic of China State Council, dividing the country into four major regions. The Northern Region includes the eastern monsoon region north of the Qinling–Huaihe line, which encompasses North China and parts of Northeast China. The Southern Region is the eastern monsoon region south of the Qinling–Huaihe line, covering East China, South China and Central China. The Northwest Region consists of arid areas, including Xinjiang, Gansu, Ningxia and others. The Qinghai–Tibet Region includes high-altitude plateau areas, mainly Tibet and Qinghai. The comparative results of the tourism economic effects after HSR operation under these heterogeneity characteristics are shown in Figure 4.

In Figure 4, the policy effects of HSR operation exhibit clear structural differences across various types of cities. The larger the city size, the stronger the policy effects. The annual growth rate for large cities reaches 15.4%, significantly higher than the 9.1% for medium and small cities. This reflects the greater ability of larger cities to absorb policy changes due to their role as traffic hubs, consumption capacity and industrial support.

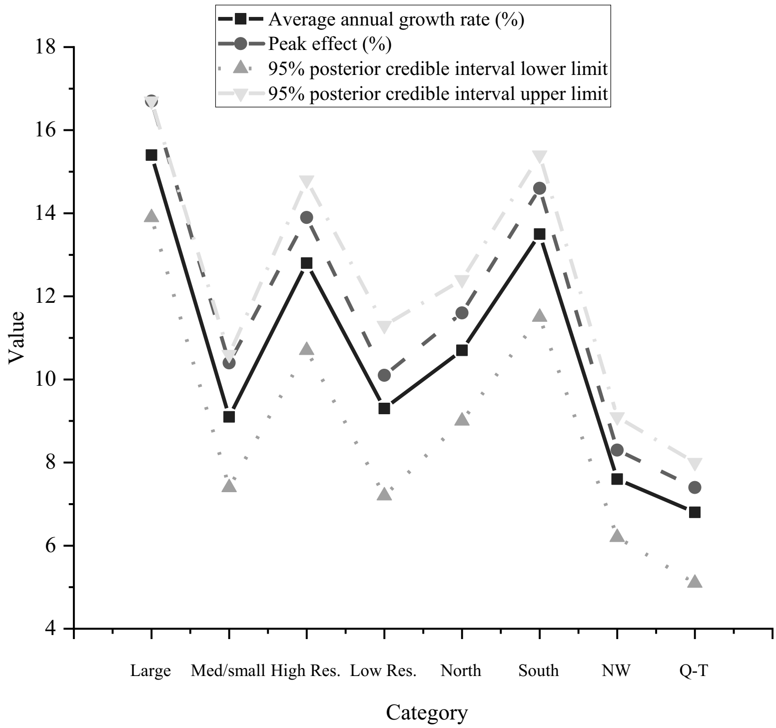

Figure 4. Comparison of tourism economic effects after HSR operation based on heterogeneous characteristics (average over five years post-operation)

Note(s): "Large" denotes large cities; "Med/Small" denotes medium and small cities; "High Res." and "Low Res." refer to tourism resource intensity; "North," "South," "NW" and "Q-T" denote regional classifications

The endowment of tourism resources is a key factor in determining the policy multiplier effect. High-resource cities, such as Zhangjiajie and Guilin, maintain relatively high growth rates (12.8%) over the five years following rail operation, while cities with weaker resource bases show more stage-dependent growth. The natural location significantly affects the speed and intensity of the HSR economic returns. The Southern Region, benefiting from a well-established service industry and higher tourist capacity, shows an early start and larger effects. In contrast, the Northwest and Qinghai–Tibet regions exhibit lagging growth, indicating that the policy effects have distinct location-based regulatory mechanisms.

Discussion

The significant positive impact of HSR openings on regional tourism economies has been confirmed through multiple methods. However, the underlying mechanisms and regional outcomes show notable heterogeneity, requiring further analysis to guide more targeted policy design. First, a city's economic absorption capacity and industrial structure greatly influence the returns from HSR. First-tier and strong second-tier cities – with a high share of services and abundant tourism resources – quickly amplify accessibility advantages after HSR launches, attracting concentrated tourist flows. Small- and medium-sized cities also benefit, but their policy effects are often delayed. This is because of underdeveloped tourism products and limited reception capacity, sometimes resulting in a "no conversion" effect despite improved connectivity. The heterogeneity observed in different cities also echoes the literature on tourism resilience, which emphasizes that performance under shocks depends on governance quality and adaptability. Liang et al. (2025) demonstrated in a recent study how responsible tourism scene construction could regulate economic outcomes, while Gomes et al. (2025) indicated that dynamic management capability was a key driver for performance in uncertain environments. The findings extend this research direction to the field of infrastructure, indicating that regional adaptability can amplify the long-term benefits of HSR expansion.

Second, the benefits of HSR come with structural risks. Increased tourism demand can lead to higher housing prices, environmental stress and overuse of key attractions. This is especially true in resource-rich but poorly regulated destinations such as certain mountain and historic towns. Sudden tourist surges strain fragile ecosystems and threaten long-term sustainability. Additionally, HSR may cause uneven flows of people and capital, intensifying "siphoning effects" that harm less-developed areas and worsen regional disparities.

Therefore, policies should emphasize "differentiated approaches" and "tailored matching." Medium-sized cities and regions with untapped tourism potential need targeted infrastructure subsidies and branding incentives. Ecologically sensitive or overcrowded cities require visitor capacity assessments and strict land-use controls. For lagging areas, coordinated infrastructure investments by central and local governments are essential to avoid "empty" connectivity without real benefits. Moreover, integrating tourism carrying capacity assessments early in HSR planning and establishing a coordinated "transport–economy–ecology" framework will help ensure sustainable and effective use of infrastructure investments.

These policy effects also have broader social implications. By improving access to tourist destinations and expanding employment in the service sector, HSR investment can contribute to achieving the United Nations Sustainable Development Goals, particularly those that emphasize decent work and inclusive economic growth. When infrastructure planning is combined with tourism carrying-capacity assessment and ecological regulation, HSR development can also support the Sustainable Development Goals by promoting more sustainable cities, communities and tourism destinations. In addition, the heterogeneous effects identified in this study suggest that infrastructure-driven tourism growth should not be evaluated solely by aggregate economic gains. For smaller and resource-constrained cities, complementary investment in local services, destination branding and feeder transportation can help narrow regional development gaps and further align with the Sustainable Development Goals. In this sense, the social contribution of HSR depends on whether improvements in accessibility are translated into inclusive, balanced and environmentally responsible regional development, rather than concentrating growth in cities that already possess structural advantages.

Although recent studies have examined performance, resilience and digital transformation at the organizational and regional levels (e.g. Gomes et al., 2025; Della Corte et al., 2021), few studies have combined multi-method causal inference with long-term dynamic evaluation under uncertainty. By integrating an IV-DID approach with a Bayesian dynamic panel model, this study identifies both the causal effects and the dynamic pathways through which HSR expansion affects regional tourism performance.

The findings of this study also have important implications for other emerging markets. Countries and regions such as India, Southeast Asia and Latin America similarly rely on large-scale transportation infrastructure to promote tourism development and regional coordination. These regions often face challenges such as pronounced disparities in urban hierarchy, limited tourism service capacity and local fiscal constraints. The results suggest that infrastructure investment alone cannot automatically generate inclusive tourism benefits. Sustainable social outcomes require simultaneous improvements in transportation accessibility, tourism product development, service capacity and local governance.

Conclusion

This study uses panel data of Chinese prefecture-level cities between 2005 and 2023 and constructs a multi-method identification framework. The framework includes SCM, IV-DID and Bayesian dynamic panel models. These methods are used to systematically assess the short-term effects, employment impacts and long-term growth trajectory of HSR operations on regional tourism economies. The study finds that HSR significantly promotes tourism-related GDP growth, drives service sector employment expansion and exhibits cumulative and time-lag effects. Furthermore, the policy effects show significant heterogeneity by city size, resource endowment and geographic location, with larger cities, high-resource areas and southern regions benefiting more. Although the study strives for rigorous identification strategies, certain limitations remain, such as the exclusion of micro-level tourist behavior data, which prevents direct identification of changes in tourism decision paths and consumption preferences. Additionally, there is a lack of in-depth exploration of inter-industry linkages between tourism and non-tourism industries. Future research could incorporate high-frequency travel big data and platform consumption data to further explore the deep mechanisms by which HSR affects tourist flow patterns and industrial structure evolution. Moreover, future studies should explore the interactions among HSR infrastructure, local governance and industrial collaboration to deepen understanding of the infrastructure-driven regional economic growth mechanism. This study introduces an integrated identification framework that provides a systematic approach for causal inference in high-dimensional spatial policies. The framework offers strong theoretical flexibility and holds significant potential for practical policy evaluation.

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References

Abdelati, H. M. (2024). Egypt's high-speed rail revolution: Integrating innovation, sustainability, and economic growth. *International Journal of Advanced Engineering and Business Sciences*, *5*(3), 1-15, 10.21608/ijaebs.2024.302018.1097.

Boto-García, D., Baños-Pino, J. F., & Cazón-Flores, A. (2025). Do new high-speed rail lines stimulate tourism demand in left-behind regions? *Current Issues in Tourism*, *29*(14), 10.1080/13683500.2025.2468740.

Cabrilo, S., Dahms, S., & Tsai, F. S. (2024). Synergy between multidimensional intellectual capital and digital knowledge management: Uncovering innovation performance complexities. *Journal of Innovation & Knowledge*, *9*(4), 100568, 10.1016/j.jik.2024.100568.

Chen, H., Cheng, K., & Zhang, M. (2023). Does geographic proximity affect firms' cross-regional development? Evidence from high-speed rail construction in China. *Economic Modelling*, *126*, 106402, 10.1016/j.econmod.2023.106402.

Della Corte, V., Del Gaudio, G., Sepe, F., & Luongo, S. (2021). Destination resilience and innovation for advanced sustainable tourism management: A bibliometric analysis. *Sustainability*, *13*(22), 12632, 10.3390/su132212632.

Di Matteo, D. (2023). Does high-speed rail matter for tourism? Evidence from Italy. *Research in Transportation Business & Management*, *48*, 100881, 10.1016/j.rtbm.2022.100881.

Di Ruocco, I., & D'Auria, A. (2024). The economic impact of high-speed rail on rural and inner urban areas economy: The case study of HSR Naples–Bari in South of Italy. *Rural and Regional Development*, *2*(4), 10017, 10.70322/rrd.2024.10017.

Fan, Z., Long, R., & Shen, Z. (2024). Regional digitalization, dynamic capabilities and green innovation: Evidence from e-commerce demonstration cities in China. *Economic Modelling*, *139*, 106846, 10.1016/j.econmod.2024.106846.

Fang, J., Fu, F., Zhang, X., Yao, S., & Ou, J. (2024). Impact of high-speed rail on the mismatch of labor and industry allocations: Evidence from Chinese cities in 2000–2019. *Journal of Asian Economics*, *92*, 101744, 10.1016/j.asieco.2024.101744.

Gallo, M., & La Rocca, R. A. (2022). The impact of high-speed rail systems on tourist attractiveness in Italy: Regression models and numerical results. *Sustainability*, *14*(21), 13818, 10.3390/su142113818.

Gomes, J. M., Carvalho, F., Alves, A., & Cabral, Â. (2025). Dynamic managerial capabilities' impact on international overall performance. *Revista De Administração De Empresas*, *65*(6), e2023-0552, 10.1590/S0034-759020250605.

Guan, C., & Hu, Q. (2023). Does high-speed railway impact urban logistics industry agglomeration? Empirical evidence from China's prefecture-level cities. *Socio-Economic Planning Sciences*, *87*, 101557, 10.1016/j.seps.2023.101557.

Hamza, S. M., Aysan, A. F., & Kayani, U. N. (2025). Cultural catalysts of FinTech: Baring long-term orientation and indulgent cultures in OECD countries. *Economics*, *19*(1), 20250137, 10.1515/econ-2025-0137.

Hu, M. Y., & Xu, J. (2022). How does high-speed rail impact the industry structure? Evidence from China. *Urban Rail Transit*, *8*(3-4), 296-317, 10.1007/s40864-022-00175-w.

Jou, R. C., & Chen, K. H. (2020). The relationship between high speed rail and tourism. *Sustainability*, *12*(12), 5103, 10.3390/su12125103.

Lertpusit, S., & Suvakanta, P. (2023). Challenges to Thailand's negotiating strategy in the thai–China high-speed railway project. *East Asian Policy*, *15*(03), 34-48, 10.1142/S179393052300020X.

Li, G., Pu, K., & Long, M. (2023). High-speed rail connectivity, space-time distance compression, and trans-regional tourism flows: Evidence from China's inbound tourism. *Journal of Transport Geography*, *109*, 103592, 10.1016/j.jtrangeo.2023.103592.

Li, Y., & Terason, S. (2023). Configuring the pattern of sustainable tourism development as affected by the construction of a high-speed railway system. *Sage Open*, *13*(3), 1-17, 10.1177/21582440231181368.

Liang, F., Liu, Y., Gu, M., Pan, Y., & Wu, X. (2025). Construction of responsible tourism scenes in urban blocks. *Revista De Administração De Empresas*, *65*(1), e2024-0068, 10.1590/S0034-759020250103.

Martínez-García, M. Á., & Cámara, Á. (2022). Impact of an economic crisis on youth employment: Evidence from the 2008 financial crisis in Spain. *Economics*, *16*(1), 276-287, 10.1515/econ-2022-0033.

Nokkaew, M., Nongpong, K., Yeophantong, T., Ploykitikoon, P., Arjharn, W., Phonak, D., … Surawanitkun, C. (2024). Hidden emotional trends on social media regarding the Thailand–China high-speed railway project: A deep learning approach with ChatGPT integration. *Social Network Analysis and Mining*, *14*(1), 175, 10.1007/s13278-024-01340-8.

Roldan, A. (2022). The golden fetters in the mediterranean periphery: How Spain and Italy overcame business cycles between 1870 and 1913? *Economics*, *16*(1), 170-193, 10.1515/econ-2022-0025.

Russell, C. J., Chen, C. L., & Wong, C. Y. (2024). Bridging the gap between high-speed rail transport studies and cluster economics through social knowledge exchange: Future research potential. *Transport Reviews*, *44*(5), 1103-1127, 10.1080/01441647.2024.2366201.

Seo, H., Lee, H., & Tsai, F. S. (2025). Impact of perception of intelligent information technology (IIT) on IIT-Based policy Decision-Making in the public sector: Moderating effect of social capital. *Journal of Organizational and End User Computing (JOEUC)*, *37*(1), 1-38, 10.4018/JOEUC.379768.

Shi, K., Wang, J., Liu, X., & Zhao, X. (2022). Impact of high-speed rail on tourism in China. *Plos One*, *17*(12), e0276403, 10.1371/journal.pone.0276403.

Shu, H., Zha, J., Tan, T., & Li, C. (2023). How does high-speed railway affect tourism efficiency? An empirical study in China. *Current Issues in Tourism*, *26*(16), 2647-2663, 10.1080/13683500.2022.2091431.

Snower, D. J., & Wilson, D. S. (2025). Rethinking the theoretical foundation of economics II: Core themes of the multilevel paradigm. *Economics*, *19*(1), 20250133, 10.1515/econ-2025-0133.

Sudan, F. K. (2022). Socioeconomic and spatial impacts of high-speed rail on enterprises: An ex-ante case study of Ahmedabad station area, India. *Global Economics Science*, 235-257, 10.20944/preprints202108.0070.v1.

Tsai, F. S. (2022). Guest editorial: Sustainable creativity, innovation and entrepreneurship: Concerning failures and resilience in hard times, difficult conditions and special communities. *Journal of Organizational Change Management*, *35*(7), 965-968, 10.1108/JOCM-11-2022-509.

Wang, S., Zhou, Y., Guo, J., & Mao, J. (2023a). Did high speed rail accelerate the development of tourism economy? Empirical analysis from northeast China. *Transport Policy*, *143*, 25-35, 10.1016/j.tranpol.2023.09.004.

Wang, C., Chen, J., Li, B., Chen, N., & Wang, W. (2023b). Impact of high-speed railway construction on spatial patterns of regional economic development along the route: A case study of the Shanghai–Kunming high-speed railway. *Socio-Economic Planning Sciences*, *87*, 101583, 10.1016/j.seps.2023.101583.

Wang, B., de Jong, M., van Bueren, E., Ersoy, A., & Meng, Y. (2023c). Transit-oriented development in China: A comparative content analysis of the spatial plans of high-speed railway station areas. *Land*, *12*(9), 1818, 10.3390/land12091818.

Yao, S., Yan, X., Lei, C. K., & Wang, F. (2022). High-speed railway and tourism development in China. *Tourism Economics*, *28*(6), 1520-1544, 10.1177/1354816621998520.

Zhang, Y., Liu, J., & Wang, B. (2022). The impact of high-speed rails on urban expansion: An investigation using an SDID with dynamic effects method. *Socio-Economic Planning Sciences*, *82*, 101294, 10.1016/j.seps.2022.101294.

Zhao, J., Yan, J., Ran, Q., Yang, X., Su, X., & Shen, J. (2022). Does the opening of high-speed railways improve urban livability? Evidence from a quasi-natural experiment in China. *Socio-Economic Planning Sciences*, *82*, 101275, 10.1016/j.seps.2022.101275.

Zhou, B., Wen, Z., Sutherland, I., & Lee, S. K. (2022). The spatial heterogeneity and dynamics of tourism-flow spillover effect: The role of high-speed train in China. *Tourism Economics*, *28*(2), 300-324, 10.1177/1354816620958309.

Further reading

Yoo, S., Kumagai, J., & Managi, S. (2024). Urban–rural gap induced by high-speed rail: 35 years of evidence from Japan. *Research in Transportation Business & Management*, *55*, 101131, 10.1016/j.rtbm.2024.101131.

Appendix. Bayesian dynamic panel model specification and estimation

To characterize the dynamic evolution of tourism's economic effects after HSR operation, a dynamic panel structure was introduced and estimated within a Bayesian framework. A lagged dependent variable was incorporated into the model to capture path dependence and inertia in tourism economic indicators, while controlling for unobserved heterogeneity across cities and time.

(A1) Model specification

Let y_{it} denote the tourism economic indicator of city i in year t. The model is specified as:

$$y_{it} = \alpha y_{i,t-1} + \beta HSR_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where $y_{i,t-1}$ is the first-order lag of the dependent variable. HSR_{it} is a binary indicator for HSR operation. X_{it} is a vector of control variables, including per capita GDP, population density, infrastructure investment and night-time light intensity. γ is the corresponding coefficient vector. μ_i and λ_t represent city and year fixed effects, respectively. ε_{it} is the idiosyncratic error term.

(A2) Likelihood function

Assuming that the error term follows a normal distribution:

$$\varepsilon_{it} \sim \mathcal{N}\left(0, \sigma^2\right)$$

The parameter vector is defined as:

$$\Theta = \left\{\alpha, \beta, \gamma, \sigma^2\right\}$$

The conditional likelihood function is given by:

$$\mathcal{L}(\Theta) = \prod_{i=1}^{N} \prod_{t=1}^{T} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{\left(y_{it} - \alpha y_{i,t-1} - \beta HSR_{it} - \gamma' X_{it} - \mu_i - \lambda_t\right)^2}{2\sigma^2}\right)$$

(A3) Prior distributions

To avoid overly restrictive prior information, weakly informative priors were adopted:

$$\alpha \sim \mathcal{N}\left(0, \tau_\alpha^2\right), \beta \sim \mathcal{N}\left(0, \tau_\beta^2\right), \gamma \sim \mathcal{N}\left(0, \tau_\gamma^2 \mathrm{I}\right)$$

$$\sigma^2 \sim \text{Inverse} - \text{Gamma}(a_0, b_0)$$

where τ_α^2, τ_β^2 and τ_γ^2 were set to large values (e.g. 100), while a_0 and b_0 were set to small values to ensure weak informativeness.

(A4) Posterior distribution

According to Bayes' theorem, the posterior distribution is as follows:

$$p(\Theta|\mathrm{y}) \propto \mathcal{L}(\Theta) \cdot p(\Theta)$$

As the posterior distribution does not have a closed-form solution, numerical approximation methods were used.

(A5) Markov Chain Monte Carlo sampling procedure

Markov Chain Monte Carlo methods were used to draw samples from the posterior distribution. The estimation procedure was implemented as follows:

- Sampling strategy: a hybrid of Gibbs sampling and Metropolis–Hastings algorithms
- Total iterations: 10,000
- Burn-in period: first 2,000 iterations discarded
- Effective samples: 8,000 iterations

Parameter updates were performed iteratively using conditional posterior distributions, enabling approximation of the joint posterior distribution.

(A6) Convergence diagnostics

Convergence was assessed using multiple complementary diagnostics:

- Gelman–Rubin statistic: $\widehat{R} < 1.01$, indicating that multiple chains converged to the same stable posterior distribution.
- Geweke diagnostic: The test compares the mean of the first 10% and the last 50% of the Markov chain. Insignificant standardized differences indicate convergence.
- Autocorrelation function: Posterior samples exhibit decaying autocorrelation rapidly as lag increases, suggesting strong sample independence.

(A7) Estimation of dynamic effects

Based on the posterior distribution, the average treatment effect at different durations since HSR operation k was estimated as:

$$ATE_k = \mathbb{E}\left(y_{it} - y_{it}^{(0)} | \text{ years since HSR} = k\right)$$

The corresponding 95% posterior credible interval is defined as:

$$CI_{95\%} = [Q_{2.5\%}, \quad Q_{97.5\%}]$$

Where Q denotes posterior quantiles. The resulting dynamic path captures both the cumulative and lagged characteristics of policy effects over time.

(A8) Methodological characteristics (additional clarification)

The proposed model extends a fixed-effects framework by incorporating a dynamic structure and explicitly modeling parameter uncertainty through Bayesian estimation. Compared with traditional econometric approaches, this method allows for the simultaneous identification of temporal dependence effects and uncertainty intervals. As a result, it improves both the stability and interpretability of long-term policy evaluation in tourism economics.

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Data availability
The entire data set supporting the findings of this study is available upon request from the corresponding author.