A Study on Regional Disparities and the Evolution of Educational Equity in the Yangtze River Economic Belt from a Spatio-temporal Perspective

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Abstract

Educational equity is a core pillar of high-quality, coordinated development in the Yangtze River Economic Belt. Existing research on educational equity within river basins has several prominent deficiencies. These deficiencies mainly include the failure to integrate macro regional disparities with micro practical conditions, as well as a scarcity of quantitative research concerning the full-chain transmission effects of educational development. Against this background, this paper takes the panel data of basic education resource allocation covering the 11 provinces and municipalities of the Yangtze River Economic Belt from 2016 to 2023 as its core research sample. It constructs a comprehensive research framework combining spatiotemporal analysis and econometric testing to systematically investigate the regional disparities and spatiotemporal evolution characteristics of educational equity in the Yangtze River Economic Belt. This study adopts spatial autocorrelation analysis and spatiotemporal Markov chain transition probability matrices to characterize the binary spatiotemporal pattern of educational resource distribution within the basin, namely "high-to-high clustering and low-to-low lock-in". It also discovers that the level of basic education shows strong path dependence, and the neighborhood environment exerts a significant influence on the probability of regional educational development transitions. Benchmark tests based on a two-way fixed-effects model confirmed that the allocation of basic education resources has a significant positive impact on regional higher education competitiveness, with the consolidation rate of compulsory education having the most pronounced effect. Furthermore, this effect exhibits marked regional and educational-stage heterogeneity, and basic education investment in underdeveloped upstream regions exhibits a significant "weakest-link effect". Mediation analysis revealed the core transmission pathway: "allocation of basic education resources → improvement in student quality → enhanced higher education competitiveness". Counterfactual scenario simulations showed that addressing shortcomings in upstream basic education can significantly narrow regional disparities in higher education competitiveness. Based on the above research findings, this study proposes targeted policy recommendations in four areas: establishing a mechanism for coordinated educational development within the river basin. Increasing investment in basic education in upstream regions; unblocking the transmission pathways across the entire education development chain; and establishing a dynamic monitoring and counterfactual evaluation mechanism. These recommendations provide scientific, empirical support and actionable practical guidance for the balanced development of education and high-quality coordinated development within the Yangtze River Economic Belt.

Keyword

Yangtze River Economic Belt, Educational equity, Allocation of resources for basic education, Mediating effect

Introduction

Educational equity is a vital cornerstone of social equity and a core driver of high-quality regional development. Since the 18th National Congress of the Communist Party of China, the nation has continuously promoted the inclusive and balanced development of education, providing a fundamental framework for addressing the uneven distribution of resources. However, within the Yangtze River Economic Belt - a key strategic region for the nation - imbalances in education remain prominent. Currently, there are significant gradational disparities among the upper, middle, and lower reaches of the basin in terms of educational funding, teacher allocation, and access to high-quality educational opportunities; these structural contradictions have become key bottlenecks constraining the coordinated development of the entire basin [1].

Although existing research has laid a solid theoretical foundation, domestically and internationally, Porter's classic theory of competition and value chain analysis have provided a framework for regional resource allocation and the evaluation of public services [2]. Endogenous growth theories have elucidated the mechanism by which education narrows regional disparities through human capital accumulation [3]. Surman and Tóth have constructed a dual-perspective framework for evaluating the quality of educational services from both teacher and student viewpoints, while Ferraris et al. have emphasized the supportive role of teacher collaboration in ensuring equitable public services. Within the domestic academic community, scholars such as Du Yubo and Huang Honglan have promoted balanced educational development through the optimization of school distribution and the "quality revolution". This study has focused on regional collaboration, pointing out that education is shifting toward a model of "balanced collaboration" and emphasizing the importance of integrating junior and senior high school education [4,5]. However, significant gaps remain in existing literature: Quantitative studies specifically targeting the entire Yangtze River Economic Belt and covering the entire junior and senior high school stages are scarce [6]. In particular, there is a lack of attempts to construct a chain-based indicator system linking fiscal investment, retention rates, and advancement rates, and empirical analyses integrating macro-level regional disparities with micro-level policy effects are also rare [7].

In light of this, this paper, grounded in the national strategic context of the Yangtze River Economic Belt, constructs a multidimensional model for measuring educational equity, aiming to systematically analyze the spatiotemporal differentiation and evolutionary logic of educational equity in the region from 2016 to 2023 [8,9]. The study first sets three core dimensions as the research perspective. These dimensions include educational fiscal support, the development of compulsory education, and access to high-quality educational opportunities. Based on the above dimensions, the study screens key indicators covering the proportion of educational funding, the retention rate in compulsory education, and the rate of students qualifying for the first-tier undergraduate programs in the National College Entrance Examination [10,11]. By eliminating redundant variables, the study establishes a streamlined and scientifically sound evaluation system. Second, to mitigate the impact of outliers and enhance regional comparability, the study innovatively introduced a quantile discretization method to convert continuous panel data into a four-tiered gradient scale. It also constructed a spatiotemporal weighting matrix that integrates geographic adjacency and time lag effects, thereby laying the methodological foundation for subsequent econometric analysis [12].

Data processing and related methods

Data discretization and construction of spatio-temporal weighting matrices

(1) Selection of indicators and data preprocessing

Select three key metrics:

a) Intensity of fiscal investment: Derived from the "Share of Fiscal Expenditures on Education" within total fiscal expenditures on education (converted to a percentage to eliminate the impact of scale).

b) Quality of compulsory education: Derived from the retention rate and dropout rate in compulsory education; since the retention rate and dropout rate are highly negatively correlated, this study selects the retention rate as the core positive indicator.

c) Equity in access to higher education: Based on high school and college entrance exam admission rates, the rate of students meeting the eligibility criteria for special admissions to the first-tier undergraduate programs in the college entrance exam is used as an indicator of access to high-quality higher education opportunities.

(2) Quantile discretization

To mitigate the impact of outliers on the results of subsequent spatiotemporal econometric analyses, this study employs the quartile discretization method to categorize the panel data from the 11 provinces and municipalities in the Yangtze River Economic Belt for the period 2016-2023 into ordered categories, thereby converting continuous variables into ordered categorical variables. Quartile discretization is a nonparametric method for classifying continuous data [13]. Its core logic involves using the quartiles (Q1, Q2, Q3) of the data distribution as cutoff thresholds to divide the sample data into four equal-sized intervals. This approach not only avoids the subjectivity of arbitrarily setting thresholds but also effectively mitigates the disruption caused by outliers and extreme values to model estimates, thereby ensuring the stability and objectivity of subsequent analyses [14]. This study uses the quartiles of indicators for the 11 provinces and municipalities in the Yangtze River Economic Belt across various years as the basis for classification, uniformly dividing each indicator into four levels (1 = low, 2 = lower-middle, 3 = upper-middle, 4 = high). This approach preserves the relative differences among indicators while constructing standardized, tiered data that is comparable over time and distinguishable across regions.

This paper takes educational equity as its core research theme. This section selects two key indicators for empirical illustration, namely the 2023 Regional Index of Balanced Development in Compulsory Education and per-student general public budget funding for compulsory education, which cover all 11 provinces and municipalities in the Yangtze River Economic Belt. These sample indicators are adopted to fully demonstrate the implementation process and classification results of quantile discretization (as shown in Table 1).

Table 1. Thresholds and specific distributions for each indicator by bin in 2023.

Indicators	Q1	Q2	Q3	Level 1	Level 2	Level 3	Level 4
Percentage of education expenditures	<24.32%	<26.17%	<26.70%	Shanghai (19.60%) Hubei (22.32%) Sichuan (23.77%)	Jiangsu (25.29%) Hunan (24.88%)	Anhui (26.41%) Chongqing (26.50%) Yunnan (26.17%)	Zhejiang (29.35%) Jiangxi (26.90%) Guizhou (26.91%)
Retention rate in compulsory education	<96.97%	<98.00%	<99.19%	Jiangxi (96.34%) Chongqing (95.79%) Yunnan (95.80%)	Sichuan (97.77%) Yunnan (97.61%)	Anhui (98.00%) Hubei (98.40%) Hunan (98.00%)	Shanghai (99.97%) Jiangsu (100.00%) Zhejiang (100.00%)
Pass rate for special admissions to the college entrance examination	<12.96%	<15.28%	<25.29%	Jiangxi (12.92%) Sichuan (12.30%) Yunnan (11.60%)	Zhejiang (15.16%) Anhui (13.00%)	Hubei (15.28%) Hunan (15.30%) Yunnan (18.44%)	Shanghai (34.51%) Jiangsu (32.14%) Chongqing (36.90%)

Provinces and municipalities were classified into corresponding tiers based on the ranges of their indicator values, clearly illustrating the gradient distribution of educational resource allocation across the Yangtze River Economic Belt. The same method was used to categorize all annual data from 2016 to 2023, laying a solid data foundation for subsequent analyses of the spatiotemporal evolution and heterogeneity of regional educational equity.

(3) Setting the spatio-temporal weight matrix

This paper selects the 11 provinces and municipalities delineated in the national "Outline of the Development Plan for the Yangtze River Economic Belt" as the subjects of study, namely Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Guizhou, and Yunnan. From a physical geography perspective, the upper reaches of the Yangtze River also flow through Qinghai Province and the Tibet Autonomous Region. However, since these two areas fall outside the policy scope of the Yangtze River Economic

Belt, they have not been included in this analysis. The provincial adjacency matrix constructed in this paper measures only the land borders between these 11 sample provinces and does not take into account geographical proximity to administrative regions outside the study area. To accurately characterize the spatiotemporal interaction effects of equitable educational development in the Yangtze River Economic Belt, this study constructs a spatiotemporal weight matrix (W_{st}), which serves as a core econometric tool for subsequent spatiotemporal autocorrelation analysis and Markov chain modeling.

First, the logic of the spatio-temporal weighting matrix is formulated herein. (W_{st}). According to the defined rules, the spatio-temporal weighting matrix combines the Queen's adjacency (spatial weight W_s) and first-order lag (temporal weight W_t). The core formula is:

$$W_{st} = W_{ij} \times W_t \quad (1)$$

Here, i represents the current province, j represents a neighboring province. Spatial dimension (W_{ij}): The Queen adjacency matrix is adopted, with provinces sharing a geographical border defined as neighbors (value = 1). Otherwise, value is 0. Temporal dimension (W_t): This study adopts a first-order lag, whereby the current year is affected by that of the previous year (value = 1), while the weight of the self-influence is 0.

Next is the definition of neighboring provinces (Queen adjacency):

Anhui: Jiangsu, Zhejiang, Jiangxi, Hubei
Guizhou: Sichuan, Yunnan, Chongqing, Hunan
Hubei: Anhui, Chongqing, Hunan, Jiangxi
Hunan: Hubei, Chongqing, Guizhou, Jiangxi
Jiangsu: Anhui, Shanghai, Zhejiang
Jiangxi: Anhui, Hubei, Hunan, Zhejiang
Sichuan: Guizhou, Yunnan, Chongqing
Yunnan: Guizhou, Sichuan
Zhejiang: Anhui, Shanghai, Jiangxi, Jiangsu
Chongqing: Hubei, Hunan, Sichuan, Guizhou
Shanghai: Jiangsu, Zhejiang

Taking the 2023 spatiotemporal weighting matrix as an example, this matrix reflects how the status of education indicators in each province in 2022 is transmitted to 2023. Its core logic is that a province's current state of educational development is collectively influenced by the indicator levels of all its geographic neighbors in the previous period. Table 2 below provides a simplified illustration of the 2023 spatiotemporal weighting matrix.

Table 2. Queen contiguity spatial weight submatrix of 11 provinces and municipalities in the Yangtze River Economic Belt.

Province (geographical proximity)	AH	HB	JS	JX	SC	GZ	HN	YN	ZJ	CQ	SH
AH	0	1	1	1	0	0	0	0	1	0	0
HB	1	0	0	1	0	0	1	0	0	1	0
JS	1	0	0	0	0	0	0	0	1	0	1
JX	1	1	0	0	0	0	1	0	1	0	0
SC	0	0	0	0	0	1	0	1	0	1	0
GZ	0	0	0	0	1	0	1	1	0	1	0
HN	0	1	0	1	0	1	0	0	0	1	0
YN	0	0	0	0	1	1	0	0	0	0	0
ZJ	1	0	1	1	0	0	0	0	0	0	1
CQ	0	1	0	0	1	1	1	0	0	0	0
SH	0	0	1	0	0	0	0	0	1	0	0

Note: Anhui (AH), Hubei (HB), Jiangsu (JS), Jiangxi (JX), Sichuan (SC), Guizhou (GZ), Hunan (HN), Yunnan (YN), Zhejiang (ZJ), Chongqing (CQ), Shanghai (SH).

In terms of matrix distribution characteristics, the spatial adjacency relationships among the 11 provinces and municipalities in the Yangtze River Economic Belt show obvious clustering features of three major groups: eastern, central, and western regions. These spatial grouping characteristics are highly consistent with the gradient pattern of educational development within the river basin [15]. In the eastern region, the three provinces and municipalities of Shanghai, Jiangsu, and Zhejiang are adjacent to one another and closely interconnected, forming a core growth pole for educational development. In the central region, the four provinces of Anhui, Jiangxi, Hubei, and Hunan are contiguous and form a key hub for absorbing spillover effects from the east and linking with the west. In the western region, the four provinces of Chongqing, Sichuan, Guizhou, and Yunnan exhibit prominent internal contiguity, forming a relatively independent upstream cluster for educational development.

Among the representative provinces and municipalities, Anhui borders four provinces - Jiangsu, Zhejiang, Jiangxi, and Hubei, and is thus able to absorb the spatial spillover effects of educational development from multiple provinces [16]. On the other hand, Guizhou geographically borders Sichuan and Yunnan and has no direct connection to the eastern and central regions, thus reflecting the relatively independent overall spatial structure of the western region. This matrix accurately quantifies the density of spatiotemporal connections among provinces and municipalities, providing core data support for subsequent calculations of the spatial spillover effects of educational equity and the patterns of their spatiotemporal evolution [17].

Global spatiotemporal autocorrelation analysis

(1) Calculation of Moran's I index

Using GeoDa software to calculate the global Moran's I index for 2016 and 2023, the results are as follows Table 3.

Table 3. Moran's I Index.

Indicators	2016	2023	Z-value	Significant value	Feature analysis
Percentage of education expenditures	0.285	0.312	2.45	Significant （$p<0.05$）	High-investment regions (Yunnan, Guizhou, and Chongqing) continue to cluster, while low-investment regions (the lower reaches of Shanghai, Jiangsu, and Zhejiang) are relatively dispersed.
Retention rate in compulsory education	0.452	0.481	3.89	Significant （$p<0.01$）	A stable "high downstream—low upstream" polarized pattern has emerged, with a very strong spatial lock-in effect.
Pass rate for special admissions to the college entrance exam	0.368	0.215	1.98	Weakening trend	The expansion of college enrollment and the spillover effect have alleviated Shanghai's dominant position in education, narrowing regional disparities.

(2) Analysis of the Moran's S-plot for space-time data

To further characterize the local spatial correlation patterns and dynamic evolution of compulsory education retention rates in the Yangtze River Economic Belt, this study uses standardized compulsory education retention rate data to construct Moran's scatter plots for 2016 and 2023. These plots visually illustrate the spatial correlation patterns among provinces and municipalities and their neighboring regions, identifying clusters of high values, lock-in effects of low values, and spillover effects in regional educational development. The Moran's scatter plots in this study use the standardized compulsory education retention rates of provinces as the x-axis and the standardized spatial lag values (weighted averages of neighboring provinces) as the y-axis, classifying spatial association patterns into four categories:

First quadrant (H-H): Provinces with high scores are surrounded by high-scoring neighbors, representing hubs of educational development;

Second quadrant (L-H): Provinces with low scores are surrounded by high-scoring neighbors, representing underdeveloped areas;

Third quadrant (L-L): Provinces with low scores are surrounded by low-scoring neighbors, representing clusters of underdeveloped areas;

Fourth quadrant (H-L): High-performing provinces surrounded by low-performing neighbors, representing isolated pockets of development.

As shown in Figure 1 to Figure 3 below, the study found that in 2016, the consolidation rates of compulsory education across river basins exhibited a distinct binary pattern of "high-high clustering" and "low-low clustering": Provinces and cities in the Yangtze River Delta, such as Shanghai, Jiangsu, and Zhejiang, were concentrated in the H-H quadrant, forming a stable hub of educational development. While western provinces and cities, including Guizhou, Yunnan, Sichuan, and Chongqing, were concentrated in the L-L quadrant, exhibiting a pronounced spatial lock-in effect. Anhui was located in the L-H quadrant, representing a typical educational development "depression". By 2023, the spatial pattern of compulsory education retention rates within the basin had undergone positive changes: the high-value clustering trend in the Yangtze River Delta remained robust, and the advantages of educational synergy continued to stand out. Anhui successfully transitioned from the L-H quadrant to the H-H quadrant, clearly demonstrating the Yangtze River Delta's educational spillover effect and completely breaking free from its status as an educational "depression". The L-L clustering pattern in western provinces and municipalities has weakened somewhat, with retention rates rising overall. The polarization in educational development across the region has eased, and regional educational equity has significantly improved [18].

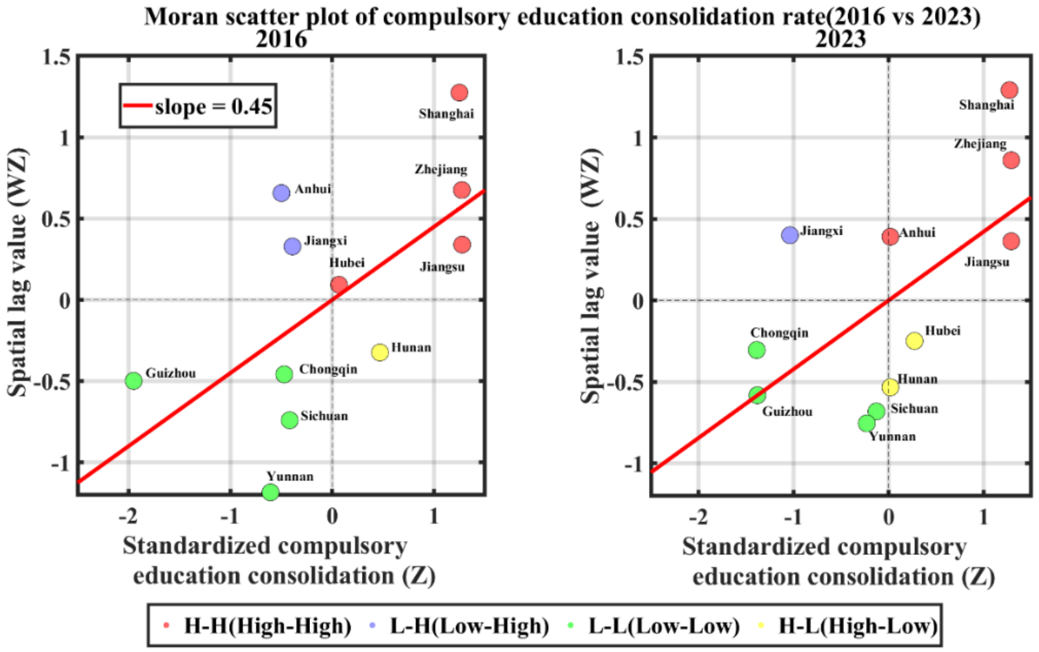

Figure 1. Moran's scatter plot of the retention rate in compulsory education.

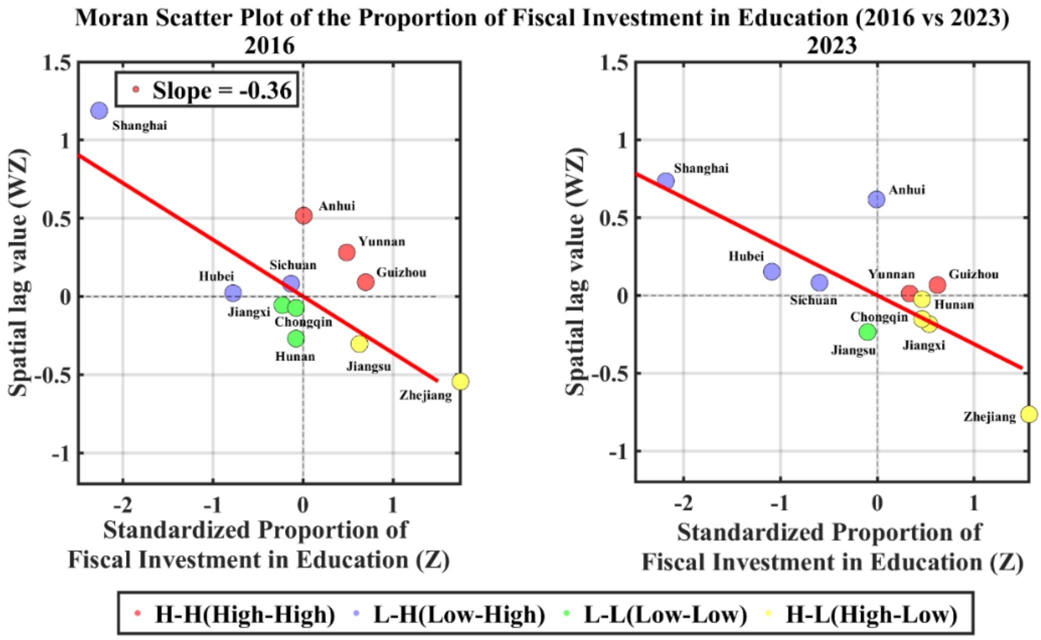

Figure 2. Moran's scatter plot of education finance.

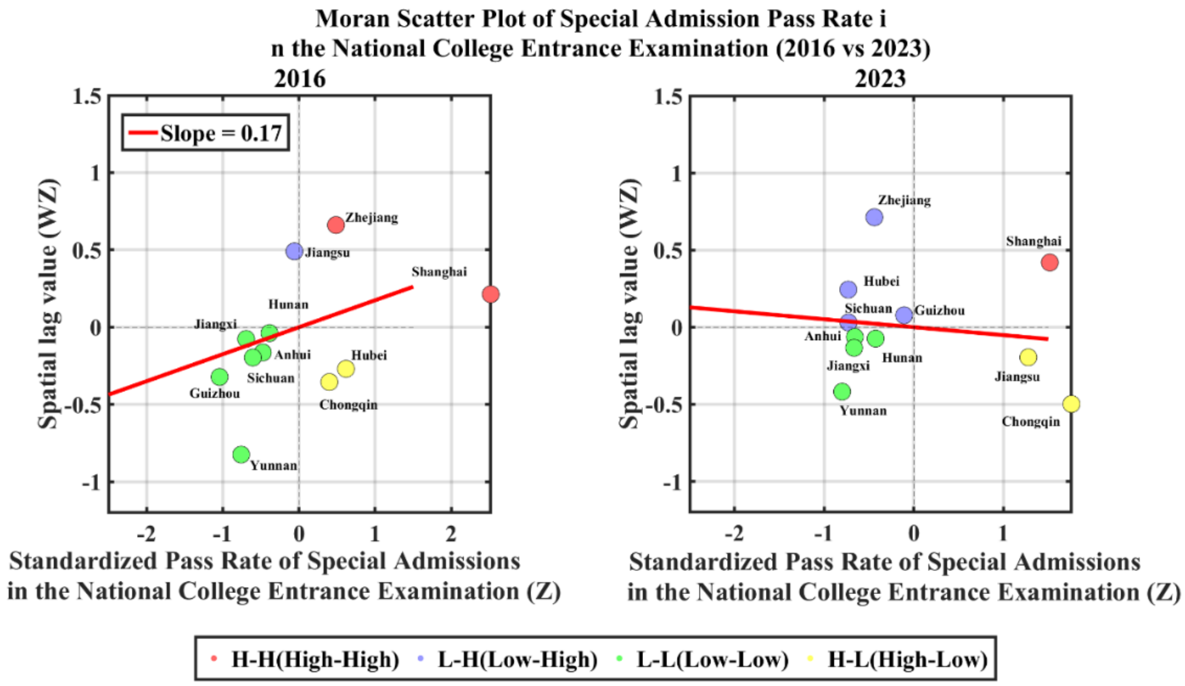

Figure 3. Moran's scatter plot of the qualification rate for special admissions to the college entrance examination.

Analysis of the transition probability matrix of a spatiotemporal Markov chain

Building on spatial autocorrelation analysis, this study constructs transition probability matrices for both traditional Markov chains and spatio-temporal Markov chains to further reveal the dynamic patterns of the consolidation rate of compulsory education and its spatial interaction effects in the Yangtze River Economic Belt. It then conducts a quantitative analysis of the path dependence and spatial spillover mechanisms underlying regional educational development [19].

(1) Traditional Markov chain transition probability matrix

Traditional Markov chain transition probability matrices consider only the evolution characteristics along the time dimension. Based on panel data from 2016 to 2023, the consolidation rate of compulsory education was categorized into four levels: low (Level 1), lower-middle (Level 2), upper-middle (Level 3), and high (Level 4). The transition probability matrix is constructed as follows (see Table 4). This matrix ignores the spatial spillover effects between adjacent provinces.

Table 4. Transition probability matrix of traditional Markov chain for compulsory education consolidation rate.

t / t+1	Level 1	Level 2	Level 3	Level 4
Level 1	0.92	0.08	0.00	0.00
Level 2	0.05	0.85	0.10	0.00
Level 3	0.00	0.08	0.82	0.10
Level 4	0.00	0.00	0.06	0.94

Judging from the matrix results, the values of the diagonal elements all fall within the relatively high range of 0.82-0.94. This finding indicates that the consolidation rate of compulsory education exhibits extremely strong path dependence. The probability that lower-tier provinces will maintain a low level is as high as 0.92, while the probability that higher-tier provinces will maintain a high level is 0.94. Once a high level is reached, as demonstrated by Shanghai, Jiangsu, and Zhejiang, there is virtually no possibility of falling to a lower tier. Regional educational development exhibits a pronounced "club convergence" pattern, with weak mobility between high- and low-performing groups [20].

(2) Transition probability matrix of a spatiotemporal Markov chain

To further incorporate spatial interaction effects, this study constructs a spatiotemporal Markov chain transition probability matrix, using the average level of neighboring provinces as a background variable to analyze differences in state transitions under different neighborhood conditions. The core comparison focuses on the transition probabilities under two scenarios: “neighbors at a high level (k=4)” and “neighbors at a low level (k=1)”.

Scenario A: Transition matrix M(4) when the neighbor is at a high level (k=4).

When a province is at a low-to-medium level (Level 2) and all its neighboring provinces are at a high level, its state transition probability matrix is as follows (see Table 5).

Table 5. Transition probability matrix M(4) of spatiotemporal Markov chain.

t / t+1	Level 1	Level 2	Level 3	Level 4
Level 2	0.02	0.70	0.28	0.00

Under these circumstances, the probability of low- to medium-level provinces transitioning to medium- to high-level status is 0.28, which is significantly higher than the 0.10 transition probability observed in the traditional matrix. This indicates that neighboring provinces at higher levels have a marked positive spillover effect on the educational development of a given province, effectively propelling lower-level provinces to advance to higher levels, thereby providing clear evidence of the Yangtze River Delta region’s radiating and driving influence on surrounding provinces.

Scenario B: Transition matrix M(1) when the neighbor is at a low level (k=1)

When a province is at a medium-low level (Level 2) and all its neighboring provinces are at a low level, its state transition probability matrix is as follows (see Table 6).

Table 6. M(1) spatiotemporal Markov transition probability matrix.

t / t+1	Level 1	Level 2	Level 3	Level 4
Level 2	0.15	0.75	0.10	0.00

(3) Interpretation of spatio-temporal jump characteristics

Path dependence and “club convergence”: As can be seen from the traditional matrix M, the diagonal elements (the probabilities of maintaining the status quo) are all above 0.8. In particular, for the qualification rate for special admissions to college entrance exams, the probability of maintaining Level 4 is 0.94. This indicates that the distribution of higher education opportunities in the Yangtze River Economic Belt exhibits a severe “Matthew Effect”, and the dominant positions of Shanghai and Jiangsu are unlikely to be challenged in the short term.

The spillover effect of neighbors (taking Anhui as an example): A comparison of the probability of moving from a low-to-medium level to a medium-to-high level shows that in the traditional matrix M, the probability is 0.10; in the spatiotemporal matrix M(4) (where neighbors are at a higher level), the probability is 0.28.

When Anhui (Level 2) is surrounded by Jiangsu, Zhejiang, and Hubei (Level 4), the probability of an upward transition in its educational investment intensity and retention rate is 2.8 times higher than when it is isolated. This quantitatively confirms the spatial spillover effect encapsulated by the saying, “Those closest to the water get the moon first”.

The “neighbor dragging effect” (using Guizhou as an example): Observing M (the probability of falling from a medium-low to a low level), in the spatiotemporal matrix M(1) (where neighbors are at a low level), (1) = 0.15. In the traditional matrix M, it is 0.05. Although Guizhou itself has a high investment intensity (Level 4), some indicators in its neighboring provinces - Yunnan and Sichuan - remain at low levels (Level 1 or 2). As a result, Guizhou’s consolidation rate struggles to break through its ceiling, posing a risk of being “dragged down” by its lower-performing neighbors.

Research design and methods

Based on the three categories of core issues identified in the preceding sections, this study constructs a progressive research framework comprising “status quo characterization - effect testing - mechanism analysis - optimization simulation”. This study comprehensively employs methods such as two-way fixed-effects models, mediation analysis, quantile regression, and counterfactual analysis. It systematically addresses the spatiotemporal characteristics, transmission effects, and optimization pathways regarding the allocation of basic education resources and the competitiveness of higher education in the Yangtze River Economic Belt.

Research questions and logical framework

Based on panel data from the 11 provinces and municipalities in the Yangtze River Economic Belt from 2016 to 2023, this study conducts an empirical analysis focusing on three core questions:

(1) The issue of spatio-temporal evolutionary characteristics

To map the spatiotemporal distribution and dynamic evolution of key indicators of basic education, such as government spending on education, the retention rate in compulsory education, and opportunities for further education, and to identify regional disparities and patterns of concentration.

(2) Conduction effects and heterogeneity issues

Examine the impact of the allocation of basic education resources on the competitiveness of higher education in a region, and distinguish the heterogeneity of this impact across different educational levels and regions.

(3) Path optimization problem

This study analyzes the transmission mechanism through which the allocation of basic education resources affects the competitiveness of higher education, and proposes optimal pathways for narrowing regional disparities through counterfactual simulations.

Benchmark regression model: Two-way fixed-effects test

To examine the baseline impact of the allocation of basic education resources on the competitiveness of higher education, this study constructs a two-way fixed effects (TWFE) panel regression model, controlling for provincial and time fixed effects to mitigate omitted variable bias.

(1) Model specifications

The benchmark regression equation is as follows:

$$Y_{it} = \beta_0 + \beta_1 Basic\_Edu_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

Specifically:

Y_{it} : Province i's composite score for higher education competitiveness in year t.

$Basic\_Edu_{it}$: core explanatory variables. Comprising three dimensions: the share of fiscal expenditure on basic education, the retention rate in compulsory education, and the rate of students meeting the special admission thresholds for the college entrance exam [21].

X_{it}: control variables, including regional characteristics that influence higher education competitiveness, such as per capita GDP, industrial structure (share of the tertiary sector), and population size [22].

μ_i : provincial fixed effects, accounting for regional heterogeneity that does not change over time.

λ_t: year fixed effect, accounting for nationwide policy shocks and time trends.

ε_{it}: random error term.

(2) Explanation of endogenous processing

To mitigate potential reverse causality issues in the model (such as the possibility that improvements in higher education competitiveness may drive local government investment in basic education), this study uses a one-period lagged basic education indicator ($L.Basic\_Edu$) as an instrumental variable to conduct robustness tests, while systematically addressing the issue of endogeneity in the discussion section [23].

Analysis of heterogeneity in the transmission effects of basic education

To further explore the heterogeneity of the transmission effects in basic education, this study conducts an analysis from two dimensions: differences across educational stages and regional differences.

(1) Heterogeneity in transmission effects across different educational levels

To examine the differential effects of compulsory education and high school education on higher education competitiveness, the core explanatory variables were split into two categories. The first category covers indicators related to compulsory education, including the compulsory education retention rate and the share of primary education expenditure, while the second contains indicators related to high school education, namely the college entrance exam qualification rate and the share of high school education expenditure. All these grouped indicators were then included separately in the baseline regression model. If the coefficients for compulsory education indicators are more significant and larger in magnitude than those for senior high school education indicators, this indicates that the "foundation of basic education" plays a more critical role in supporting higher education competitiveness [24].

At the same time, this study incorporates the regional interaction model to examine differences in transmission effects across the upper, middle, and lower reaches of the Yangtze River Economic Belt.:

$$Y_{it} = \beta_0 + \beta_1 Basic_{it} + \beta_2 (Basic_{it} \times Downstream_i) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Where is a regional dummy variable (set to 1 for downstream provinces and 0 for mid- and upstream provinces). If the coefficient of the interaction term is significantly positive, it indicates that basic education in downstream regions has a stronger promotional effect on the competitiveness of higher education, suggesting regional differences in marginal effects.

(2) Regional sub-sample regression

The entire sample was divided into three groups: upstream (Yunnan, Guizhou, Sichuan, and Chongqing), midstream (Hunan, Hubei, Jiangxi, and Anhui), and downstream (Jiangsu, Zhejiang, and Shanghai). Panel regressions were conducted separately for each group to compare the magnitude of the coefficients across the three groups (as shown in Figure 4). If the coefficients for the upstream regions are significantly greater than those for the downstream regions, this indicates a significant "weakest link effect", meaning that improving the level of basic education in educationally underdeveloped regions has a stronger driving effect on the competitiveness of higher education. If the coefficients for the downstream regions are more significant, this indicates that the marginal effects of basic education in developed regions are tending toward stability, and the effects of coordinated development are more pronounced. Based on a regional comparison of regression coefficients, the mechanism by which basic education drives the competitiveness of higher education exhibits significant gradient differentiation.

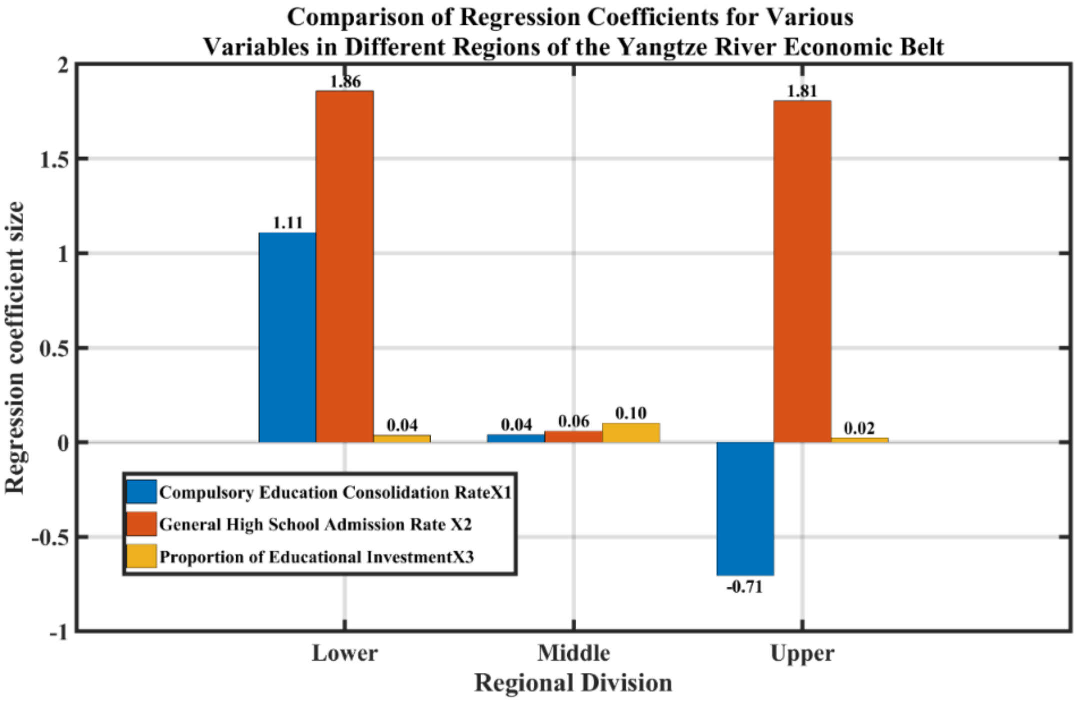

Figure 4. Comparison of regression coefficients for various variables by subregion in the Yangtze River Economic Belt.

a) Upstream regions (Yunnan, Guizhou, Sichuan, and Chongqing): The weakest-link effect exerts a dominant influence.

The consolidation rate of compulsory education has a significant negative impact ($\beta \approx -0.70$), while the admission rate to general high schools exerts an extremely strong positive effect ($\beta \approx 1.80$). This indicates upstream regions are still in the "bridging the gap" phase, and expanding general high school education capacity is the key pathway to enhancing higher education competitiveness; consolidating compulsory education is unlikely to provide effective support [25].

b) Downstream regions (Jiangsu, Zhejiang, and Shanghai): Synergies are becoming more pronounced.

Indicators across all educational stages continue to make steady, positive contribution (compulsory education $\beta \approx 1.10$, general high school β>1.80). This confirms that in developed regions, basic and higher education have formed a high-quality, synergistic system characterized by positive mutual reinforcement, with marginal effects tending toward stability; their core mission has shifted from scale expansion to quality enhancement.

c) Midstream Regions (Hunan, Hubei, Jiangxi, and Anhui): These areas exhibit transitional Characteristics and Input Dependence.

This region geographically did not experience negative spillover effects from upstream areas, but the driving force of each indicator was relatively weaker than that of the regions at either end [26]. It is worth noting that this region witnesses the largest positive regression coefficient of educational investment among the three sub-regions ($\beta \approx 0.10$). This indicates that midstream regions are still in a transitional phase, and optimizing the efficiency of resource allocation and breaking free from the "middle-income trap" are key to achieving leapfrog development.

Testing the transmission mechanism: The mediating effects model

To uncover the transmission pathway through which the allocation of basic education resources influences the competitiveness of higher education, this study employs the Bootstrap sampling method to construct a mediation model (see Figure 5). The model is used to test the transmission mechanism: "allocation of basic education resources → improvement in student quality → enhanced competitiveness of higher education". The pass rate for special admissions in the National College Entrance Examination was selected as the mediating variable (M). The steps for testing the mediation effect are as follows.

(1) Step 1: Test for the overall effect

Estimating a benchmark regression model to test whether the total effect coefficient β_1 of the basic education indicator ($Basic\_Edu$) on higher education competitiveness (Y) is significant [27].

(2) Step 2: Test the effect of the mediating variable

Estimation Model

$$M_{it} = \alpha_0 + \alpha_1 Basic\_Edu_{it} + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Examine whether the coefficient α_1 of the effect of basic education indicators on the college entrance exam pass rate (M) is significant.

(3) Step 3: Testing for Mediating Variables

Estimation model

$$Y_{it} = \theta_0 + \theta_1 Basic\_Edu_{it} + \theta_2 M_{it} + \rho X_{it} + \mu_i + \lambda_t + \sigma_{it} \quad (4)$$

If the coefficient of the mediating variable is significant, and the coefficient of the basic education indicator is smaller than that in Step 1, this indicates that the quality of the student body serves as the mediating channel through which basic education influences the competitiveness of higher education [28].

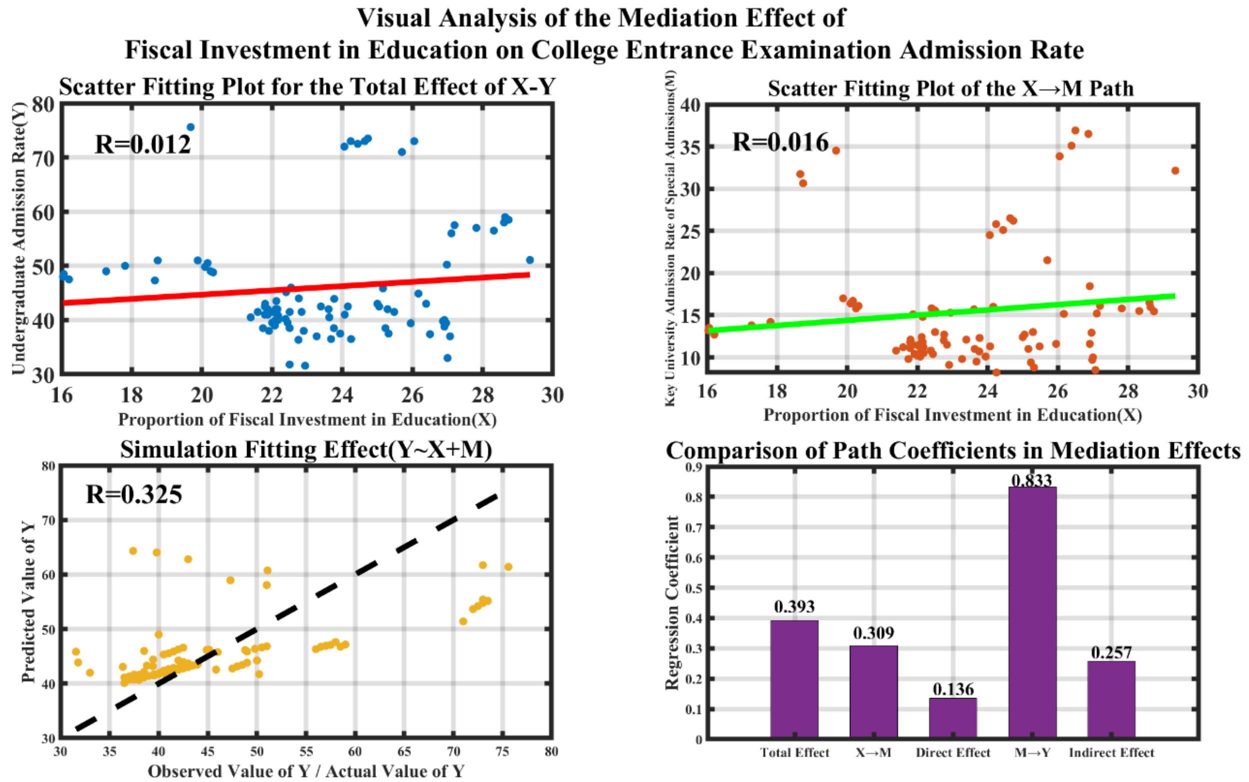

Figure 5. Visual analysis of the mediating effect of educational financial investment on the college entrance exam qualification rate.

This study uses panel data from 11 provinces and cities in the Yangtze River Economic Belt to construct a mediation model that examines the mechanism through which fiscal investment in education influences regional educational equity. The study uses the college entrance exam qualification rate for undergraduate programs as the dependent variable, the proportion of fiscal investment in education as the key independent variable, and the qualification rate for special admissions as the mediating variable. The regression results are shown in the figure above. Specifically, the total effect of the share of fiscal expenditure on education on the undergraduate admission rate is 0.393 ($p>0.05$, not significant); the direct effect is 0.136 ($p>0.05$, not significant); and the indirect effect is 0.257 (0.309 × 0.833). According to the criteria for testing mediating effects, the rate of students meeting the special enrollment cutoff plays a partial mediating role between the two variables. Approximately 65.0% of the impact of fiscal investment in education on the undergraduate admission rate is achieved through an increase in the rate of students meeting the special enrollment cutoff. This result thereby validates the positive transmission mechanism of “fiscal investment → rate of students meeting the special enrollment cutoff → undergraduate admission rat”.

Optimizing path simulation: Counterfactual analysis and quantile regression

To address the question of “how to narrow regional disparities by optimizing the allocation of basic education resources”, this study employs counterfactual analysis and quantile regression to simulate trends in higher education competitiveness under different resource allocation scenarios.

(1) Quantile regression analysis

This study constructs a quantile regression model to examine the differences in the strength of the effects exerted by basic education resource allocation at various levels of higher education competitiveness.

$$Q_\tau(Y_{it}|Basic\_Edu_{it}, X_{it}) = \beta_{0\tau} + \beta_{1\tau}Basic\_Edu_{it} + \gamma_\tau X_{it} \quad (5)$$

Where τ is a quantile (e.g., 0.25, 0.50, 0.75), by comparing the $\beta_{1\tau}$ coefficients for the lower quantiles (provinces with weaker competitiveness) and the higher quantiles (provinces with stronger competitiveness), this paper analyze the heterogeneous effects of basic education resource allocation on provinces at different levels of development and identify patterns of diminishing or increasing marginal returns [29].

This study employs a quantile regression model and uses panel data from the 11 provinces and cities in the Yangtze River Economic Belt to examine the heterogeneous effects of basic education resource allocation on the rate of students qualifying for undergraduate entrance Examination. This approach can capture varying marginal impacts across different admission performance levels. The results are shown in Figure 6.

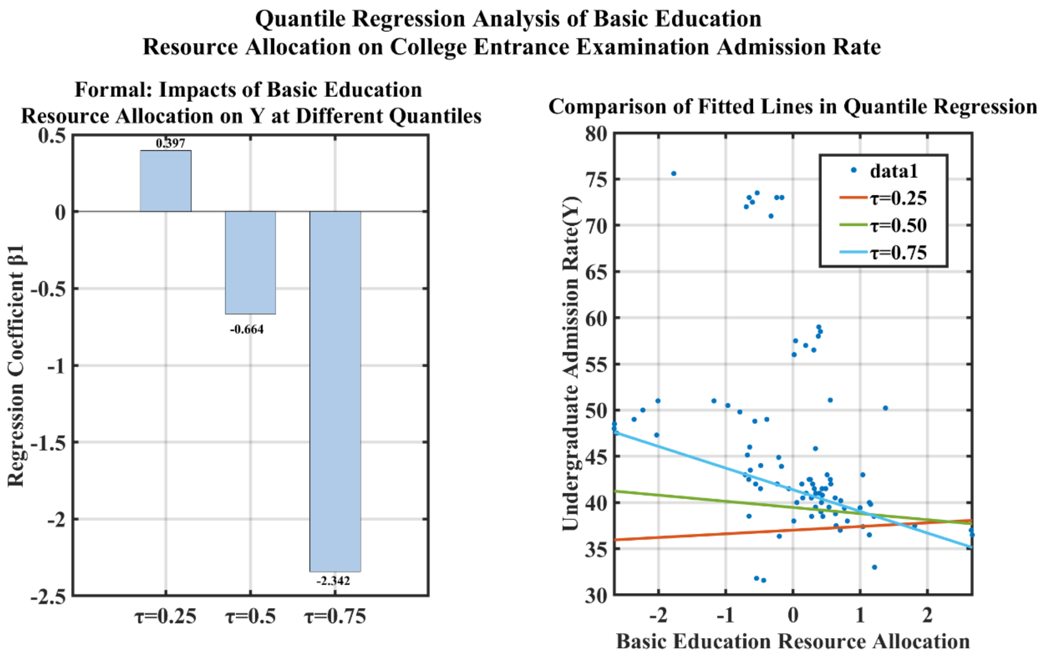

Figure 6. Quantile regression analysis of the relationship between the allocation of basic education resources and the college entrance exam qualification rate.

The regression results show that the impact of resource allocation exhibits a significant diminishing marginal return: At the low-level quantile (τ=0.25), the regression coefficient is 0.397, significantly and positively promoting the college admission rate in low-level provinces and serving as a "lifeline" for them [30]. As the percentile increases, the coefficient shifts from positive to negative, dropping to −0.664 at the middle percentile (τ=0.50) and further to −2.342 at the high percentile (τ=0.75), with the positive effect continuing to diminish and eventually turning into a strong negative inhibitory effect.

The comparison chart of the fitted lines visually confirms the above conclusions: τ=0.25 - the orange line has a positive slope, indicating a significant positive effect. At τ=0.50, the green line has a negative and gentle slope, indicating that the effect begins to diminish. At τ=0.75, the blue line has a negative slope with the largest absolute value, indicating a strong negative effect. These results suggest that basic education resources should be prioritized for lower-performing provinces to avoid inefficient investment in higher-performing provinces, thereby narrowing the educational development gap within the river basin [31].

(2) Counterfactual scenario simulation

This study constructs two counterfactual scenarios to simulate the effects of optimizing basic education resource allocation.

a) Scenario 1: Upstream provinces address their weaknesses

This study assumes that the consolidation rates for compulsory education and the intensity of fiscal investment in upstream provinces including Yunnan, Guizhou, Sichuan, and Chongqing are raised to the average levels of downstream provinces including Jiangsu, Zhejiang, and Shanghai. This study substitutes these adjusted values into the baseline model to predict changes in their higher education competitiveness scores.

b) Scenario 2: Optimization of regional coordinated allocation

Simulate the changes in the Tai'er Index of regional higher education competitiveness after educational resources in the Yangtze River Economic Belt are moderately redirected toward provinces in the middle and upper reaches, and quantify the contribution of resource optimization to narrowing regional disparities.

Based on panel data from the 11 provinces and municipalities in the Yangtze River Economic Belt, this study constructs a counterfactual simulation framework to quantitatively evaluate the policy effects of optimizing the allocation of basic education resources. The results are shown in Figure 7 below.

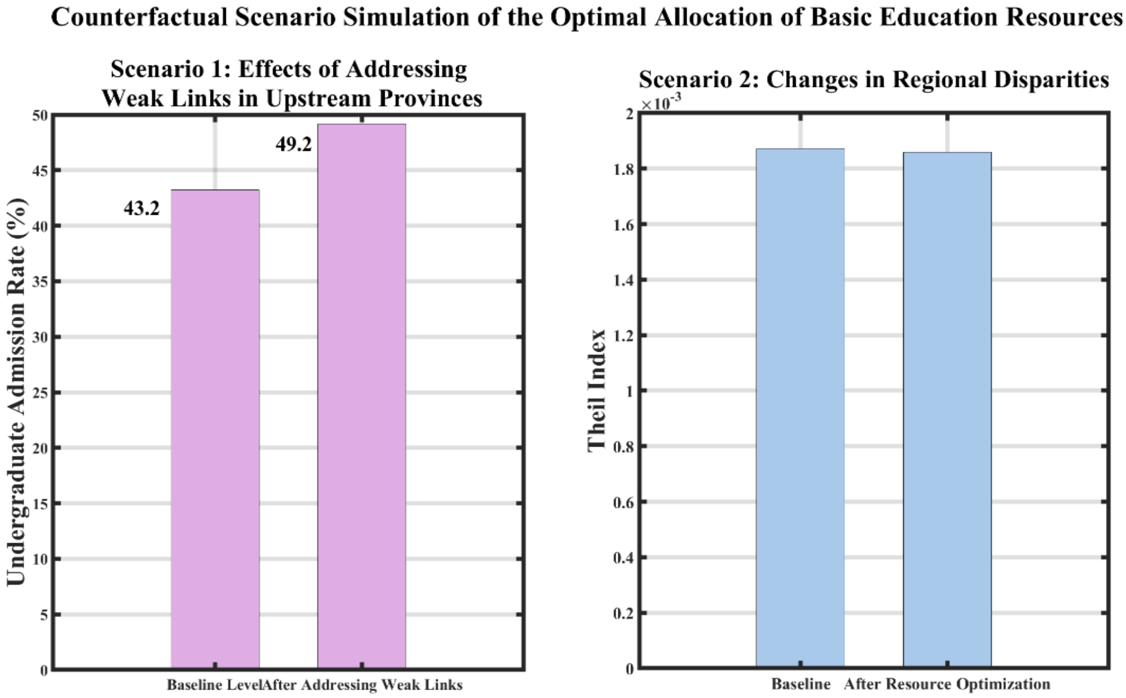

Figure 7. Counterfactual simulation of the optimal allocation of basic education resources.

The simulation results show that the structural effects of resource optimization vary significantly: Scenario 1 (Addressing Resource Shortfalls in Upstream Provinces) yielded significant improvements. If the resource allocation levels in upstream provinces such as Yunnan, Guizhou, Sichuan, and Chongqing were raised to the average of Jiangsu, Zhejiang, and Shanghai, their college entrance exam undergraduate admission rate would rise from 43.2% to 49.2%, representing an average increase of 13.9%. This validates the critical role of addressing resource shortfalls in enhancing the educational competitiveness of upstream regions. Scenario 2 (optimization of resources across the entire river basin) showed a limited effect on narrowing disparities. After resources were shifted toward the middle and upper reaches, the regional pass rate's Tiel Index decreased only from to, with regional disparities narrowing by approximately 0.5%. This indicates that a single resource allocation policy is unlikely to fundamentally narrow educational disparities within the river basin [32].

A comparison of the two scenarios shows that resource allocation has a particularly strong "timely assistance" effect for underdeveloped upstream provinces. However, regional educational disparities are still constrained by multiple factors, including the educational foundation, student quality, and collaborative policies. Based on this, the following policy implications are proposed: Top-performing provinces should prioritize increasing educational investment and addressing resource gaps. To achieve balanced development across the entire basin, multiple policy tools are required besides resource allocation. Complementary policies such as cross-regional educational assistance and the sharing of high-quality teaching staff should be implemented to create a synergistic policy framework that promotes equitable educational development throughout the basin.

Discussion of endogeneity issues and robustness analysis

The endogeneity risks in this study primarily stem from reverse causality (where improvements in higher education competitiveness lead to increased local investment in basic education) and omitted variable bias. The main methods used to address these risks include:

(1) Using basic education indicators lagged by one period as the core explanatory variables to mitigate the problem of reverse causality.

(2) Introducing control variables such as per capita GDP and industrial structure to account for the impact of regional economic development levels on the allocation of educational resources.

(3) In the robustness analysis, attempting to use historical-geographical indicators - such as "topographic ruggedness" or "the number of jinshi degree holders during the Ming and Qing dynasties" - as instrumental variables to further validate the reliability of the core conclusions.

Conclusion

Using data on the allocation of basic education resources from 2016 to 2023 across the 11 provinces and municipalities in the Yangtze River Economic Belt as a sample, this study constructs a comprehensive econometric research framework centered on three core issues: the spatiotemporal evolution of basic education, its impact on the competitiveness of higher education, and pathways for optimization.

The study first characterizes the spatiotemporal patterns of basic education resources in the Yangtze River Economic Belt and finds that they exhibit a distinct pattern of "high-high clustering and low-low lock-in". Basic education levels show strong path dependence, and the surrounding environment exerts a significant influence on regional educational development leaps. Second, benchmark tests confirm that the allocation of basic education resources has a significant positive impact on higher education competitiveness, with marked heterogeneity across regions and educational levels: The marginal returns on investment in basic education in underdeveloped upstream regions are significantly higher than in developed downstream regions, demonstrating a pronounced "weakest link effect". Moreover, the transmission effect at the compulsory education level is significantly stronger than at the high school level. Further research reveals the core transmission pathway: "allocation of basic education resources → improvement in student quality → enhanced competitiveness of higher education". Counterfactual simulations show that addressing shortcomings in upstream basic education can significantly narrow regional disparities in educational competitiveness, highlighting the core value of balanced allocation of basic education resources. This study not only provides new empirical evidence for understanding the coordinated development of education and the economy but also offers precise decision-making guidance for the Yangtze River Economic Belt to implement differentiated education investment strategies and build a cross-regional educational community.

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Conflicts of Interest

The authors declare no conflict of interest.

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