Spatial Inequality in Access to Elite Public Schools

Evidence from India's Jawahar Navodaya Vidyalaya System

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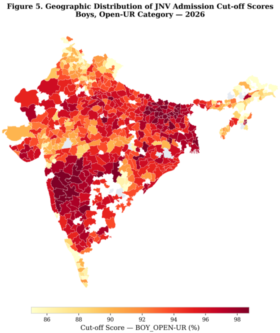
Motivation
JNVST at a Glance

Applicant Numbers and Selection Rates by NVS Region

Region	States/UTs Covered	Registered	Appeared	Selected (Seats Filled)	Attendance Rate (%)	Success Rate (%)
Bhopal	MP, Chhattisgarh, Odisha	5,84,282	4,54,093	8,320	77.72%	1.83%
Pune	Maharashtra, Gujarat, Goa, UTs	4,55,524	4,07,920	5,628	89.55%	1.38%
Lucknow	Uttar Pradesh, Uttarakhand	3,89,936	2,68,489	6,840	68.85%	2.55%
Hyderabad	AP, Karnataka, Kerala, Telangana, UTs	3,08,261	2,62,793	5,860	85.25%	2.23%
Patna	Bihar, Jharkhand, West Bengal	2,99,565	2,18,685	6,120	73.00%	2.80%
Jaipur	Rajasthan, Haryana, Delhi	2,27,007	1,65,945	4,600	73.10%	2.77%
Chandigarh	Punjab, HP, J&K, Ladakh, Chandigarh	1,11,290	84,761	3,920	76.16%	4.62%
Shillong	North Eastern States	91,482	59,137	5,964	64.64%	10.09%
Total		24,67,347	19,21,823	47,252	77.89%	2.46%

District-wise Cut-off Distribution



Key Contrast

Bihar has a mean cut-off of 96.8, whereas Kerala has a mean cut-off of 75.

Research Questions

1. **Persistence of Admission Thresholds** Do districts remain in similar positions in the cut-off distribution over time? High persistence indicates that disparities reflect **slow-moving structural differences** in applicant preparedness rather than short-term fluctuations.
2. **Mechanisms: What Drives Differences in Cut-offs?** Are differences explained by school infrastructure or by the composition of the applicant pool? This distinguishes **supply-side inputs** from deeper **structural differences in student preparedness** across districts.
3. **Spatial Dependence Across Districts** Do admission thresholds cluster geographically across neighbouring districts? Spatial dependence implies a **regional equilibrium**, where differences in applicant preparedness are correlated across space and reinforce local inequality.

The JNV System

- Established under the **1986 National Policy on Education**
- Mandate: high-quality residential schooling for talented rural students *irrespective of socioeconomic background*
- >650 schools (2026), covering nearly every district; Classes VI–XII; **fully centrally funded**
- Administered by Navodaya Vidyalaya Samiti (NVS), Ministry of Education

JNVST Admission Mechanism

- 100-mark MCQ: mental ability, arithmetic, language
- Administered annually (December/January)
- District-level selection: cut-off set by marginal qualified applicant *within* each district
- Block-level seat allocation rules ensure within-district geographic spread
- The exam is conducted by **CBSE**

Reservation Architecture

- $\geq 75\%$ seats from **rural** areas
- $\geq 1/3$ reserved for **girls**
- SC, ST, OBC reservations $\propto$ district population shares

Expected Quota Hierarchy:

$$C_{\text{Open-UR}} \geq C_{\text{Rural-OBC}} \geq C_{\text{Rural-SC}} \geq C_{\text{Rural-ST}}$$

Any violation = *hierarchy inversion*

Key Feature

Because selection is district-specific, cross-district variation in cut-offs directly measures differences in **applicant pool quality**.

Data Sources & Construction

Panel Dataset: 2025–2026

JNVST Cut-off Data (Primary)

- District-level cut-offs for **2025 and 2026**
- By gender $\times$ reservation category (16 cells)
- Compiled from official NVS notifications
- **978** district–year observations; **530** districts in balanced panel
- 27 states and union territories

UDISE+ Infrastructure Controls

- Schools with functional electricity (%)
- Trained teaching staff (%)
- Pupil–teacher ratio
- SC/ST student share (%) – *demographic proxy*

Spatial Data

- Survey of India district shapefiles (2011 Census delimitation)
- **Queen contiguity** weights matrix W (row-standardised)
- Island & non-contiguous UTs excluded from W
- Merge rate $> 70\%$; analytical cross-section: **562 districts**

Data Engineering Done

- Exact Name matching of districts
- Manual fuzzy-match crosswalk for unmatched districts.
- Multi-campus districts: cut-offs averaged, rates averaged

Descriptive Statistics

Variable	N	Mean	SD	Min	p25	Median	Max
Cut-off: Boys, Open-UR (%)	978	93.54	4.26	65.0	91.0	94.0	100.0
Cut-off: Girls, Open-UR (%)	978	93.27	4.41	60.0	90.0	94.0	100.0
Gender Gap (Boys−Girls, pp)	978	0.27	2.27	−13.0	−1.0	0.0	15.0
Urban–Rural OBC Gap (pp)	978	10.47	8.49	−7.0	5.0	9.0	46.0
Urban–Rural SC Gap (pp)	978	13.17	9.52	−15.0	6.0	12.0	52.0
Schools with Electricity (%)	978	87.95	17.52	7.3	80.8	93.3	100.0
Trained Teachers (%)	978	82.32	15.48	17.9	73.4	85.5	100.0
Pupil–Teacher Ratio	978	22.71	8.23	3.75	17.0	22.1	73.7
SC/ST Student Share (%)	978	27.68	19.37	0.0	12.3	23.9	100.0

Gender gaps: tightly centred around zero (mean = 0.27 pp; median = 0) — **near parity**

Urban–rural OBC gaps: large, right-skewed (mean = 10.5 pp; max = 46 pp) — **substantial inequality**

Persistence of Admission Thresholds

Research Question

- Do districts maintain similar positions in the cut-off distribution across years?

Empirical Approach

- Spearman ρ between district rankings in 2025 and 2026
- Focus on **rank stability**, not levels

Economic Interpretation (Ex-post)

- If persistence is high:
  - Differences are likely driven by **stable underlying factors**
- If persistence is low:
  - Differences may reflect **temporary or noisy variation**

Why This Matters

- Distinguishes between:
  - **Systematic differences across districts**
  - vs **year-specific fluctuations**

What Explains Cross-District Differences in Cut-offs?

Research Question

- Which observable district characteristics are associated with variation in admission cut-offs?
- Do these associations differ between **applicant composition** and **school infrastructure**?

Empirical Model

$$Y_{dt} = X'_{dt}\beta + \alpha_s + \gamma_t + u_{dt}$$

- α_s: state fixed effects (policy, institutional differences)
- γ_t: year fixed effects (common shocks, exam difficulty)
- Identification: **within-state variation across districts**

Variables

- Y_{dt}: admission cut-off level, gender gap, or urban–rural OBC gap
- Demographic composition (SC/ST share):
  - Captures variation in the **distribution of applicants**
- Infrastructure (PTR, teachers, electricity):
  - Captures **school input availability**

Why This Matters

- Helps distinguish whether observed disparities are more closely associated with:
  - differences in **applicant composition**, or
  - differences in **school inputs**

Spatial Dependence Across Districts

Step 1: Detect Spatial Correlation

$$I = \frac{n}{\sum_d \sum_j w_{dj}} \cdot \frac{\sum_d \sum_j w_{dj}(C_d - \bar{C})(C_j - \bar{C})}{\sum_d (C_d - \bar{C})^2}$$

- Moran's I tests whether nearby districts have similar outcomes
- LISA identifies local clusters (high-high, low-low)

Economic Intuition

- Neighbouring districts often share:
  - Coaching markets
  - Information networks
  - Socio-economic conditions
- Leads to **geographic clustering of opportunity**

RQ3: Spatial Equilibrium Model

Spatial Autoregressive (SAR) Model

$$C_{dt} = \rho \sum_{j \neq d} w_{dj} C_{jt} + X'_{dt}\beta + \alpha_s + \gamma_t + \varepsilon_{dt}$$

Economic Intuition

- A district's outcome depends on neighbouring districts
- Captures **spillovers in applicant quality**

Key Parameters

- ρ: strength of spatial dependence
  - $\rho > 0 \Rightarrow$ clustering and spillovers
- Spatial multiplier:

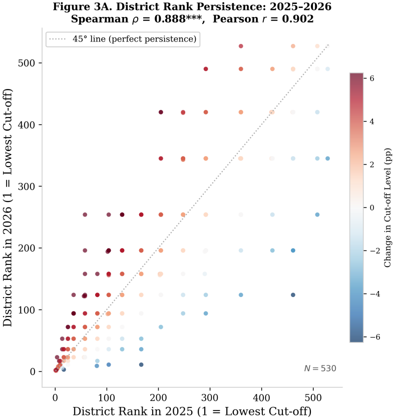
$$(1-\rho)^{-1}$$

  - Measures how local shocks spread across space

Interpretation

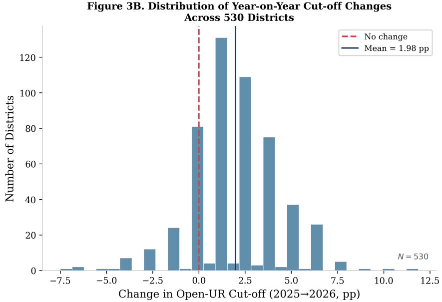
- Inequality is not isolated; it is **regionally amplified**

Rank Persistence in Admission Thresholds
2025 vs. 2026 Rankings



Note: 530 districts in balanced panel. Ranks computed within year (1 = lowest cut-off). Colour encodes change in cut-off levels (pp). Spearman rank correlation invariant to rank direction.

Figure: Rank–rank scatter, 2025 vs. 2026. Colour encodes level change (pp). Spearman $\rho = 0.888^{***}$, $N = 530$.



Note: First differences in district-level cut-offs between 2025 and 2026.

Figure: Distribution of year-on-year level changes. Mean $= +1.98$ pp; 400/530 districts improved.

High Rank Persistence

Spearman $\rho = 0.889$, Pearson $r = 0.902$. Districts maintain **stable relative positions** — reflecting slow-moving structural factors.

Correlates of Cut-off Levels and Equity Gaps
Regression Results

	(1) Cut-off Level	(2) Gender Gap	(3) Urban–Rural Gap
SC/ST Student Share (%)	-0.058^{***}	-0.007	0.148^{***}
	(0.010)	(0.005)	(0.017)
Pupil–Teacher Ratio	0.085^{**}	0.000	-0.127^{**}
	(0.033)	(0.017)	(0.053)
Trained Teachers (%)	0.031	0.010	0.064^{*}
	(0.024)	(0.013)	(0.036)
Schools with Electricity (%)	-0.016	-0.028^{**}	-0.014
	(0.023)	(0.014)	(0.033)
State FE / Year FE	Yes	Yes	Yes
Observations	978	978	978
R^2	0.677	0.147	0.621

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. SEs clustered at district level.

Demographic Dominance

SC/ST share: most robust and economically significant correlate. 10 pp ↑ SC/ST share ⇒ -0.58 pp cut-off; $+1.48$ pp OBC gap.

Infrastructure is Weak

Infrastructure variables show **weak, inconsistent** associations. Points to **demand-side** rather than supply-side importance.

Correlates: Coefficient Plot
OLS Estimates with 95% Confidence Intervals

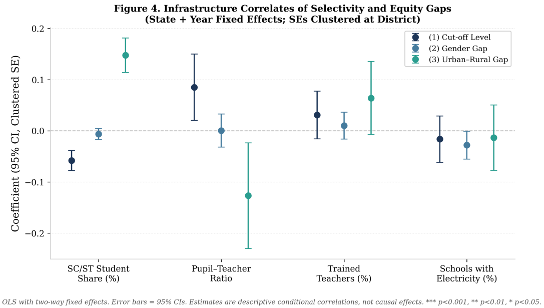


Figure: OLS coefficients with 95% CIs (clustered SEs). State and year FEs included. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Reading the Figure

- Each panel = one outcome
- **SC/ST share**: large, precisely estimated effects for cut-off level and OBC gap; near-zero for gender gap
- Infrastructure variables cluster around zero across outcomes

Asymmetry Across Dimensions

SC/ST share captures structural differences in **applicant pool composition** that affect within-category competition, but not gender competition.

Gender Gaps in Cut-off Scores
State Fixed Effects

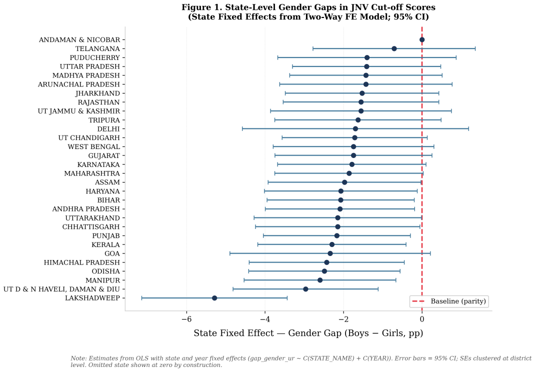


Figure: State FEs for Gender Gap (Boys−Girls, Open-UR). Two-way FE model; 95% CIs; SEs clustered at district. $N = 978$, 30 states/UTs.

Key Findings

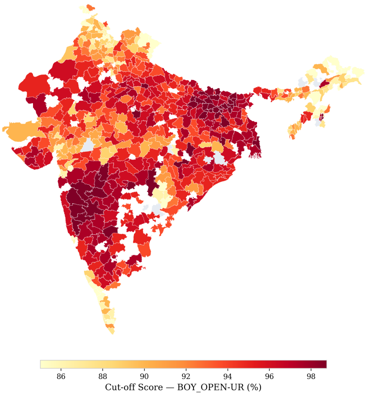
- Almost all state FEs **statistically indistinguishable from parity**
- Lakshadweep: pronounced negative outlier (≈ -5 pp) — small applicant pool
- Telangana: most positive ($\approx +1$ pp)
- Gender differences are **not systematically structured** at the state level

Takeaway

Gender gaps are **small, near-zero, and lack spatial structure** — suggesting the gender quota design broadly achieves parity.

Geographic Distribution of Admission Cut-offs
Choropleth Map: Boys Open-UR, 2026

Figure 5. Geographic Distribution of JNV Admission Cut-off Scores
Boys, Open-UR Category — 2026



Geographic Pattern

- **Central and peninsular India**: systematically higher cut-offs
- **Northwest and northeast**: lower values
- Differences are **spatially contiguous** — not randomly dispersed

Motivation for Spatial Modelling

The visual clustering in the raw data motivates formal spatial diagnostics and econometric analysis.

Global Spatial Autocorrelation

Moran's I Test

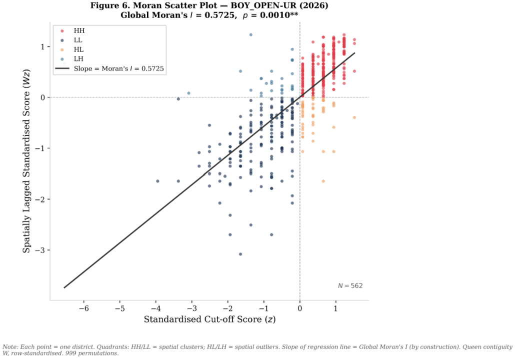


Figure: Moran scatter plot, Boys Open-UR cut-off (2026). Global Moran's $I = 0.573$, $p = 0.001$. Slope of regression line = Moran's I by construction. $N = 562$.

Variable	Moran's I	p-value
Boys Open-UR	0.573	0.001**
Urban–Rural OBC Gap	0.556	0.001**
Gender Gap	0.001	0.476

999 permutations; Queen contiguity W.

Sharp Contrast

Admission thresholds and caste-based gaps show **strong spatial clustering** ($I \approx 0.57$), whereas gender gaps appear **spatially random** ($I \approx 0$).

LISA Cluster Maps
Gender Gap & Urban–Rural OBC Gap

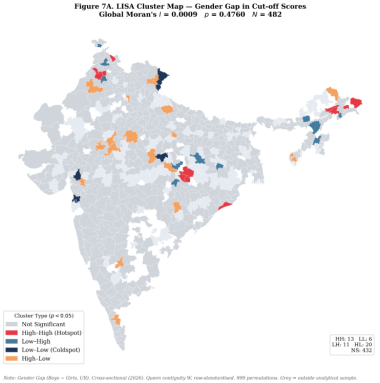


Figure: Panel A: LISA, Gender Gap. $\hat{I} = 0.001$, $p = 0.476$. HH:13, LL:6, LH:11, HL:20, NS:432.

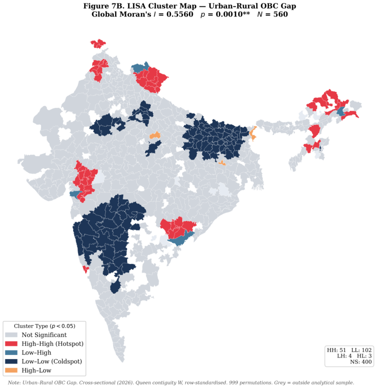


Figure: Panel B: LISA, Urban–Rural OBC Gap. $\hat{I} = 0.556$, $p = 0.001$. HH:51, LL:102, LH:4, HL:3, NS:400.

Gender gap: **no spatial structure**. Scattered significant observations, no contiguous clusters.

OBC gap: **strong regional clustering**. HH (large gaps) are concentrated in the northwest, while LL

LISA Cluster Maps

Hierarchy Inversions & . Admission Cut-off Levels

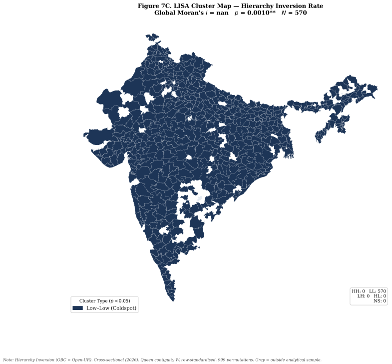


Figure: Panel C: LISA, Hierarchy Inversion. $N = 570$. All 570 districts = LL, reflecting universal zero-inversion outcome.

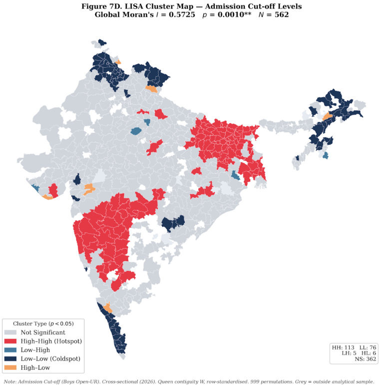


Figure: Panel D: LISA, Admission Cut-off (Boys Open–UR). $\hat{I} = 0.573$, $p = 0.001$. HH:113, LL:76, LH:5, HL:6, NS:362.

Hierarchy inversions: All 570 districts = LL, reflecting universal zero-inversion outcome.

Admission Cut-Off: **strong regional clustering**

Spatial Model Selection & ML Estimation
Anselin LM Diagnostics

Anselin LM Diagnostics

Test	Stat	p
LM-Lag (std)	326.71	$<0.001^{***}$
LM-Error (std)	306.41	$<0.001^{***}$
Robust LM-Lag	23.24	$<0.001^{***}$
Robust LM-Error	2.94	0.087
Decision: SAR (Lag) preferred		

Robust LM-Lag significant; Robust LM-Error not significant. Spatial dependence operates through the **outcome**, not through the error.

ML Spatial Regression Results

	SAR (preferred)	SEM
SC/ST Student Share	-0.026^{***}	-0.039^{***}
Pupil–Teacher Ratio	0.087^{***}	0.090^{***}
Trained Teachers (%)	-0.016	-0.042^{**}
Electricity (%)	-0.008	-0.012
$\hat{\rho}$ (spatial lag)	$\mathbf{0.655}^{***}$	—
$\hat{\lambda}$ (error)	—	0.691^{***}
N	555	555
Log-lik	-1358.92	-1362.77
AIC	2729.85	2735.54
Pseudo-R^2	0.590	0.216

Spatial Multiplier and Effect Decomposition
Direct, Indirect, and Total Effects (SAR)

Spatial Autoregressive Parameter

$$\hat{\rho} = 0.655 \quad (p < 0.001)$$

Strong positive spatial dependence: admission thresholds in each district co-move closely with neighbouring districts.

Spatial Multiplier

$$(1 - \hat{\rho})^{-1} \approx \mathbf{2.90}$$

Local variation is substantially **amplified** through equilibrium interactions across the spatial system.

Direct, Indirect, and Total Effects (SAR)

Variable	Direct	Indirect	Total
SC/ST Share	−0.026	−0.049	−0.074
PTR	+0.087	+0.164	+0.251
Trained Teach.	−0.016	−0.031	−0.047
Electricity	−0.008	−0.015	−0.023

Interpretation

For PTR: direct effect = 0.087; **total effect = 0.251**. The difference reflects **feedback through the spatial network** of neighbouring districts.

Policy Implications

- **1. Spatial Targeting**

  The estimated spatial multiplier $(1-\hat{\rho})^{-1} \approx 2.9$ implies that shocks propagate across neighbouring districts. **Geographically coordinated interventions** (regional clusters) are therefore likely to be more effective than isolated district-level policies.

- **2. Persistent Spatial Inequality**

  High rank persistence ($\rho = 0.889$) indicates that districts maintain their relative positions over time. This suggests that improvements in overall preparedness may raise cut-offs system-wide without substantially altering **relative access inequalities**.

- **3. Demand-Side Constraints**

  Weak and inconsistent associations between infrastructure variables and cut-offs point toward the importance of **demand-side factors**, such as applicant preparedness, access to information, and preparatory inputs. This is particularly relevant in districts with higher SC/ST shares and larger urban–rural gaps.

Caveat

Estimates represent descriptive conditional correlations, not causal effects. Limited data on student-level inputs constrains identification of underlying mechanisms.

Conclusion

Three Central Findings

1. **Persistent spatial hierarchy.** Spearman $\rho = 0.889$ indicates strong stability in district rankings. Relative positions remain largely unchanged over time, consistent with **persistent cross-district differences** in applicant preparedness.

2. **Composition over infrastructure.** Demographic composition (SC/ST share) is strongly associated with both cut-off levels and equity gaps, while infrastructure variables show weak and inconsistent relationships. Patterns are consistent with **demand-side variation in preparedness** rather than supply constraints alone.

3. **Spatially interdependent outcomes.** Significant spatial autocorrelation (Moran's $I = 0.573$) and a SAR coefficient $\hat{\rho} = 0.655$ imply strong cross-district linkages. The implied multiplier $(1 - \hat{\rho})^{-1} \approx 2.9$ indicates that local disparities are **amplified through spatial spillovers**.

Heterogeneity Across Dimensions

Gender gaps: small, statistically insignificant in spatial terms, and weakly related to observables — consistent with near parity under the gender quota.

Urban–rural OBC gaps: large, spatially clustered, and systematically associated with demographic composition — indicating persistent disparities in the underlying applicant pool.

Central Implication

Uniform admission rules do not guarantee equal access when applicant preparedness is **geographically concentrated and spatially interdependent**. Effective policy design must account for **regional clustering and demand-side heterogeneity**.

Thank You

Questions Welcome

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