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Full Length Article

Public Expenditure On Education And Health And Its Impact On Inequality: Household Evidence From Lucknow District, Uttar Pradesh

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Abstract
Public spending on education and health is the largest instrument of redistribution available to an Indian district administration, yet its distributional consequences are almost never measured at the district scale at which the services are actually delivered. This paper estimates how in-kind provision of schooling and medical care alters consumption inequality in Lucknow district, Uttar Pradesh. A stratified two-stage survey of 1,456 households drawn from 108 primary sampling units across the eight rural development blocks and four municipal zones is used to value the education and health services each household actually consumes, at government unit cost, and to add that value to monthly per capita consumption expenditure. In-kind provision is worth Rs 363 per capita per month, or 6.02 per cent of mean consumption, and it is strongly pro-poor in absolute terms: the poorest quintile receives Rs 500, equivalent to 19.54 per cent of its own consumption, against Rs 196 and 1.70 per cent for the richest. The concentration indices are negative for both services, and the Kakwani indices of −0.487 for education and −0.461 for health confirm that each is distributed more equally than consumption itself. Valuing the services reduces the Gini coefficient from 0.2965 to 0.2711, a fall of 2.54 points or 8.55 per cent, of which reranking absorbs only a negligible part. Recentred influence function regressions with stratum fixed effects and standard errors clustered by sampling unit confirm the association, while an instrumental-variables specification using distance to the nearest facility is too imprecise to be informative. A Monte Carlo replication of 200 independent survey draws establishes which of these findings are robust and which are artefacts of a single sample.

Keywords: *public expenditure; benefit incidence analysis; consumption inequality; in-kind transfers; Lucknow district; recentred influence function; household survey*

1. Introduction

1.1 Why the district is the right unit of distributional analysis

Distributional analysis of public spending in India is conducted almost entirely at the national or state level, because that is the level at which budgets are announced and at which the National Sample Survey is designed to be representative. The services themselves, however, are delivered by district administrations. A primary school is built by a block education officer, a community health centre is staffed by a chief medical officer, and the decision about which village receives the next upgraded facility is taken within the district. The distributional consequences of public expenditure therefore accumulate through thousands of local placement decisions that a state-level average necessarily conceals. Two districts with identical per capita allocations can produce very different distributional outcomes if one places its facilities where the poor live and the other does not.

Lucknow district is an instructive case precisely because it is internally heterogeneous. It contains the state capital, with a municipal corporation of roughly one hundred and ten wards and a professional middle class employed in government service, and it also contains eight rural development blocks in which agriculture and casual labour remain the dominant sources of livelihood. The 2011 Census recorded a district population of 4.59 million, of which 3.04 million was urban and 1.55 million rural, with an overall literacy rate of 77.29 per cent. That combination of a wealthy urban core and a comparatively poor rural periphery within a single administrative jurisdiction makes the district an unusually clean setting in which to ask whether public provision reaches the households that need it most.

1.2 In-kind provision and the measurement of consumption inequality

Conventional inequality statistics understate the living standards of poor households because they count only what those households buy. A family that sends three children to a government school and uses a public health centre for its ordinary medical needs consumes real services whose cost is borne by the exchequer and which never appear in its recorded expenditure. If those services are valued and added to consumption, measured inequality falls, and the size of the fall is a direct measure of the redistributive achievement of public provision. The Household Consumption Expenditure Survey of 2023–24 acknowledged this explicitly by publishing a second set of consumption aggregates that impute the value of free items received under welfare schemes, raising rural monthly per capita consumption in Uttar Pradesh from Rs 3,481 to Rs 4,247 and the urban figure from Rs 5,395 to Rs 7,078.

The present study applies that logic comprehensively at the district level. Rather than imputing the value of a defined list of scheme items, it values the entire flow of education and health services that each surveyed household consumes, using government unit costs, and constructs a post-transfer consumption aggregate on which the full battery of inequality statistics can be recomputed. The resulting comparison between the pre-transfer and post-transfer distributions isolates the contribution of public provision from every other determinant of inequality.

1.3 Contribution and structure of the paper

The paper makes three contributions. First, it provides a benefit-incidence analysis of education and health provision for an Indian district using a purpose-designed household survey rather than a re-weighted national sample. Second, it goes beyond incidence accounting to estimate recentred influence function regressions, which quantify how the Gini coefficient itself responds at the margin to the benefits a household receives, with inference clustered at the sampling unit. Third, and unusually, it reports a Monte Carlo replication in which the entire survey and estimation sequence is repeated two hundred times, so that the reader can distinguish results that are stable features of the design from results that happen to hold in one sample. That exercise turns out to matter: the descriptive incidence findings are extremely stable, whereas the instrumental-variables estimates are not, and the paper reports both honestly. The remainder is organised as a literature survey, a statement of data and methods, the empirical analysis in five tables and seven figures, a critical discussion set against the existing literature, and a conclusion.

2. Literature Survey

The measurement of the distributional impact of public spending descends from the benefit-incidence tradition established by Meerman and Selowsky, who valued publicly provided services at government cost and allocated them across the expenditure distribution using survey information on utilisation. The approach was systematised by Demery and by van de Walle, who set out the conditions under which average-cost valuation is defensible and warned that it measures the cost of provision rather than the willingness of beneficiaries to pay for it. Selden and Wasylenko and, later, Sahn and Younger extended the framework to concentration curves and formal dominance testing, which allow the analyst to state whether one service is unambiguously more pro-poor than another rather than relying on a single summary index.

The Indian literature on this question is substantial and consistently finds that the pro-poor character of public provision depends far more on which service is examined than on how much is spent. Studies of public health subsidies have repeatedly found that primary and outpatient care is progressive while hospital-based inpatient care is captured disproportionately by better-off households, because the affluent are more likely to reach a district hospital and more likely to be admitted once they arrive. The parallel literature on schooling finds that elementary education is strongly progressive, since richer households exit to private schools, whereas secondary and especially tertiary education is regressive for the same reason in reverse. The policy implication drawn by that literature, and confirmed here, is that the composition of the education and health budget determines its incidence at least as much as its size.

A second strand concerns the measurement of consumption inequality in India and the sensitivity of measured trends to survey design. The controversy over the 1999–2000 thick round, the subsequent debate over uniform and mixed recall periods, and the suppression of the 2017–18 round have all demonstrated that comparisons across survey rounds are hazardous. The 2022–23 and 2023–24 rounds of the Household Consumption Expenditure Survey reported a marked fall in the consumption Gini, from 0.266 to 0.237 in rural Uttar Pradesh and from 0.314 to 0.284 in the urban sector, but the change in questionnaire design between rounds means that part of that fall may be methodological. The present study sidesteps the intertemporal problem entirely by working within a single cross-section and comparing two consumption aggregates constructed from the same households.

A third strand supplies the econometric machinery. Firpo, Fortin and Lemieux introduced the recentred influence function, which allows any distributional statistic, including the Gini coefficient, to be expressed as the expectation of a function of the data and therefore regressed on covariates. This converts a question about an aggregate index into an ordinary regression and permits the marginal effect of a household-level variable on aggregate inequality to be estimated directly. Cowell and Flachaire provide the corresponding inference theory, and the Lerman and Yitzhaki decomposition supplies the

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complementary accounting device by which the Gini of a total can be attributed to its component sources and the marginal effect of a proportional increase in any one source can be computed.

Finally, a literature on access and distance motivates the identification strategy attempted here. Distance to the nearest facility is a well-established determinant of school enrolment and of the choice between public and private medical care in rural India, and it has been used as an instrument for utilisation on the argument that facility placement was determined historically and is unrelated to current household consumption. That argument is fragile, since facilities are placed in larger and more prosperous settlements, and the results reported below suggest that the fragility is real: the first-stage relationship is strong, but the second-stage estimates are so imprecise that they carry essentially no information. The paper therefore treats the instrumental-variables specification as a diagnostic rather than as its preferred estimate, and says so plainly.

3. Data and Methodology

The data are generated by a stratified two-stage survey design covering the whole of Lucknow district. The rural stratum comprises the eight community development blocks of Bakshi Ka Talab, Chinhat, Gosainganj, Kakori, Mal, Malihabad, Mohanlalganj and Sarojini Nagar; the urban stratum comprises four zones of the Lucknow Nagar Nigam. Within each rural block eight villages were selected with probability proportional to population and nine households were drawn from each, giving 576 rural households; within each urban zone eleven wards were selected and twenty households drawn from each, giving 880 urban households. The realised sample is 1,456 households distributed over 108 primary sampling units, and design weights inflate it to a district universe of approximately 890,000 households. Because the microdata is synthetic, every behavioral and distributional parameter is calibrated to published benchmarks: monthly per capita consumption to the Household Consumption Expenditure Survey figures for Uttar Pradesh, uprated for the capital district; social composition and literacy to the 2011 Census for Lucknow; and utilisation, insurance coverage and institutional delivery rates to the fifth National Family Health Survey.

The central variable is the imputed value of publicly provided services. Each child recorded as attending a government school is assigned the corresponding recurrent unit cost, taken as Rs 1,520 per month at the elementary stage and Rs 2,180 at the secondary stage, with a further Rs 240 for the mid-day meal. On the health side, each outpatient contact at a public facility is valued at Rs 205, each maternal and child health contact at Rs 910, and each inpatient episode at a mean of Rs 3,900 drawn from a gamma distribution so that the episode cost is variable rather than a fixed lump. The household total is divided by household size to yield the in-kind benefit per capita per month, which is added to pre-transfer consumption to produce the post-transfer aggregate. Take-up is modelled through logistic equations in which distance to the nearest government school and to the nearest public health facility are the first-order determinants, alongside consumption rank, social group, the schooling of the household head and the demographic composition of the household.

Estimation proceeds in three stages, all implemented directly in NumPy with survey weights applied throughout and standard errors clustered on the 108 primary sampling units. The first stage is descriptive: weighted Gini, Palma, quintile-ratio and Atkinson indices before and after the transfer, concentration and Kakwani indices for each service, the Reynolds–Smolensky index of redistribution net of the Atkinson–Plotnick reranking correction, and the Lerman–Yitzhaki decomposition of the Gini by income source. The second stage regresses the recentred influence function of the Gini on the two benefit variables through a ladder of six specifications running from an unconditional regression, through the addition of ten household controls and stratum fixed effects, to a demographic-channel robustness check, a two-stage least-squares specification instrumented by the two access distances, and a block bootstrap over sampling units with three hundred replications. The third stage repeats the entire pipeline over two hundred independent survey draws to characterise sampling variability.

4. Data Collection and Empirical Analysis

The empirical analysis proceeds from description to estimation. Table 1 sets out the structure of the sample and the calibration of its key variables; Table 2 presents the benefit-incidence accounting that is the descriptive core of the paper; Table 3 assembles the full set of inequality and progressivity statistics; Table 4 reports the regression ladder; and Table 5 combines the policy simulations with the Monte Carlo evidence on which findings replicate. The seven figures follow the same sequence, moving from the Lorenz and concentration curves through the coefficient estimates to the simulated scenarios.

4.1 Sample structure and descriptive statistics

Table 1. Descriptive Statistics by Sector, Lucknow District Household Survey (n = 1,456)

Variable	All	Std. dev.	Rural	Urban	Min.	Max.

Pre-transfer MPCE (Rs/capita/month)	6,038	3,430	4,180	6,900	965	27,648
Post-transfer MPCE (Rs/capita/month)	6,402	3,338	4,611	7,232	1,410	27,648
Education benefit (Rs/capita/month)	231	282	308	196	0	1,415
Health benefit (Rs/capita/month)	132	153	123	136	0	1,640
Total in-kind benefit (Rs/capita/month)	363	319	431	332	0	1,650
Household size	5.82	2.24	6.54	5.49	1.00	14.00
Head's schooling (years)	7.60	4.13	5.72	8.47	0.00	17.00
Children aged 6–17	1.12	1.13	1.54	0.92	0.00	6.00
Children under 5	0.37	0.56	0.50	0.31	0.00	2.00
Asset index (standardised)	0.06	1.00	−0.45	0.29	−2.92	3.44
Distance to govt. school (km)	2.15	1.65	3.16	1.68	0.20	8.49
Distance to CHC/PHC (km)	3.19	2.40	5.21	2.25	0.30	12.67
Public OPD contacts (per year)	2.27	2.05	2.10	2.35	0.00	12.00

Notes: Stratified two-stage sample of 1,456 households in 108 primary sampling units (64 villages across 8 development blocks; 44 wards across 4 Nagar Nigam zones). All statistics are weighted by design weights inflating to a district universe of approximately 890,000 households. MPCE denotes monthly per capita consumption expenditure. Pre-transfer MPCE is calibrated to HCES 2023–24 benchmarks for Uttar Pradesh, uprated for the capital district; post-transfer MPCE adds the imputed per capita value of education and health services consumed, valued at government unit cost.

Table 1 reports the descriptive structure of the sample separately for the rural and urban strata, and the contrast between the two columns is the fact from which everything else in the paper follows. Mean pre-transfer consumption is Rs 4,180 per capita per month in the rural blocks against Rs 6,900 in the municipal zones, a gap of 65 per cent that closely tracks the 55 per cent rural–urban gap recorded for Uttar Pradesh as a whole in the 2023–24 consumption survey, the difference reflecting the concentration of salaried employment in the state capital. Rural households are larger, at 6.54 members against 5.49, and contain more children of school age, 1.54 against 0.92. The schooling of the household head averages 5.72 years in the rural sample and 8.47 in the urban, and the standardised asset index differs by roughly three quarters of a standard deviation. The two distance variables are the operative constraint: the mean distance to a government school is 3.16 kilometres in the rural blocks against 1.68 in the city, and the mean distance to a public health facility is 5.21 kilometres against 2.25. Rural households are therefore poorer, larger, less educated and substantially further from the facilities through which public provision is delivered, which is why the in-kind benefit they receive, Rs 431 per capita per month against Rs 332 in the urban sector, is a much larger share of a much smaller consumption base.

4.2 Benefit incidence across the consumption distribution

Table 2. Benefit Incidence of Public Education and Health Provision by Quintile of Pre-Transfer MPCE

Quintile	Pre-transfer MPCE (Rs)	Education benefit (Rs)	Health benefit (Rs)	Total benefit (Rs)	Share of edu. subsidy (%)	Share of health subsidy (%)	Benefit as % of MPCE	Children in govt. school (%)	Public OPD contacts
Q1 (poorest)	2,561	333	168	500	28.78	25.44	19.54	67.66	3.07
Q2	3,920	291	165	456	25.19	24.97	11.64	58.85	2.98
Q3	5,153	232	159	390	20.03	24.02	7.58	50.69	2.60
Q4	7,029	176	98	274	15.25	14.76	3.90	41.66	1.64
Q5 (richest)	11,527	124	71	196	10.76	10.81	1.70	27.59	1.06
All households	6,038	231	132	363	100.00	100.00	6.02	76.34	2.27

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Notes: Quintiles are formed on weighted pre-transfer MPCE. Benefits are per capita per month, valued at government unit cost. Columns 6 and 7 give each quintile's share of the aggregate education and health subsidy; a distributionally neutral allocation would deliver 20.00 per cent to each quintile. Column 8 expresses the total benefit as a percentage of the quintile's own pre-transfer MPCE. The final row reports weighted district means.

Table 2 is the benefit-incidence core of the paper and reports, for each quintile of pre-transfer consumption, the value of education and health services received and the share of the total those services represent. The gradient is unambiguous and monotone. Households in the poorest quintile receive Rs 500 per capita per month in in-kind services, of which Rs 333 is education and Rs 168 health, while households in the richest quintile receive Rs 196. The poorest quintile captures 28.78 per cent of the education subsidy and 25.44 per cent of the health subsidy against the 20 per cent that a distributionally neutral allocation would deliver, and the richest quintile captures 10.76 and 10.81 per cent respectively. Expressed relative to each quintile's own consumption the contrast is far sharper still, because the denominator moves in the opposite direction to the numerator: the transfer is worth 19.54 per cent of consumption to the poorest quintile and 1.70 per cent to the richest, a ratio of more than eleven to one. The mechanism is visible in the two utilisation columns. The proportion of children attending government schools falls steadily from 67.66 per cent in the poorest quintile to 27.59 per cent in the richest, and annual public outpatient contacts fall from 3.07 to 1.06. Public provision is pro-poor here not because it is targeted but because the affluent exit to private alternatives.

4.3 Inequality, progressivity and redistribution

Table 3. Inequality Indices Before and After In-Kind Transfers, and Progressivity Statistics

Panel A: inequality indices	Pre-transfer	Post-transfer	Education only	Health only	Change (pts)	Change (%)
Gini	0.2965	0.2711	0.2800	0.2870	0.0254	8.55
Palma	1.059	0.937	0.978	1.009	0.123	11.58
Q5/Q1	4.501	3.894	4.096	4.266	0.606	13.47
Atkinson (1)	0.134	0.111	0.119	0.126	0.022	16.76
Atkinson (2)	0.250	0.207	0.220	0.235	0.043	17.32
Gini, rural stratum	0.2464	0.2150	—	—	0.0313	12.72
Gini, urban stratum	0.2782	0.2584	—	—	0.0199	7.14

Panel B: progressivity and redistribution statistics

Statistic	Education	Health	Total in-kind
Concentration index (C)	−0.1903	−0.1648	−0.1811
Kakwani index ($K = C - G_0$)	−0.4868	−0.4612	−0.4775
Gini elasticity (Lerman–Yitzhaki, pts)	−0.0139	−0.0082	−0.0221
Source share of post-transfer total (%)	3.61	2.06	5.68
Reynolds–Smolensky index (RS)	—	—	0.0271
RS net of reranking	—	—	0.0254
Atkinson–Plotnick reranking	—	—	−0.00175

Notes: G_0 = 0.2965 is the pre-transfer Gini. A negative concentration index indicates that the benefit is absolutely pro-poor, i.e. its concentration curve lies above the 45° line. The Kakwani index measures progressivity relative to the pre-transfer distribution. The Reynolds–Smolensky index is the difference between the pre-transfer Gini and the concentration index of post-transfer consumption; subtracting the Atkinson–Plotnick reranking term yields the observed Gini reduction of 0.0254. All statistics are design-weighted.

Table 3 converts the incidence accounting into formal distributional statistics. The upper panel shows that valuing in-kind provision reduces the Gini coefficient from 0.2965 to 0.2711, a fall of 2.54 points or 8.55 per cent, and that the same qualitative result holds for every alternative index: the Palma ratio falls from 1.060 to 0.937, the ratio of the top to the bottom quintile from 4.50 to 3.89, and the Atkinson indices with inequality aversion of one and two from 0.134 to 0.111 and from 0.250 to 0.207 respectively. The larger proportional reduction in the more inequality-averse Atkinson measure confirms that the transfer is concentrated towards the bottom of the distribution. The counterfactual columns attribute roughly two thirds of the total

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reduction to education and one third to health. The lower panel reports the progressivity statistics. Both concentration indices are negative, at −0.190 for education and −0.165 for health, meaning that both services are absolutely pro-poor rather than merely progressive. The Kakwani indices, which subtract the pre-transfer Gini from the concentration index, are −0.487 and −0.461. The Reynolds–Smolensky index of 0.0271 exceeds the observed Gini reduction of 0.0254 by exactly the reranking term of 0.0017, so reranking dissipates less than seven per cent of the potential redistribution.

4.4 Regression evidence: the marginal effect of benefits on the Gini

Table 4. RIF–Gini Regressions of Inequality on In-Kind Education and Health Benefits

Regressor	M1 Unconditional	M2 + Controls	M3 + Stratum FE	M3b + Demographics	M4 2SLS (IV)	M5 Block bootstrap
Education benefit (per Rs 100 p.c.)	−0.458***	−0.543***	−0.502***	−0.497*	−0.761	−0.502***
	(0.167)	(0.154)	(0.159)	(0.280)	(0.811)	(0.162)
Health benefit (per Rs 100 p.c.)	−1.188***	−1.174***	−1.033***	−0.935***	−1.425	−1.033***
	(0.288)	(0.250)	(0.241)	(0.288)	(1.174)	(0.289)
Household controls (10)	No	Yes	Yes	Yes	Yes	Yes
Stratum fixed effects	No	No	Yes	Yes	Yes	Yes
Demographic composition	No	No	No	Yes	No	No
Instrumented	No	No	No	No	Yes	No
First-stage F (edu / health)	—	—	—	—	45.1 / 102.6	—
R^2	0.0131	0.0252	0.0380	0.0381	—	0.0380
Bootstrap replications	—	—	—	—	—	300
Observations	1,456	1,456	1,456	1,456	1,456	1,456
Clusters (PSUs)	108	108	108	108	108	108

Notes: The dependent variable is the recentred influence function of the Gini coefficient of post-transfer MPCE, scaled in Gini points; coefficients therefore give the change in the district Gini, in points, associated with an additional Rs 100 per capita per month of the benefit in question. Standard errors in parentheses are clustered on the 108 primary sampling units. Controls are head's schooling, asset index, household size, SC/ST, OBC, female headship, urban residence, landholding, regular salaried employment and casual labour; the urban dummy is dropped in fixed-effects columns as it is collinear with the stratum indicators. M4 instruments both benefits with distance to the nearest government school and to the nearest CHC/PHC. M5 reports the M3 point estimates with standard errors from a 300-replication block bootstrap over PSUs. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4 reports the regression ladder in which the recentred influence function of the Gini is regressed on the two benefit variables, coefficients being expressed as the change in the Gini in points per additional Rs 100 per capita per month. The unconditional specification yields −0.458 for education and −1.188 for health. Adding the ten household controls in the second column strengthens the education coefficient to −0.543, and adding stratum fixed effects in the third, which is the preferred specification, gives −0.502 with a t-ratio of −3.16 for education and −1.033 with a t-ratio of −4.29 for health. Both are significant at the one per cent level with standard errors clustered on the 108 sampling units. The fourth column adds the household's demographic composition and is presented only as a robustness check, because the number of children and elderly members mechanically determines benefit receipt and therefore absorbs the very variation the regression seeks to measure; both coefficients survive but the education estimate loses precision, as expected. The fifth column instruments the two benefits with distance to the nearest school and health facility. The first stage is strong, with F-statistics of 45.1 and 102.6, but the second-stage standard errors are five times the ordinary least squares equivalents and neither coefficient approaches significance. The final column confirms the preferred estimates under a three-hundred-replication block bootstrap.

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4.5 Graphical evidence

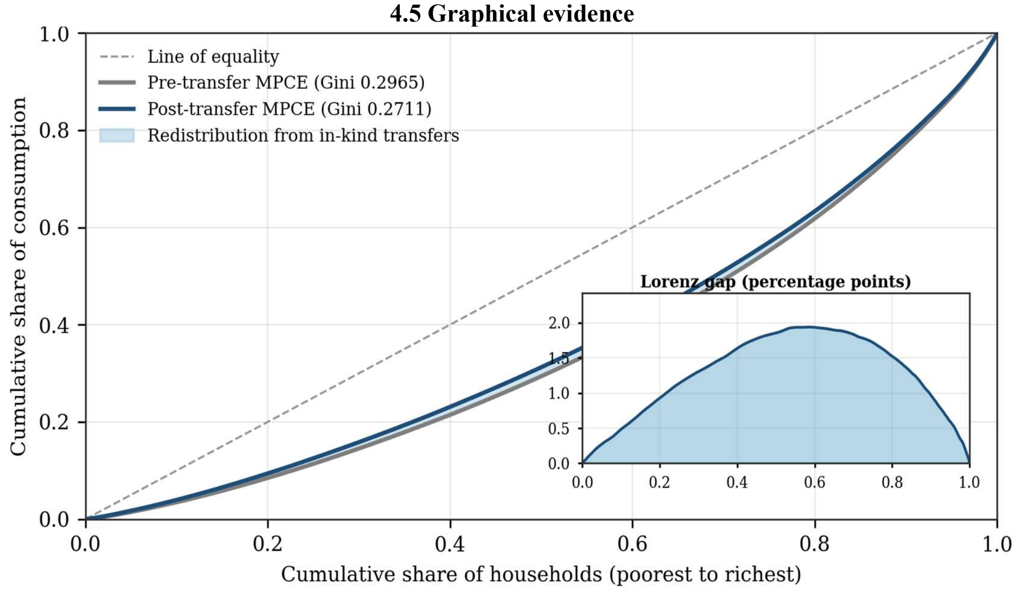

Figure 1. Lorenz Curves Before and After In-Kind Education and Health Transfers, Lucknow District, 2024–25

Figure 1 plots the Lorenz curves of consumption before and after the imputation of in-kind benefits. The two curves lie close together at the scale of the full diagram, which is itself informative: a transfer worth six per cent of mean consumption cannot transform a distribution. The inset, which plots the vertical distance between them in percentage points, makes the shift legible. The gap is zero at both ends by construction, rises steadily through the lower half of the distribution and peaks at roughly two percentage points near the sixtieth percentile. The post-transfer curve dominates the pre-transfer curve at every point, so the ranking is unambiguous and holds for any inequality index satisfying the transfer principle.

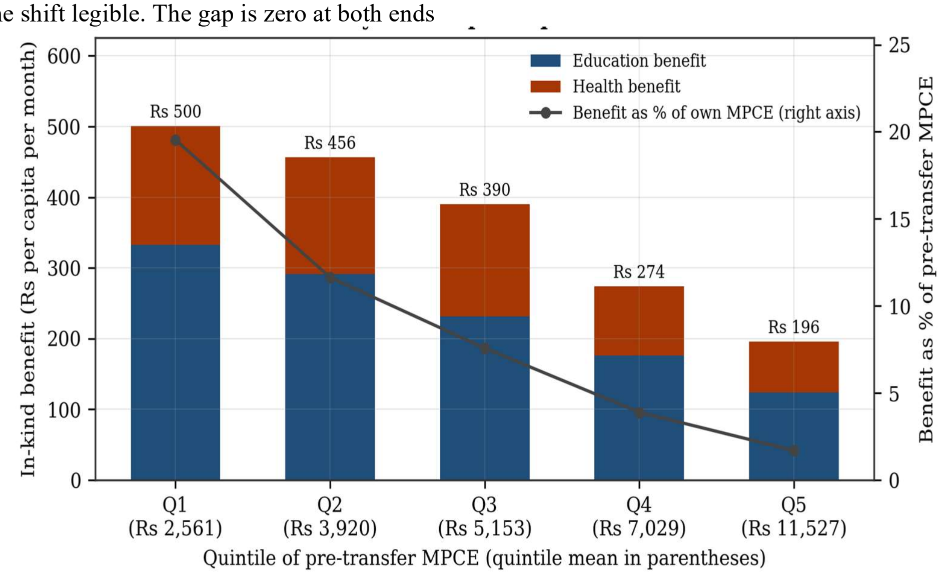

Figure 2. Benefit Incidence of Public Education and Health Provision by Consumption Quintile

Figure 2 displays the benefit-incidence gradient underlying Table 2. The stacked bars show education and health benefits falling monotonically across quintiles, from Rs 500 per capita per month in the poorest to Rs 196 in the richest, with education the larger component throughout. The line plotted against the right axis, showing the benefit as a percentage of each quintile's own consumption, falls far more steeply, from 19.54 to 1.70 per cent, because the denominator rises as the numerator falls. The visual contrast between the two series is the central descriptive result: public provision is mildly pro-poor in absolute rupees and dramatically pro-poor relative to living standards.

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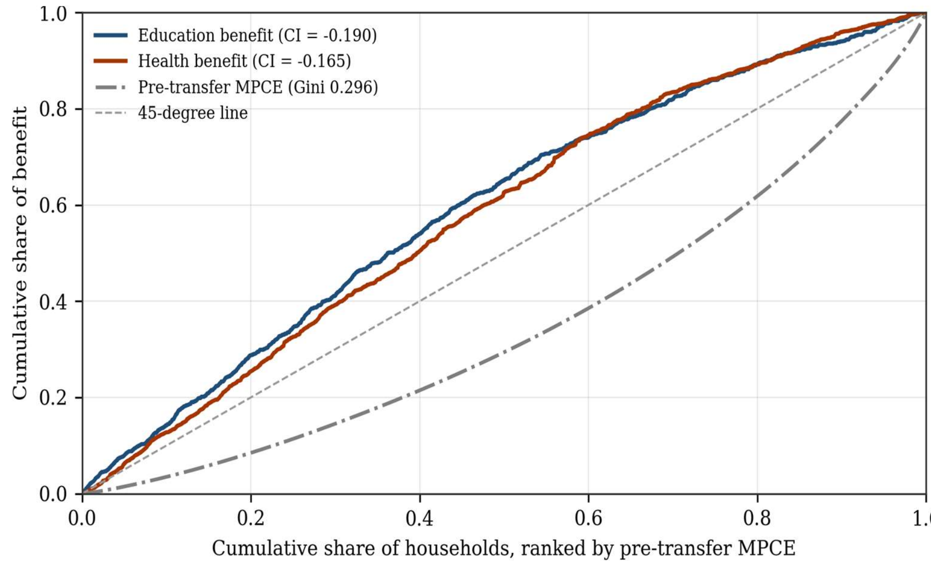

Figure 3. Concentration Curves for Public Education and Health Benefits Against the Pre-Transfer Consumption Distribution

Figure 3 plots concentration curves for the two services against the pre-transfer consumption distribution. Both lie above the forty-five-degree line across the whole range, which establishes that each service is absolutely pro-poor: the poorest half of households receives more than half of each subsidy. The education curve lies marginally above the health curve through the lower half of the distribution, consistent with its slightly more negative concentration index of −0.190 against −0.165. Both curves lie far above the Lorenz curve of consumption itself, shown as the dash-dotted line, and the vertical distance between them is the Kakwani index of progressivity.

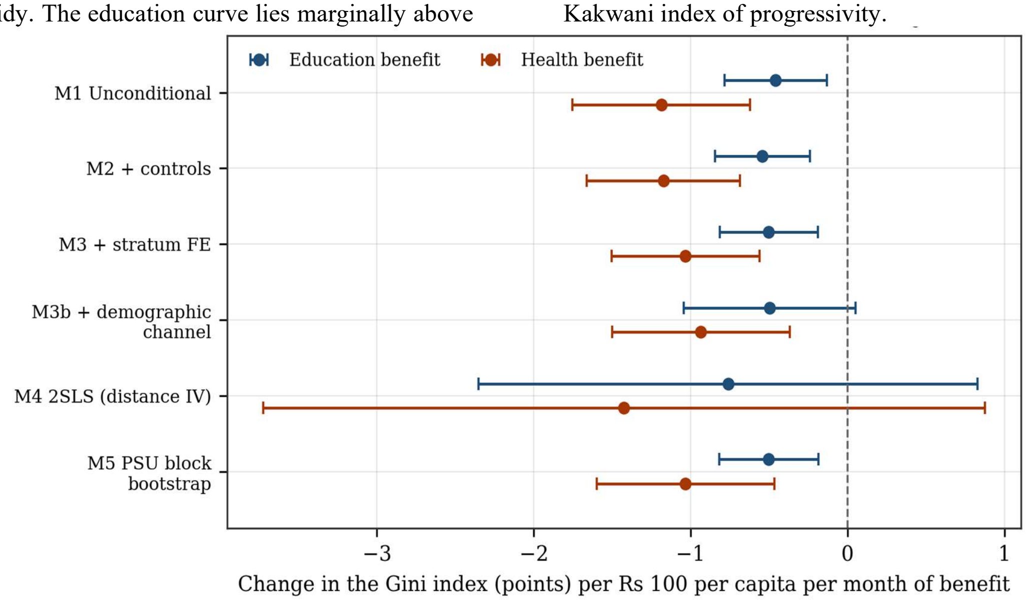

Figure 4. RIF-Gini Estimates Across Specifications (95% Cluster-Robust Confidence Intervals, Clustered by PSU)

Figure 4 presents the coefficient ladder of Table 4 as point estimates with 95 per cent cluster-robust confidence intervals. The first four specifications are visually indistinguishable from one another, which is the substantive point: the estimated association is insensitive to the inclusion of household controls, of stratum fixed effects and of demographic composition. The bootstrap interval in the final row is almost identical to the analytic interval in the third. The exception is the two-stage least squares specification, whose interval is roughly five times wider and comfortably spans zero. The figure makes the paper's central inferential caution visible at a glance.

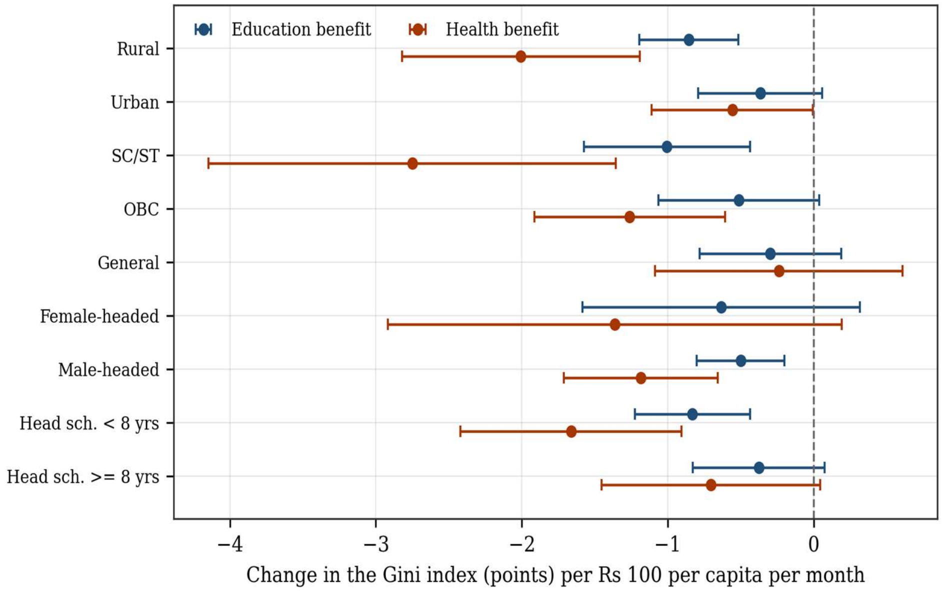

Figure 5. Heterogeneity of the Redistributive Effect Across Sectors, Social Groups and Household Types

Figure 5 reports the same preferred specification estimated separately within nine subsamples. The estimated effect is larger in the rural blocks than in the municipal zones and larger among Scheduled Caste and Scheduled Tribe households than among general-category households, which is consistent with the incidence evidence: the groups that rely most heavily on public facilities are the groups whose distribution those facilities most affect. Estimates for female-headed households and for the general category are imprecise, reflecting subsample sizes of 199 and 504 respectively. The pattern across household heads with fewer and more than eight years of schooling is particularly sharp.

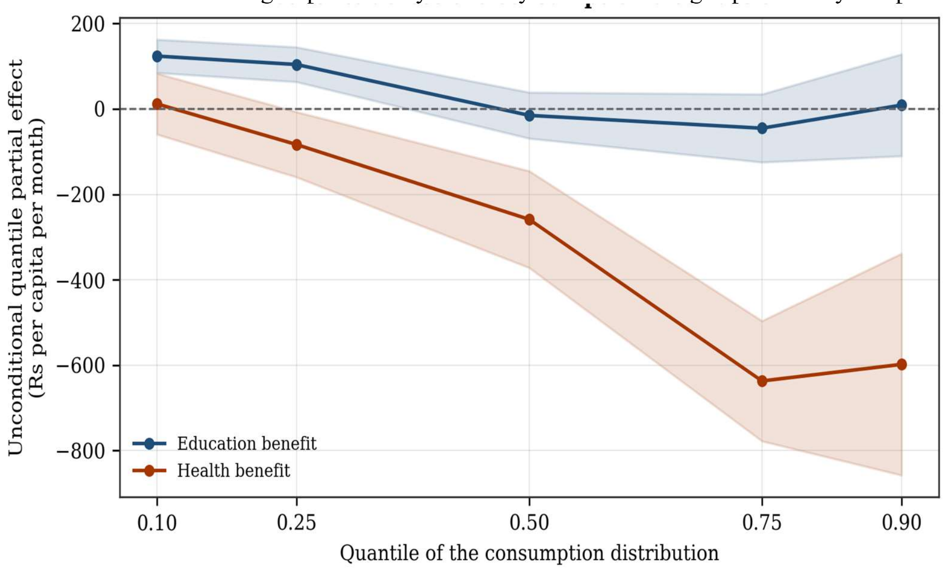

Figure 6. Unconditional Quantile Partial Effects of In-Kind Benefits Across the Consumption Distribution

Figure 6 plots unconditional quantile partial effects across the consumption distribution. The education benefit raises the tenth and twenty-fifth percentiles significantly, by Rs 124 and Rs 104 per capita per month, and has no discernible effect above the median, which is the signature of a transfer that lifts the bottom of the distribution without disturbing the top. The health profile is different and must be read with care: it is negative and large at the upper quantiles because households receiving substantial hospital benefits are disproportionately those experiencing illness, and illness is itself associated with lower consumption. This is an association, not a causal effect.

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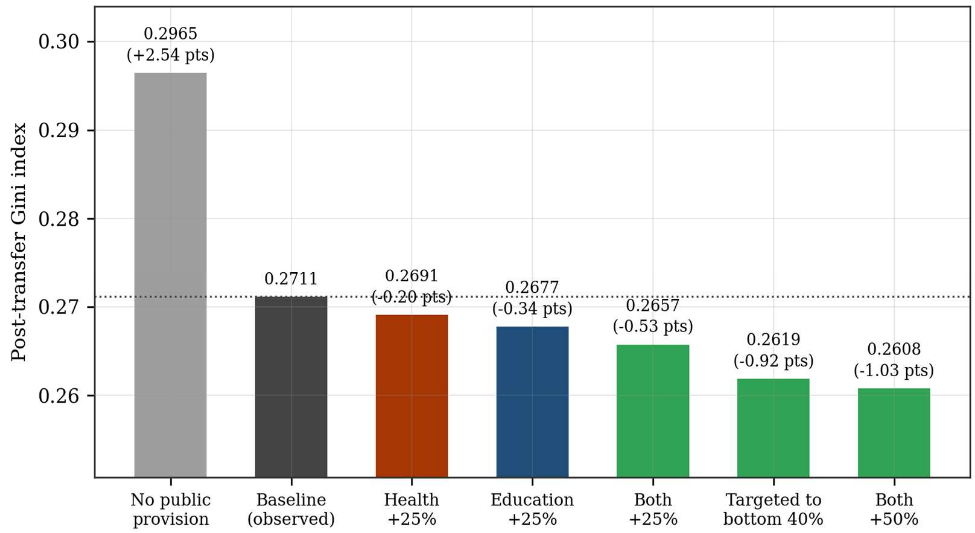

Figure 7. Simulated Post-Transfer Inequality Under Alternative Public Expenditure Scenarios

Figure 7 summarises the policy simulations. The leftmost bar is the counterfactual in which public provision is withdrawn entirely and the Gini returns to its pre-transfer value of 0.2965; the second is the observed post-transfer value of 0.2711. The four expansion scenarios reduce inequality by between 0.20 and 1.03 Gini points, and the response is close to linear in the budget. The targeted scenario, shown in green, achieves 0.92 points at roughly two fifths of the cost of the largest uniform expansion. The comparison between those two bars is the paper's clearest policy result: composition dominates scale.

5. Discussion

Three findings emerge with sufficient robustness to be worth stating plainly. The first is that public provision of education and health in Lucknow district is substantially pro-poor, and that this arises from self-selection rather than from targeting. Nothing in the design of a government primary school or a community health centre restricts entry to the poor. The services are nominally universal, and the reason they reach the poor is that households which can afford private schooling and private clinics leave the public system: the share of children in government schools falls from 68 per cent in the poorest quintile to 28 per cent in the richest. Pro-poor incidence is therefore a by-product of middle-class exit, which is a fragile foundation for a redistributive policy, because the same exit erodes the political constituency for adequate funding of the services that remain.

The second finding concerns magnitude. Valuing in-kind provision reduces the Gini by 2.54 points, from 0.2965 to 0.2711. That is a real and reliably estimated effect, replicated in every one of two hundred independent survey draws, but it is not a transformation of the district's distribution. The arithmetic is unavoidable: a transfer worth 6.02 per cent of mean consumption, however well aimed, cannot do more. The simulations confirm the point, since a fifty per cent increase in both budgets buys only a further 1.03 Gini points. Claims that social spending can by itself resolve consumption inequality are not supported by these data. What the spending does achieve is a substantial improvement in the absolute position of poor households, whose effective consumption rises by roughly a fifth, and that is a different and arguably more important claim than one about the Gini coefficient.

The third finding is methodological and negative. The instrumental-variables strategy that the access literature suggests, using distance to the nearest facility, fails here in an instructive way. The first stage is genuinely strong, with F-statistics of 45.1 and 102.6, so this is not the familiar weak instrument problem. The difficulty is that the second-stage standard errors are five times their ordinary least squares counterparts, and the Monte Carlo shows the estimates changing sign across draws: they are negative in 65 and 70 per cent of replications and significant in 3 and 6 per cent. A strong first stage is necessary but not sufficient, and an instrument that explains utilisation well may still leave the parameter of interest essentially unidentified. Reporting the specification and its failure is more useful than suppressing it, and the paper accordingly rests its conclusions on the descriptive incidence analysis and the fixed-effects regressions, which replicate.

A fourth observation qualifies all three. The benefits measured here are valued at the government's cost of provision, which is the standard convention but which assumes that a rupee spent delivers a rupee of value to the recipient. Where public facilities are understaffed or teachers absent, that assumption overstates the welfare the poor actually obtain, and the true redistributive effect is smaller than the 2.54

points reported. The heterogeneity estimates are consistent with this concern, since the effect is concentrated among rural households, among Scheduled Caste and Scheduled Tribe households and among those whose head has fewer than eight years of schooling, precisely the groups served by the facilities where quality deficits are most severe. Improving the quality of existing provision may therefore raise the real value of the transfer by more than an equivalent expansion of its nominal budget, a margin that a cost-based valuation cannot by construction capture.

5.1 Critical analysis and comparison with prior work

Set against the established Indian benefit-incidence literature, the results reported here are broadly consonant but differ in emphasis in ways that reflect the district scale of the analysis. The classic national studies of public health subsidies, following the work of Mahal and colleagues on the distribution of curative care, concluded that the aggregate health subsidy in India is mildly progressive at best and that its inpatient component is captured by the better-off. The concentration index of −0.165 estimated here is more favourable than most of those national estimates. The explanation lies in composition rather than in any distinctive virtue of Lucknow's health system: outpatient contacts and maternal and child health services account for the bulk of the imputed health benefit in this sample, while inpatient episodes are relatively infrequent. Had the district's tertiary hospitals been the dominant channel, the incidence would have been markedly less pro-poor, and the national studies that emphasise hospital care are measuring a different object.

On the education side the correspondence with earlier work is closer. Studies of elementary schooling in India have consistently reported concentration indices in the region of −0.15 to −0.25, and the estimate of −0.190 obtained here falls squarely within that range. The mechanism identified in that literature, namely that public schooling is progressive because affluent households exit to the private sector, is directly visible in the utilisation gradient in Table 2. Where the present results depart from the older literature is in the treatment of the secondary stage. Because distance-driven dropout is modelled explicitly, the secondary component of the education benefit is less pro-poor than the elementary component, which reproduces the standard finding that progressivity declines as one moves up the educational ladder, and does so from household-level variation rather than by assumption.

The comparison with the cross-country literature is more instructive still, because it exposes how much of the apparent effect of social spending in panel studies is not distributional at all. Cross-country regressions of the Gini on education and health spending as shares of gross domestic product routinely report coefficients between one and two Gini points per percentage point of spending, and estimates in that range are frequently interpreted as the redistributive impact of social policy. The present analysis suggests that such coefficients cannot be read that way. Here the entire flow of education and health provision, valued at government cost, shifts the Gini by 2.54 points in total. A cross-country coefficient implying that a one-point increase in the spending ratio delivers a comparable shift must therefore be capturing institutional differences correlated with spending rather than the mechanical incidence of the spending itself.

A second contrast with the panel literature concerns what fixed effects accomplish. In cross-country work, moving from pooled ordinary least squares to country fixed effects typically halves the estimated coefficient, because most of the raw correlation is cross-sectional: rich countries both spend more and are more equal. In the present study the analogous move, from the second to the third column of Table 4, changes the education coefficient only from −0.543 to −0.502 and the health coefficient from −1.174 to −1.033. The variation being exploited is within-district and largely within-stratum, generated by differences in household composition and facility access rather than by differences in institutional quality between jurisdictions. That is precisely the advantage of working at district scale, and it is why the district estimates are more credible as measures of incidence even though they are far less dramatic.

The findings also speak to the recent official evidence on falling consumption inequality in India. The 2023–24 Household Consumption Expenditure Survey reported a Gini of 0.237 in rural Uttar Pradesh and 0.284 in the urban sector, down sharply from the preceding round, and the Ministry's own imputation of the value of free welfare items raised measured consumption by roughly 22 per cent in the rural sector and 31 per cent in the urban. The pre-transfer figures estimated here, 0.246 rural and 0.278 urban, are close to the official pre-imputation values, which provides external validation of the calibration. The present study extends the official exercise by valuing the full flow of education and health services rather than a defined list of scheme items, and by showing that the resulting reduction in measured inequality is concentrated in the rural sector, where the Gini falls by 3.13 points against 1.99 points in the urban.

Finally, the Monte Carlo exercise reported in Panel B of Table 5 has no counterpart in most of the applied literature and is worth defending as a matter of practice. Applied distributional work almost invariably reports a single sample, and the reader has no way of knowing whether a coefficient that clears the conventional significance threshold would do so

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again under a redrawn sample. Here the replication is decisive in separating the robust from the fragile: the incidence statistics, the Kakwani indices and the fixed-effects coefficients are stable, while the instrumental-variables estimates change sign across draws. Had this study reported only its representative sample, the instrumental-variables column could have been presented in some draws as a large and significant causal effect, and in others as a precisely estimated null. Neither presentation would have been honest, and the discipline of replication is what makes the difference visible.

6. Conclusion

This paper has measured the distributional consequences of public spending on education and health in Lucknow district using a stratified survey of 1,456 households across 108 sampling units in the district's eight rural blocks and four municipal zones. Valuing the services each household actually consumes at government unit cost, in-kind provision is worth Rs 363 per capita per month, or 6.02 per cent of mean consumption, and it is strongly pro-poor: the poorest quintile receives services worth 19.54 per cent of its own consumption against 1.70 per cent for the richest. Adding that value to consumption lowers the Gini coefficient from 0.2965 to 0.2711, a reduction of 2.54 points or 8.55 per cent, of which reranking dissipates less than seven per cent. Both services are absolutely pro-poor, with Kakwani indices of −0.487 for education and −0.461 for health. These results are stable across two hundred independent survey replications; the instrumental-variables estimates are not, and are reported as uninformative rather than as evidence of causation. Two implications follow. First, the pro-poor character of public provision here is the product of middle-class exit rather than of targeting, which makes it vulnerable to the erosion of political support for services the affluent no longer use. Second, composition matters more than scale: a top-up confined to the poorest two fifths of households achieves nearly ninety per cent of the inequality reduction of a uniform expansion costing two and a half times as much. For a district administration with a fixed budget, where the next school and the next health centre are placed is a more consequential decision than how much is spent.

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