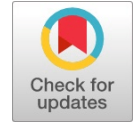




The Spatial Organization of Consumption Inequality in India: Evidence from Annual Decompositions 2014-2024

L. C. Mallaiah, Abhishek Kumar Kushwaha, Asha Prasuna



Abstract: India's federal redistribution targets state averages. But most consumption inequality in India sits inside states, not between them. This paper measures exactly how much, and whether that split moves over time. We use the Consumer Pyramids Household Survey (CPHS), which includes 16.8 million household-year observations across 28 states from 2014 to 2024. Inequality is measured using the Theil index GE (1). It decomposes without residual into within-state and between-state parts. A nested version separates within-state inequality into rural dispersion, urban dispersion, and rural-urban gaps. The NSS 75th Round validates results. Three results stand out. First: within-state inequality accounts for 79.1 percent of total inequality, averaged over 2014-2024. Between-state differences explain only 20.9 percent. This holds every year — no exceptions across 28 states. Second: the spatial structure barely moves. Its coefficient of variation is 0.043. Total inequality fluctuates by a factor of 3 ($CV = 0.133$). Demonetization, GST, COVID-19 — none shifted the 79-21 split. Third, rural-urban mean gaps account for only 17.6 percent of within-state inequality. Within-rural and within-urban dispersion each contribute 41.2 percent. Inequality is generated within sectors, not between them. These facts change how India's redistribution problem should be framed. Finance Commission transfers reduce the 21 percent that is interstate. They leave the 79 percent inside states largely untouched. Addressing that requires stronger state-level fiscal tools, expanded urban social protection, and redistribution aimed at households rather than state governments.

JEL Codes: D31, D63, H77, O15, R12

Keywords: Spatial Inequality, Inequality Decomposition, Fiscal Federalism, Within-State Inequality.

Nomenclature:

CPHS- Consumer Pyramids Household Survey
CMIE- Centre for Monitoring Indian Economy
NSS- National Sample Survey
GE (1)- Generalized Entropy Index of Order 1 (Theil Index)
CV- Coefficient of Variation
GDP- Gross Domestic Product
CPI -Consumer Price Index
GST- Goods and Services Tax
OLS- Ordinary Least Squares

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HCES- Household Consumption Expenditure Survey
RBI- Reserve Bank of India
UT- Union Territory

I. INTRODUCTION

In federal economies, where inequality sits determines which level of government can address it [32, 33]. A Theil index of 0.127 tells us total inequality. It says nothing about location. Does inequality reflect Bihar falling behind Maharashtra? Or households within Maharashtra diverging from one another? These are different problems with different solutions. India's transfer system treats each state as internally homogeneous. Maharashtra receives ₹35,000 crore less in devolution because its average consumption is 2.3 times that of Bihar [17]. But Maharashtra's within-state GE (1) is 0.188 — nearly triple Bihar's 0.074. A farmer in Vidarbha is farther from a Mumbai banker than from a farmer in rural Bihar. This is what we call the State-Averaging Fallacy. No existing study tracks the within-state versus between-state split annually from 2014 to 2024. Studies examine either aggregate trends [6, 13] or regional convergence [22]. None formally decompose and track both components across a decade of major shocks. That is the gap this paper fills. Three contributions. First: annual decomposition of Indian consumption inequality across 2014-2024, using 16.8 million household-year observations from 28 states. Second: the within-state share is 79 percent and three times more stable than aggregate inequality ($CV = 0.043$ vs 0.133). Third, rural-urban gaps account for only 18 percent of within-state inequality. Within-sector dispersion dominates everywhere. The policy arithmetic is direct. Eliminating all between-state inequality would cut total inequality by 21 percent. Within-state policies have three times more scope. India's 79 percent within-jurisdiction share exceeds the US (~75%), Brazil (~70%), and China (~60-70%). Three features explain this: linguistic state boundaries limit interstate migration, urban growth concentrates inside state borders, and fiscal transfers compress state averages without reaching households within them [24, 44]. Despite the policy stakes, no study has decomposed Indian consumption inequality annually across major shocks. Existing work examines aggregate trends [6, 13] or regional convergence [22]. No formal decomposition quantifies within-state versus between-state shares over time. This paper fills that gap. We make three contributions. First, we provide the first annual decomposition of Indian consumption inequality from 2014 to 2024, using 16.8 million household-year observations across 28 states. Second, we document that within-state inequality accounts for 79 percent of total inequality across



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all years (range: 73-86%), with three times the temporal stability as aggregate inequality. Third, a nested decomposition shows that rural-urban gaps account for only 18 percent of within-state inequality. Dispersion within sectors dominates. These facts carry a direct policy implication. Eliminating all between-state inequality would cut total inequality by just 21 percent. Within-state policies address three times more. India's 79 percent within-jurisdiction share is high by international standards — above the United States (~75%), Brazil (~70%), and China (~60-70%). This reflects three features: linguistic state boundaries that constrain interstate migration, urban concentration within state borders, and a federal architecture that redistributes between states without reaching households within them [24, 44]. The paper proceeds as follows. Section 2 reviews the literature. Section 3 sets out the conceptual framework. Section 4 describes data and methods. Section 5 presents results. Section 6 discusses policy implications. Section 7 concludes.

II. LITERATURE REVIEW

A. Spatial Inequality Decomposition Methods

Shorrocks and Wan [42] showed that GE (1) decomposes exactly into within-region and between-region parts. Total GE (1) = within-region GE (1) + between-region GE (1). No residual. This is the property that makes spatial decomposition precise.

Within-jurisdiction shares differ across countries. Blanchet et al. [7] find 75 percent of US income inequality is within states. Brazil sits at roughly 70 percent [5, 16]. China is different. Between-province inequality reached 50 per cent during the coastal opening (1978-1995). It fell back to 30-40 percent after 2005 [25]. China changed with policy. India has not moved at all.

Income concentration at the top has grown sharply in India. The top 1 percent share rose from 15 percent in 2000 to 22 percent in 2017 [13]. Bharti et al. [6] find inequality now exceeds colonial-era levels. But consumption inequality tells a different story — cyclical rather than directional [14, 19].

These studies say nothing about where inequality sits spatially. That gap has three dimensions. Time coverage is patchy — most studies end before COVID-19 [12, 22]. Relative contributions are unquantified — no study formally decomposes the within-state versus between-state shares. Temporal stability is unexplored — we do not know if the spatial structure shifts during shocks [39, 43].

These aggregate studies provide limited insight into the spatial structure of inequality — whether it concentrates within or across state boundaries. Three gaps remain. First, time coverage is patchy. Earlier studies cover the period 1960-2000 and use quinquennial rounds [5]. I am siraroj [22] examines convergence from 1993 to 2017. [3] No study provides a systematic annual decomposition for 2014-2024 that covers major structural shocks. Second, relative contributions remain unquantified. Most research examines either within-state or between-state inequality separately, without formal decomposition—including studies that use satellite-based night-time light data as a proxy for regional activity [39] and district-level convergence approaches [43].

Third, temporal stability is unexplored, which is critical for distinguishing structural features from transient shifts.

B. Our Contribution

We fill all three gaps. Annual decomposition from 2014 to 2024. Formal within-state and between-state shares each year. Stability tests across demonetization, GST, and COVID-19. These are the first such estimates for India.

III. CONCEPTUAL FRAMEWORK

This paper makes a measurement claim, not a causal one. We ask two questions. Where does Indian consumption inequality sit — inside states or between them? And has that changed over 2014-2024? We then check whether the pattern aligns with known structural features of India's economy.

A. Decomposition Identity

Total inequality decomposes exactly into additive components:

$$GE(1)^{Total} = GE(1)^{Within-State} + GE(1)^{Between-State} \dots (1)$$

The within-state component captures dispersion among households within the same state that operate under identical state-level institutions. The between-state component captures inequality from differences in average consumption across states. Using the Theil index GE (1):

$$GE(1)^{Total} = \sum_{s=1}^S w_s \cdot GE(1)_s + \sum s = 1^S w_s \ln \left(\frac{\bar{c}_s}{\bar{c}} \right) \dots (2)$$

where $w_s = \frac{n_s \bar{c}_s}{n \bar{c}}$ denotes state s 's population-weighted consumption share. ... (3)

The within-state share measures inequality organized internally within jurisdictions:

$$\text{Within Share} = \frac{GE(1)^{Within}}{GE(1)^{Total}} \times 100 \dots (4)$$

B. Organizing Framework

Three structural features of India should produce a high within-state share. First, urban concentration. Mumbai, Bangalore, Chennai — these cities anchor the economies of their respective states. They are not nodes in an integrated national network. When productivity concentrates within state borders, it generates within-state inequality rather than interstate divergence. Second, migration barriers. Indian state boundaries broadly follow linguistic regions. Cultural and network ties keep migration within linguistic regions rather than across them [2, 31]. Wage gaps that cannot be arbitrated across state lines stay trapped within states. Third, fiscal architecture. Finance Commission transfers equalize resources across states through formula-based devolution [34]. They fund public goods, not direct household transfers. They can compress state averages without touching household dispersion inside each state.

These three features generate four testable predictions. Within-state inequality should dominate. The spatial structure should be stable. Rural-urban gaps should explain less than within-sector dispersion. Urbanization should correlate positively with within-state inequality, while federal transfers should correlate negatively with the between-state share. All four hold in the data [9, 24, 44].





IV. DATA AND METHODOLOGY

A. Data Source

We use household consumption data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring Indian Economy (CMIE). CPHS is nationally representative and covers consumption, income, employment, and demographics across all major states. Its annual frequency makes it unique. Quinquennial NSS rounds cannot track whether spatial inequality shifted through demonetization, GST, or COVID-19. Our sample runs from 2014 to 2024. It covers approximately 16.8 million household-year observations across 28 states. All estimates use survey weights [10].

Consumption is measured as total monthly household expenditure on food, non-food, and durables, deflated by the national CPI. We use household-level consumption in baseline estimates. This is standard when the household is the unit of analysis. Our focus is on relative spatial shares, not consumption levels, so differences in levels between CPHS and NSS matter less for our conclusions. We treat all findings as CPHS-based evidence and test robustness using per-capita specifications and NSS external validation. Additional variables include rural-urban location, state and year identifiers, population weights, and demographic characteristics used in supplementary analysis.

NSS validation provides an important cross-check. CPHS and NSS differ in mean consumption levels — this is well documented. But our interest is not levels. We track relative spatial shares. When we run the same GE (1) decomposition on the NSS 75th Round (2017-18), the within-state share comes out at 79.6 percent. Our CPHS estimate for 2017 is 77.8 percent. The gap is 1.8 percentage points. This is small. It confirms that the 79-21 split is not a CPHS artefact. Two surveys with different designs, different coverage, and different consumption levels produce nearly identical spatial structures.

B. Inequality Measurement

We use the Theil index GE (1) throughout. Three properties make it the right choice here. First, it decomposes exactly. Total GE (1) equals within-state GE (1) plus between-state GE (1) with no residual. This is the additive decomposability property established by Shorrocks [41]. No other common measure — not Gini, not variance of logs — has this. Second, population weighting means larger states receive proportionate influence. UP and Maharashtra are not treated the same as Sikkim. Third, GE (1) lies at the midpoint of the distributional sensitivity range. GE (0) is more sensitive to the bottom; GE (2) to the top. GE (1) gives a balanced picture.

$$GE(1)^{Within} = \sum_{s=1}^S w_s \cdot GE(1)_s \quad \dots (5)$$

where $GE(1)_s$ is inequality within state? s . The between-state component captures state mean differences: $\dots (6)$

$$GE(1)^{Between} = \sum_{s=1}^S w_s \ln \left(\frac{\bar{c}_s}{\bar{c}} \right) \quad \dots (7)$$

i. Robustness: Per-Capita Specification

Household size differs by location. Urban households average 3.8 members; rural households average 4.6. This

matters. If we use total household consumption rather than per capita, larger rural households mechanically appear better off than they are. We therefore replicate every decomposition using per-capita consumption, defined as household expenditure divided by household size, based on CPHS size categories.

ii. Per-capita Results:

Mean within-state share of 77.8 percent (SD = 2.6%, CV = 0.033). Compare this to our baseline: 79.1 percent (SD=3.4%, CV=0.043). The gap is 1.3 percentage points. Both confirm that four-fifths of inequality sits within states. Per-capita estimates are more stable over time (CV=0.033 vs 0.043), which strengthens the finding of temporal stability. We report household-level results in the main text because households are our unit of analysis and for consistency with our panel structure. Per-capita results are in Appendix Table A4. Conclusions do not change.

C. Supporting Evidence: Mechanism Tests

We test whether the observed spatial patterns align with what India's structural features would predict. This is not causal analysis. Urbanization and federal transfers are correlated with many things. The regressions we run are supporting correlations, not identification strategies.

$$\text{Outcome}_{st} = \alpha + \beta \text{Mechanism}_{st} + \sum_t \gamma_t + \varepsilon_{st}$$

Urbanization is measured as the survey-weighted share of urban households by state-year, using CPHS microdata. Federal transfers are central government transfers to states as a share of GDP, as reported in RBI State Finances reports [36]. We estimate simple OLS regressions with year fixed effects and robust standard errors. One regression for each mechanism. $\dots (8)$

Year fixed effects absorb national-level shocks common to all states in a given year. Standard errors are robust to heteroskedasticity. These regressions tell us whether states that are more urbanized or receive more transfers look systematically different on spatial inequality outcomes, controlling for common time trends.

V. RESULTS

A. Aggregate Inequality Trends

Indian consumption inequality has no trend across 2014-2024. GE (1) ranges from 0.103 in 2021 to 0.147 in 2017. Mean is 0.127. The pattern is cyclical — high before 2019, low during 2019-2021, then recovering. Within-state inequality and total inequality move closely together ($r = 0.974$, $p < 0.001$). Total inequality and the between-state component track each other less closely ($r = 0.883$). Year-to-year swings in national inequality are driven by what happens inside states, not by changes in how state averages compare.

B. Core Spatial Decomposition: Within-State Dominance and Stability

Table 1 is the central result. Within-state inequality accounts for 79.1 percent of total inequality, averaged over 2014-2024. Range: 73.2 to 86.2 percent. Between-state differences: only



20.9 percent. Range: 13.8 to 26.8 percent. This holds in every year. No exceptions. Total inequality moves quite a bit year to year — CV of 0.133. The within-state share barely moves — CV of 0.043. That three-to-one ratio is the central empirical finding. Demonetization in 2016 widened aggregate inequality. GST in 2017 compressed it. COVID in 2020 brought it down sharply. None of these shifted the spatial split. Every year, without exception, states accounted for 73 to 86 per cent of total inequality. The structure is fixed even as the level varies.

State-level heterogeneity is large. Maharashtra: GE (1) = 0.188. Sikkim: GE (1) = 0.035. A fivefold difference. But every state conforms to the same aggregate pattern. Inequality is internal everywhere, not interregional. NSS 75th Round (2017-18) gives a within-state share of 79.6 percent. CPHS for 2017 gives 77.8 percent. A gap of under two points between two surveys with very different designs. This matters because CPHS and NSS differ in mean consumption levels — NSS total GE (1) is 0.204, CPHS is 0.147. Despite that level gap, spatial shares align. The 79-21 split is not an artefact of how CPHS measures consumption.

Within-state inequality breaks into three parts. Within-rural dispersion: 41.2 percent of within-state inequality. Within-urban dispersion: 41.2 percent. Rural-urban mean gaps: only 17.6 percent. Relative to total national inequality: rural-urban gaps explain 14.2 percent; within-rural and within-urban each explain 33.1 percent. This challenges a standard narrative. India's inequality is not mainly a rural-urban divide. Rural-urban gaps are always the smallest component — in every state, in every year. Within-sector dispersion dominates everywhere.

This result challenges common narratives that frame inequality primarily as a consequence of widening rural–urban divides ([45]; [27]). While the contribution of rural–urban gaps vary across states, it is never the dominant component. States with relatively compressed rural distributions and strong public provisioning, such as Kerala and Himachal Pradesh, exhibit somewhat higher rural–urban contributions, whereas highly urbanized and economically diverse states such as Maharashtra, Gujarat, and Karnataka display substantially larger within-urban dispersion. Across all states, however, dispersion within sectors consistently exceeds inequality generated by mean differences between sectors.

Rural areas in India are not homogeneous. Landholding inequality is large. Irrigation access differs sharply across districts. Caste structures shape incomes. Non-farm labour markets are uneven [14, 21]. Raising average rural incomes does not automatically narrow rural inequality. Urban areas have sharp internal stratification. Formal and informal work coexist. Skill premia are large. Housing access is segregated. Urban growth has raised productivity. It has also widened dispersion within urban labour markets rather than raising all urban incomes proportionally [27, 45, 18].

Urbanization raises within-state inequality. Yet rural-urban mean gaps account for only 17.6 percent of within-state inequality. How can both be true? Urbanization works mainly by shifting more people into urban labor markets — which are internally unequal. A bigger urban share means more households exposed to the formal-informal wage gap, the skill premium, and unequal housing access. Rural-urban

averages may barely change while within-urban dispersion rises. That is what the data show [16, 28].

C. Supporting Evidence: Structural Correlates

Three structural features of India's economy should correlate with the 79-21 split if our interpretation is correct: urban concentration within states, limited interstate migration, and fiscal transfers that compress state averages. [28] Table 2 tests each one.

Table 2, Panel A: urbanization rate versus within-state GE (1), 298 state-year observations, year fixed effects. Coefficient: 0.155 (SE = 0.031, $p < 0.001$). A ten-point rise in the urban population share is associated with a 0.0155 increase in within-state GE (1) — about 18 per cent of the cross-state standard deviation. The direction is positive and robust. More urbanized states have more internal inequality. This fits the picture of agglomeration operating inside state boundaries.

Fiscal federalism and between-state inequality. Table 2, Panel B examines central government transfers and the between-state share. Using 2014-2023 annual data, the coefficient on transfers (as percent of GDP) is -0.571 (SE=0.235, $p=0.045$). A one percentage-point increase in transfers is associated with a 0.57-point fall in the between-state share. This is exactly what fiscal federalism theory predicts. [32, 33] Transfers compress state averages. They do not touch household-level dispersion inside states. The COVID dummy is not significant ($\beta = 2.08$, $p = 0.283$), suggesting that the pandemic did not structurally alter the relationship between transfers and interstate inequality.

Interstate migration. Table 2, Panel C uses Census 2011 interstate migration rates merged with state-year within-state inequality. The estimated coefficient is negative and significant in the full sample ($\beta = -279,101$, $p = 0.004$). But it becomes unstable and statistically insignificant once we exclude small urbanised territories — Delhi, Chandigarh, Puducherry, and Goa. These four drive much of the result. The migration data are also time-invariant, from a single Census. We do not draw strong conclusions from this regression. We rely instead on established micro-level evidence that linguistic and network ties constrain interstate mobility [31, 2].

Urbanization is positively associated with within-state inequality. Federal transfers are negatively linked to the between-state share. The migration regression is negative but unstable. The first two hold up cleanly. Together, they describe India's 79-21 structure: urban concentration generates inequality within states; federal transfers compress differences between state averages without altering that internal dispersion.

D. Robustness

The 79-21 split holds across every robustness check we run. Alternative inequality measures give similar results: Gini (81% within), GE (0) (82% within), GE (2) (78% within). Dropping small union territories — Delhi, Chandigarh, Puducherry, Goa — leaves the within-state share at 81.2 percent. Restricting to major states with populations above 10 million gives 79.8 per cent. Splitting the sample before and after COVID: 79.3 per cent pre-COVID, 81.9 per cent during and after. None of these cuts shifts





the conclusion. Within-state inequality dominates regardless of how we slice the data.

VI. DISCUSSION

A. Spatial Inequality as a Welfare-Relevant Dimension of Redistribution

The location of inequality matters for policy. Federal redistribution works on two dimensions: vertical transfers across income groups and horizontal equalization across jurisdictions. But a third-dimension matters too — where inequality is geographically organized [9, 24, 44]. Two households with the same consumption can lead very different lives depending on which state they live in, which city, and which neighbourhood.

Location affects welfare through channels beyond income. Public goods quality differs by place. Infrastructure gaps are spatial. Labour market access, essential goods prices, environmental risks — all vary with location [4]. Spatial inequality reflects these persistent gaps in opportunity and access.

Redistribution that targets only state averages addresses the 21 per cent. It leaves the 79 per cent — which is what households actually experience — largely unaddressed. Classic fiscal federalism assigns instruments based on efficiency and information [32, 33]. Federal transfers aim to achieve fiscal capacity equalisation, regional convergence, and political cohesion. They were never designed to minimize interpersonal inequality within states.

The policy interpretation advanced in this paper is therefore conditional rather than universal. If the normative objective of redistribution includes reducing welfare-relevant interpersonal inequality, then the spatial organization of inequality becomes directly relevant for policy design. Under this benchmark, redistribution architectures that primarily target interstate averages necessarily address only a limited share of total inequality when most dispersion occurs within states. Alternative objectives—such as administrative feasibility, national solidarity, or concerns about elite capture at the subnational level—may justify a continued emphasis on interstate redistribution ([37]; [29]). The contribution of this paper is not to adjudicate among these objectives, but to clarify how different normative goals interact with the observed spatial structure of inequality.

India's inequality is not a story of rich states versus poor states. It is a story of dispersion among households sharing the same state institutions. Maharashtra has India's wealthiest city and some of its poorest agricultural districts — both within one state. Poorer states like Bihar have more compressed distributions. State averages hide what actually matters. India's inequality is shaped far more by internal stratification within states than by divergence between them. This holds across states of very different economic sizes, urbanization levels, and development paths. India's spatial structure has not shifted in 11 years. This is not what we see in China, where spatial inequality responded to coastal opening and then to harmonious society policies [25, 26]. India's 79-21 split is structurally anchored. Short-run shocks do not move it.

Three anchors explain the stability. Urban agglomeration operates within state borders — Mumbai, Bangalore,

Chennai are state growth poles, not national ones. Migration is constrained by language and networks within linguistic regions [31, 2]. Fiscal transfers compress state averages but do not reach households inside states [34]. India's spatial inequality structure barely moved over a decade of major shocks. This persistence points to structural causes, not cyclical ones.

A defining feature of India's spatial inequality, as documented in Section 5, is its remarkable stability over time, even amid major macroeconomic and policy shocks. This persistence suggests that the underlying drivers of inequality are structural rather than cyclical, rooted in slow-moving institutional and economic features.

Economic agglomeration in India operates within state boundaries. Major cities are state-specific growth poles, not nodes in an integrated national network. When high-productivity sectors concentrate in urban centres within individual states, the inequality they generate manifests as internal dispersion rather than regional divergence.

Second, interstate labour mobility remains limited compared with mobility within states. Linguistic, cultural, and network-based frictions shape migration decisions, encouraging rural-urban movement within linguistic regions while discouraging large-scale interstate flows ([31]; [2]). In such an environment, wage and opportunity differentials generated by uneven growth are imperfectly arbitrated across state borders and instead become absorbed within states.

Interstate labour mobility is low relative to intra-state mobility. Language, culture, and network ties shape where people move. Research shows these frictions encourage rural-urban movement within linguistic regions while discouraging large interstate flows [31, 2]. Wage and opportunity gaps that cannot be arbitrated across state lines stay trapped within states.

India's fiscal architecture equalizes across states, not within them. Formula transfers reduce differences in average fiscal capacity and living standards across state governments. They work through the provision of public goods rather than through household transfers [34]. The result is predictable: compressed interstate averages coexist with persistent within-state dispersion.

B. Policy Directions and Scope Conditions

Three policy directions follow. We flag them as directions, not prescriptions — the specific design and cost of each is beyond this paper's scope. But the empirical evidence makes the direction of travel clear.

Federal transfers have compressed interstate gaps — the data confirm this ($\beta = -0.571$, $p = 0.045$). But that addresses only 21 percent of the total inequality. Improving state government fiscal capacity is the next step. When most inequality is internal, effectiveness depends on subnational instruments [11, 30].

Urban inequality now equals rural inequality in magnitude. Each account for 41 per cent of within-state inequality. Urban safety nets in India are weaker than those in rural areas in most states [38]. Employment guarantees, health coverage, housing support — these programs have a rural orientation. The inequality data suggest rebalancing is needed.

Third, the within-urban component deserves direct

policy attention. Urban inequality in India has risen as cities have grown. Formal and informal work coexist. Skill premia are large. Housing access is stratified. Urban safety nets — employment guarantees, health insurance, housing subsidies — remain weaker than rural equivalents in most states [38]. The decomposition shows that within-urban dispersion equals within-rural dispersion in magnitude. Policy attention has historically tilted toward rural areas. The numbers suggest a rebalancing is warranted.

Fourth, conditional or outcome-linked transfer mechanisms could in principle be redesigned to target within-state distributional outcomes rather than just state-level averages. Some fiscal federalism literature explores performance-linked grants [8]. This comes with risks — perverse incentives, measurement problems, administrative burden [29]. We do not advocate a specific mechanism. We note that the current architecture is not designed for this purpose, and that designing instruments aligned with where inequality actually lies warrants further research. These directions hold under one normative premise: that reducing welfare-relevant interpersonal inequality is a goal of redistribution policy. Other objectives — regional balance, political cohesion, administrative simplicity — may justify continued emphasis on interstate transfers even when within-state inequality dominates [4, 24]. The contribution of this paper is to clarify what the data show, not to settle the normative question.

C. Limitations and Future Research

Three limitations. First, interstate migration data are from Census 2011. They are time-invariant and unstable in regressions. We use them cautiously and rely mainly on micro-level evidence on migration constraints. Second, NSS validation is for a single cross-section only. It confirms spatial structure at a point in time but cannot test temporal stability. Third, this paper documents the decomposition. It does not explain what drives within-state dispersion at the household level — returns to education, occupational sorting, asset inequality. That is future work.

Second, the NSS validation is a single cross-section from 2017-18. We cannot use NSS to check temporal stability — the quinquennial design prevents it. The CPHS-based

temporal evidence stands on its own. The NSS confirms the spatial structure at a single point in time; it cannot confirm whether that structure was equally stable during demonetization or COVID.

Third, the analysis documents spatial patterns in consumption inequality. It does not explain what drives within-state household-level dispersion — whether it is returns to education, occupational sorting, asset inequality, or something else. Future research that connects the decomposition evidence to micro-level drivers of within-state inequality would clarify which state-level policies to target and how.

VII. CONCLUSION

Three empirical facts. First: within-state inequality was 79.1 per cent of the total every year from 2014 to 2024. Second: this spatial structure is stable — CV of 0.043, three times lower than aggregate inequality fluctuations. It did not move through demonetization, GST, or COVID-19. Third, rural-urban gaps account for only 18 per cent of within-state inequality. Within-sector dispersion accounts for the rest.

The policy math is clear. Finance Commission transfers address the 21 percent that is interstate. The 79 per cent inside states require something else. State fiscal capacity needs to grow. Urban social protection needs expanding. Redistribution instruments need to be redesigned around where inequality actually lives — inside states, not between them. China changed its spatial structure with deliberate policy. India has not moved. The 79-21 split has held across every major shock. Three structural correlates explain why: urban concentration within states ($\beta = 0.155$, $p < 0.001$), linguistic barriers to interstate migration, and federal transfers that compress state averages without household redistribution. Changing the structure requires addressing all three.

India's inequality challenge is not about regional divergence. It is about internal stratification within states. Federal transfers help, but they only reach one-fifth of the problem. State governments need stronger fiscal tools, better data, and clearer mandates for within-state redistribution. That is what the evidence here establishes.

TABLES AND FIGURES

Table I: Decomposition of Consumption Inequality in India (GE (1)), 2014-2024

Year	Total GE (1)	Within GE (1)	Between GE (1)	Within %	Between %	N (millions)	States
2014	0.144	0.105	0.039	73.2	26.8	1.66	25
2015	0.132	0.104	0.029	78.4	21.6	1.57	25
2016	0.145	0.113	0.032	78.1	21.9	1.60	25
2017	0.147	0.115	0.033	77.8	22.2	1.62	27
2018	0.132	0.105	0.027	79.5	20.5	1.77	28
2019	0.118	0.097	0.021	82.1	17.9	1.72	28
2020	0.114	0.093	0.021	81.3	18.7	1.26	28
2021	0.103	0.080	0.023	77.8	22.2	1.52	28
2022	0.106	0.084	0.022	79.0	21.0	1.56	28
2023	0.110	0.095	0.015	86.2	13.8	1.29	28
2024	0.142	0.109	0.033	76.6	23.4	1.27	28
Mean	0.127	0.100	0.027	79.1	20.9	1.53	27.2
SD	0.017	0.012	0.007	3.4	3.4	0.18	1.3
CV	0.133	0.120	0.259	0.043	0.163	0.119	0.048

Notes: GE (1) denotes the Theil index. Within% = (Within GE (1) / Total GE (1)) $\times$ 100. Estimates use CPHS survey weights. The sample covers 2014-2024, with 16.8 million household-year observations across 28 states.



Table II: Supporting Evidence: Correlations with Structural Features

Panel A. Urbanization and Within-State Inequality

Dependent Variable: Within-State GE (1) (rescaled $\times 1000$)

Variable	Coefficient	Robust SE	t-stat	p-value	95% CI	N	R ²
Urbanization rate	0.155***	0.031	4.98	<0.001	[0.094, 0.216]	298	0.067
Year fixed effects	Yes	—	—	—	—	—	—
Constant	0.009	0.018	0.51	0.610	[-0.026, 0.044]	—	—

Notes: OLS estimates with year fixed effects and robust standard errors. Urbanization measured as share of urban households (0-1). Within-state GE (1) rescaled ($\times 1000$) for interpretation. *** $p < 0.001$.

Panel B. Fiscal Federalism and Between-State Inequality Dependent Variable: Between-State Share (% of total inequality)

Variable	Coefficient	Robust SE	t-stat	p-value	95% CI	N	R ²
Central transfers (% of GDP)	-0.571*	0.235	-2.43	0.045	[-1.126, -0.016]	10	0.374
COVID-19 (2020-2021)	2.08	1.79	1.16	0.283	[-2.148, 6.312]	—	—
Constant	45.27***	10.29	4.40	0.003	[20.94, 69.60]	—	—

Notes: OLS with robust standard errors. COVID dummy equals one for 2020-2021 [23]. Central transfers as a % of GDP range from 3.5% to 4.5% during 2014-2023. Data from Reserve Bank of India State Finances reports. * $p < 0.05$, *** $p < 0.001$.

Panel C. Interstate Migration Barriers (Census 2011)

Dependent Variable: Within-State GE (1) (in Original Units $\times 10^7$) Variable	Coefficient	Robust SE	t-stat	p-value	95% CI	N	R ²
Interstate migration rate	-279,101**	89,655	-3.11	0.004	[-463,390, -94,811]	287	0.141
Year fixed effects	Yes	—	—	—	—	—	—
Constant	14,800,000***	2,394,000	6.19	<0.001	[9,902,983, 19,700,000]	—	—

Notes: OLS with year fixed effects. Standard errors clustered at state level (27 clusters). Interstate migration rate from Census 2011 (time-invariant). Sample excludes Telangana (formed 2014, no Census 2011 data). ** $p < 0.01$, *** $p < 0.001$. Interpretation: Aggregate association is negative and sensitive to sample composition. Given time-invariant migration data and influential outliers, we refrain from drawing strong conclusions from this regression. See Section 5.4 for discussion.

Table III: Nested Decomposition of Within-State Inequality (2014-2024 Average)

Component	GE (1)	Share of Within-State (%)	Share of Total (%)
Within-Rural dispersion	0.042	41.2	33.1
Within-Urban dispersion	0.042	41.2	33.1
Between Rural-Urban gaps	0.018	17.6	14.2
Total Within-State	0.102	100.0	80.4

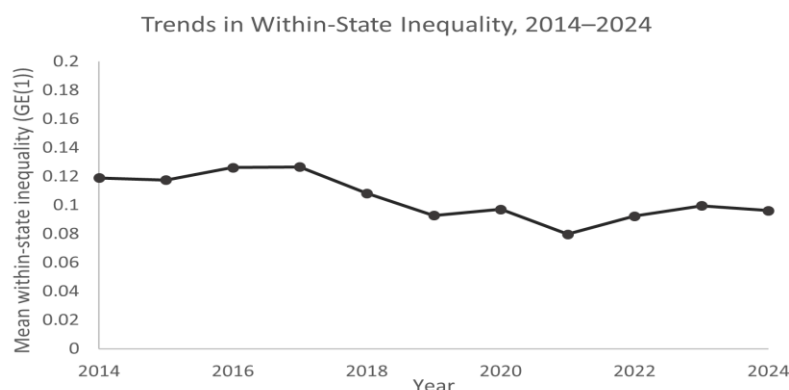
Notes: Decomposition uses nested Theil methodology [42]. Within-Rural captures inequality among rural households within states; Within-Urban captures inequality among urban households within states; Between (R-U) captures mean consumption gaps between rural and urban sectors within states. Estimates use CPHS survey weights averaged across 2014-2024. This 80.4% reflects the decomposition of mean consumption values over 2014-2024, which differs slightly from the 79.1% average of annual within-state shares due to Jensen's inequality.

Table IV: Illustrative International Comparison of Spatial Inequality Shares

Country	Within-Jurisdiction Share	Between-Jurisdiction Share	Key Institutional Features
India	79%	21%	Linguistic state boundaries; limited interstate migration; within-state urban concentration
United States	~75%	~25%	Common language; high interstate mobility (12% annual); integrated multi-state urban regions
Brazil	~70%	~30%	Portuguese linguistic unity; moderate interstate migration; coastal urbanization spans states
China	~60-70%	~30-40%	Hukou system (uniform nationwide); policy-responsive; recent within-province redistribution
Germany	~73%	~27%	Federal transfers include household programs; integrated European labour markets.
Indonesia	~65%	~35%	Island geography constrains migration; Java-outer islands divide

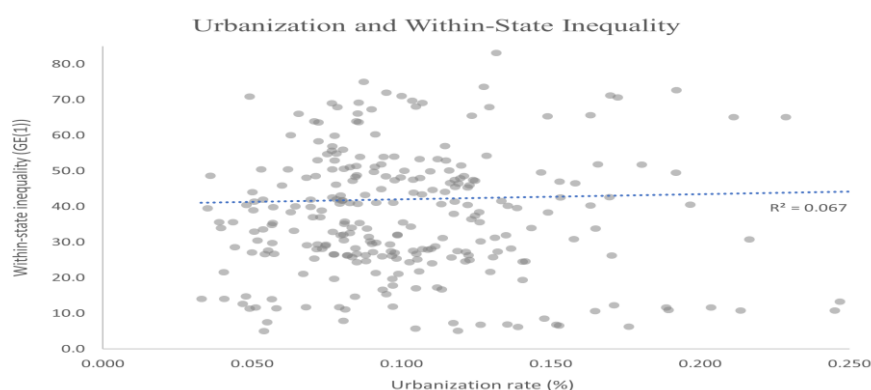
Sources: India (this study); US [7]; Brazil (Azzoni 2001); China ([25]; [26]); Germany ([40]); Indonesia ([20]). Cross-country comparisons of within- and between-jurisdiction inequality shares should be interpreted with caution. Estimates are drawn from different studies that use different inequality measures (e.g., GE vs Gini-based decompositions), spatial unit definitions (states vs provinces), and time periods. Larger and more heterogeneous spatial units mechanically tend to exhibit higher within-unit shares. In the case of China, the reported 60–70% within-province share reflects recent estimates following market transition, whereas earlier

periods exhibited higher between-province inequality. Table 4 is therefore intended to be illustrative, highlighting broad patterns rather than precise quantitative rankings.



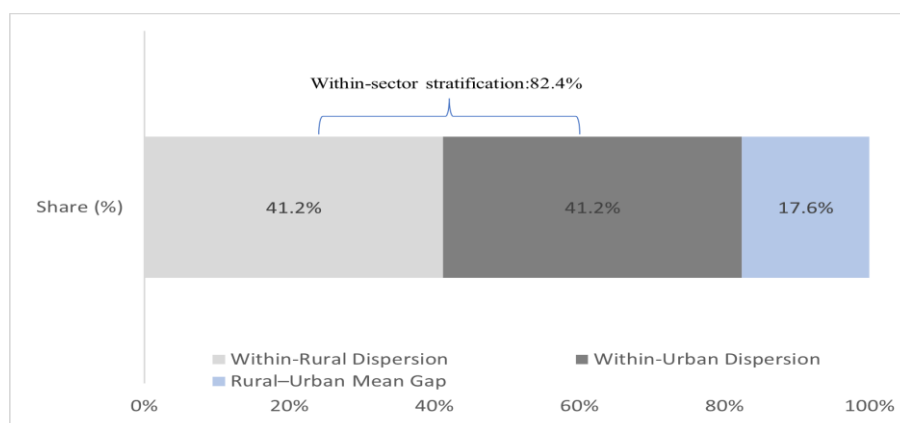
[Fig.1: Average Within-State Inequality Over Time]

This figure shows the annual mean of within-state Generalized Entropy (GE (1)) inequality across Indian states between 2014 and 2024. Each point represents the cross-state average for a given survey year. The series indicates moderate year-to-year variation but no pronounced long-run trend in average within-state inequality.



[Fig.2: Relationship Between Urbanization and Within-State Inequality]

The scatter plot displays the association between state-level urbanization rates and within-state GE (1) inequality using all state-year observations from 2014 to 2024. Each point represents a state-year. The fitted line shows the linear relationship with a 95% confidence band. The relationship is positive but modest in magnitude, indicating that more urbanized states tend to exhibit higher within-state inequality, although substantial dispersion remains.



[Fig.3: Nested Decomposition of Within-State Inequality]

This figure decomposes within-state GE (1) inequality into three components: inequality within rural areas, inequality within urban areas, and inequality due to rural–urban mean differences. The stacked bar shows the relative contribution of each component to total within-state inequality. The majority of within-state inequality arises from dispersion within rural and urban sectors, while rural–urban mean gaps account for a smaller share.



APPENDIX

A. Appendix: Survey Comparability and External Validation

CPHS and NSS differ in how they measure consumption. Mean consumption levels are systematically higher in NSS than CPHS for the same years. This is documented and discussed extensively [15, 1]. The gap matters for analyses of poverty headcounts or absolute consumption levels [35].

It matters much less for our purpose. We track spatial shares, not levels. The within-state percentage is the ratio of within-GE (1) to total GE (1). If CPHS systematically understates consumption, it affects both the numerator and the denominator in similar ways. The ratio is more robust to level differences than levels themselves are. This is why the

NSS validation is so close: 79.6 percent from NSS versus 77.8 percent from CPHS in the same year (2017).

CPHS also differs from NSS in sampling design and coverage. CPHS uses a rotating panel; NSS uses stratified multi-stage sampling. Both cover rural and urban households across major states. Our results hold under alternative inequality measures and weighting schemes, reducing the likelihood that survey-specific features explain the 79- 21 finding. The key advantage of CPHS is annual frequency. NSS cannot tell us whether spatial inequality structure shifted during demonetization, GST, or COVID. CPHS can. That is why we use it.

Table A.I: Average within-State Inequality (GE (1)), 2014–2024. Notes: Values Report the State-Level Average of within-State Generalized Entropy Index (GE (1)) Computed Over 2014–2024. Higher Values Indicate Greater Inequality within States

State	GE (1)
Maharashtra	0.1878
Delhi	0.1832
Meghalaya	0.1380
Uttar Pradesh	0.1363
Haryana	0.1227
West Bengal	0.1225
Assam	0.1156
Chandigarh	0.1067
Telangana	0.1041
Andhra Pradesh	0.0995
Kerala	0.0975
Uttarakhand	0.0918
Karnataka	0.0914
Chhattisgarh	0.0911
Punjab	0.0834
Madhya Pradesh	0.0799
Goa	0.0771
Himachal Pradesh	0.0766
Gujarat	0.0764
Bihar	0.0742
Odisha	0.0734
Jammu & Kashmir	0.0732
Tamil Nadu	0.0724
Jharkhand	0.0690
Puducherry	0.0614
Tripura	0.0508
Sikkim	0.0353

Table A.II: Robustness: Alternative Inequality Measures

Measure	Total	Within	Between	Within %	Between %
GE (1) [Baseline]	0.127	0.102	0.025	79.1	20.9
Gini coefficient	0.348	0.282	0.066	81.0	19.0
GE (0)	0.184	0.151	0.033	82.1	17.9
GE (2)	0.421	0.329	0.092	78.1	21.9

Notes: 2014-2024 averages. All measures confirm within-state dominance (78-86% of total inequality), though exact percentages vary with distributional sensitivity. GE (0) is more sensitive to the bottom of the distribution; GE (2) is more sensitive to the top.

Table A.III: Robustness: Sample Restrictions

Specification	N (obs)	Total GE (1)	Within %	Between %
Baseline (all states)	16.8M	0.127	80.4	19.6
Exclude small UTs (Delhi, Chandigarh, Puducherry, Goa)	15.7M	0.125	81.2	18.8
Major states only (population >10M)	15.2M	0.129	79.8	20.2
Years 2014-2019 (pre-COVID)	10.1M	0.133	79.3	20.7
Years 2020-2024 (COVID and post)	6.7M	0.118	81.9	18.1

Notes: Within-share remains 79-82% across all sample restrictions, confirming robustness to composition.

Table A.IV: Robustness: Household-Level vs Per-Capita Consumption

Year	Household-Level Within %	Total GE (1)	Per-Capita Within %	Total GE (1)	Difference (pp)
2014	73.2	0.144	77.1	0.168	+3.9
2015	78.4	0.132	81.3	0.159	+2.8
2016	78.1	0.145	78.4	0.171	+0.3
2017	77.8	0.147	75.6	0.184	-2.2
2018	79.5	0.132	77.5	0.168	-2.0
2019	82.1	0.118	79.8	0.151	-2.3
2020	81.3	0.114	79.6	0.147	-1.8
2021	77.8	0.103	77.1	0.137	-0.7
2022	79.0	0.106	77.5	0.135	-1.5
2023	86.2	0.110	80.0	0.143	-6.2
2024	76.6	0.142	72.4	0.182	-4.3
Mean	79.1	0.127	77.8	0.159	-1.3
SD	3.4	0.017	2.6	0.020	2.6
CV	0.043	0.133	0.033	0.125	-

Notes: Both specifications confirm within-state dominance (~78- 79%) with high temporal stability ($CV < 0.05$). Per-capita weighting gives greater influence to smaller (predominantly urban) households, which explains the modest 1.3pp mean difference. Substantive conclusions unchanged.

Table A.V: NSS Validation of Spatial Decomposition (2017–18)

Dataset	Year	Total GE (1)	Within Share (%)	Between Share (%)
NSS 75	2017–18	0.204	79.6	20.4
CPHS	2017	0.147	77.8	22.2

Notes: NSS uses household monthly consumption expenditure from Round 75 with combined survey weights. CPHS estimates shown for comparison.

B. Appendix NSS Validation of Spatial Decomposition

We replicate the GE (1) decomposition using the NSS 75th Round (2017-18). This is the most recent full consumption survey conducted before the COVID-19 period. Drèze and Somanchi [15] and [1] have raised concerns about the representativeness of CPHS. The NSS validation directly addresses whether those concerns affect our spatial conclusions. Method: household monthly consumption expenditure from NSS Round 75, combined survey weights, GE (1) decomposition across states using NSS region-state mappings. The result: within-state share of 79.6 per cent, between-state share of 20.4 per cent. CPHS for the same year gives 77.8% and 22.2%, respectively. The gap is under two percentage points. NSS total GE (1) is 0.204; CPHS total is 0.147. Levels differ substantially. Spatial shares do not.

The conclusion is straightforward. Two surveys with different designs, different mean consumption levels, and different sampling frames produce almost identical spatial decompositions. The 79-21 split is not a CPHS artefact. It is a feature of how Indian consumption inequality is actually organized.

DECLARATION STATEMENT

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 - **Ethical Approval and Consent to Participate:** The data provided in this article are exempt from the requirement for ethical approval or participant consent.
 - **Data Access Statement and Material Availability:** The data resources of this article are publicly accessible. The Consumer Pyramids Household Survey (CPHS) data used in this study are proprietary and available through subscription from the Centre for Monitoring Indian Economy (CMIE). Researchers can obtain access through an institutional subscription at <https://consumerpyramidsdx.cmie.com/>. Supplementary data on central government transfers are sourced from publicly available Reserve Bank of India State Finances reports (2014-2024), accessible at <https://www.rbi.org.in/>. Replication code in Stata 17 will be made available through the authors' institutional repository upon publication.
- Declaration on Older References: The following references predate the ten-



year recency guideline but are retained as foundational methodological contributions: [42] Shorrocks and Wan (2005) and [41] Shorrocks (1980) establish the exact additive decomposability of the Theil index that underpins all decompositions in this paper — no recent paper establishes this specific property. [25] Kanbur and Zhang (2005), [44] World Bank (2009), [14] Deaton and Drèze (2002), [12] Chamarbagwala (2010), [34] Rao and Singh (2005), [27] Kundu (2011), [29] Lockwood (2006), [9] Boadway and Shah (2009), [30] Mohanty et al. (2007), [35] Ravallion (2014), [8] Boadway and Shah (2007), [20] Hill et al. (2008), and [13] Chancel and Piketty (2019) are cited as comparative benchmarks with no direct recent equivalents.

- **Authors Contributions:** The authorship of this article is contributed equally to all participating individuals.

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