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Rising Income Inequality in India: A Race to the Top — With Many Left Behind

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Abstract

Income inequality in India has risen substantially since the economic liberalisation of 1991, manifesting across states, between rural and urban sectors, and within both sectors. This paper argues that the dynamics of divergence have taken the form of a "race to the top" — every segment of the population, including the rural poor in lagging states, has registered gains in average consumption expenditure, but the gains have been dramatically larger for the educated, skilled, and urban. Using National Sample Survey (NSS/HCES) data from 1993-94 to 2023-24 and Periodic Labour Force Survey (PLFS) data, we document the evolution of inequality across multiple dimensions. The Gini coefficient of income, estimated using income tax tabulations and World Inequality Database series, rose from approximately 0.45 in 1990 to above 0.51 by 2013 and further, with the top 1 per cent now commanding 22.6 per cent of national income — higher than the United States, Brazil, and China. A Bourguignon-style poverty-growth-inequality decomposition demonstrates that while growth has been the dominant force reducing poverty headcount ratios, worsening distributional effects have partially offset growth gains, especially in urban areas. A wage equation decomposition shows that rising returns to tertiary education account for roughly 55-65 per cent of urban income growth and nearly 20 per cent of rural income growth between 1993-94 and 2022-23. Regional divergence between richer southern and western states and lagging northern and eastern states has intensified, with the richest state (Goa/Sikkim) boasting per capita income more than six times that of the poorest (Bihar). The paper concludes that while inequality of outcome may be an inevitable transitional phase, persistent inequality of opportunity — differential access to quality education, healthcare, and productive employment — threatens both social cohesion and sustainable growth. Broad-based investment in human capital and inclusive structural transformation remain the most effective long-run policy levers.

JEL Classification: *D31, O15, O53, I24, R12*

Keywords: *Income inequality, India, poverty, rural-urban divide, returns to education, regional inequality, growth incidence curve.*

1. Introduction

India's economic trajectory since the landmark liberalisation of 1991 represents one of the most consequential experiments in development economics of the late twentieth century. With average annual GDP growth exceeding 6 per cent in the 1990s, accelerating to above 7 per cent in the 2000s, and touching 8 per cent in several recent years, India has emerged as one of the world's fastest-growing major economies.[1] By 2024, India's GDP surpassed $3.9 trillion, and it stands on the threshold of becoming the world's third-largest economy.[2] This spectacular growth has lifted hundreds of millions out of poverty: the share of India's population living below $2.15 per day (2017 PPP) fell from an estimated 45 per cent in 1993-94 to around 10 per cent by 2019.[3]

Yet growth has been profoundly uneven. The income share of the top 1 per cent of Indians rose from around 6 per cent in 1982-83 — when equality was at its post-independence peak — to over 22.6 per cent by 2022-23, surpassing levels of inequality seen in the United States, Brazil, South Africa, and China.[4] The top 10 per cent now command nearly 57.7 per cent of national income, while the bottom 50 per cent receive only 15 per cent.[5] Average incomes of the top 1 per cent are 23 times the national mean.[6] India's Billionaire Raj, as researchers at the World Inequality Lab have termed it, is now documented to be more unequal than the British colonial Raj.

The spatial dimension of inequality is equally striking. The richest state by per capita income — Goa, with a per capita NSDP exceeding ₹5,00,000 — is more than ten times richer than Bihar, India's poorest state, at below ₹50,000.[7] Southern states — Karnataka, Telangana, Tamil Nadu, and Kerala — have forged ahead in per capita income, driven by services-led and IT-driven growth, while large northern states like Uttar Pradesh and Bihar, despite their demographic weight, remain mired in low productivity and limited structural transformation. Rural-urban disparities remain pronounced: in 2022-23, average monthly per capita consumption expenditure (MPCE) was ₹3,773 in rural India versus ₹6,459 in urban India, a gap of 71 per cent, though this has narrowed from 84 per cent in 2011-12 and 91 per cent in 2004-05.[8]

Understanding the drivers and dynamics of this inequality is not merely an academic exercise. It has direct bearing on social stability, democratic legitimacy, and the sustainability of growth itself. Inequality of outcomes reflects and perpetuates inequality of opportunity — in access to schooling, nutrition, healthcare, and credit — creating poverty traps that concentrate advantages in successive generations. The World Inequality Lab's 2024 study warns that if left unaddressed, India risks sliding into a plutocracy.[9]

This paper contributes to the literature in several ways. First, it provides a comprehensive empirical account of income and consumption inequality across multiple dimensions — sectoral, regional, and distributional — using NSS/HCES household survey data spanning 1993-94 to 2023-24, supplemented by PLFS data and World Inequality Database income series. Second, using Growth Incidence Curves (GICs) in the tradition of Ravallion and Chen (2003), it characterises the distributional nature of India's growth, demonstrating that India's inequality is not a story of absolute immiserisation but rather of dramatically differential gains — a race to the top in which all segments have benefited, but the already advantaged have benefited far more. Third, applying the Bourguignon (2003, 2005) poverty-growth-inequality decomposition framework, it separates the contributions of growth and distributional change to poverty reduction. Fourth, using Oaxaca-Blinder decomposition of wage/income equations estimated from NSS and PLFS data, it identifies rising returns to education and sector-of-employment as the dominant proximate drivers of income divergence.

The paper proceeds as follows. Section 2 describes the data sources and methodology. Section 3 reviews the literature on inequality in India since liberalisation. Section 4 presents the empirical methodology. Section 5 documents the extent and evolution of income inequality, supplemented by evidence on non-income inequality. Section 6 decomposes the sources of widening income differentials. Section 7 concludes with policy implications.

2. Data

This study draws on four main data sources to construct a consistent picture of income and consumption inequality in India from the early 1990s through 2023-24.

2.1. National Sample Survey / Household Consumption Expenditure Surveys

The primary source for distributional analysis is the series of large-scale household surveys conducted by the National Sample Survey Office (NSSO), now merged into the National Statistical Office (NSO), under the Ministry of Statistics and Programme Implementation. Since its inception in 1950, the NSSO has conducted quinquennial large-scale household consumption expenditure surveys (CES). The principal rounds used in this study are the 50th Round (1993-94, N ≈ 115,000 households), 61st Round (2004-05, N ≈ 124,000), 68th Round (2011-12, N ≈ 101,000), and the more recent Household Consumption Expenditure Surveys of 2022-23 (N = 261,746) and 2023-24.[10]

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The primary indicator of living standards in these surveys is Monthly Per Capita Consumption Expenditure (MPCE), measured at 2011-12 constant prices using state-specific rural and urban CPIs. The use of consumption rather than income as the welfare metric is standard practice in the India context, given the well-documented difficulty of accurately measuring income — particularly for the self-employed, agricultural workers, and informal-sector workers who constitute the vast majority of India's workforce.[11] Given the unavailability of comprehensive income distribution data, following the practice of Datt and Ravallion (1992) and Chaudhuri and Ravallion (2007), consumption expenditure serves as the primary metric for distributional analysis in Sections 5.1 and 5.3.

2.2. World Inequality Database Income Series

For income inequality analysis, which captures a broader range of factor incomes including capital income, we rely on the harmonised income inequality series for India maintained by the World Inequality Database (WID.world). Specifically, we draw on Bharti, Chancel, Piketty, and Somanchi (2024), who combine national income accounts, tax tabulations, household surveys, and Forbes/Hurun rich lists to construct long-run homogeneous series of pre-tax income shares from 1922 to 2023.[12] These series are particularly valuable for capturing top-end inequality, which household surveys systematically under-represent due to survey non-response by the wealthy.

2.3. Periodic Labour Force Survey

For wage and employment analysis, the Periodic Labour Force Survey (PLFS), introduced by NSO in 2017, is used. The PLFS follows a methodology broadly comparable to the earlier Employment and Unemployment Surveys (EUS) of NSSO and provides data on wages, employment, education, and occupational composition at the household and individual level. Annual rounds for 2017-18, 2018-19, 2019-20, 2020-21, 2021-22, and 2022-23 are available. For the long-run perspective, comparisons are made with NSS EUS 50th (1993-94), 61st (2004-05), and 68th (2011-12) rounds.

2.4. State-level GDP and Demographic Data

For the regional analysis of Section 5.2, we use Net State Domestic Product (NSDP) per capita data from the Reserve Bank of India's Handbook of Statistics on the Indian Economy, supplemented by the Economic Advisory Council to the Prime Minister's working paper on the Relative Economic Performance of Indian States (EAC-PM, 2024). Population data are drawn from Census 2011 (with interpolations for intercensal years).

3. Changes in Inequality in India Since Liberalisation

India's pattern of income distribution has changed dramatically across three broad phases since independence: (i) an equalising phase from 1947 to approximately 1980, during which top income shares declined substantially; (ii) a phase of moderate increase in inequality during the 1980s; and (iii) a sharply disequalising phase from the early 1990s onward, coinciding with and accelerating after economic liberalisation.

Chancel and Piketty (2019), in the most comprehensive pre-2024 treatment of Indian income inequality, combined national accounts with NSS consumption data and income tax tabulations to show that the top 1 per cent income share fell from about 20 per cent in the 1950s to a post-independence low of 6.2 per cent in 1982-83, before rising sharply to 21.7 per cent by 2013-14 — the highest level since the establishment of income tax in 1922.[13] The updated and extended series in Bharti et al. (2024) confirms that this trend continued, with the top 1 per cent share reaching 22.6 per cent in 2022-23, now higher than in South Africa, Brazil, China, and the United States.[14]

The pre-liberalisation period of declining inequality reflected the combined effects of land reforms, public sector wage compression, licensing restrictions that limited capital accumulation by the private sector, and the "iron rice bowl" culture of public employment with compressed wage differentials. The reversal from 1980 onward — accelerating post-1991 — reflects market liberalisation that increased private sector returns to capital and skill, financialisation of wealth, technology adoption that is skill-biased, and the opening of the economy to global trade which boosted demand for skilled labour in export-oriented services.[15]

The sectoral dimension of inequality has been prominent in the literature. Chaudhuri and Ravallion (2007), in an influential comparison of India and China, find that while national growth in India has been rapid, the pattern of growth has been biased toward the urban sector and away from agriculture, which matters greatly for poverty reduction given the rural concentration of the poor. They show that Indian growth has been less pro-poor than Chinese growth in part because India's structural transformation from agriculture to industry has been slower and more lopsided.

The rural-urban income gap has been extensively documented. NSS data show that the urban-to-rural ratio of average MPCE rose from approximately 1.9 in 1993-94 to around 2.0 in 2004-05, remained at 1.84 in 2011-12, and was 1.71 in 2022-23, with a modest further narrowing to 1.70 in 2023-24.[16] While these consumption-based ratios appear to have stabilised and even narrowed slightly — driven partly by social transfer programmes and rural wage increases — income-based measures show continued divergence, as urban areas continue to capture a disproportionate share of the gains from services-led growth.

Regional inequality has also received significant scholarly attention. Ghosh, Marjit, and Neogi (1998) and Ahluwalia (2000) documented significant divergence in per capita NSDP across Indian states in the 1990s, with southern and western states pulling ahead of northern and eastern ones. The Economic Advisory Council to the Prime Minister's 2024 working paper shows that among the major states, those that were above-average performers in 1990-91 have generally maintained or extended their leads, while lagging states, particularly Bihar and Uttar Pradesh, have struggled to converge.[17]

The role of education in driving inequality is a recurring theme in the Indian literature. Kijima (2006) finds that returns to higher education increased sharply after 1991, using NSS data from 1983 to 1999, and uses this increase to explain a significant portion of rising urban wage inequality. Azam (2012), using quantile regression over three NSS rounds, confirms that returns to education increased across the wage distribution after liberalisation. Duraisamy (2002) finds that private rates of return to secondary and higher education in India are in the range of 10-16 per cent, substantially above returns in many other developing countries. More recently, the literature from the PLFS era confirms continued increases in the education premium, with college graduates earning three to four times the wages of workers with only primary education.[18]

The impact of labour market restructuring — specifically the decline of public sector employment relative to private, informal, and gig employment — is identified by Murgai and Ravallion (2005) and the State of Working India reports (Azim Premji University, 2018, 2021, 2023) as another important driver. The share of regular wage employment in total employment remains low at around 23 per cent as of 2022-23, while informal employment — with lower wages, no social protection, and high vulnerability — dominates, especially in rural areas and among women.

4. Methodology

4.1. Growth Incidence Curves

Following Ravallion and Chen (2003), we employ Growth Incidence Curves (GICs) to characterise the distributional nature of consumption growth across the population. The GIC maps the growth rate of real per capita consumption at each percentile of the distribution between two survey periods. Formally, if $y_t(p)$ denotes the pth quantile of the distribution at time t, the GIC is:

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$g\_t(p) = [y\_t(p) / y\_{t-1}(p)] - 1$

A GIC lying entirely above zero indicates that all segments of the population have experienced absolute gains — a condition for first-order stochastic dominance of the terminal-year distribution over the base-year distribution. If the GIC is positively sloped — higher growth rates at higher percentiles — then inequality is rising. If it is negatively sloped — higher growth at lower percentiles — then inequality is falling and growth is "pro-poor" in the relative sense. Mean growth, marked as a horizontal line on the GIC, indicates the growth rate of average consumption.

We present GICs for: (i) all-India, (ii) rural India only, (iii) urban India only, (iv) high-income states versus low-income states, and (v) sub-groups stratified by educational attainment. These GICs are constructed from the NSS 50th Round (1993-94), the 68th Round (2011-12), and the HCES 2022-23 data. For educational attainment comparisons, we define five groups: no formal education, below primary, primary-completed, secondary-completed, and higher secondary or above.

4.2. The Poverty-Growth-Inequality Decomposition

To understand the interaction between income growth, changes in the distribution of income, and poverty reduction, we employ the Bourguignon (2003, 2005) poverty-growth-inequality triangle decomposition. This framework decomposes the change in a poverty measure between two periods into: (a) a growth effect — the change in poverty holding the Lorenz curve constant at the base-year value, allowing only the mean to change; and (b) a distributional effect — the change in poverty holding the mean constant at the terminal-year value, allowing the Lorenz curve (inequality) to change.[19]

Assuming log-normality of the income/consumption distribution — a maintained assumption that allows closed-form computation — the decomposition is:

$\Delta H = H(z/\mu\_t, \sigma\_t) - H(z/\mu\_0, \sigma\_0) = [H(z/\mu\_t, \sigma\_0) - H(z/\mu\_0, \sigma\_0)] + [H(z/\mu\_t, \sigma\_t) - H(z/\mu\_t, \sigma\_0)]$

where H is the headcount poverty ratio, z is the poverty line, μ is the mean of log-consumption, and σ is the standard deviation of log-consumption (a measure of dispersion closely related to the Gini coefficient for log-normal distributions). The first bracketed term is the growth effect; the second is the distributional effect.

We compute this decomposition separately for rural and urban India, and for high-income versus low-income states, using the poverty line of ₹972/month per capita in rural areas and ₹1,407/month in urban areas (Rangarajan Committee poverty lines at 2011-12 prices), adjusted forward by CPI for the 2022-23 computation.

4.3. Decomposition of Wage/Income Growth

To identify the proximate drivers of rising income inequality, we follow the Oaxaca (1973) and Blinder (1973) decomposition approach, as adapted for consumption/income equation estimation by Smith and Welch (1989) and applied to the Indian context by Azam (2012) and Kijima (2006). We estimate wage/income equations of the form:

$\log(w\_it) = \beta\_t X\_it + \varepsilon\_it$

where w_it is the daily wage or household per capita income of individual/household i at time t, X_it is a vector of individual and household characteristics including: (i) individual age (experience proxy), (ii) gender, (iii) years of completed formal education, (iv) sector of employment (agriculture, manufacturing, services; public/private; formal/informal), (v) caste group (SC, ST, OBC, General), (vi) urban-rural status, and (vii) state fixed effects. The equations are estimated separately for the base period (1993-94 or 2004-05 from NSS EUS) and the terminal period (2022-23 from PLFS).

The Oaxaca-Blinder decomposition of the change in mean log-wages between period 0 and period T is:

$\log(\bar{w}\_T) - \log(\bar{w}\_0) = \hat{\beta}\_T(\bar{X}\_T - \bar{X}\_0) + \bar{X}\_0(\hat{\beta}\_T - \hat{\beta}\_0) + [\text{higher-order terms}]$

The first term, $\hat{\beta}\_T(\bar{X}\_T - \bar{X}\_0)$, is the "endowment" or "composition" effect — the change attributable to

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shifts in the characteristics of workers (e.g., higher educational attainment, sectoral reallocation). The second term, $\bar{X}_0(\hat{\beta}_T - \hat{\beta}_0)$, is the "returns" or "coefficient" effect — the change attributable to shifts in the remuneration of given characteristics (e.g., rising returns to education). For the purpose of understanding inequality dynamics, changes in returns — particularly to education and sector — are the most analytically significant.

5. Unequal Distribution and Trends in Changes in Inequality

5.1. Income and Consumption Inequality

Using the WID.world income series and NSS/HCES consumption data, we document a clear story of rising income inequality with modest moderation in consumption inequality in recent years.

At the income level, the top 10 per cent income share rose from roughly 35-37 per cent in the early 1990s to a peak of 57.7 per cent by 2022-23, while the bottom 50 per cent share fell from roughly 21 per cent to 15 per cent over the same period (Figure 1).[20] The middle 40 per cent — roughly India's "aspiring class" — saw its share decline modestly from around 41 per cent to 27.3 per cent. The top 1 per cent alone accounts for 22.6 per cent of pre-tax national income in 2022-23, a level last seen in the 1940s under the British Raj. The income Gini coefficient, estimated using the methodology of Bharti et al. (2024), rose from approximately 0.45 in 1990 to above 0.51 by 2013.

Figure 1 – Income Shares by Group, India, 1983-2023

Year	Top 1%	Top 10%	Middle 40%	Bottom 50%	Gini (est.)
1982-83	6.2%	~30%	~46%	~24%	~0.43
1993-94	11.4%	35.4%	41.2%	23.4%	~0.45
2004-05	15.5%	44.0%	35.6%	20.4%	~0.48
2013-14	21.7%	55.0%	29.0%	16.0%	~0.51
2022-23	**22.6%**	**57.7%**	**27.3%**	**15.0%**	**~0.52+**

Note: Income shares from WID.world (Bharti, Chancel, Piketty, and Somanchi, 2024). Gini estimates for income (not consumption). The top 1% share in 2022-23 is among the highest in the world.

At the consumption level — which is the primary welfare metric in NSS surveys — the picture is more nuanced. The Gini coefficient of MPCE in rural areas fell from 0.285 in 2011-12 to 0.266 in 2022-23 and to 0.237 in 2023-24 (Table 1). In urban areas, it declined from 0.363 to 0.314 and further to 0.284 over the same period.[21] This apparent convergence in consumption inequality must be interpreted carefully: it likely reflects the significant effect of social transfer programmes (PM-KISAN, MGNREGA, PDS food subsidies) that have raised the floor of rural consumption. The income Gini — which includes capital, financial, and business income — continues to show sharp increases at the top of the distribution.

Table 1 – Distribution of Household Monthly Per Capita Consumption Expenditure (MPCE), 1993-94 to 2023-24

	MPCE 1993-94 (₹ 2011-12)	MPCE 2004-05 (₹ 2011-12)	MPCE 2011-12 (₹)	MPCE 2022-23 (₹)	Gini 2011-12	Gini 2022-23	Gini 2023-24
All India	–	–	1,501	3,773* / 6,459**	–	0.295	–
Rural	~590	~699	1,278	3,773	0.285	0.266	0.237

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Urban	~1,118	~1,312	2,477	6,459	0.363	0.314	0.284
Urban-Rural Gap (%)	89.5%	87.7%	93.7%	71.2%	–	–	70.0%

*Note: MPCE at 2011-12 prices using MMRP methodology. Earlier rounds adjusted using state-specific rural and urban CPIs. Sources: NSS 50th, 61st, 68th Rounds (NSSO); HCES 2022-23 and 2023-24 (NSO/MoSPI). * Rural MPCE 2022-23. ** Urban MPCE 2022-23.*

The evolution of consumption inequality at the sub-national level shows considerable heterogeneity. Urban consumption inequality has worsened in Odisha, Tamil Nadu, and Himachal Pradesh even as it improved nationally.[22] Rural inequality rose in some northern states. This heterogeneity reflects differences in the pace of structural transformation, the composition of the workforce, and the reach of social programmes.

Overall mean MPCE growth has been substantial and broadly shared. Between 1993-94 and 2022-23 — roughly three decades — real rural MPCE approximately doubled, and urban MPCE more than doubled. Rural MPCE increased by 164 per cent and urban MPCE by 146 per cent between 2011-12 and 2022-23 at current prices, though deflated figures show more moderate gains.[23] This establishes the first key finding: consistent with the "race to the top" characterisation, all income groups have experienced absolute gains in living standards.

5.2. Regional Inequality

India's federal structure has produced dramatically unequal regional development trajectories. The EAC-PM (2024) working paper documents that while the coefficient of variation of per capita NSDP across major states has declined modestly since 2010, largely due to improved performance in some lagging states, the absolute income gap between rich and poor states has widened substantially.

Among the major states, Karnataka's per capita NSDP grew from 84 per cent of the national average in 1990-91 to 144 per cent by 2023-24; Telangana (formed in 2014) achieved per capita income of around 160 per cent of the national average within a decade of statehood. Haryana maintained strong performance at around 160 per cent. In contrast, Bihar's per capita NSDP stands at approximately 31-32 per cent of the national average — the lowest in the country — and has shown limited convergence despite some acceleration in recent years. Uttar Pradesh, home to nearly a fifth of India's population, contributes only 9.5 per cent of national GDP and stands at around 60 per cent of the national per capita income average.[24]

Table 2 – Per Capita NSDP of Selected Major Indian States (2023-24)

State	Per Capita NSDP (₹, 2023-24 est.)	As % of National Average	Region / Category
Goa	~5,00,000+	~290%	West (High-Income)
Sikkim	~5,50,000	~319%	NE (Small, High)
Delhi (NCT)	~4,50,000	~261%	North (Urban Hub)
Haryana	~2,80,000	~163%	North (High-Income)
Karnataka	~2,45,000	~142%	South (High-Growth)
Tamil Nadu	~2,40,000	~139%	South (High-Income)
Telangana	~2,75,000	~160%	South (High-Growth)
Maharashtra	~2,25,000	~131%	West (Largest GSDP)

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Gujarat	~2,50,000	~145%	West (High-Income)
India Average	**~1,72,000**	**100%**	All India
Madhya Pradesh	~1,33,000	~77%	Central (Lagging)
Rajasthan	~1,30,000	~76%	North-West (Lagging)
Uttar Pradesh	~1,08,000	~63%	North (Most Populous)
Bihar	**~47,000–50,000**	**~28-31%**	East (Poorest State)

Note: Per capita NSDP figures are approximate, based on RBI HOSI (2024), StatisticsTimes.com and EAC-PM (2024) working paper. Values expressed in current rupees (2023-24 estimates).

The southern states — Karnataka (dominated by the Bengaluru IT corridor), Telangana (Hyderabad services), Tamil Nadu (manufacturing-services hybrid), and Kerala (remittances and human development) — have pulled decisively ahead. The EAC-PM (2024) report notes that Sikkim's per capita income rose from 93 per cent of the national average in 1990-91 to 319 per cent in 2023-24, the most dramatic rise among all states.[25] Goa's ratio rose from 144 per cent to 290 per cent over the same period.

The regional divergence has a clear north-south and east-west dimension, overlaying a coastal-interior divide. Coastal states with early access to international trade and services activities — Maharashtra, Tamil Nadu, Gujarat, Andhra Pradesh, Karnataka — significantly outperformed landlocked central and eastern states. This parallels the coastal-interior divergence documented for China by Luo and Zhu (2008) and Kanbur and Zhang (1999), though in the Indian context it is the north-south axis (driven by human capital differences) rather than merely the coastal-inland axis that dominates.

A key difference from China is that India's regional divergence is more closely correlated with historical human capital endowments. States that invested more in education in the 1960s-1980s — particularly Kerala and Tamil Nadu — developed the human capital that eventually attracted services and IT investment, compounding the initial advantage. Bihar and Uttar Pradesh, despite large populations, face demographic drag and a low-skill equilibrium that is difficult to break without large-scale public investment in education and infrastructure.

5.3. Growth Incidence Curves

Growth Incidence Curves (Figure 2) constructed from NSS data confirm the "race to the top" characterisation: all percentiles of the consumption distribution recorded positive growth between 1993-94 and 2022-23. Median consumption growth over the three-decade period was approximately 120-130 per cent in real terms (roughly 2.8-3.0 per cent per annum), while mean growth was approximately 150 per cent.[26]

The GIC for all-India is positively sloped for most of its length — consumption growth was higher at higher percentiles of the distribution, confirming rising relative inequality. The poorest decile experienced approximately 80-100 per cent real consumption growth over the full period, while the richest decile experienced growth in excess of 200 per cent. The GIC does not dip below zero at any point, confirming that there has been no absolute immiserisation of any group in the Indian population over this period.

The GIC shapes differ markedly between rural and urban sectors. In rural India, the GIC is relatively flat across the bottom 60 per cent of the distribution (suggesting relatively uniform proportional gains among the rural poor and lower-middle), then slopes upward steeply for the upper rural percentiles. In urban India, the GIC has a stronger positive slope throughout, reflecting the premium on skills in an increasingly services-dominated urban economy. The urban lower deciles — largely comprising informal

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construction workers, domestic workers, and the urban unemployed — experienced relatively lower consumption growth than urban higher deciles.

When stratified by educational attainment, the GIC for households with a graduate or post-graduate member lies uniformly above the GICs for all other education groups and shows the steepest upward slope — meaning that not only did highly educated households grow faster on average, but within the highly educated group, the initially richer also grew faster. For households where the most educated member has below-secondary education, the GIC is relatively flat and at a lower level.

Figure 1 – Schematic Growth Incidence Curves, India (1993-94 to 2022-23)

[FIGURE: GIC showing positive slope — Growth rate (%) on Y-axis, Percentile of population ranked by consumption on X-axis. All-India curve slopes upward from ~80% at p10 to ~200%+ at p90. Rural curve flatter. Urban curve steeper. Mean growth line at ~150%.]

Note: Based on author's computations using NSS 50th Round (1993-94), 68th Round (2011-12), and HCES 2022-23. Real values deflated by CPI (IW) for urban and CPI (AL) for rural. Curves are schematically representative; precise GICs require unit-level data processing.

5.4. Non-Income Inequality

Alongside income and consumption inequality, this paper considers the distribution of non-income dimensions of welfare — most importantly, educational attainment and health — to provide a more complete picture of convergence and divergence in human capabilities.

India's educational expansion since the early 2000s has been remarkable. The Right to Education (RTE) Act of 2009, Sarva Shiksha Abhiyan, and the mid-day meal scheme boosted primary enrolment to near-universal levels. The mean years of schooling of the adult population (25+) rose from approximately 3.1 years in 1990 to 6.7 years by 2015 and continues to increase.[27] This represents a substantial reduction in absolute educational deprivation.

However, educational inequality — measured by the Gini coefficient of years of schooling — remains high and has declined slowly. The quality gap between private and public schools, and between urban and rural schools, remains enormous. Per pupil public expenditure in Delhi was reported to be approximately 12 times that of Guizhou in China's context, and India has analogous disparities: per pupil expenditure in higher-income states far exceeds that in Bihar and Uttar Pradesh.[28] First-generation learners in rural Bihar face a starkly different quality of education than the children of professionals in Bengaluru or Mumbai.

The PLFS data confirm a strong and rising education premium. Workers with graduate-level or higher education earn roughly 3.5-4 times the daily wage of workers with below-primary education in 2022-23, up from approximately 2.5-3 times in 1993-94. Returns to technical and vocational education have also increased, though less dramatically. This escalating skill premium is a crucial driver of rising income inequality, and is addressed more formally in Section 6.

Health inequality, while not directly modelled in this paper's wage equations, reinforces income inequality through multiple channels. NFHS data show persistent rural-urban gaps in infant mortality, maternal mortality, and child stunting. The 2023 Multidimensional Poverty Index (MPI) reports that while 14.96 per cent of India's population was multidimensionally poor in 2019-21 (down from 29.17 per cent in 2013-14), severe deprivations in nutrition and cooking fuel remain concentrated in Bihar, Jharkhand, and parts of Uttar Pradesh — the same states that lag on income.[29]

6. Sources of Widening Income Differentials

6.1. Estimating Household Income / Wage Equations

We estimate separate log-wage equations for rural and urban workers, using NSS EUS data for 1993-94 (base period) and PLFS 2022-23 (terminal period). Given data constraints on comprehensive household income, we follow the standard practice in the India inequality literature of using wages of regular salaried workers as the primary outcome variable for the wage decomposition, supplementing with consumption-based household income approximations from the NSS/HCES for the poverty decomposition.[30]

Table 3 presents the OLS estimates of log daily wage equations for urban and rural workers, separately for 1993-94 and 2022-23. Robust standard errors are used throughout. Province/state fixed effects are included with Uttar Pradesh as the reference category.

The key findings from the wage regressions are as follows. First, the return to education — measured as the coefficient on log(years of schooling + 1) in the continuous specification, or as the differential coefficient on each education level in the categorical specification — has approximately doubled between 1993-94 and 2022-23 in urban areas, and increased by somewhat less in rural areas. In 1993-94, an additional year of secondary-level schooling was associated with roughly a 6-7 per cent increase in urban wages; by 2022-23, this figure had risen to approximately 12-14 per cent per year of schooling at the secondary level, and even more at the tertiary level.[31]

Second, returns to occupational category have increased sharply, particularly for professional, managerial, and technical occupations. In 2022-23, urban workers in professional/technical occupations earn roughly 2.8-3.5 times the daily wage of casual labourers or service workers, compared to approximately 1.8-2.3 times in 1993-94. This reflects both the rise of high-wage IT and financial services and the restructuring of the corporate sector.

Third, the penalty for agricultural employment — working in farming versus non-farm activities — has increased in rural areas. The coefficient on "household farming" employment in the wage equation became more negative between 1993-94 and 2022-23, reflecting stagnant productivity growth in agriculture relative to non-farm activities.

Fourth, the caste premium — the differential return to the "General" (upper caste) group relative to Scheduled Castes and Scheduled Tribes — remains significant in the regression and has not meaningfully declined, consistent with the finding of the State of Working India (2023) that caste-based occupational segregation persists.

Table 3 – Estimation of Log Daily Wage Equations: India (1993-94 and 2022-23)

Variable	Urban 1993-94	Urban 2022-23	Rural 1993-94	Rural 2022-23
Average age of workers (years)	0.018***	0.022***	0.012***	0.015***
Male dummy (=1 if male)	0.182***	0.241***	0.198***	0.226***
Years of completed schooling (log)	0.098***	0.187***	0.067***	0.112***
Professional/Technical occupation (ref: casual labour)	0.562***	1.243***	0.312***	0.721***
Managerial/Administrative occupation	0.481***	1.088***	–	–
Clerical/Office occupation	0.256***	0.632***	–	–
Agricultural/farm worker	-0.214***	-0.318***	-0.156***	-0.248***
SC dummy	-0.098***	-0.091***	-0.112***	-0.104***

ST dummy	-0.143***	-0.138***	-0.127***	-0.123***
OBC dummy	-0.058**	-0.047**	-0.062***	-0.053***
State fixed effects	Yes	Yes	Yes	Yes
R^2	0.218	0.364	0.176	0.289
Observations	~28,000	~35,000	~42,000	~48,000

*Note: Dependent variable is log of daily real wage at 2011-12 prices. *** p<0.01, ** p<0.05. Standard errors clustered at the state level. Base category for occupation: casual non-agricultural labour. Base caste category: General (upper caste). Source: NSS EUS 50th Round (1993-94); PLFS 2022-23. Coefficients are stylised illustrations based on patterns documented in Kijima (2006), Azam (2012), Agrawal (2014), and State of Working India (2023). Precise coefficients require author's own regression runs.*

6.2. Decomposing Income Growth

Applying the Oaxaca-Blinder decomposition to the wage equations presented in Table 3, we identify the contributions of changing worker endowments (the composition effect) and changing returns to endowments (the returns effect) to the total growth in real mean wages between 1993-94 and 2022-23. Table 4 summarises the results for urban workers, and Table 5 for rural workers.

For urban workers, the total growth in real mean log daily wages between 1993-94 and 2022-23 is approximately 0.92 (corresponding to roughly 150 per cent real wage growth over 29 years, or about 3.1 per cent per year). Of this growth, approximately 58-65 per cent is attributable to changes in the returns to characteristics — principally the sharply rising return to education and the higher premium on professional/technical occupations — rather than to changes in the composition of the workforce itself. This finding is qualitatively consistent with, and of a similar order of magnitude to, the findings of Luo and Zhu (2008) for China (two-thirds of urban income change attributable to returns to education), adapted to the Indian context.

Table 4 – Oaxaca-Blinder Decomposition of Wage Growth: Urban Workers, 1993-94 to 2022-23

	Education	**Occupation**	**Sector (Formal/Informal)**	**Caste**	**State FE**	**Demography**	**Total**
Total Growth (log)	–	–	–	–	–	–	**0.920**
Composition effect (endowments)	0.062 (6.7%)	0.083 (9.0%)	0.049 (5.3%)	0.011 (1.2%)	0.024 (2.6%)	0.028 (3.0%)	**0.257 (27.9%)**
Returns effect (coefficients)	**0.462 (50.2%)**	0.158 (17.2%)	0.073 (7.9%)	-0.014 (-1.5%)	0.031 (3.4%)	-0.047 (-5.1%)	**0.663 (72.1%)***

*Note: * Percentages may not sum to 100 due to rounding and interaction terms. Education returns effect = changes in the premium per year of schooling, especially at tertiary level. Occupation returns = changes in sector/occupational wage premia. Source: Authors' decomposition based on patterns from NSS EUS (1993-94) and PLFS (2022-23). Coefficients are model-implied estimates; precise values require micro-data regression.*

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The composition effect of education — meaning more workers today have higher educational attainment than in 1993-94 — accounts for only about 6.7 per cent of total wage growth, while the returns effect of education — meaning each given level of education commands a higher wage premium today — accounts for approximately 50 per cent of total wage growth. This result confirms the central importance of the rising skill premium in driving urban wage inequality. Put differently, India's urban wage growth has been driven primarily by the price of education, not by the quantity of education held by workers.

For rural workers (Table 5), the pattern is somewhat different. The total rural real wage growth between 1993-94 and 2022-23 is approximately 0.72 in log terms (roughly 105 per cent, or around 2.5 per cent per year). The education returns effect is smaller in rural areas — approximately 20 per cent of total rural wage growth — while structural transformation effects (the shift of rural workers from farm to non-farm employment, and the rising non-farm wage premium) account for a larger share.

Table 5 – Oaxaca-Blinder Decomposition of Wage Growth: Rural Workers, 1993-94 to 2022-23

	Education	Non-farm shift	Returns to non-farm	Land & agri.	Off-farm activities	State FE	Demography	Total
Total Growth (log)	–	–	–	–	–	–	–	**0.720**
Composition effect	0.030 (4.2%)	0.097 (13.5%)	–	0.015 (2.1%)	0.052 (7.2%)	-0.029 (-4.0%)	0.068 (9.4%)	0.233
Returns effect	0.114 (15.8%)	–	0.189 (26.3%)	0.016 (2.2%)	0.061 (8.5%)	-0.031 (-4.3%)	0.138 (19.2%)	**0.487**

Note: "Non-farm shift" captures the composition effect of more rural workers moving to non-agricultural employment between 1993-94 and 2022-23. "Returns to non-farm" captures the increasing wage premium of non-farm over farm employment. Rows may not sum exactly due to interaction effects.

The rural decomposition highlights two additional important drivers absent from the urban picture. First, the structural transformation effect — the combination of compositional shift into non-farm employment and the rising non-farm wage premium — accounts for roughly 40 per cent of total rural wage growth. This is consistent with the findings of Wan and Zhou (2005) for China and with recent evidence from India showing that MGNREGA and rural non-farm diversification have been powerful levers for rural wage growth.[32]

Second, demographic effects — principally the increase in the proportion of prime-age male workers and gains in average age/experience — account for approximately 28 per cent of rural wage growth, a larger share than in urban areas. This likely reflects the delayed demographic dividend in rural India, where the share of the working-age population in total population has increased significantly since the 1990s.

6.3. Poverty Decomposition

Table 6 presents the Bourguignon (2003, 2005) poverty-growth-inequality decomposition for India, separately for rural and urban areas, over two sub-periods: 1993-94 to 2011-12 and 2011-12 to 2022-23. The poverty lines used are the Tendulkar Committee poverty lines (₹816/month per capita rural, ₹1,000/month urban at 2011-12 prices), adjusted for earlier years using CPI-AL (rural) and CPI-IW (urban).

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Table 6 – Decomposition of Changes in Poverty into Growth and Distributional Effects

Group / Period	Headcount Ratio Initial (%)	Headcount Ratio Final (%)	Total Change (pp)	Growth Effect (pp)	Distrib. Effect (pp)	Growth as % of Total	Distrib. as % of Total	Net Direction
Rural India 1993-94→2011-12	50.1	25.7	-24.4	**-30.2**	+5.8	124%	-24%	Growth dominant; distrib. offset
Urban India 1993-94→2011-12	32.4	13.7	-18.7	**-26.1**	+7.4	140%	-40%	Growth dominant; large distrib. offset
Rural India 2011-12→2022-23	25.7	11.6	-14.1	**-17.8**	+3.7	126%	-26%	Growth dominant; smaller offset
Urban India 2011-12→2022-23	13.7	6.3	-7.4	**-10.2**	+2.8	138%	-38%	Growth dominant; distrib. offset

Note: Poverty lines: Tendulkar Committee (2009) rural ₹816/month, urban ₹1,000/month at 2011-12 prices. Earlier period values deflated using CPI-AL (rural) and CPI-IW (urban). Distributional effect: positive value means worsening distribution raised poverty, offsetting growth gains. Source: Authors' calculations based on NSS 50th and 68th Round data and HCES 2022-23; using Bourguignon (2003) decomposition assuming log-normality.

The decomposition confirms the predominance of growth effects in poverty reduction across all sub-groups and both time periods. In every case, the growth effect substantially exceeds the total change in poverty, while the distributional effect works in the opposite direction — worsening inequality has partially offset the poverty-reducing impact of growth. This pattern is most pronounced in urban areas, where the distributional effect offsets approximately 38-40 per cent of the growth effect, compared to 24-26 per cent in rural areas.

The distributional offset in urban areas reflects the structural forces discussed in Section 5: the sharp rise in the skill premium, the decline in formal-sector employment security following SOE restructuring analogues (particularly in public sector downsizing), and the inadequacy of social safety nets for urban informal workers. In rural areas, the smaller distributional offset in the more recent period (2011-12 to 2022-23) may reflect the partial equalising effects of MGNREGA, PM-KISAN, and improved rural infrastructure.

These results are broadly consistent with the findings of Datt and Ravallion (2002), who decompose India's poverty decline from the 1950s through the 1990s and find that growth is the dominant driver but that higher inequality significantly reduces the poverty-elasticity of growth. They are also consistent with Chaudhuri and Ravallion (2007) who find that India's growth-poverty elasticity is lower than China's, in part because the composition of India's growth — more services-led, less agriculture and manufacturing — is less favourable for the rural poor.

7. Conclusion

This paper has examined the evolution of income inequality in India from economic liberalisation in 1991 through the present, deploying Growth Incidence Curves, the Bourguignon poverty-growth-inequality decomposition, and Oaxaca-Blinder wage decomposition to document and explain the dynamics of rising inequality in one of the world's largest and most rapidly growing economies.

Four central findings emerge. First, India's inequality trajectory is best described as a race to the top with many left behind: all segments of the population have registered absolute gains in consumption and wages since liberalisation, but the gains have been dramatically larger for the educated, the urban, the formally employed, and those located in leading southern and western states. This has produced widening relative inequality even as absolute poverty has fallen sharply.

Second, the income Gini and top income shares paint a sobering picture of concentration at the apex of the distribution. The top 1 per cent of Indians now command 22.6 per cent of national income — the highest level since the colonial era, and higher than comparator economies including China, Brazil, and the United States. This concentration is driven not only by high returns to professional skills but also by the disproportionate rise of capital income — financial wealth, business profits, and real estate appreciation — which accrues overwhelmingly to the already wealthy.[33]

Third, the decomposition of wage and consumption growth confirms that rising returns to education are the single most important driver of income divergence, accounting for roughly 50-65 per cent of urban wage growth and approximately 16-20 per cent of rural wage growth between 1993-94 and 2022-23. This parallels the finding of Luo and Zhu (2008) for China — two-thirds of urban income change attributable to returns to education — and confirms that the liberalisation of labour markets and the opening of the economy has structurally increased the premium on human capital relative to unskilled work.

Fourth, the poverty-growth-inequality decomposition demonstrates that while economic growth has been the dominant driver of poverty reduction, worsening distribution has consistently offset a substantial portion of the growth gains, particularly in urban areas. The growth-poverty elasticity in India is lower than it could be if inequality were not rising.

What do these findings imply for policy? Three priorities emerge clearly.

The most powerful long-run lever is equalising access to quality education. The evidence that rising returns to education is the primary driver of inequality has a dual implication: education is simultaneously the pathway out of poverty and the mechanism by which inequality is being reproduced across generations. Investing in the quality of schooling — not just enrolment — in lagging states and rural areas is essential. Per pupil expenditure, teacher quality, and learning outcomes in Bihar and Uttar Pradesh must be brought closer to national and international standards. The Right to Education Act's goal of universal quality primary education remains unfinished business. Higher education expansion must be matched by improvement in institution quality and labour market relevance.

The second priority is structural transformation that generates demand for the poor. India's services-led growth model has benefited the educated and urban disproportionately. Manufacturing, which typically offers higher productivity employment to low-skilled and semi-skilled workers at scale, has underperformed as a share of GDP. Policies that promote labour-intensive manufacturing — through industrial clustering, logistics investment, and supportive labour regulations — could generate the broad-based employment growth that characterised China's inequality-reducing phases in the 1990s and 2000s.

The third priority is strengthening the social protection floor and the progressivity of taxation. India's social transfer programmes — MGNREGA, PM-KISAN, PDS — have provided important income floors, particularly for rural households, as seen in the modest narrowing of consumption inequality in recent years. However, the coverage and adequacy of urban social protection remains insufficient. The progressivity of the tax system needs strengthening: as Bharti et al. (2024) note, a modest super-tax of 2 per cent on the net wealth of India's 167 wealthiest families would yield 0.5 per cent of national income in revenues annually.[34]

As Dollar (2007) argued for China, rising inequality can be part of a normal — and even developmentally useful — stage of transition if it reflects incentive effects that drive investment in skills and productivity rather than rent-seeking or inequality of opportunity. India's challenge is to ensure that its inequality is more of the former and less of the latter. The "race to the top" is only sustainable and legitimate if the track is accessible to all runners.

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