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Income and Wealth Inequality in India, 1922–2023: The Rise of the Billionaire Raj

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Abstract

Integrating national income accounts, wealth aggregates, tax data, rich lists, and surveys on income, consumption, and wealth in a consistent framework, long-run and short-run trends of income and wealth inequality in India are analyzed. Inequality declined post-independence, began rising in the early 1980s, and has skyrocketed since the early 2000s. Income and wealth inequality trends closely track each other over the entire period, with the rise in wealth concentration at the top being more pronounced in the most recent decade. By 2022–23, the top 1 percent income and wealth shares (23.3 percent and 40.1 percent) were at their highest historical levels with India's top 1 percent income share among the highest in the world. While the best available data sources at hand are used, it is emphasized that the poor and declining quality of economic data in India poses significant challenges for inequality measurement.

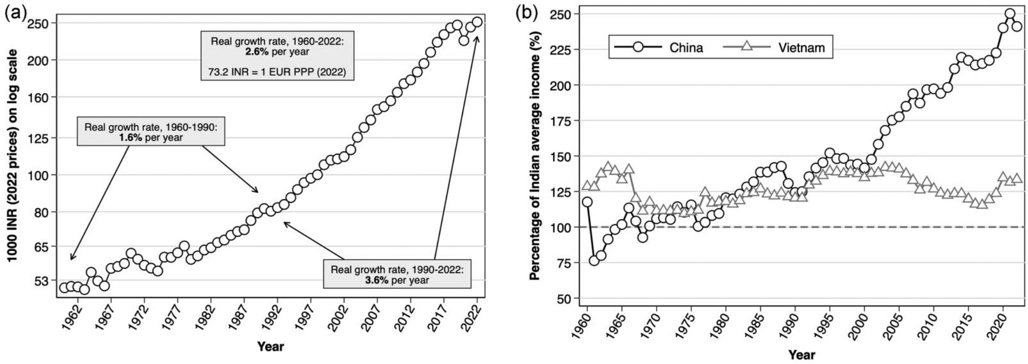
JEL classification D31, E01, E21, N35, O15

Keywords India, income inequality, wealth inequality, top shares

1. Introduction

Given its geographical size and population, now the highest in the world, the distribution of economic growth in India has significant consequences for global inequality dynamics, which in turn are crucial to the understanding of global economic arrangements. This makes careful measurement of income and wealth inequality in India an important exercise. This is especially so in light of India's relatively rapid macroeconomic growth in the last three decades. To put things into perspective, between 1960 and 2022, India's average income grew at 2.6 percent per year in real terms (fig. 1a). Until the mid-1970s, aggregate national income experienced significant year-on-year volatility and growth remained sluggish. It was only sometime in the 1980s that growth really picked up and then accelerated during the 1990s and 2000s. Compared to a real growth rate of 1.6 percent per year between 1960 and 1990, average

Figure 1 (a) Evolution of average income in India, 1960–2022. (b) Indian incomes in comparative perspective, 1960–2022



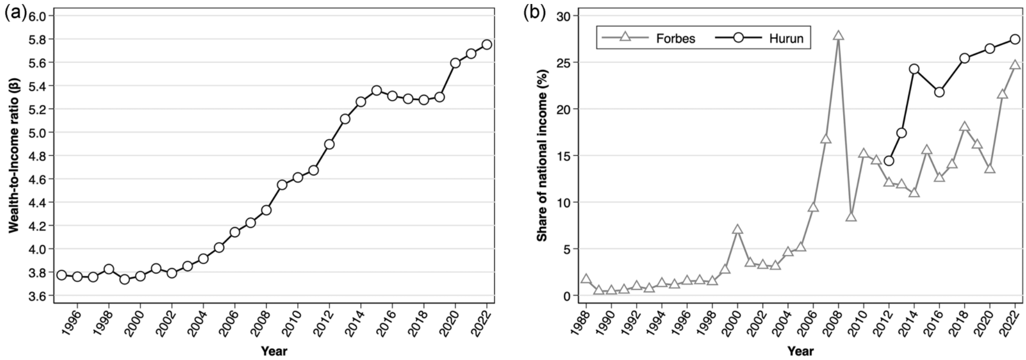
Source: Authors' estimates combining national income accounts data, adult population from World Inequality Database (WID) and price index (GDP deflator) from WID and World Bank's World Development Indicators.
Note: Figure 1 a presents India's average income (= net national income / adult population) on log scale. Figure 1 b presents average incomes in China and Vietnam as a percentage of India's average. Incomes in nominal local currency converted to 2022 euros PPP to account for local inflation and purchasing power differentials.

incomes grew by 3.6 percent per year between 1990 and 2022. The periods 2005–2010 and 2010–2015 saw the fastest growth at 4.3 percent and 4.9 percent per year respectively. Placing India in comparative perspective with China and Vietnam, average incomes were similar in the three countries till about 1975, adjusting for local inflation and purchasing power differentials (fig. 1b). Subsequently, Chinese and Vietnamese incomes grew to become 35–50 percent higher than India's by 2000. At the turn of the new century, Chinese incomes began galloping ahead and are now about 2.5 times larger than Indian incomes. Despite the absence of democracy, incomes in both China and Vietnam grew faster than in India over the 1960–2022 period.[1]

Notwithstanding the relatively timid performance compared to China, the Indian economy did experience significant growth in absolute terms during the last three decades. The income growth of nearly 3.6 percent per year during 1990–2022 was accompanied by a rise in national wealth—India's aggregate wealth-to-income ratio (β) rose from 3.83 in 1995 to 5.75 in 2022 (fig. 2a). This period also saw the emergence of ultrahigh-net-worth individuals. As per data from Forbes billionaire rankings, the number of Indians with net wealth exceeding 1 billion USD at market exchange rate (MER) increased from 1 to 52 to 162 in 1991, 2011, and 2022 respectively. Over this period, the total net wealth of these individuals as a share of India's net national income boomed from under 1 percent in 1991 to a whopping 25 percent in 2022 (fig. 2b). Perhaps not surprisingly, the share of adult population that paid income taxes, which had remained under 1 percent till the 1990s, also grew significantly in the three decades post the economic reforms of 1991. By 2011, the share had crossed 5 percent and the last decade also saw sustained growth with over 10 percent of adults filing a return in 2022 (fig. 3). What were the distributional consequences of this sustained economic growth in recent decades when looked at from a historical perspective? For developed economies, like the United States and France, quasi-exhaustive micro-data from income and estate taxes, covering themajority of the population, form the core basis for measuring inequality (Piketty, Saez, and Zucman 2018; Garbinti, Goupille-Lebert, and Piketty 2018). In contrast, tracking the dynamics of inequality in a country like India is fraught with various empirical challenges relating to data coverage, quality, and availability. Tax data at best covers about 10 percent of the adult population in recent years; household surveys, while having the broadest coverage, are notorious for severely missing the right tail of income and wealth distributions, owing to a mixture of non-response, non-sampling, and measurement issues (Bourguinon 2018; Korinek, Mistiaen, and Ravallion 2006; Vermeulen 2016).

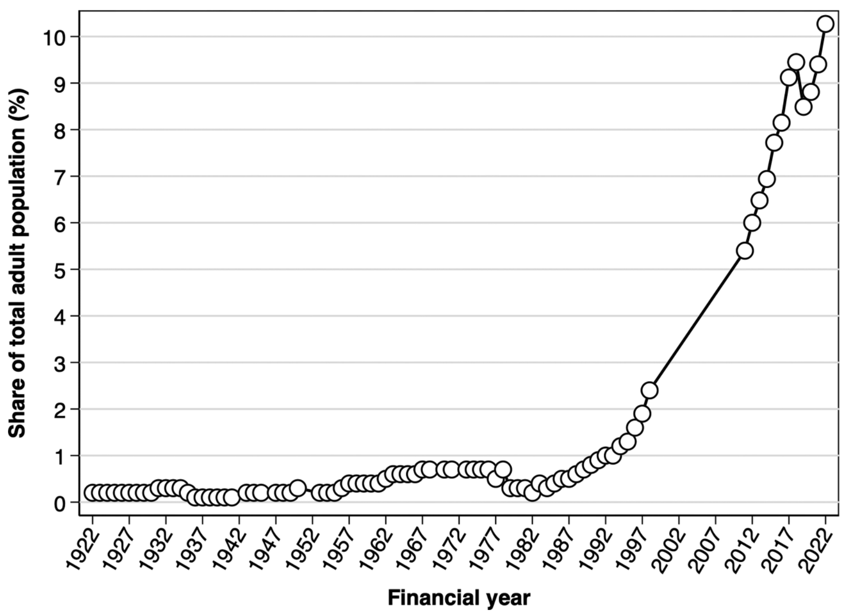
[1] Both China and Vietnam have consistently invested much more on health and education than India. In 1980, India's adult (15+) literacy rate was just 41 percent compared to 65 percent in China and 84 percent in Vietnam; in 2010, India's expenditure on health was 1.2 percent of its gross domestic product (GDP) compared to 2.7 percent in China (Drèze and Sen 2013).

Figure 2 (a) National wealth-to-income ratio, 1995–2022. (b) Wealth of richest Indians, 1988–2022



Source: Figure 2 a—Data from the World Inequality Database based on Kumar (2019). Figure 2 b—Authors' estimates combining national income accounts data from WID data for pre-2014 and table 1.1, Statistical Appendix, Economic Survey 2022–23 for post-2014, with data from Forbes billionaire rankings and Hurun rich lists.
Note: Figure 2 a presents India's aggregate wealth-to-income ratio (β) over 1995–2022. Figure 2 b presents the wealth of Indian billionaires and multi-millionaires as a percentage of net national incomes. The Forbes data track all individuals with net wealth exceeding 1 billion USD MER. The Hurun rich list tracks all individuals with net wealth exceeding 1,000 crore INR (roughly 120 million USD MER as of March 2024). See supplementary online appendix table S2.8 for further details.

Figure 3 Proportion of income-tax-return filers in India, 1922–2022



Source: Authors' computations based on Indian income tax administration statistics, adult population figures from UN World Population Prospects, and Banerjee and Piketty (2005).
Note: The figures relate to individuals and Hindu Undivided Families (HUF) and include those that paid income tax at source but did not file a return and those that filed a return but did not pay income tax because they fell below the taxable threshold and/or on account of deductions. The figures exclude returns with zero or negative gross incomes.

This paper combines national income accounts and wealth aggregates with tax tabulations, rich lists, and a range of household surveys on income, consumption, and wealth in a consistent framework suitable for India's unique data challenges, to present long-run income and wealth inequality series updated to the most recent years. More specifically, the main contributions of this paper are two-fold. It is the first to present long-run series of wealth inequality spanning the 1961–2023 period based on consistent data sources and methodology. The series begins in 1961 when the Government of India began conducting the All-India Debt and Investment Survey (AIDIS) tracking household assets and liabilities. The AIDIS is combined with data from rich lists like Forbes and Hurun in recent years to correct for the missing right tail in surveys in a consistent manner. Second, income inequality estimates are presented for the most recent years (2015–2022). Despite numerous empirical challenges including non-availability of crucial data sources, this paper extends the long-run income inequality series presented in Chancel and Piketty (2019) in a consistent and comparable manner. This enables shedding light on and evaluating the dynamics of top incomes (top 1 percent, top 0.1 percent, top 0.001 percent) in India over an entire century, 1922–2023. The robustness of the benchmark series years is tested by using alternate methods and sources to estimate bottom incomes from surveys in recent years.

The main results are as follows. Wealth inequality was relatively stable post-independence till the 1980s, while income inequality fell over the same period. Starting in the mid-1980s, however, both income and wealth inequality began to rise and has increased sharply since the 2000s. By 2022–23, 23.3 percent of national income went to just the top 1 percent, the highest level recorded in the series since 1922, higher than even during the inter-war colonial period. The top 1 percent wealth share stood at 40.1 percent in 2022–23, also at its highest level since 1961 when the wealth series begins. During the last decade or so, the rise of top-end inequality has been particularly pronounced in terms of wealth concentration.[2] In other words, the “Billionaire Raj” headed by India’s modern bourgeoisie is now more unequal than the British Raj headed by the colonialist forces. Moreover, these inequalities are high even by international standards. In 2022–23, India’s top 1 percent income share is among the very highest in the world, higher than Brazil, South Africa, and the United States, and behind perhaps only Peru, Yemen, and a few other small countries. Lastly, an India–China comparison is telling: Despite growing much faster than India in recent decades, China experienced comparatively lower levels of inequality.

The paper contributes to three main strands of literature. First, it speaks to the growing literature on wealth inequality in India. There is a general consensus that wealth inequality was largely stable till the 1990s, after which top wealth shares began rising fast (Subramanian and Jayaraj 2006; Sinha 2006; Jayadev, Motiram, and Vakulabharanam 2007; Anand and Thampi 2016; Jayaraj and Subramanian 2018; Bharti 2018). Between 2012 and 2018, the years of the two latest rounds of the All India Debt and Investment Survey (AIDIS), the picture is more complicated. Relying solely on surveys would suggest that wealth inequality declined during this period, with the important caveat that the AIDIS quite surely misses the right tail of the wealth distribution (Ghatak, Raghavan, and Xu 2022). On the other hand, data from rich lists published by luxury magazines like Forbes and Hurun over the same period suggest increased concentration at the top of the wealth distribution. Combining the AIDIS with rich lists suggests a rise in top wealth shares in recent years (Anand and Kumar 2023). Despite being rich and comprehensive, there are at least three limitations with the literature as it stands. First, while there is general consistency in the use of the AIDIS across all papers, there is irregularity in terms of the use of rich lists to top-correct these surveys, and when used, in terms of the methodology used to combine the two sources. Second, the present inequality estimates in the literature are essentially only available on a decadal basis given the decennial nature of the AIDIS, with last available estimates being for 2018 using the latest round. Third, no paper has consistently studied wealth inequality over the entire 1961–2023 period. This paper improves upon these limitations by presenting long-run wealth inequality series covering the entire 1961–2023 period, including annual estimates starting in 2002, all while using consistent definitions, data sources, and methodology.

Second, the paper contributes to the literature studying income and consumption inequality in India (Deaton and Drèze 2002; Banerjee and Piketty 2005; Chancel and Piketty 2019).[3] Evaluating the dynamics of income or consumption inequality during the last decade has been challenging given the limited

[2] Other innovative pieces of evidence point to serious inequalities in recent years. Based on legally mandated disclosures, Khera and Yadav (2020) find starkly unequal median-to-top pay ratios among the NIFTY50 companies. Pai and Vats (2023) find a “brutal power law in most Indian consumer transactions”—as per their data, 1 percent of Indians take 45 percent of flights, 2.6 percent of Indians invest in mutual funds, 6.5 percent of users are responsible for 44 percent of digital transactions on the Unified Payment Interface (UPI), and 5 percent of users account for a third of the orders placed on Zomato (the most prominent food-delivery application).

[3] See also Alvaredo, Bergeron, and Cassan (2017) who present income inequality estimates for India under the British colonial period (1885–1946).

availability of relevant data. As amply demonstrated by the revival of poverty debates in India in recent years, the numerous challenges involved in estimating consumption and income for the bottom part of the distribution cannot be stressed enough.[4] Ghatak, Raghavan, and Xu (2022) use data from the privately executed Consumer Pyramids Household Survey (CPHS), along with tabulations from the 2017–18 consumption survey that the government suppressed to argue that income and consumption inequality may have slowed down in recent years. Gupta, Malani, and Woda (2021) use monthly CPHS data to argue that consumption and income inequality declined during the COVID-19 pandemic and associated lockdowns. Both of these studies, however, do not use tax tabulations and hence fail to shed light at the very top of the income distribution (as they themselves acknowledge). The estimates for the last decade, based on combining the Periodic Labour Force Surveys with income tax tabulations for top incomes, suggest that the top 10 percent income share continued to rise till 2017–18, after which it has stabilized. This is attributable to the post-2017 growth slowdown combined with the pro-cyclical nature of inequality, as also argued by Ghatak, Raghavan, and Xu (2022) for the last decade and Gupta, Malani, and Woda (2021) in the context of COVID. Focusing on the top 1 percent share, the trends are broadly similar, except that it temporarily fell during 2019 and 2020 (both years when growth rates collapsed) followed by a particularly sharp rise post-COVID in 2021 and 2022.

Third, the results presented here are of relevance to the literature on global inequalities. Given India's population (now the highest in the world), the results have direct implications for recent assessments of global inequality and the global income distribution (Chancel and Piketty 2021; Milanovic 2024). Placing India in comparative perspective shows that the top 1 percent income share in 2022–23 exceeded that of South Africa, Brazil, and the United States, placing India among the most unequal countries (Assouad, Chancel, and Morgan 2018; Chatterjee, Czajka, and Gethin 2022). This paper also contributes to the comparative literature on the economic evolution of India and China (Chaudhuri and Ravallion 2006; Basu 2009; Piketty and Qian 2009; Bharti and Yang 2025). Over the 1980–2020 period, methodologically comparable estimates indicate that liberalization reforms in India were associated with slower growth and higher inequality relative to China.[5]

The rest of the paper is organized into the following sections: Data and Methodology, Wealth inequality in historical perspective, Income inequality estimates, Co-evolution of income and wealth inequality, Indian inequalities in comparative perspective, and Potential mechanisms behind rising economic inequality in India since the 1990s.

2. Data and methodology

Tracking the dynamics of income and wealth inequality in a country like India is fraught with serious empirical challenges relating to data coverage, quality, and availability. To begin with, the large-scale relevance of informal employment, relatively low income levels, and relatively high thresholds for non-taxable incomes means tax data (in whatever form they are available) cover only a tiny fraction of the adult population—less than 10 percent as recently as 2020. This means tax data can at best shed light on top incomes. In the case of wealth, the absence of wealth tax tabulations necessitates reliance on rich lists that cover only a small number of ultra-rich households. Consequently, nationally representative household surveys on consumption expenditure and asset/debt holdings, conducted periodically by the National Sample Survey Organization (NSSO), have formed the basis for income and wealth inequality. However, there are at least two issues with using surveys for estimating income and wealth inequality. First, surveys (everywhere, not just in India) are known to be fraught with concerns of under-reporting and differential non-response by the rich and wealthy (Korinek, Mistiaen, and Ravallion 2006; Bourguinon 2018). Moreover, simply owing to their small numbers, unless explicitly oversampled, the very rich and wealthy are unlikely to make it into usual samples (Vermeulen 2016). This has meant that

[4] While the focus in this paper is on inequality, it is broadly also related to recent literature that has aimed at estimating poverty in India (Ghatak and Kumar 2024; Himanshu, Lanjouw, and Schrimer 2024; Sinha Roy and van der Weide 2025; Subramanian 2024). See also Ghatak (2022) for an introduction and overview to an earlier e-symposium on poverty hosted by *Ideas for India*.

[5] This was likely the result of a combination of policy changes and a slowdown in China's structural transformation (Piketty, Yang, and Zucman 2019; Kanbur, Wang, and Zhang 2021).

Table 1 Summary of data sources used in this research

Data	Source	Years	Type
Adult (20+) population	UN-WPP	1960–2022	Aggregates
National Income Accounts	MoF, GoI	2014–2022	Aggregates
Price Index (GDP deflator)	WB-WDI	1960–2022	Aggregates
All-India Income Tax Returns Statistics	MoF, GoI	2011–2020	Tabulated
All-India Income Tax Time Series Data	MoF, GoI	2011–2020	Aggregates
India Billionaire Rankings	Forbes	1988–2022	Tabulated
India Rich Lists	Hurun	2012–2023	Tabulated
All India Debt and Investment Survey (AIDIS)		1961–2018	
Pre-1991	RBI/NSSO	1961–1981	Tabulated
Post-1991	NSSO	1991–2018	Micro-data
India Human Development Survey (IHDS)	NCAER/UMD	2005 & 2011	Micro-data
Consumption Expenditure Survey (CES)		2011–2022	
2011–12 & 2022–23	NSSO	2011 & 2022	Micro-data
2017–18	NSSO	2017–18	Tabulated
Consumer Pyramid Household Survey (CPHS)	CMIE	2014–2019	Micro-data
Periodic Labour Force Survey (PLFS)	NSSO	2017–2022	Micro-data

Source: Authors' compilation.
Note: (1) UN-WPP—United Nations World Population Prospects; WID—World Inequality Database; MoF—Ministry of Finance; GoI—Government of India; WB-WDI—World Bank World Development Indicators; WB-PGID—World Bank Poverty and Growth in India Database (Özler, Datt, and Ravallion 1996); NSSO—National Sample Survey Organization; RBI—Reserve Bank of India; NCAER—National Council of Applied Economic Research; UMD—University of Maryland; CMIE—Centre for Monitoring Indian Economy. (2) Most datasets more or less correspond to financial year (so 2011 here means FY2011–12), except for adult population, Forbes billionaire rankings, and Hurun rich lists, which are available by calendar year. (3) In the "Type" column, "Aggregates" refer to all-India totals while "Tabulated" data contain some form of distributional information (e.g., fractile thresholds and/or averages and/or rankings).

surveys alone are not sufficient to accurately estimate inequality where the right tails matter a lot. Second, with regard to incomes, NSSO steered clear from measuring incomes (on the grounds that agricultural incomes—which are highly seasonal—are hard to decipher) and instead focused on measuring consumption expenditure.[6] While certainly a good proxy for incomes, consumption dynamics significantly differ from income dynamics, and given that the rich only consume a fraction of their incomes, consumption inequality tends to understate income inequality. To make progress in this context, data from a wide variety of sources are assembled within a consistent framework to shed light on income and wealth inequality in India (table 1). The exact role these datasets play in the methodology is elaborated upon in detail in the subsequent subsections.

2.1. Methodology for wealth series

Pre-2002: The wealth inequality series spans the period 1961–2023 and the estimates for 1961–1991 are based on Bharti (2018). Three points are worth noting. First, the 1961–1991 estimates are based solely on the All India Debt and Investment Survey (AIDIS) survey due to the unavailability of any billionaire rich lists. While the Forbes billionaire rankings started in 1988, it covered too few individuals (fewer than 5) in the early years to be meaningfully used. Consequently, wealth inequality levels till 1991 are likely lower bounds and the evolution of inequality between 1991 and 2002 must be interpreted with some caution. Second, the 1961 and 1971 rounds of the AIDIS were conducted only in rural areas—to generate all-India estimates, the rural distribution is rescaled by a multiplicative factor given by the ratio of

[6] The recent move by the Government of India to launch a National Household Income Survey (NHIS) is a very welcome step (Kundu 2025). The release is expected in February 2026, and the new data will be incorporated to improve the estimates once available.

all-India wealth to rural wealth at each percentile in 1981.[7] Third, data from the 1961, 1971, and 1981 AIDIS rounds are only available in tabulated form with information on average wealth and number of households by wealth brackets. Generalized Pareto interpolation techniques were used to extract a full distribution from these wealth tabulations.[8]

Post-2002: Beginning in 2002, household surveys are top corrected using data from rich lists. The decennial AIDIS wealth surveys have the advantage of having the largest coverage of the population, but at the same time grossly miss the right tail of the wealth distribution, either due to non-responses or non-sampling of very wealth households (Subramanian and Jayaraj 2006; Jayadev, Motiram, and Vakulabharanam 2007). To put numbers to the issue at hand, consider this: the ratio of maximum wealth in the Forbes rich list to the maximum wealth observed in AIDIS was 3,279 in 2012 and 7,163 in 2018. In other words, there is enormous underestimation of wealth at the top in surveys. Further, the issue of non-representativeness of the rich population appears to be worsening over time, especially with the last round of the survey conducted in 2018—the total net wealth from the Forbes list as a percentage of total survey-based wealth increased from 1.26 percent in 2002 to 2.74 percent in 2012 to 6.01 percent in 2018 (based on 5, 46, and 117 individuals respectively). Clearly, Forbes and Hurun rich lists (starting in 1988 and 2012 respectively) provide much better information on the wealthiest Indians than surveys. However, as with tax tabulations, the coverage of these rich lists in terms of number of individuals is very small and hence they are reliable only for the very top of the wealth distribution. Consequently, wealth surveys are supplemented with data from rich lists. The methodology for the post-2002 period can be described in four broad steps.

Step 1: Estimating wealth distribution from surveys

The analysis begins by using the AIDIS micro-data to estimate a survey-based all-India wealth distribution for the years 2002, 2012, and 2018. While the coverage of asset classes has remained largely consistent over time, household durables were excluded in the 2012 and 2018 rounds on the pretext of valuation concerns, except for metals (gold and silver) which were collected under financial assets (see table S2.7 in the supplementary online appendix for more details). Hence, household durables are removed from earlier rounds—while metals are retained—to ensure comparability of the series. Although concerns have been raised regarding the reliability of debt levels estimated in AIDIS (Chavan 2012; Narayanan 1988), the analysis focuses on *net* wealth rather than *total* wealth to remain consistent with rich lists that track only *net* wealth. If debt is underestimated in AIDIS as the literature suggests, then the top shares (at least the top 1 percent and beyond) presented here would be lower bounds since the survey-based estimates would be overestimating the net wealth for the bottom of the distribution.[9]

Step 2: Simulating wealth at the top from rich lists

Rich list data are used to top-correct the AIDIS wealth surveys. It is assumed that surveys are not representative above some percentile p_0 of the wealth distribution, with an associated survey-based wealth w_0. Wealth for the remaining $(1 - p_0)$ percent of the population is simulated by assuming that a Pareto distribution describes the top of the wealth distribution starting w_0. To simulate incomes above w_0, the tail parameter α of the Pareto distribution is needed. It is estimated in two ways using rich lists: the log-linear method and the constant Pareto coefficient method. In the log-linear method, log-wealth is regressed on the log of the normalized rank and α_l is estimated using ordinary least squares as the slope of the line of best fit (based on the power law property of the Pareto distribution). On the other hand, the constant Pareto method assumes a constant inverted Pareto coefficient, leading to $\alpha_c = w/(w - w_0)$, where w is the average wealth of the rich list individuals. Both methods are used to generate the entire top $(1 - p_0)$ percent of the distribution. Compared to the constant Pareto coefficient method, the log-linear simulations produce total wealth estimates at the top that are closer in level to those reported in the rich lists, and therefore appear more accurate (see supplementary online appendix table S2.5).

[7] This remains a crude adjustment necessitated by data constraints. The approach would underestimate true inequality if urban wealth were more skewed in 1961–1971 than in 1981 (less likely scenario) and would overestimate inequality if urban wealth were less skewed in 1961–1971 than in 1981 (more likely scenario).

[8] A non-parametric correction is then applied to convert the household-level distribution to an individual-level distribution—see Bharti (2018, Appendix 7.3.2) for full technical details.

[9] At the same time, rich lists—used to estimate the top tail of the wealth distribution—may also underestimate debt, given the greater visibility of assets relative to liabilities for ultrahigh-net-worth individuals.

Accordingly, the log-linear estimates are retained for the benchmark series.[10] The survey distribution is truncated at p_0 and replaced with the simulated wealth distribution at the top to get a complete distribution. For the survey rounds in 2002 and 2012, $p_0 = 0.999$ implying surveys are assumed to be representative for the bottom 99.9 percent the population. Since the issue of non-coverage of the rich worsened in the 2018 AIDIS round (discussed below), p_0 is set at 0.995 in 2018, implying that the survey is assumed to be non-representative for the top 0.5 percent of the population. It must be stressed that these are likely conservative choices in that surveys are quite likely to be non-representative even at lower percentiles. However, given the limited size of rich lists, a conservative choice is preferred here. The chosen p_0 for each year is presented in supplementary online appendix table S2.2. Robustness of the results to different choices of p_0 are presented later in the paper.

The choice of downward adjusting p_0 for the 2018 round is driven by multiple pieces of evidence on the worsening ability of the AIDIS to capture the right tail. Anand and Kumar (2023) compare the 2012 and 2018 AIDIS rounds and make a strong case for this. First, the wealthiest households in the 2018 survey are located in relatively poorer states and not in states where billionaires are known to live. Second, the shares of households owning equities dropped in 2018, against the backdrop of rising stock-market trading during this period. Third, the contribution of equities in the total net wealth among the top 1 percent is found to be extremely small (just 0.1 percent) and has remained stagnant even though real equity prices grew much faster than precious metal. To these, two further pieces of evidence can be added. The maximum net wealth observed in the 2018 Forbes list was 7,163 times the maximum found in surveys, compared to 3,279 in 2012, indicating a widening gap between surveys and rich lists. Second, there was an overall decline in the real price of agricultural land from 2012 to 2018, dropping from Rs 1.5 million/acre to Rs 1.3 million/acre. This decline was primarily concentrated among the top 10 percent (5.2 million/acre to 3.3 million/acre) while the bottom 50 percent experienced an increase (0.45 million/acre to 0.76 million/acre). In light of these various concerns of growing non-coverage of the top of the distribution, p_0 is downward adjusted from 0.999 to 0.995 from 2018 onward.

Two sources are available to simulate top wealth: the Forbes billionaire rankings and the Hurun rich lists. The final benchmark wealth series relies on the Forbes billionaire rankings rather than the Hurun rich lists, given the substantially longer time coverage (2002 vs. 2012). Both sources, however, yield very similar results. A detailed comparison is provided in the section on wealth inequality. Nonetheless, it is also worth noting that the use of rich lists to estimate top wealth comes with certain limitations. Such rankings involve little transparency about the concepts and methods they use (and rely in practice on limited and unsystematic information sources). As a consequence, they are likely to contain non-trivial measurement error (Davies and Shorrocks 1999; Vermeulen 2016). Moreover, it is possible that these lists entirely miss a small number of individuals, particularly those whose wealth is held through opaque private companies or offshore structures that cannot be linked to a named individual in public filings.[11] Notwithstanding these legitimate concerns, in the absence of any wealth census or tax records, these rich lists provide the best available information on top wealth in India.

Step 3: Generalized Pareto interpolation

Although wealth shares could in principle be estimated at the end of Step 2, the simulations for the very top assume that a *strict* Pareto law applies. Generalized Pareto interpolation techniques provide an alternative, less restrictive approach that does not rely on parametric assumptions, thereby possibly improving the estimation of top wealth over the standard interpolation methods. Using the distribution generated in Step 2, 12 wealth brackets are constructed corresponding to fractiles $p0$, $p0.1$, $p0.2$, $p0.3$, $p0.4$, $p0.5$, $p0.6$, $p0.7$, $p0.8$, $p0.9$, $p0.99$, and $p0.999$, with data on bracket thresholds and averages. These serve as inputs to the generalized Pareto interpolation algorithm.[12] The procedure yields

[10] Supplementary online appendix table S2.6 presents the estimated Pareto parameter based on the log-linear method (α_l) using Forbes and Hurun rich lists.

[11] How would such "missingness" affect the results? If some billionaires are "missing at random," the results should remain unaffected. If missingness is more prevalent at the top (bottom) of the distribution, inequality would be underestimated (overestimated).

[12] The choice of number of fractiles and rank is arbitrary. The rule of thumb is that the number of fractiles should not be very small. Blanchet, Fournier, and Piketty (2022) show that choosing more than 10 fractiles has no discernible effect on the estimates.

a smooth wealth distribution with estimated thresholds, top averages, and shares for 127 generalized percentiles up to $p = 0.99999$ (the wealthiest 0.001 percent).

Step 4: Anchoring to national wealth

From 1995 onwards, estimates of aggregate national wealth (covering household, corporate, and government sectors) are available from Kumar (2019). As with incomes (discussed below), the final wealth distribution is scaled to align aggregate wealth in the series with aggregate national wealth totals, thereby facilitating cross-country comparisons. This step is distributionally neutral and involves scaling up all bracket averages and thresholds by a scaling factor. At the end of this scaling exercise, full wealth distributions matched to national aggregates are available only for years in which both surveys and rich lists are observed. For all other years, only rich lists are available. For missing years after 2002, a survey-based wealth distribution is interpolated by applying the annual growth rate of aggregate national wealth to the entire distribution.[13] The upper tail is then adjusted in each year using annual rich lists (Steps 2 and 3), and the corrected distribution is rescaled to match aggregate national wealth.[14] This procedure yields annual wealth distributions for 2002–2023 that are consistent with the growth of national wealth aggregates over this period.[15]

2.2. Methodology for income series

Combining national accounts, surveys, and tax tabulations in a consistent framework, Chancel and Piketty (2019) present long-run income inequality estimates for India, spanning the period 1922–2014. The series is extended to 2022–23 in a comparable manner. The distributional national accounts (DINA) framework is then followed to combine surveys and tax data. The overall methodology can be described in four broad steps.

Step 1: Estimating top incomes from tax tabulations

Annual tax tabulations published by the Indian income tax authorities are used to extract the distribution of top income earners between 2014 and 2022. These tabulations report the total number of income tax returns filed and total assessed income across 25 income brackets, disaggregated by type of tax filer (individuals, corporations, etc.). Individuals and Hindu Undivided Families (HUFs) are treated as the relevant tax units and combined at the bracket level for the analysis.[16] The adult (20+) population is used to define fractiles corresponding to income thresholds in the tax data, based on the number of returns in each bracket. Generalized Pareto interpolation techniques developed in Blanchet, Fournier, and Piketty (2022) are then applied to extract a smooth distribution of top income earners from the tax tabulations. These techniques relax the strict Paretian assumption, operate without imposing parametric restrictions, and have been shown to outperform standard Pareto interpolation methods. The result is an annual smooth distribution of top income earners.

Step 2: Estimating middle and bottom incomes from surveys

Given the limited coverage of tax data, it can be considered reliable only for top incomes, covering at most about 10 percent of the adult population in recent years. To estimate incomes for the rest of the population, household surveys must be used. Chancel and Piketty (2019) use successive rounds of

[13] For example, the 2012 survey distribution is grown using the aggregate wealth growth rate between 2012 and 2013 to obtain the survey-based wealth distribution for 2013.

[14] With extremely skewed distributions (as is very much case with wealth in India), a lot of the action in terms of inequality is often happening in the right tail and these annual top corrections using rich lists speak to that fact. Indeed, as Atkinson (2007) highlighted, letting S^* be the wealth share of a tiny (infinitesimal) group at the very top, the Gini coefficient of the distribution can be approximated as $S^* + (1 - S^*)G$, where G is the Gini coefficient for the rest of the population. See also Alvaredo (2011) on the relationship between top shares and the Gini coefficient.

[15] For 2023, the full Hurun rich list is available, whereas the Forbes billionaire rankings are not. To construct 2023 estimates consistent with prior years, Hurun-based estimates are first generated and then multiplied by the ratio of Forbes to Hurun estimates over 2018–2022, when both sources are available. As shown below, the levels and trends from Forbes and Hurun are highly similar throughout the study.

[16] Starting in 2011, the tax authorities also began publishing a separate annual volume titled "Income Tax Time Series Data" (ITSD), which reports the total number of *effective* taxpayers—defined as the sum of units filing income tax returns and those paying tax at source without filing a return. Comparing total filers in the tax tabulations with total effective taxpayers in the ITSD yields an estimate of non-filers missing from the tabulations, which are used to scale up total returns. Because the ITSD does not provide bracket-level information on effective taxpayers, non-filers are distributed proportionally across brackets, implicitly assuming identical distributions. Chancel and Piketty (2019) examine alternative allocation methods—for example, assigning all non-filers to the lowest brackets—and find limited quantitative differences.

NSSO's Consumption Expenditure Surveys (CES), available at regular intervals between 1951 and 2011, to estimate a per-adult equal-split consumption distribution. To move from a consumption distribution to an income distribution, they apply "consumption-to-income" scaling ratios estimated from two rounds of the India Human Development Survey (IHDS) conducted in 2004–05 and 2011–12. Further, for the period 2004–2011, they find growth rates of per capita income in IHDS to be higher across the entire distribution than the growth rates in per capita consumption in CES over the same period. Therefore, they use the IHDS growth rates to generate an income distribution for the period 2004–2011, which deliver lower inequality than using the CES.

The main challenge with extending the series to the most recent years is the absence of any reliable and temporally comparable income or consumption or survey post 2011–12. Another scheduled CES round was conducted in 2017–18, but the survey report and micro-data were suppressed on grounds of poor data quality.[17] An analysis of the numbers in a leaked summary of the report suggests that the consumption levels in real terms may have fallen across the distribution (Subramanian 2019). Fresh CES rounds were then conducted in 2022–23 and 2023–24 and comparing them to the CES 2011–12 round would suggest that both inequality and poverty declined. However, as it turns out, there were key changes to the methodology that raise serious issues for inter-temporal comparability (Anand 2024; Manna 2024; Mohanan and Kundu 2025; National Sample Survey Office 2024). These include multiple visits to canvas the questionnaire compared to a single visit in earlier rounds, an expanded list of items for which consumption was recorded, and the inclusion of imputed value of consumption goods received free of cost through various social welfare benefits. Additionally, the updated sampling design meant that a certain proportion of the rural sample came from villages close to urban areas (Anand 2024).

To address these concerns, the analysis draws on the Periodic Labour Force Survey (PLFS), available annually since 2017. While PLFS is primarily a labor force survey, it collects data on households' "usual" consumption expenditure as part of its household listing exercise. Unlike the traditional approach of CES, which collects detailed data on expenditures on individual commodities, the consumption data in PLFS are based on four or five very broad questions. This difference in measurement is likely to render the consumption measures in PLFS and CES incomparable (Deaton and Kozel 2005). To address this issue, the analysis exploits the fact that the suppressed 2017–18 CES round roughly coincided with the 2017–18 PLFS round. Because both surveys were conducted by the NSSO and their sampling designs were quite similar, differences in reported consumption are attributed to differences in measurement across the survey instruments.[18] A pointwise comparison of the CES and PLFS consumption distributions in 2017–18, separately for rural and urban areas, yields a mapping between the two consumption concepts.[19] The resulting PLFS-to-CES scaling ratios show that, absent this correction, inequality would be systematically overestimated because PLFS tends to under-record consumption among poorer households relative to richer ones (supplementary online appendix fig. S3.1).[20] Applying these scaling ratios yields CES-comparable annual consumption distributions for 2017–2022. Following Chancel and Piketty (2019), consumption-to-income scaling ratios are then applied to obtain survey-based income distributions (supplementary online appendix fig. S3.2). Finally, missing years between 2011 and 2017 are interpolated to construct a continuous annual series of survey-based incomes spanning 2011–2022.

[17] On the heels of this decision, 108 eminent economists and social scientists made a public appeal to the government to "restore access and integrity to public statistics...that would feed into economic policy-making and that would make for honest and democratic public discourse"—see Kazmin (2019) for details.

[18] While the sampling designs of PLFS and CES 2017–18 were broadly similar, they were not identical. First, the urban PLFS sample follows a quarterly panel design, whereas CES is cross-sectional. Since the objective is to produce *annual* estimates, only first-visit observations are retained, effectively rendering the PLFS cross-sectional. Second, the PLFS employs a different second-stage stratification variable for household sampling. With appropriate sampling weights, however, estimates remain unbiased and comparable across designs, although variances may differ.

[19] For 2017–18, this procedure exactly reproduces the CES distribution. Although the resulting scaling ratios strictly apply only to 2017–18, they are likely to remain stable over time if differences across surveys stem primarily from differences in survey instruments, which did not change in this respect for PLFS. These ratios are therefore applied to subsequent years (2019–2022).

[20] This is unsurprising given that PLFS records consumption using a limited set of questions.

Robustness to alternative survey-based estimates of bottom incomes is assessed using CPHS, PLFS, and the 2022–23 CES round. These alternate approaches are discussed in the section on income inequality results.

Step 3: Combining tax and survey distributions

Upon completion of Steps 1 and 2, two income distributions are obtained: one generalized from tax data and the other estimated from household surveys. The former is more reliable for top incomes, whereas the latter is more reliable for bottom incomes. For $0 < p_1 < p_2 < 1$ denoting percentiles in the distribution, surveys are assumed to be reliable up to some percentile p_1, while tax data are assumed to be reliable between p_2 and 1. Following Chancel and Piketty (2019), p_1 is set at the 90th percentile, and p_2 is determined in a data-driven manner and allowed to vary by year based on the growth rate of the adult population and the total number of effective tax filers. In 2015, p_2 is set at 0.92, declining to 0.90 by 2022 (see supplementary online appendix table S3.2). With p_1 and p_2 determined, a "growth rate" approach is employed to extend the inequality series to 2022. The full income distribution for 2014 estimated by Chancel and Piketty (2019) serves as the baseline. For each year t from 2015 onward, percentile-specific growth rates between years t and $t-1$ are estimated using both survey and tax data.[21] For percentiles below p_2, survey-based growth rates are applied, whereas for percentiles above p_2, growth rates derived from tax data are used. This approach is conceptually identical to that used pre-2014 but is more flexible in requiring only representative growth rates at each percentile between two consecutive years.

Step 4: Anchoring to national income aggregates

A long-standing and well-acknowledged issue in the Indian context since the 1980s is the sharp divergence of growth rates of consumption observed in NSSO household surveys and those inferred from national accounts data. Chancel and Piketty (2019) show that some of this gap can be explained by missing top incomes in surveys, but a non-trivial fraction of the gap remains unexplained. To facilitate cross-country comparisons and ensure consistency with DINA guidelines, the merged survey–tax distribution is scaled so that aggregate income matches national income accounts totals. This step is distribution-neutral as it involves scaling all income threshold and averages by a constant factor, but leaves income shares unchanged. A significant part of this gap may be explained by undistributed profits of corporations (that is, profits part of national income estimates that are not reported in tax data or survey data). Therefore, it is likely that the method underestimates incomes of the richest segments of the population, as evidence from other countries suggests.[22]. This procedure implies the growth rate of average incomes in the series matches the growth rates observed in national accounts data. The result is a set of annual estimates of the full income distribution for 2015–2022 that are consistent with aggregate national income growth over this period.

At this stage, it is worth highlighting that various concerns have been raised regarding the reliability of Indian national accounts data in recent years, in particular that they overstate economic growth (stemming partly from the use of highly outdated data inputs—see supplementary online appendix S4). For the purposes of the analysis here, the official statistics are taken as given. If this is indeed the case, true inequality would be underestimated.

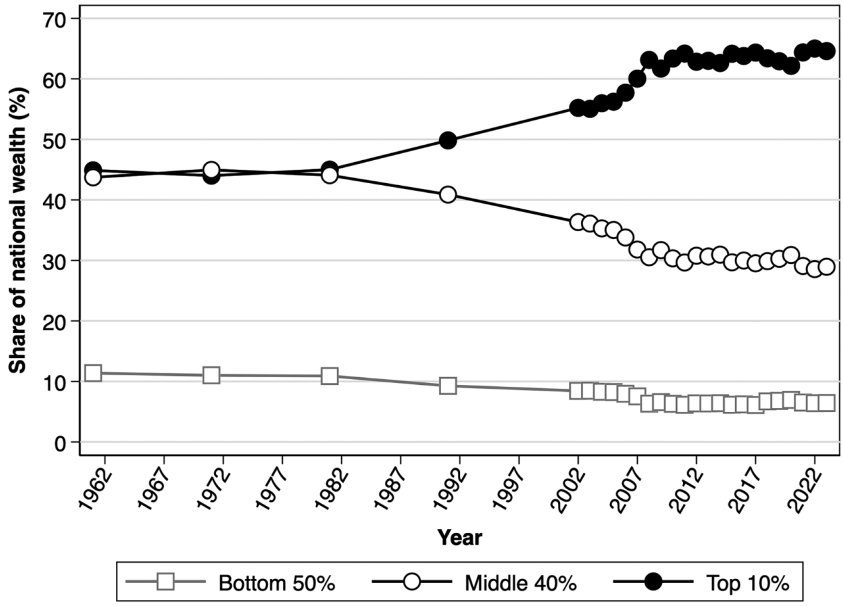
3. Wealth inequality in historical perspective

The wealth series begins in 1961 when AIDIS began. Between 1961 and 1991, only decadal estimates are available. From 2002 onward, sufficiently comprehensive rich lists and aggregate wealth estimates allow the construction of an annual series. Figure 4 presents a summary of long-run wealth inequality. Between 1961 and 1981, the wealth shares of different groups remained stable. From 1991 onward, wealth concentration exhibits an uptick that accelerates through the 2000s, mirroring the pattern observed for incomes. From 45 percent in 1961, the top 10 percent wealth shares increased to 65 percent in 2022–23. On the other hand, both the bottom 50 percent and middle 40 percent shares have

[21] A kink in the growth rates at the merging point p_2 is corrected through linear interpolation between adjacent percentiles. For 2020, unusually high growth rates at $p93$, $p94$, and $p95$, which appear inconsistent with neighboring percentiles, are similarly adjusted using linear interpolation.

[22] See DINA Guidelines (Blanchet et al. 2017)

Figure 4 Long-run wealth inequality in India, 1961–2023



Source: Authors' estimates combining national wealth aggregates, wealth surveys, and Forbes billionaire data.
Note: The figure presents the distribution of per-adult national wealth.

Table 2 Wealth inequality in India, 2022–2023

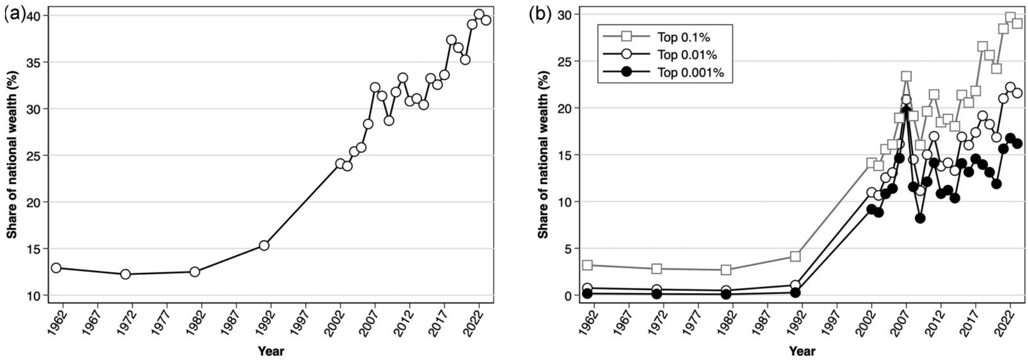
Wealth group	Adults	Wealth share (percent)	Threshold (INR)	Average wealth (INR)	Ratio to average
Average	922,344,832	100.0	−41,000,000	1,349,029	1.0
Bottom 50 percent	461,172,416	6.4	−41,000,000	173,184	0.1
Middle 40 percent	368,937,933	28.6	431,138	963,560	0.7
Top 10 percent	92,234,483	65.0	2,198,344	8,770,132	6.5
Top 1 percent	9,223,448	40.1	8,160,022	54,141,525	40.1
incl. top 0.1 percent	922,345	29.7	52,617,860	400,454,807	296.8
incl. top 0.01 percent	92,234	22.2	368,680,160	2,996,773,491	2,221.4
incl. top 0.001 percent	9,223	16.8	2,756,699,904	22,613,354,928	16,762.7

Source: Authors' estimates combining national wealth aggregates, wealth surveys , and Forbes billionaire rankings.
Note: The table presents a summary of wealth inequality in India in 2022–23. All INR values in current (2022) prices. Adult population estimates for 2022 from UN World Population Prospects. Average wealth scaled to match aggregate national wealth as per World Inequality Database data. See Data and methodology section for details. The threshold of INR −4.1 crore for the bottom 50 percent is driven by one observation in All India Debt & Investment Survey (AIDIS) with enormous debt. The *p*2 in the distribution is INR −4, 000 and the average wealth for the bottom 50 percent after dropping the extreme negative outlier is 193,031.

significantly fallen over this period. Supplementary online appendix table S2.1 presents the full series of the bottom 50 percent, middle 40 percent, top 10 percent, top 1 percent, and top 0.1 percent wealth shares.

Table 2 summarizes wealth inequality in 2022–23 and presents wealth levels and thresholds for different wealth groups. The top 1 percent possesses an average of INR 54 million in wealth, 40 times the average Indian. The bottom 50 percent and the middle 40 percent hold INR 0.17 million (0.1 times national average) and INR 0.96 million (0.7 times national average) respectively. At the very top of the

Figure 5 (a) Top 1 percent national wealth share, 1961–2023. (b) Inequality within the wealthiest 1 percent, 1951–2023



Source: Authors' estimates combining national wealth aggregates, wealth surveys, and Forbes billionaire data.
Note: The figures present the distribution of per-adult national wealth.

distribution, the wealthiest ∼10,000 individuals out of 920 million Indian adults own an average of INR 22.6 billion in wealth, 16,763 times the average Indian.

3.1. Top 1 percent and top 10 percent shares

Between 1961 and 2023, the top 1 percent wealth share increased three-fold, from 13 percent to 39 percent (fig. 5a). Most of these gains came post-1991 after which point the top 1 percent shares have been on a steep upward trend right until 2022–23. Moreover, wealth is highly concentrated even *within* the top 1 percent (fig. 5b). Consider this: in 2022–23, the top 1 percent wealth share was 39.5 percent of which 74 percent went just to the top 0.1 percent (29 percent wealth share), 55 percent to just the top 0.01 percent (22 percent wealth share), and 40 percent to just the top 0.001 percent (16 percent wealth share). In 1961, the top 10 percent wealth share was 45 percent. It declined by 1 percentage point between 1961 and 1971, the only decade when a decline is observed.[23] Between 1961 and 1981, the top 10 percent shares did not change much. The same applies to the top 1 percent and top 0.1 percent shares as well. This pattern is perhaps unsurprising, as this was the period when socialist policies were at their peak and the process of wealth concentration was largely brought to a standstill. After 1981, with the shift from socialist policies toward market-based reforms, the top 10 percent wealth shares have risen steadily over the next three decades, reaching 63 percent in 2012.

From 2012 onwards, the growth of the top 10 percent shares seems to have slowed down. In between 2012 and 2018 (the last two AIDIS rounds), the top 10 percent shares increased marginally by 0.6 percentage points from 62.8 percent to 63.4 percent. This contrasts with the shares of the top 1 percent and beyond which have continued to rise even over the last decade. These trends are consistent with those reported in Anand and Kumar (2023), albeit at lower inequality levels.[24] Nonetheless, as it happens, the annual series suggests that 2020 was the year with the lowest top 10 percent shares during the entire last decade. In 2019, the top 10 percent shares remained almost the same, before falling to 62 percent in 2020 at the time of the COVID-19 crisis. Since then, the top 10 percent shares reverted to an upward trend over the next three years and were at 65 percent in 2023.

[23] The piecemeal land redistribution that happened in some parts of the country could have contributed to this.

[24] This is due to methodological differences. They supplement AIDIS using Hurun rich lists (the benchmark series relies on Forbes) to estimate a Pareto tail parameter (using the log-linear approach), but they assume a much lower cutoff point ($p0$) from which surveys are deemed non-representative. Their choice (INR 1 million) in 2012 leads to correcting approximately the top 10 percent of the distribution. In the analysis presented in this paper, a power law is assumed to apply only at the very top of the distribution, correcting the AIDIS survey for the top 0.1 percent before 2018 and the top 0.5 percent thereafter.

3.2. Bottom 50 percent and middle 40 percent shares

The sharp rise in the top 10 percent shares from 1991 onwards came at the loss of both the bottom 50 percent and middle 40 percent shares. From stagnating at 11 percent between 1961 and 1981, the bottom 50 percent shares first fell to 9.3 percent in 1991 and further to 8.5 percent by 2002 (fig. 4). Since then, they consistently declined, to reach 6.3 percent in 2008, and hovered between 6 and 7 percent over the next two decades, with no signs of recovery. In 1961, the bottom 50 percent and top 1 percent shares were identical; by 2022–23, the top 1 percent share was more than 5 times larger (supplementary online appendix fig. S2.1a). Nonetheless, while extremely low, when placed in comparative perspective, the bottom 50 percent shares in India are comparable to those in China (6 percent), United Kingdom (5 percent), and France (5 percent) in 2022, and significantly higher than the United States (1 percent).

In the post-liberalization years of high growth and rising inequality, the wealth shares of the middle 40 percent have taken the greatest hit. This is partly since the bottom 50 percent wealth shares were so low to begin with (9 percent in 1991) that the large gains made by the top 10 percent in terms of their wealth share in the subsequent years could only come at the expense of the middle 40 percent shares. Between 1961 and 1981, the middle 40 percent and top 10 percent were nearly identical (between 40 and 45 percent). Over the next three decades, the top 10 percent shares pulled ahead, while the middle 40 percent shares consistently fell, to reach 31 percent by 2012, marginally rising to 32 percent in 2018, and have since fallen to 29 percent by 2023 (supplementary online appendix fig. S2.1b). The proximate factors behind these patterns are discussed in the mechanism section.

3.3. Robustness of wealth series

Constructing the long-run benchmark wealth inequality series requires several key methodological choices. This section assesses the robustness of the series to alternative specifications.

The first choice to be made is whether to use the Forbes billionaire lists or the Hurun rich lists to top-correct the AIDIS. Starting in 1988, the Forbes magazine has been tracking the wealth of all Indians with net wealth exceeding 1 billion USD MER and publishing an annual billionaire ranking. Similarly, since 2012, the luxury research organization Hurun has been publishing an annual rich list for India, going beyond just USD billionaires, covering all Indians with a net wealth exceeding INR 1,000 crore (roughly 120 million USD MER as on March 1, 2024). Given the lower threshold for inclusion, the Hurun rich list has the clear advantage of covering a larger number of individuals than the Forbes. Over the most recent years (2018–2022), Hurun covers between 830 and 1,100 individuals compared to 119–162 in the Forbes rankings. Given the longer time coverage, the benchmark series is based on the Forbes data. Sensitivity to the choice between Forbes and Hurun is assessed for the years 2012 onward, when both series are available. The two sources yield nearly identical levels and trends over the 2012–2022 period, with the exception of 2022, when they diverge (see fig. S2.2 and table S2.6 in the supplementary online appendix).

The other choice to be to made is the cutoff point beyond which the wealth survey is considered non-representative. To gauge how the choice of p_0 affects the inequality estimates, tables S2.3 and S2.4 along with supplementary online appendix figs S2.3a, S2.3b, and S2.3c present the top shares for 2012 and 2018 under different choices of p_0. Not surprisingly, assuming a lower p_0 delivers higher top shares (except at the very top—top 0.001 percent—where the threshold choice matters little). For example, the top 10 percent share rises from 62.8 percent with $p_0 = 99.9$ to 69.5 percent with $p_0 = 90.0$ in 2012. The top shares based solely using the AIDIS (without any top correction) are provided in the last row of each table.

For the benchmark series, the cutoff point (p_0) is set at $p0.999$ till 2017 and $p0.995$ from 2018 onward. Supplementary online appendix figs S2.3a and S2.3b show that irrespective of the choice of the p_0, the top 0.1 percent and top 1 percent wealth shares increased between 2012 and 2018. With regard to the top 10 percent shares, however, the matter is a bit more complicated (see supplementary online appendix fig. S2.3c). In particular, if p_0 is kept fixed at $p0.999$ in 2018, then the top 10 percent shares are found to be marginally lower in 2018. However, as discussed earlier in the paper, multiple pieces of evidence show that the issue of non-coverage of the rich in the AIDIS worsened between 2012 and 2018,

Table 3 Survey-based asset composition of wealth

Year	Wealth group	Real estate	Business	Metal	Finance	Debt
1991	Average	87.2	6.9	3.9	4.1	−2.1
2002	Average	87.9	8.0	1.9	5.3	−3.2
2012	Average	92.4	3.8	3.8	3.5	−3.5
2018	Average	91.5	4.0	3.2	6.9	−5.6
1991	Bottom 50%	83.6	10.9	8.1	5.5	−8.1
2002	Bottom 50%	88.6	11.4	4.9	5.5	−10.5
2012	Bottom 50%	90.0	8.6	12.1	5.3	−16.0
2018	Bottom 50%	96.1	8.7	10.1	10.2	−25.0
1991	Middle 40%	86.3	7.1	4.5	4.2	−2.1
2002	Middle 40%	88.0	8.0	2.1	5.0	−3.0
2012	Middle 40%	89.7	4.9	5.3	3.9	−3.8
2018	Middle 40%	90.0	4.3	3.8	7.2	−5.3
1991	Top 10%	88.6	6.0	2.7	3.7	−1.1
2002	Top 10%	87.7	7.4	1.3	5.5	−1.9
2012	Top 10%	94.2	2.7	2.1	3.0	−2.0
2018	Top 10%	91.8	3.0	1.6	6.2	−2.5

Source: Authors' estimates from successive rounds of the All India Debt and Investment Surveys (AIDIS).
Note: The table presents a decomposition of net wealth by asset class for the average household (first panel) and the bottom 50 percent, middle 40 percent and top 10 percent (last three panels respectively). The last column presents household debt and the rows sum to 100 percent. Real estate includes both land and building. Note, however, that since these results are based solely on the AIDIS survey rounds (without any top-correction using rich lists), they are likely miss the right tail of the distribution.

in light of which the choice to downward adjust p_0 in 2018 is made. Overall, these choices of p_0 are likely to be conservative given that the AIDIS is likely to be unrepresentative at even lower percentiles.

Lastly, because AIDIS surveys stopped recording durable goods after the 2002 round, household durable assets are excluded from earlier years as well—except for metals, which are recorded under financial assets in later rounds—to ensure consistency across years. The implications of this adjustment are assessed by comparing wealth shares with and without durable assets for 2002, the final survey year that recorded household durables and the first year with sufficient coverage in the Forbes rich list. The inequality estimates are very close to each other. The exclusion of durable assets (as is in the benchmark series) leads to only a small decrease in the top shares. For e.g., the top 1 percent wealth share decreases by 0.3 percentage points (pp) and the top 10 percent wealth share is lower by 0.4 pp.

3.4. Survey-based decomposition of asset classes

The AIDIS wealth surveys provide a rich data source that allows total wealth to be disaggregated into various asset classes. However, the rich lists used to top-correct the AIDIS do not provide any decomposition by asset class. Therefore, the methodology and main results abstract away from the underlying assets and focus on the total net wealth distribution. This subsection examines the composition of the wealth portfolios of Indian households using the AIDIS surveys, with the important caveat that these surveys capture the right tail of the distribution imperfectly. These results are, therefore, unlikely to be reliable for the top of the distribution. Nonetheless, it allows an assessment of how different assets are distributed across the wealth distribution and of the components driving inequality in the final wealth index.

The analysis begins by decomposing the wealth basket of the average Indian household over the 1991–2018 period using AIDIS micro-data (see table 3). The asset types include—real estate (land and building), business assets (consisting of productive capital—livestock, transport, farm, and non-farm equipment), metal (gold, silver, or any bullion), and financial wealth, while the last column is overall debt. Two observations are worth making. First, physical assets dominate household wealth—land and building jointly make up almost 90 percent of the total household wealth, a share that has remained very stable.[25] Second, the share of financial assets increased between 1991 and 2018, but only modestly from 4 percent to 7 percent. The estimates for recent years are likely to be underestimates as surveys are known to capture financial wealth only imperfectly.[26]

Next, asset shares are decomposed along the survey-based *net wealth* distribution, focusing on the bottom 50 percent, middle 40 percent, and top 10 percent. The importance of real estate runs throughout the wealth distribution and has remained the most prominent asset over time. In fact, its share in the wealth basket has grown over the years. For e.g. the share of real estate in the net wealth of the middle 40 percent increased from 86 percent in 1991 to 90 percent in 2002. At the same, there is a notable declining trend in the share of business assets (including productive capital) in total net wealth, throughout the distribution. For e.g. in the bottom 50 percent, the business assets shares declined from 11 percent in 1991 to 9 percent in 2018. Further, among the bottom 50 percent, there is an increasing share of unproductive capital in the form of metals (gold, silver etc.). The rising financial assets share is also prevalent across the wealth distribution, despite the fact that it is poorly captured in surveys. The wealth basket of an average Indian household appears quite unique. For instance, in South Africa in 2017—of all the assets owned by the bottom 50 percent—real estate formed 46 percent and financial assets 49 percent (Chatterjee, Czajka, and Gethin 2022).[27] China comes closer in comparison, where in 2012, real estate formed 74 percent, rising from 35 percent in 1995, 58 percent in 2002—though still much lower than India. Financial assets are also relatively lower in China at around 11 percent, which is around 30 percent in OECD countries (Xie and Jin 2015). The comparison with developed economies is bound to show differences; however, the magnitudes are of interest. Sabet and Gathen (2025) compare the asset-holding shares between India and the United States in the 2010s, and highlight three important differences. First, net financial assets shares in India are just one-third of the United States. Second, business wealth is much larger in India due to the prevalence of high shares of self-employment and the majority in the agriculture sector. Third, gold plays a central role in Indian households, while it is almost absent in US households. Similar to the findings presented here, they find that poor households hold a much higher share of gold in their wealth portfolios.[28] Next, the drivers of observed trends in survey-based wealth inequality are examined component by component. These results are reported in table 4, which presents the component-by-component analysis by constructing distributions by asset type and reporting the bottom 50 percent, middle 40 percent, and top 10 percent shares. The analysis begins with the land value distribution, the most important asset in the household wealth basket. Building values are then incorporated to obtain the real estate distribution, followed by the inclusion of business assets, metals, and financial assets. Finally, debt is subtracted to derive the survey-based *net wealth* distribution. Several interesting findings emerge. First, while land is the most important asset, it is also worst distributed across the population. In each year, the bottom 50 percent shares are the lowest based on the land value, at about 5 percent. The bottom 50 percent shares jump to 8–9 percent after adding the building value. This jump shows that the poorest strata owns some form of homestead land in India, especially in the rural areas, which keeps the bottom 50 percent shares slightly higher when compared to other countries. Business assets or productive capital also have an inequality decreasing impact across the years. In each survey round, the bottom 50 percent share increases by 0.5 percentage points once business assets are added to real estate values. Similarly, adding gold and financial asset values increases the bottom 50 percent shares. However, the jump observed in the bottom 50 percent shares after adding business, gold, and silver in each subsequent step, is lower than the jump observed earlier after adding the building value, as their contribution in the total assets is much lower. Finally, once

[25] In fact, the shares have remained stable over the last six decades (1961–2018) based on the AIDIS reports.

[26] For instance, as per Sabet and Gathen (2025), the total bank deposits (classified under financial assets) recorded in the AIDIS 2012 round add up to only roughly 30 percent of the macro-level data from banks provided by the Reserve Bank of India.

[27] Chatterjee, Czajka, and Gethin (2022) also note that surveys severely underestimate financial assets, which surely applies to the results for India, as discussed further below.

[28] In France the share of financial assets stood at 30.9 percent in 1979 (Kessler and Wolff 1991). With regards to the share of real estate in total wealth, it stood at 54.2 percent in Austria in 2002, 38 percent in Italy in 2000, and 52 percent in the United States in 2002 Xie and Jin (2015).

Table 4 Survey-based decomposition of wealth inequality by asset

Year	Asset	Bottom 50%	Middle 40%	Top 10%
1991	Land	5.0	38.0	57.0
1991	+ Building	8.1	40.8	51.1
1991	+ Business	8.7	40.9	50.5
1991	+ Metals	9.3	41.0	49.7
1991	+ Finance	9.7	40.9	49.4
1991	− Debt (= net wealth)	9.3	40.9	49.8
2002	Land	5.3	37.2	57.5
2002	+ Building	8.9	40.6	50.5
2002	+ Business	9.4	40.7	49.9
2002	+ Metals	9.7	40.7	49.6
2002	+ Finance	10.0	40.6	49.4
2002	− Debt (= net wealth)	9.4	40.6	49.9
2012	Land	3.8	31.0	65.2
2012	+ Building	6.1	32.4	61.5
2012	+ Business	6.5	32.8	60.7
2012	+ Metals	7.2	33.2	59.6
2012	+ Finance	7.4	33.4	59.2
2012	− Debt (= net wealth)	6.9	33.2	59.9
2018	Land	4.8	35.4	59.8
2018	+ Building	8.1	38.8	53.2
2018	+ Business	8.6	38.9	52.5
2018	+ Metals	9.3	39.1	51.6
2018	+ Finance	9.7	39.2	51.1
2018	− Debt (= net wealth)	8.8	39.1	52.1

Source: Authors' estimates from succesive rounds of the All India Debt & Investment Surveys (AIDIS).
Note: The table presents the bottom 50 percent, middle 40 percent, and top 10 percent wealth shares, adding one asset class at a time. It begins with estimating wealth shares when looking only at land. Then buildings are added to land and wealth shares are recomputed, and so on for other assets. This allows quantification of the contribution of each asset class to the total wealth inequality. The final row (after accounting for debt) equals the net wealth concept that is observed in the AIDIS. Note, however, that since these results are based solely on the AIDIS survey rounds (without any top correction using rich lists), they likely miss the right tail of the distribution.

debt is subtracted to construct the survey-based distribution, the bottom 50 percent share declines. This is because the bottom 50 percent in the survey have a considerably larger debt share.

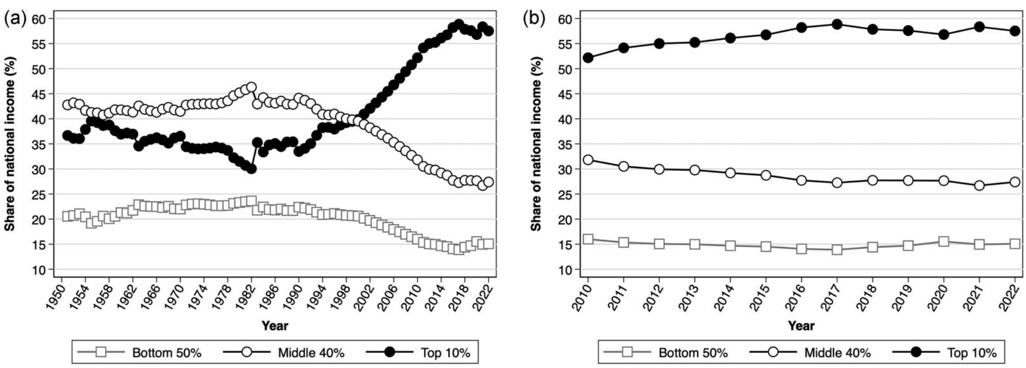
As noted earlier, these results on the asset class decomposition based on the AIDIS rounds must be interpreted cautiously given the absence of the right tail in the surveys, combined with the high levels of concentration at the top that are driving recent trends of overall wealth inequality. Systematic data on the asset portfolio of the very wealthy are hard to come by, but some information can be gleaned based on reports by wealth management funds. For instance, the 2024 "Top of the Pyramid" report by Kotak Mahindra Bank provides some insights on the investment portfolio of ultrahigh-net-worth individuals (UHNI) based on in-depth interviews with 150 UHNIs across 12 Indian cities. As per their results, UHNIs allocated one-third of their portfolio to equity, roughly one-third to real estate, about one-fifth to debt, and the remainder in other assets like gold and currency. These figures differ markedly from those reported in the AIDIS. For instance, the share of equities has remained below 1 percent in recent years even at the very top of the distribution, despite the expansion of stock-market trading.

Table 5 Income inequality in India, 2022–2023

Income group	Adults	Income share (percent)	Threshold (INR)	Average income (INR)	Ratio to average
Average	922,344,832	100.0	0	234,551	1.0
Bottom 50 percent	461,172,416	15.1	0	71,472	0.3
Middle 40 percent	368,937,933	27.4	105,817	165,710	0.6
Top 10 percent	92,234,483	57.5	284,718	1,348,991	5.8
Top 1 percent	9,223,448	23.3	2,271,695	5,456,962	23.2
incl. top 0.1 percent	922,345	9.2	8,239,304	21,616,466	92.1
incl. top 0.01 percent	92,234	4.1	32,386,494	95,569,439	407.5
incl. top 0.001 percent	9,223	2.0	191,194,127	463,373,934	1,976.6

Source: Authors' estimates combining national income accounts aggregates, tax tabulations, and surveys on income and consumption.
Note: The table presents a summary of income inequality in India in 2022–23. All INR values in current 2022 prices. Adult population estimates for 2022 from UN World Population Prospects. Average income scaled to match national income accounts totals from the World Inequality Database (which differs marginally from official sources). See Data and methodology section for details.

Figure 6 (a) Long-run income inequality in India, 1951–2022.(b) Short-run income inequality in India, 2010–2022

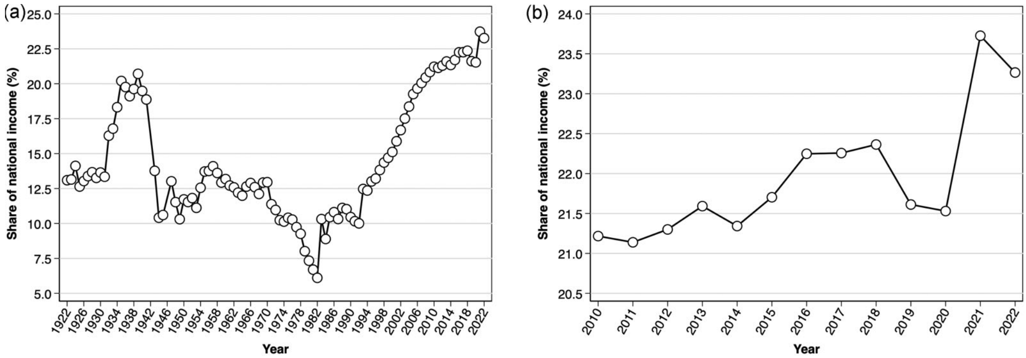


Source: Chancel and Piketty (2019) for pre-2015 estimates and authors' estimates for the 2015–2022 period.
Note: The figures present the long-run and short-run trends of per-adult net national income shares.

4. Income inequality in historical perspective

In 2022–23, the top 1 percent earn on average 5.5 million, 23 times the average Indian (INR 0.23 million)—see table 5. Average incomes for the bottom 50 percent and the middle 40 percent stood at INR 71,000 (0.3 times national average) and INR 165,000 (0.7 times national average) respectively. At the very top of the distribution, the richest ∼10,000 individuals (of 920 million Indian adults) earn on average INR 463 million (1,977 times the average Indian). To get a sense of just how skewed the distribution is, one would have to be at nearly the 90th percentile to earn the average income in India. Supplementary online appendix table S3.1 presents the full series of the bottom 50 percent, middle 40 percent, top 10 percent, top 1 percent, and top 0.1 percent income shares. Figure 6 a presents a summary of long-run income inequality dynamics in India over 1951–2022, combining the series for the latest years with the long-run series presented in Chancel and Piketty (2019). Figure 6 b presents the short-run trends over the 2010–2022 period. The share of national income going to the top 10 percent fell from 37 percent in 1951 to 30 percent by 1982 after which it began steadily rising. From the early 1990s onwards, the top 10 percent share increased substantially over the next three decades, nearly touching 60 percent in the most recent

Figure 7 (a) Top 1 percent national income share in the long run, 1922–2022. (b) Top 1 percent national income share in the short run, 2010–2022



Source: Chancel and Piketty (2019) for pre-2015 estimates and authors' estimates for the 2015–2022 period.
Note: The figures present the long-run and short-run trends of the pre-tax per-adult net national income going to the top 1 percent.

years. At the other end of the distribution, the bottom 50 percent were getting only 15 percent of India's national income in 2022–23.

4.1. Top income shares

The availability of tax tabulations going back to 1922 when the Income Tax Act was enacted by the British administration allows for documenting the evolution of the top 1 percent income share over an entire century (fig. 7a). The top 1 percent share increased significantly (to over 20 percent) during in the inter-war period, then experienced a dramatic fall during the 1940s (to 13 percent by the time of India's independence). After briefly rising during the 1950s, the top 1 percent shares consistently fell over the next two decades and reached 6.1 percent by 1982. A fall in the top 10 percent share is also observed, though the decline was smaller than at the very top. Since the early 1980s, when the Indian government began initiating a broad range of economic reforms leading up to the liberalization in 1991, the decline in the top 1 percent and top 10 percent shares halted, and from the early 1990s onwards, top shares began sharply rising and have continued to do so in recent years. By 2021–22, the top 1 percent share was at an all-time high of nearly 24 percent. Focusing on the last decade (fig. 7b), the top 1 percent share rises gradually between 2010 and 2018, experiences a minor dip in 2019 (when tax filings fell) and 2020 (during COVID-19 waves and lockdowns), and then increases sharply in the post-COVID period.

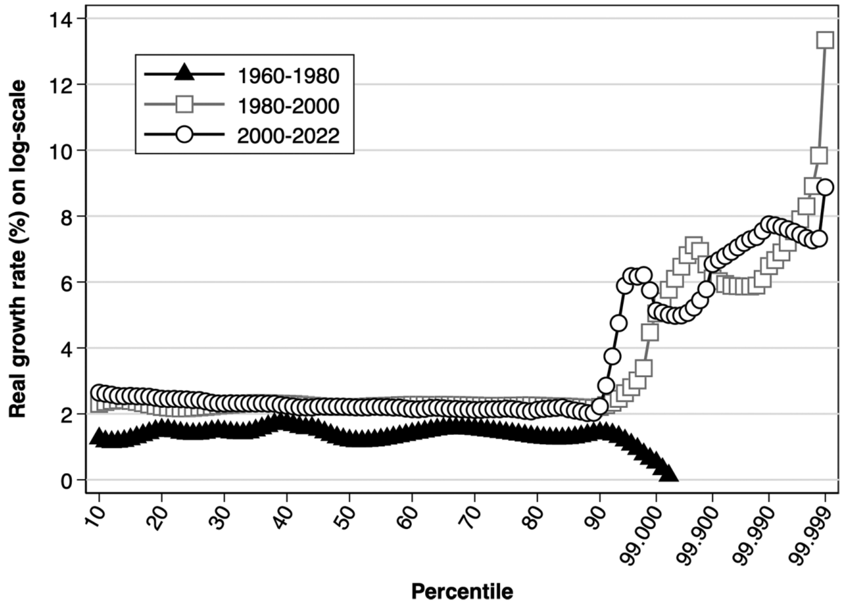
With regard to the top 10 percent share, it continues to rise until 2017, after which it stabilized (fig. 6b). What made the top 10 percent shares stabilize after 2017? The evidence suggests that this was driven by the slowdown in economic growth after 2017 combined with the pro-cyclical nature of inequality in India (and elsewhere). More specifically, growth rates of average incomes fell from over 6 percent in 2015 and 2016, to 4.7 percent in 2017, 4.2 percent in 2018, and then dramatically to 1.6 percent in 2019, after which incomes took a severe hit during the COVID-year of 2020 (see supplementary online appendix fig. S3.3). Given that growth in India in recent decades has exhibited a clear pro-rich bias, it is then not surprising to find a stabilization in inequality when growth slows down (Ghatak, Raghavan, and Xu 2022).[29] Once COVID lockdowns were lifted and growth resumed in 2021 and 2022, the top 1 percent share rises sharply, accompanied by a modest increase in the top 10 percent share.

4.2. Bottom shares and growth incidence curves

Till the turn of the 21st century, the share of national income going to the middle 40 percent remained firmly higher than the top 10 percent. For instance, the middle 40 percent share and top 10 percent share

[29] Gupta, Malani, and Woda (2021) make a similar argument in the context of the COVID shock, that business incomes of the rich are more strongly correlated with aggregate shocks.

Figure 8 Income growth incidence curves, 1960–2022



Source: Authors' estimates combining income and consumption surveys, tax tabulations, and national income accounts aggregates.
Note: The figure presents the real compound annual growth rate of incomes at each percentile of the distribution starting at *p*10 for three different periods. Growth rates are plotted on a log scale. The estimates for 1960–1980 do not go much beyond *p*99 as the top 1 percent experienced severely negative real growth rates (−1.6 percent at *p*99.3, −46.5 percent at *p*99.9, −63.0 percent at *p*99.998) which cannot be plotted on a log scale.

were 42.8 percent and 36.7 percent respectively in 1951, and 44.1 percent and 33.5 percent respectively in 1990. However, starting in the early 2000s, the top 10 percent overtook the middle 40 percent and by 2022, they stood at 27.3 percent and 57.7 percent respectively (figs 6 a and 6b). The exact same story applies to the bottom 50 percent and top 1 percent shares; starting out at 22.4 percent and 10.5 percent respectively in 1990, the bottom 50 percent and top 1 percent shares stood at 15 percent and 23.3 percent by 2022. Focusing on the bottom 50 percent share, it increases from 19 percent in the mid-1950s and then hovers around 22–23 percent during the 1960s–1980s. The share stabilizes during the 1980s, and then consistently falls between 1993 and 2011. From 2012 onward, the bottom 50 percent share stabilizes at around 15 percent, where it remains through 2022.

The long-run harmonized income series makes it possible to study the distributional consequences of different growth phases in India since independence. Compound annual growth rates of income are estimated at each percentile of the distribution for three distinct periods: 1960–1980, 1980–2000, and 2000–2022. Over the 1960–1980 period, the bottom 90 percent experienced significantly higher growth than the top 10 percent (fig. 8). The top 1 percent in fact recorded *negative* growth rates during this period, reaching as low as −46.5 percent and −63 percent at *p*99.9 and *p*99.998, respectively. By contrast, during 1980–2000 and 2000–2022, growth for the top decile substantially outpaced that of the rest of the population. Even within the top 10 percent, growth rates increase with rank, such that those at the very top benefited disproportionately. This pattern drives the widening disparities in income shares beginning in the 1980s and 1990s and persisting through 2022.

4.3. Robustness of income series in recent years

The benchmark series for recent years begins by correcting the PLFS consumption distribution to make it CES-comparable, after which a consumption-to-income scaling factor is applied to estimate incomes. The *growth rates* of income at each percentile—derived from the corrected PLFS distribution and combined with tax tabulations for top incomes—are then used to extend the income series from 2015 to 2022.

Table 6 Alternate estimates for top income shares in recent years

Year	Benchmark	Raw CPHS (Lower bound)	PLFS + CPHS (Matching)
	A: Top 1 percent income shares		
2014	21.3	20.4	—
2015	21.7	20.9	—
2016	22.2	21.7	—
2017	22.3	20.3	22.1
2018	22.4	20.0	22.1
2019	21.6	20.1	22.1
	B: Top 10 percent income shares		
2014	56.1	51.2	—
2015	56.7	53.0	—
2016	58.2	55.2	—
2017	58.8	53.3	57.9
2018	57.8	51.4	56.8
2019	57.6	52.5	57.3

Source: Authors' estimates combining income tax tabulations with unit-level data PLFS and CPHS.
Note: The table compares the benchmark estimates of the top 1 percent and top 10 percent income shares in recent years with two alternate estimates based on different ways of estimating bottom incomes. See text for more details.

Although this approach enables the estimation of annual survey-based consumption distributions starting in 2017–18, it remains imperfect and presents additional challenges. In particular, it requires assuming that the suppressed 2017–18 CES round provides a reliable consumption distribution, which serves as the basis for correcting PLFS-based consumption. However, the CES 2017–18 suggested that average per capita consumption *declined* between 2011 and 2017, in contrast to the strong growth reflected in national accounts data over the same period, as well as positive growth of wages and agricultural incomes (Sinha Roy and van der Weide 2025). Second, the "usual" consumption expenditure reported in PLFS suffers from bunching at multiples of INR 500 and 1,000, consistent with theories of satisficing (Gideon, Helppie-McFall, and Hsu 2017; Krosnick 2017). Based on simulations, Sinha Roy and van der Weide (2025) show that such rounding off can result in errors of ± 2 percentage points in the Gini coefficient.[30] Third, reliance on IHDS-based scaling factors remains necessary to move from a consumption to an income distribution. In light of these concerns, the robustness of the benchmark income inequality series for recent years is assessed by estimating survey-based bottom incomes using alternative approaches and sources.

The robustness analysis begins by using surveys that directly record incomes. The first is the PLFS, available annually from 2017 onward, which records labor incomes and earnings from self-employment. It, however, does not capture any capital incomes (rents, interest, dividends, etc.). The second survey is the privately executed CPHS, which in principle captures all sources of incomes (labor, self-employment, and capital incomes), but which is shown to be a non-representative sample. These two surveys are used to estimate bottom incomes in two different ways to assess the robustness of the benchmark series. The results for the top 10 percent and top 1 percent income shares are presented in table 6.

The raw CPHS data (along with the original survey weights) are first used to compute bottom incomes for the period 2014–2019.[31] Total incomes are directly observed in the CPHS and therefore do not require imputation from consumption. As in the benchmark series, CPHS data are treated as reliable up to the 90th percentile, with tax data used above that threshold; the two distributions are then combined. Given

[30] Although this effect is not formally simulated here, the impact of such rounding on the overall Gini coefficient is likely smaller once the survey is merged with tax data.
[31] CPHS-based estimates end in 2019, the last financial year (April 2019–March 2020) for which complete CPHS data are available.

evidence that CPHS under-represents less educated and less well-off households (Somanchi 2021; Sinha Roy and van der Weide 2025), this approach likely provides a credible *lower bound* to inequality, as bottom incomes may be overstated. Consistent with this interpretation, the top 10 percent shares are lower than the benchmark series, with a gap of 3–6 percentage points in a given year. When looking at the top 1 percent share, the gap is smaller, about 1–2 percentage points. Note that the gap was quite small for the years 2014–2016 but it widens somewhat starting 2017, the same time that the upward bias in the CPHS sample appears to have become more severe.[32]

Next, a statistical matching technique is employed to combine information from the PLFS and CPHS in order to estimate incomes. The PLFS, which as its name suggests is a labor force survey, records labor incomes and self-employment earnings for all individuals in the sample. It, however, does not record any capital incomes (rents, interests, dividend, etc.). On the other hand, despite its non-representative sample, CPHS captures *total incomes* from all sources (including capital incomes) for each household. To leverage the strengths of both surveys, a statistical matching procedure is employed to combine information from the PLFS and CPHS. For years in which both surveys are available (2017–2019), each PLFS household is matched to the most similar household in the CPHS sample for the same year. This approach is broadly similar to that of Sinha Roy and van der Weide (2025), who reweight the CPHS using external data sources to correct sample bias when estimating poverty in recent years. The present strategy differs in using the PLFS as the base survey—thereby mitigating sample bias concerns—and relying on the CPHS to impute missing income components, particularly non-labor income. The matching is performed using covariates observed in both surveys, most importantly total labor income and self-employment earnings.[33] For each of the years 2017, 2018, and 2019, each PLFS household is matched to a CPHS household by minimizing the Mahalanobis distance metric.[34] Using this approach, the resulting top 10 percent and top 1 percent shares are very close to the benchmark series. This is quite reassuring and suggests that the benchmark approach of using the corrected PLFS consumption distribution to calculate *growth rates* for the bottom 90 percent delivers results that are very similar to estimating the *levels* of bottom incomes directly from PLFS and CPHS. In conjunction with the lower bound estimates based on the raw CPHS series, this suggests that the benchmark series delivers reliable results.

Finally, sensitivity for 2022–23 is assessed by exploiting the availability of consumption estimates from both the PLFS and the CES. In computing growth rates between 2021 and 2022 for the bottom 90 percent, the PLFS 2022–23 round is replaced with the CES 2022–23 round. This substitution yields a top 10 percent share of 53.2 percent and a top 1 percent share of 21 percent, compared to 57.5 percent and 23.7 percent, respectively, in the benchmark series. At the same time, the bottom 50 percent share is slightly lower (13.7 percent vs. 15.1 percent in the benchmark). In other words, the alternative specification implies a modest redistribution away from both the bottom 50 percent and the top 10 percent, toward the middle 40 percent. This pattern arises because PLFS-based estimates for 2022–23 are close to CES-based estimates at the bottom of the distribution. Moving up the distribution, however, PLFS-based estimates fall below CES estimates—by as much as 20–25 percent between the 40th and 90th percentiles.[35] However, as noted earlier, the various methodological changes in the recent CES rounds complicate comparability with earlier estimates, as has been widely discussed in the growing body of works that have studied poverty in India in recent years (Anand 2024; Ghatak and Kumar 2024; Himanshu, Lanjouw, and Schrimer 2024; Subramanian 2024; Sinha Roy and van der Weide 2025).

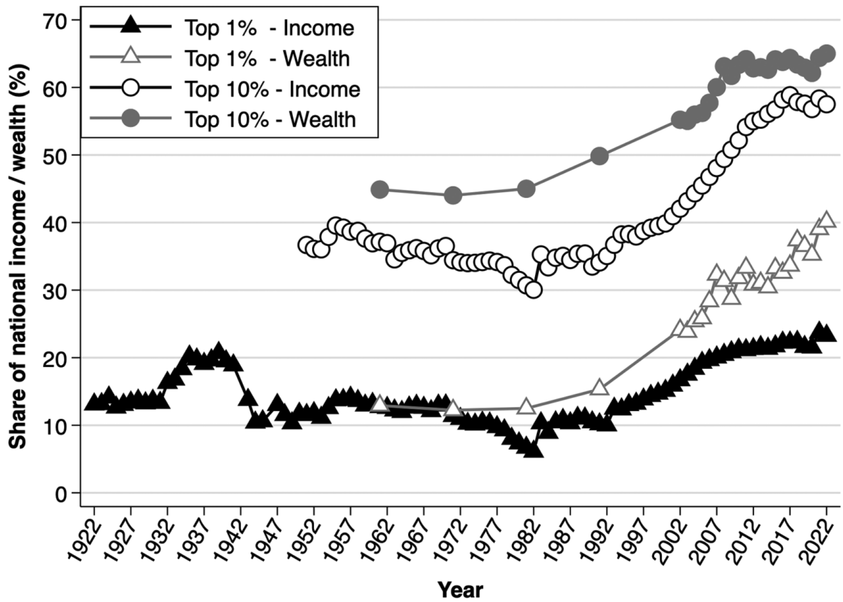
[32] See Somanchi (2021, fig. 2), which shows that literacy rates in the CPHS sample began sharply rising starting 2017.

[33] The full set of covariates included is (a) state, (b) rural/urban, (c) occupation group of household, (d) discrete bins of labor + self-employment income (bin size = INR 100), (e) religion, (f) caste, (g) household size, (h) mean education years of household members, (i) mean age of household members. Since matching is at the household level, all covariates are also defined at the household level as well. An exact match is enforced on (a) rural/urban, (b) occupation group, (c) labor + self-employment income bin.

[34] A nearest-neighbor matching procedure is employed such that each PLFS household is matched to a single CPHS household. In cases with multiple potential matches, one is selected at random. Implementation is carried out using the `kmatch` package in Stata.

[35] These patterns are consistent with the results in Sinha Roy and van der Weide (2025) They estimate an (imputed) consumption distribution using CPHS for 2022–23 and find that their results are quite close for the bottom deciles but lower for the upper deciles.

Figure 9 Long-run co-evolution of income and wealth inequality, 1922–2022



Source: Authors' estimates combining national income and wealth aggregates, surveys, tax tabulations, and Forbes data.
Note: The figure presents the distribution of per-adult net national income and national wealth.

Overall, the three alternative methods for estimating bottom incomes presented here—each testing different assumptions underlying the recent estimates—yield top 10 percent shares within 3–4 percentage points of the benchmark and top 1 percent shares within 1–2 percentage points for most years.

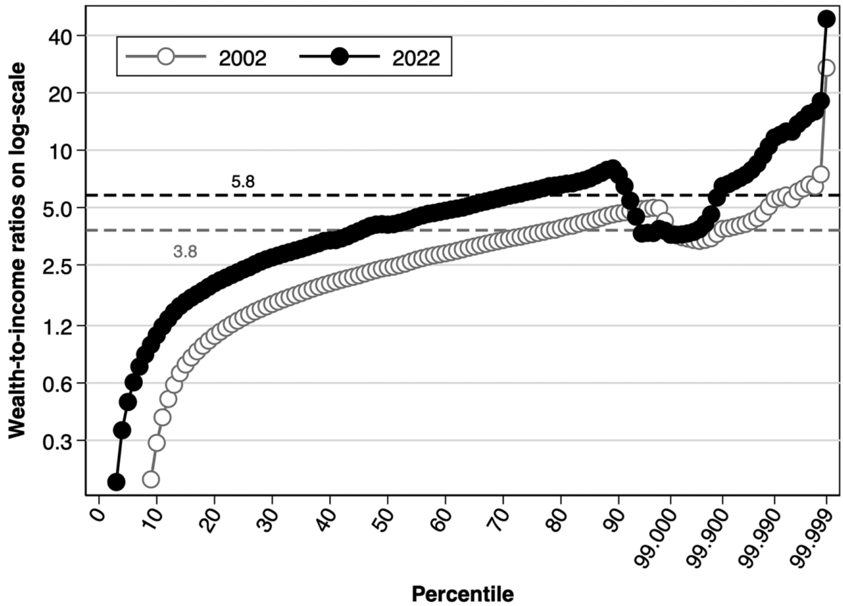
5. Co-evolution of income and wealth inequality

The income and wealth series are combined in couple of ways to shed further light on inequality dynamics in India. To begin, long-run trends in income and wealth inequality are compared (fig. 9). Overall, the top 1 percent and top 10 percent income and wealth shares track each other closely over the full period of the study. A number of notable patterns emerge when focusing on the last two decades (supplementary online appendix fig. S3.4). At the turn of the 21st century, in 2002, the top 10 percent wealth share stood at 55.2 percent, compared to a top 10 percent income share of 42.1 percent, a gap of 13 percentage points. Over the subsequent two decades, the top 10 percent income share increased more rapidly, reducing the gap substantially—to 7.5 percentage points by 2022. By contrast, the opposite pattern emerges when comparing the top 1 percent income and wealth shares over the same period. In 2002, the top 1 percent wealth share was 24.1 percent compared to 16.7 percent for incomes, a gap of 7.6 percentage points. Twenty years later, by 2022, the top 1 percent wealth share had reached 40.1 percent compared to 23.3 percent for incomes, a gap of 16.8 percentage points. These opposing trends suggest that wealth concentration is accelerating relatively faster than incomes at the very top of the distribution.

Next, the wealth and income distributions—anchored to aggregate wealth and national income, respectively—are combined to estimate wealth-to-income ratios across the distribution.[36] Between 2002 and 2022, in line with trends in aggregate β, wealth-to-income ratios increased at each point of the distribution, except for a few percentiles in the top decile (fig. 10). In both years, however, wealth-to-income ratios rise, moving up the distribution, very sharply so when reaching the very top (top 1 percent). In 2022, between the 99th and 99.999th generalized percentiles, the wealth-to-income ra-

[36] For $p \in (0, 1)$ denoting fractiles, wealth-to-income ratios are computed as $W(p)/Y(p)$, where $W(\cdot)$ and $Y(\cdot)$ denote the quantile functions associated with wealth and income, respectively.

Figure 10 Wealth-to-income ratios across the distribution, 2002 & 2022



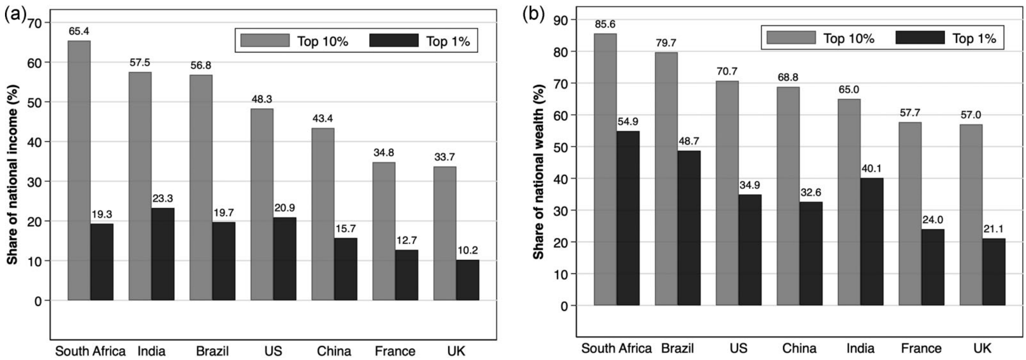
Source: Authors' estimates combining national income accounts aggregates, national wealth aggregates, tax tabulations, Forbes data, and surveys (income, consumption, wealth).
Note: Wealth-to-income ratios estimated as $W(p)/Y(p)$, where $p \in (0, 1)$ denotes fractiles and $W(\cdot)$ and $Y(\cdot)$ are the associated quantile functions of the wealth and income distributions respectively. They are plotted on a log scale. The dashed lines show India's aggregate wealth-to-income ratio (β) in 2002 and 2022. The estimates for 2002 begin at $p0.08$ because the ratios are negative below that point.

tio rose from 3.6 to 48.9. This implies that at the very top of the distribution, incomes reported in tax statistics may amount to just 2 percent of the wealth.

These results remain tentative because income and wealth are not observed for the same individuals; instead, inferences are drawn from the separately estimated full distributions of income and wealth. Nonetheless, these estimates are very much consistent with the results in Singh (2025), who uses a novel database of wealth and income tax disclosures from Indian politicians to estimate wealth-to-income ratios across the wealth distribution. By forensically comparing incomes and wealth reported on these disclosures by the same individuals (for an admittedly non-representative sample of the population), he finds that among the top 0.1 percent wealthiest individuals in his sample, the total income reported to tax authorities amounts to just 2 percent of their total wealth. As noted by Singh (2025), an income-to-wealth ratio of 2 percent (corresponding to wealth-to-income ratios of 50) seem inexplicably low given that average returns to capital at the national level over the 2010–2020 period itself were over 7 percent, even without accounting for differential returns at the top of the distribution.

In other words, these results suggest significant "missing incomes" for the very wealthy that are not reflected in income tax returns. This has two implications. First, the income inequality estimates relying on income tax returns for top incomes are bound to underestimate top shares. Second, these estimates suggest that the Indian tax system might well be *regressive* from the point of view of wealth. In particular, the tax liability as a share of net wealth may decline as one moves up the wealth distribution. While more granular and comprehensive data are needed to make conclusive claims, these results are broadly consistent with evidence emerging from other countries like France, the Netherlands, and the United States, which suggests that effective tax rates among the ultra-wealthy might be lower than the average population (Bach et al. 2025; Bruil et al. 2025; Balkir et al. 2025).

Figure 11 (a) Top income shares in global perspective, 2022–2023. (b) Top wealth shares in global perspective, 2022–2023



Source: Authors' estimates for India and World Inequality Database data based on country-specific studies for rest.
Note: The figures compare India's top 10 percent and 1 percent income and wealth shares with a handful of countries that include some of the most unequal ones.

6. Indian inequalities in comparative perspective

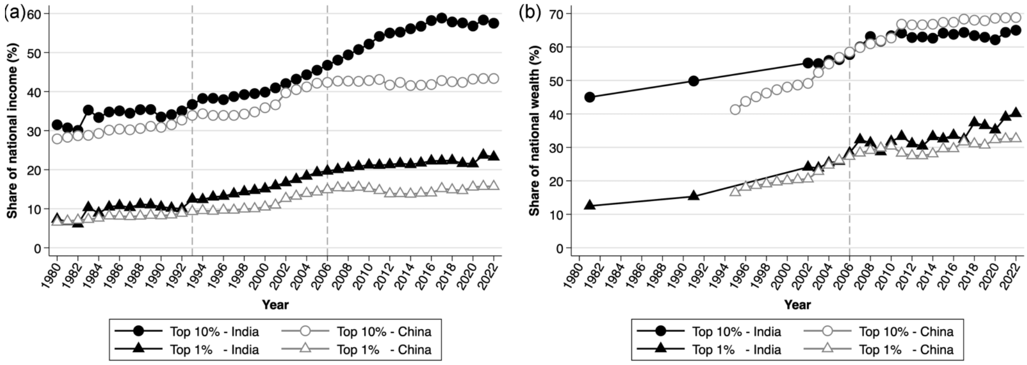
Income and wealth inequality levels in India in 2022 can be placed in global perspective by comparing India with Brazil, China, France, South Africa, the United Kingdom, and the United States. In terms of the top 10 percent income share, India ranks second only to South Africa (fig. 11a). For the top 1 percent share, however, India records the highest level at 23.3 percent. Based on World Inequality Database data, India's top 1 percent income share appears to be among the highest globally, exceeded only by Peru, Yemen, and a few smaller countries. With respect to wealth inequality (fig. 11b), India lies in the middle of the distribution for both the top 10 percent and top 1 percent shares, while Brazil and South Africa stand out for particularly high wealth concentration (top 10 percent shares of 85.6 percent and 79.7 percent, respectively). Among this group of countries, the United Kingdom and France exhibit the lowest levels of both income and wealth inequality.

An India vs. China comparison in the inequality sphere is both justified and revealing, given their comparable population levels and that the two countries started out at roughly similar income and development levels in the 1950s and 1960s. Between 1970 and 1990, Chinese incomes began growing faster than Indian incomes and then they skyrocketed both in absolute and relative terms starting the early 2000s (fig. 1b). While the growth of Indian incomes did pick up, especially in the 2000s, it was much lower than Chinese growth rates. How did the dynamics of income and wealth inequality play out in these two countries? Comparing income and wealth inequality in India and China between 1980 and 2022 presents some interesting findings. Focusing on incomes first, the top 10 percent and top 1 percent income shares were comparable in the two countries in 1980 (fig. 12a). Over the next four decades, two key trend breaks are identified. Between 1980 and the early 1990s, the top income share gradually increased in both countries. The first trend break was in 1993 when a small gap opens between Indian and Chinese top shares, particularly so for top 1 percent shares, on the back of the sharp rise in inequality in India post the liberalization reforms of 1991. The second trend break came in 2006 when Chinese top shares stabilized while Indian top shares continued to grow, creating a wide gap particularly for top 10 percent shares.[37] By 2022, the top 1 percent income shares in India were nearly 50 percent larger than those in China (23.3 percent vs. 15.7 percent) and the top 10 percent shares were nearly 35 percent larger (57.5 percent vs. 43.4 percent). One way to interpret these trends is that China shows that is possible for low- and middle-income economies to achieve high growth without generating as high inequality levels as those observed in India today.[38]

[37] Kanbur, Wang, and Zhang (2021) argue that the stabilization of Chinese top shares was likely the outcome of a mix of policy measures and a slowdown in structural transformation. At the same time, Piketty, Yang, and Zucman (2019) note that data limitations for China make the estimates for more recent years tentative.

[38] Bharti and Yang (2025) argue that higher economic inequality in India can be at least partly attributed to differences in the way their education systems developed. The Indian system expanded in a top-down fashion (neglecting primary-level

Figure 12 (a) Top income shares, India vs. China, 1980–2022. (b) Top wealth shares, India vs. China, 1980–2022



Source: Authors' estimates for India and World Inequality Database data for China based on Piketty, Yang, and Zucman (2019).
Note: The figure compares the top 10 percent and 1 percent income and wealth shares in India and China for the period 1980–2022. The vertical dashed lines point to years when divergence in top income shares grew (1983 and 2006).

Wealth concentration over the same period follows the opposite trend to income (fig. 12b). In 1995 (when the Chinese wealth series begins), the top 10 percent and top 1 percent wealth shares in China were considerably lower than India's. Between 1995 and 2006, the top wealth shares in China steadily increased and caught up with Indian levels, and from 2011 onwards the top 10 percent wealth shares have been higher in China than India. On the other hand, the top 1 percent shares in India have so far managed to keep ahead of China given the concentration of wealth in India at the very top of the distribution. The overall trends of the rising top 10 percent wealth shares in China are possibly the consequence of its wealth-to-income ratio more than doubling between 1980 and 2022 (from 3.75 to 9.41), which in turn was largely the result of rising savings rates and asset prices (Piketty, Yang, and Zucman 2019).

7. Understanding the rise of inequality since the 1990s

What has driven the sharp rise of both income and wealth inequality in India since the 1990s? There are likely numerous factors related to India's growth and development process that have contributed to the precipitous fall in the bottom 50 percent and middle 40 percent since the 1990s and 2000s. This section discusses some of the key mechanisms that have likely contributed to this observed trend.

At the time of independence, India faced the twin burden of extreme poverty and vast disparities among regions and social groups. Hence, many economic policies implemented in the 1950s/60s explicitly targeted these disparities. Fiscal redistribution was considered a major equalizing tool: most tax revenues were collected by the central government, and a significant share of them was redistributed across states based on their population share. This approach benefited the rural sector, where the majority of people lived, and supported poorer, more populated states. In the 1970s, bank nationalization combined with priority sector lending ensured capital flowed into the agricultural sector, which was a source of livelihood for a large population share.[39] Nationalization of several other sectors meant that the government set pay scales, which kept the variance in wages low. Addressing regional imbalances in human capital infrastructure, such as expanding schools, was also a key focus.

A second set of policies targeted the wealthy, including high marginal tax rates, the abolition of privy purses, and land reforms.[40] Kumar (2019) argues that land reforms and the abolition of privy purses

mass education for a long time) with lower diversification at the top (lower vocational graduates and a larger share of humanities graduates among college graduates). As a result, India has higher education inequality, contributing to 25 percent of the total wage inequality from 1988–2018 compared to 2 percent in 1988 and 12 percent in 2018 in China.

39 In 1969, 14 banks, representing 70 percent of the banking sector, were nationalized. The nationalization was a dominant feature post-1950, with railways nationalized in 1951, air transport in 1953, and the oil industry in 1974/76 (Chancel and Piketty 2019).

40 The top marginal tax rates rose from 27 percent to 97.5 percent between 1965 and 1973. The 26th Amendment of the constitution removed privy purses, where a large sum was paid to ruling princely families as part of the merger agreements

helped reduce wealth inequality. Reservation policies were implemented to support lower-caste groups. These policies possibly moderated inequality with a convergence between marginalized groups (Scheduled Caste and Schedule Tribe) and others in terms of education, occupational choice, wages, and consumption (Hnatkovska, Lahiri, and Paul 2012). However, the 1950–1980 period was marked by sluggish economic growth and a rapidly expanding population. A limited tax base weakened the government's capacity for transformative changes, resulting in an unfavorable equilibrium. Notably, government spending on human capital remained abysmal during this time; primary education continued to be neglected, leaving a large portion of the population illiterate and limiting their mobility, especially out of rural agricultural areas (Bharti and Yang 2025). This is in sharp contrast with China, which had invested quite heavily in its human capital before opening up its economy to world markets in the 1980s. The balance of payments crisis in 1990 instigated a set of economic liberalization reforms. These reforms appear to have increased overall capital, through foreign direct investment, and reduced misallocation of capital across sectors (Bau and Matray 2023), improved firm productivity (Topalova and Khandelwal 2011), and increased accessibility to new products for consumers (Goldberg et al. 2009, 2020). Concurrently, the literature has also raised concerns about distributional aspects of these reforms. Aghion et al. (2008) shows that the effect of delicensing was uneven, with states having pro-employer labor-market institutions growing faster than those with pro-worker environments. Topalova (2010) shows that in districts where the intensity of liberalization was higher, there was a relatively slower decline in poverty and lower consumption growth. Loecker et al. (2016) show that producers, especially the large firms, benefited much more relative to consumers due to trade liberalization, as the benefits from declining marginal costs (due to reduction in input tariffs)[41] did not pass off to consumers, as firms hiked their markups.[42] To boost the pro-business/pro-market sentiments and attract investments, the government responded by giving corporate tax breaks and slashing the top marginal tax rates considerably. The government's priority shifted to boost growth, and equity became a second-order concern (Kohli 2006a,b). The labor share of value-added declined dramatically in the organized manufacturing sector (Abraham and Sasikumar 2017; Jayadev and Narayan 2020) and even in the corporate sector more broadly, though less dramatically.

In line with the distributional concerns associated with liberalization, top income and wealth shares, which were declining before the 1980s for income and stable for wealth, began rising in the 1990s, quite sharply so from the 2000s onward. This is consistent with a range of studies that document rising inequalities since the 1990s. Using NSS consumption surveys for the years 1993–94 and 1999–2000, Deaton and Drèze (2002) find that economic inequality markedly increased during the 1990s in several forms—strong divergence across states, rising urban-rural inequality, and growing disparities *within* urban areas. Kundu and Varghese (2010) observe that the coefficient of variation and Gini coefficient of per capita state domestic product has increased systematically since the 1990s. While poverty certainly declined during the 1990s, the accompanying rise in inequality seems to have blunted the extent and speed of growth-driven poverty reduction during this period (Deaton and Drèze 2002; Jha 2004).

Crucially, Datt and Ravallion (2002) highlight that states with relatively low levels of initial rural development and human capital were not well suited to benefit from the growth of the 1990s and 2000s. The lack of quality broad-based education, focused on the masses and not just the elites, is likely to be an important contributor. This is clearly evident from the fact that inter-generational mobility measured using education rank has remained constant and low since liberalization (Asher, Novosad, and Rafkin 2022). In 2011, when the last population census was conducted, nearly 30 percent of Indians remained illiterate. Bharti and Yang (2025) show educational inequality explains a quarter of wage inequality in India between 1988 and 2018. On the other hand, the services-led economic growth since liberalization has

in 1947. Under land reforms, first large landlords were targeted through the Zamindari Abolition Act in the 1950s, tenants' rights were protected through tenancy regulations in the 1960s, and land ceilings were imposed in the 1970s to assign maximum land size holding.

[41] The average import tariffs were reduced from 80 percent in 1987 to 30 percent in 1997, and several import licenses were eliminated (Pavcnik 2017).

[42] Atkin and Khandelwal (2020) provide a useful review of the literature studying the interaction of trade liberalization with weak institutions, market failures, and distortion in developing countries. Similarly, Pavcnik (2017) provides a review of the literature studying the impact of trade liberalization on inequality in developing countries.

surely had unequalizing effects too (Fang, Peters, and Zilibotti 2023). The growth of the services sectors has benefited high-skill workers but slowed down the Lewisian transformation away from agricultural. As per latest NSSO data for 2022–23, 45.5 percent of the workforce was still employed in agriculture, 12.4 percent in construction, and only 11.6 percent in manufacturing, with the rest in services (Press Information Bureau 2023). India's inability to pull more of its workforce away from agriculture towards more productive and better-paying employment remains a pressing challenge. Finally, focusing specifically on wealth inequality, as noted earlier, land appears to be the key driver on wealth inequality in India given its large weight in the asset portfolio of households. Between 1991 and 2012, household surveys alone (without any top correction with rich lists) suggest a sharp increase in the top 10 percent share. This is primarily driven by a rise in land inequality (table 4). In turn, land inequality can itself be partly explained by differential land prices across the distribution.[43] Based on the AIDIS, in 1991 the average real land price of the top 10 percent was 9 times higher than that of the bottom 50 percent. By 2012, this ratio had increased to 11.2. Moreover, given the non-coverage of the ultra-wealthy in the AIDIS, these figures based on AIDIS are likely to underestimate (both the levels and trends of) the differential land returns. Overall, the post-liberalization period was characterized by persistent inequalities across socio-economic groups and a growing divergence between rural and urban areas and across slower and faster growing states (Subramanian and Jayaraj 2006; Jayadev, Motiram, and Vakulabharanam 2007; Anand and Thampi 2016). Another contributor to the rise in wealth inequality in recent years is likely to be the growing financialization of wealth as evidenced from a growing stock market as a percentage of the national GDP. The SENSEX (S&P Bombay Stock Exchange Sensitive Index), a free-float market-weighted stock-market index of 30 companies listed on the Bombay Stock Exchange, grew by 7,300 percent between 1990 and 2023. The gains from such rapid financialization are bound to be restricted to the wealthier sections that have better access and integration into the financial system.

8. Conclusion

This paper combines national income accounts, wealth aggregates, tax tabulations, billionaire rankings, rich lists, and surveys on income, consumption, and wealth in a consistent framework to present long-run and short-run income and wealth inequality series for India. The estimates suggest that inequality levels declined post-independence till the early 1980s, after which both top income and wealth shares began rising and have skyrocketed since the early 2000s. Trends of top income and wealth shares closely track each other over the period of this study. By 2022–23, the top 1 percent income and wealth shares are at their highest historical levels at 23.3 percent and 40.1 percent respectively, and India's top 1 percent income share is among the very highest in the world, higher than even South Africa, Brazil, and the United States. In other words, the Billionaire Raj headed by India's modern bourgeoisie is now more unequal than the British Raj headed by the colonialist forces. One reason to be concerned with such a scenario is that high concentration of incomes and wealth is likely to facilitate disproportionate influence of the rich and wealthy on society and government. This is even more so in contexts with weak institutions. If only for this reason, income and wealth inequality in India must be closely tracked and challenged.

Finally, as highlighted throughout the paper, the measurement of income and wealth inequality in India faces significant conceptual and empirical challenges related to data availability, quality, and coverage. Nonetheless, these challenges are not sufficient grounds for abandoning this important endeavor. The analysis presented here represents one step toward a better understanding of inequality dynamics in India using the best available data at hand in a transparent and consistent manner. There is no doubt that better data and wider democratic access to it can improve the quality of inequality estimates for India.

[43] Bharti, Blakeslee, and Malik (2025) show that there are considerable village-level land-ownership inequality patterns that are driven by historical factors including whether it was directly ruled by the British, the types of land revenue collection systems, and high-scheduled-caste population share. Market forces such as distance of road and urban areas are also important determinants.

Data Availability Statement

Replication materials (including the data underlying this article) will be made available on the World Bank Reproducible Research Repository.

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Supplementary Online Appendix

Income and Wealth Inequality in India, 1922–2023: The Rise of the Billionaire Raj

Nitin Kumar Bharti, Lucas Chancel, Thomas Piketty, and Anmol Somanchi

S1. Data sources

Population aggregates: Adult (20+) population figures are sourced from United Nations World Population Prospects (UN-WPP). The age cutoff for defining adults, as well as the data source, is chosen in line with Distributional National Accounts (DINA) guidelines to allow for consistent cross-country comparisons (Blanchet et al. 2017).

National income accounts: Aggregate totals of net national income (NNI) are obtained from the series in the World Inequality Database for the years pre-2014. For post-2014, we use the figures reported in table 1.1, Statistical Appendix of the Economic Survey 2022–23 published by the Ministry of Finance (MoF), Government of India (GoI). We assume that a set of deductions apply (e.g., to account for retained earnings of corporates, non-taxable income, etc.) to go from NNI to fiscal income (Atkinson 2007).[1] There has been an ongoing debate on the quality of Indian national accounts data in the recent years, with various observers arguing that the official statistics might be exaggerating growth—for our estimation exercise, we take the official statistics as given but return to this issue later.

Price index: The two main price indices generally used are the GDP deflator and consumer price index (CPI). While both measure changes in prices, the former focuses on changes in prices of domestic production and the latter on price changes faced by consumers. Our preferred measure is the GDP deflator, since its methodology has seen relatively greater progress in terms of bias reduction when measuring prices over time by switching to the chain-linking method (Piketty and Zucman 2014).[2] We source the annual series of the GDP deflator for India from the World Bank's World Development Indicators database for the period 1960–2022.

Tax tabulations: Since the establishment of the Income Tax Act in 1922, the Indian government has published annual tax tabulations with information on total number of tax filers and total income assessed for many income brackets (24 in recent years). These were available largely uninterrupted till 1999 when their publication was abruptly stopped. Their release began again in 2016 with retrospective data starting in 2011, and so far tax tabulations are available till 2020. We return to the issue of the release of tax tabulations later. We use these tabulations to extract a full distribution of top income earners to supplement income and consumption surveys at the top.

Rich lists: In the last few decades, two sources provide information on the wealth of the richest Indians. Starting in 1988, the Forbes magazine has been tracking the wealth of all Indians with net wealth exceeding 1 billion USD MER and publishing an annual billionaire ranking. Similarly, since 2012, the luxury research organization Hurun has been publishing an annual rich list for India, going beyond just USD billionaires, covering all Indians with a net wealth exceeding INR 1,000 crore (roughly 120 million USD MER as on March 1, 2024). These lists have become a very useful complement to wealth surveys, which tend to severely underestimate the right tail of the wealth distribution.

Consumption Expenditure Survey (CES): Starting in 1951, the National Sample Survey Organization (NSSO) has been conducting large-scale nationally representative household surveys recording household consumption expenditure. These surveys record detailed information on quantities purchased and prices paid for over 300 commodities. In the absence of any comparable large-scale income survey, the CES has over the years become the bedrock to study a range of economic issues in India, including but not limited to poverty, inequality, and nutrition. For the period 1951–1983, we use the tabulations for rural and urban per capita consumption available in the World Bank's Poverty and Growth in India database (Özler, Datt, and Ravallion 1996). From 1983–2011, we use the publicly available unit-level micro-data. Finally, for the year 2017–18, we use the leaked summary made publicly available by a journalist, since the detailed report and micro-data were suppressed by the Government of India.[3]

[1] In practice, we assume that roughly 70 percent of net national income accounts for fiscal income. This serves as the "control average" when extracting a distribution from the tax tabulations using generalized Pareto interpolation.

[2] See Blanchet (2017) for a summary and Blanchet et al. (2017) for full details of the price indices used in WID.

[3] A preliminary "fact sheet" of the 2022–23 CES round by NSSO has just been placed in the public domain (Press Information Bureau 2024). The full report and micro-data are still awaited. Unfortunately, there appear to be key changes to the instrument and interview schedules that raise issues of comparability with previous CES rounds. Indeed, a whole page in the fact sheet titled "Issues Related to Comparability" (pg. 4) is dedicated to cautioning the reader against hasty comparisons (National Sample Survey Office 2024).

All India Debt and Investment Survey (AIDIS): The AIDIS are decennial surveys conducted in 1961, 1971, 1981, 1991, 2002, 2012, and 2018, which collect detailed data on household wealth and debt.[4] Micro-individual survey files are available for the last four rounds. For previous surveys, only published reports are available with tabulations on average wealth and number of households by wealth brackets. The coverage of asset classes in these surveys has largely remained similar over the years, except for minor changes. For e.g., up to 2002, total assets included the value of seven different types of assets: (a) land, (b) buildings, (c) livestock, (d) implements, machinery, transport equipment, etc., (e) durable household assets, (f) dues receivables on loans advanced, and (g) financial assets. In terms of liabilities, the surveys capture cash loans. In 2012 and 2018, household durables were excluded on the pretext of valuation concerns. Hence, we remove them from earlier rounds to make the rounds comparable across time.[5] The valuation of assets is self-reported and is based on the market price prevalent in the area, with the noted exceptions of building values which were recorded as per book value in 2012 and land values which were recorded as per normative/book values in 2012 and 2018.[6]

India Human Development Survey (IHDS): Conducted so far in two rounds in 2004–05 and 2011–12 as a collaboration between the University of Maryland and the National Council of Applied Economic Research (NCAER), the IHDS is a nationally representative survey covering over 40,000 households in both rural and urban areas. IHDS collected data on an unusually rich set of indicators and included a panel component. The key advantage for our purpose is that it recorded information on both consumption and income of households. Consequently, IHDS plays a key role in complementing the CES in our measurement framework.

Periodic Labour Force Survey (PLFS): Starting in 2017–18, the NSSO has been conducting annual rounds of the Periodic Labour Force Survey as a replacement to the erstwhile Employment and Unemployment Surveys (EUS) that were being conducted at regular intervals till 2011–12. The PLFS largely follows a similar methodology to the earlier EUS, except that it records data on both labor incomes as well as incomes from self-employment, while EUS only recorded labor incomes. Additionally, the PLFS also provides data on "usual" consumption expenditure by households. This consumption measure is at the outset not comparable to the consumption reported in the traditional CES surveys, but we are able to find a mapping between them, as described in the next section.

Consumer Pyramids Household Survey (CPHS): The Consumer Pyramids Household Survey is a panel dataset covering over 140,000 households, which records information on consumption, income, labor-market outcomes, and ownership of household assets. CPHS is available on a monthly basis starting in January 2014. Despite the rich coverage of indicators and the high frequency of data collection, evidence suggests that the CPHS is not a representative sample as it appears to miss less educated and less well-off households in its sample, with the bias seemingly growing over time (Drèze and Somanchi 2021; Somanchi 2021; Sinha Roy and van der Weide 2025).

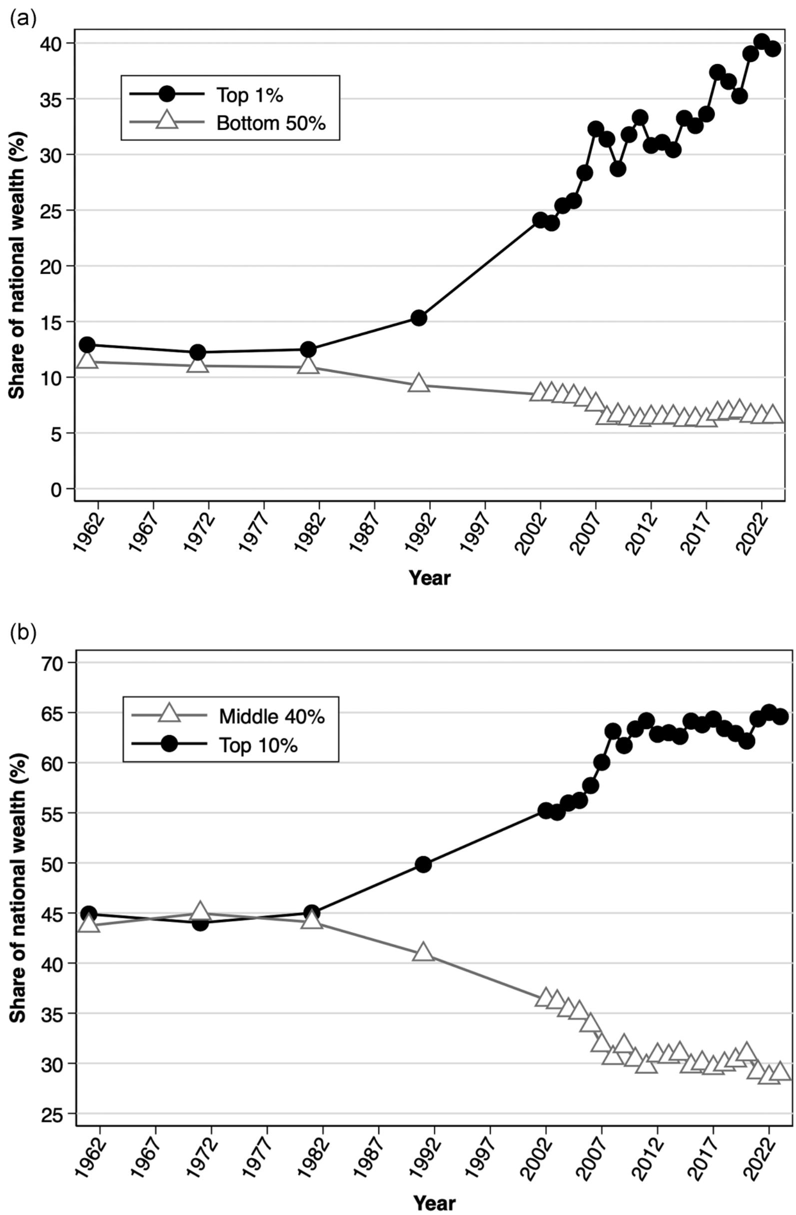
[4] The Reserve Bank of India (RBI) conducted the 1961 survey in rural areas only. The 1971–72 survey was conducted by NSSO and RBI together in rural and urban areas. The urban data were never published due to sampling issues. NSSO independently conducted all the later rounds in both rural and urban areas.

[5] The surveys collected a total of 159 items under different heads in the 1991–92 survey, 141 items in 2002–03, 86 in 2012–13, and 87 items in 2018–19.

[6] Enumerators consulted "Patwaris" in rural areas and the registrar's office in urban areas to obtain them.

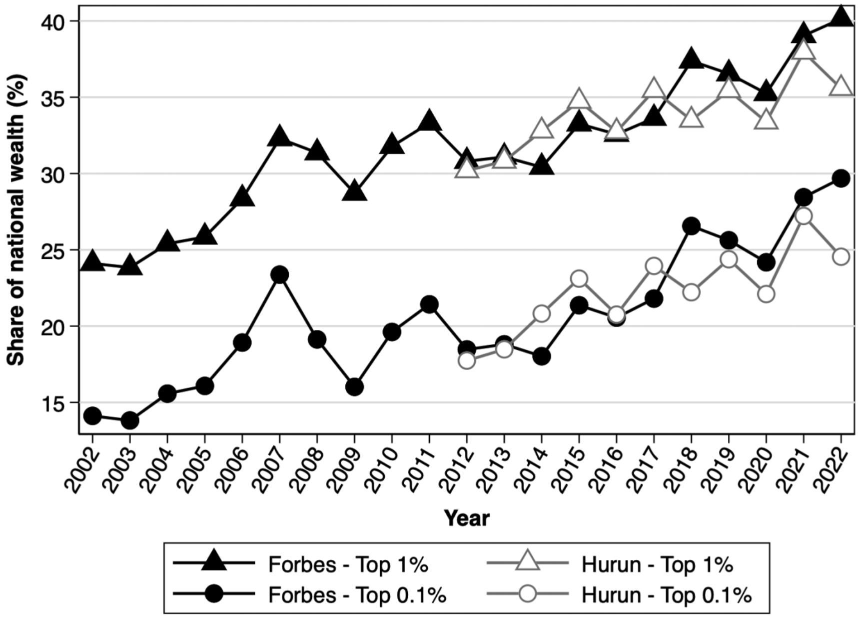
S2. Wealth series

Figure S2.1 (a) Bottom 50 percent vs. top 1 percent wealth shares, 1961–2023. (b) Middle 40 percent vs. top 10 percent wealth shares, 1961–2023



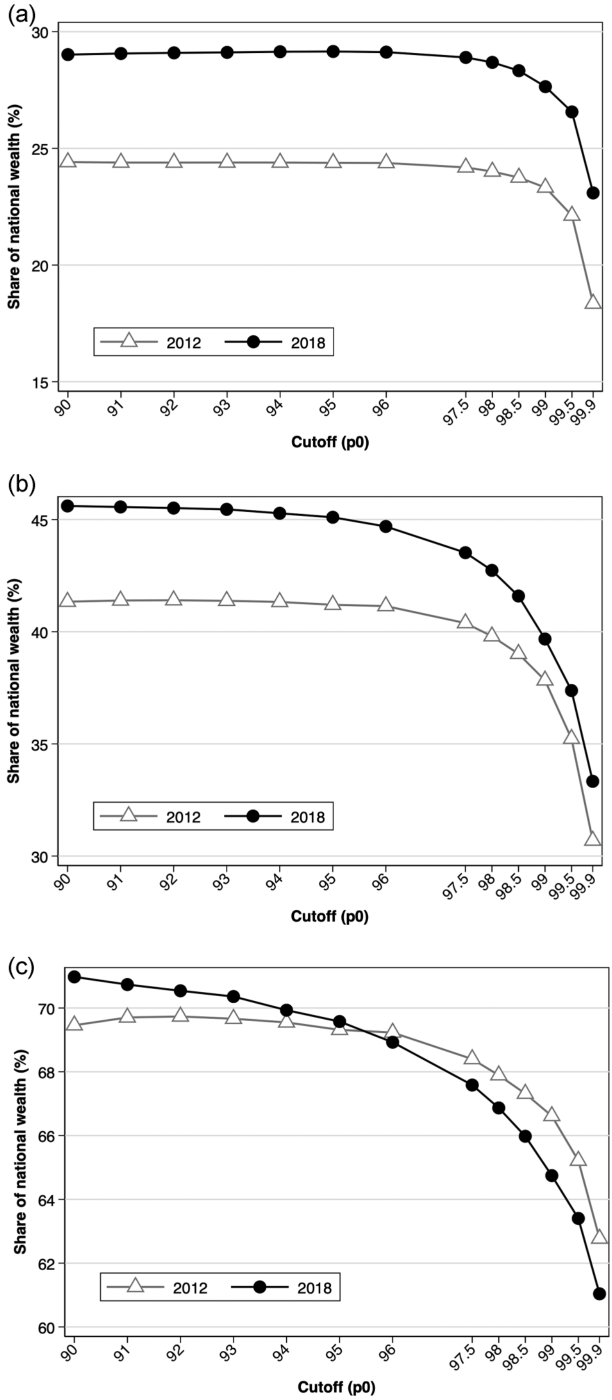
Source: Authors' estimates combining national wealth aggregates, wealth surveys, and Forbes billionaire data.
Note: The figure presents the distribution of per-adult national wealth.

Figure S2.2 Top wealth shares—Forbes vs. Hurun, 2002–2022



Source: Authors' estimates combining wealth aggregates, wealth surveys (All India Debt and Investment Survey [AIDIS]), and Forbes and Hurun rich lists.
Note: The figure presents the share of national wealth going to the top 1 percent and top 0.1 percent based on two different rich lists used to top-correct the AIDIS surveys. The Forbes series is our benchmark, while we present Hurun as a robustness check.

Figure S2.3 (a) Top 0.1 percent shares, 2012 and 2018. (b) Top 1 percent shares, 2012 and 2018. (c) Top 10 percent shares, 2012 and 2018



Source: Authors' estimates combining All India Debt and Investment Surey (AIDIS) and Forbes data.
Note: The figure presents the estimated top 0.1 percent shares, top 1 percent, and top 10 percent shares for different choices of the cutoff point p_0 in the wealth distribution beyond which the AIDIS surveys are deemed non-representative. A cutoff point of 99.9 implies the survey is taken to be representative for the bottom 99.9 percent of the population, and the top 0.1 percent comes from Pareto-simulated distribution derived from the rich lists. The results focus on 2012 and 2018, the last two rounds for which AIDIS survey data are available.

Table S2.1 Per-adult national wealth shares (percent), 1961–2023

Year	Bottom 50%	Middle 40%	Top 10%	Top 1%	Top 0.1%
1961	11.4	43.7	44.9	12.9	3.2
1971	11.0	45.0	44.0	12.2	2.8
1981	10.9	44.1	45.0	12.5	2.7
1991	9.3	40.9	49.8	15.3	4.1
2002	8.5	36.3	55.2	24.1	14.1
2003	8.5	36.1	55.1	23.8	13.8
2004	8.3	35.3	56.0	25.4	15.6
2005	8.3	35.0	56.2	25.8	16.1
2006	8.0	33.8	57.7	28.4	18.9
2007	7.5	31.8	60.0	32.3	23.4
2008	6.3	30.5	63.1	31.4	19.1
2009	6.6	31.7	61.7	28.7	16.0
2010	6.3	30.3	63.4	31.8	19.6
2011	6.2	29.7	64.2	33.3	21.4
2012	6.4	30.8	62.8	31.1	18.5
2013	6.4	31.1	63.0	30.4	18.8
2014	6.4	30.4	62.6	33.3	18.0
2015	6.2	33.3	64.1	32.6	21.4
2016	6.2	32.0	63.8	33.6	20.6
2017	6.1	29.5	64.3	32.4	21.8
2018	6.7	29.9	63.4	37.4	26.6
2019	6.8	30.3	62.9	36.5	25.6
2020	6.9	30.9	62.2	35.2	24.2
2021	6.5	29.1	64.4	39.0	28.4
2022	6.4	28.6	65.0	40.1	29.7
2023	6.5	29.0	64.6	39.5	29.0

Source: Authors' estimates combining national wealth aggregates, wealth surveys (All India Debt and Investment Survey [AIDIS]), and Forbes billionaire rankings using *harmonized* Pareto interpolation.
Note: Estimates based solely on AIDIS till 1991 and combining AIDIS with the Forbes rich list from 2002 onwards. Estimates for 2023 are tentative as they are based on Hurun's 2023 rich list (truncated at the top 100 individuals) as Forbes data were not yet out. See the methodology section in the main text for more details.

Table S2.2 Merge point for rich lists, 2002–2022

Year	Fractile
2002	0.999
2003	0.999
2004	0.999
2005	0.999
2006	0.999
2007	0.999
2008	0.999
2009	0.999
2010	0.999
2011	0.999
2012	0.999
2013	0.999
2014	0.999
2015	0.999
2016	0.999
2017	0.999
2018	0.995
2019	0.995
2020	0.995
2021	0.995
2022	0.995
2023	0.995

Source: Authors' compilation.
Note: The wealth series presented in this paper is estimated by combining wealth surveys (All India Debt and Investment Survey) with Forbes rich lists. The table presents the fractile $p \in (0, 1)$ in the distribution till where the survey is considered representative, above which a correction is applied based on data from the rich list. From 2002 till 2017, we assume that the survey is non-representative for the top 0.1 percent and from 2018 onwards for the top 0.5 percent. The downward adjustment is driven by the growing non-representativeness at the top in AIDIS, especially in the 2018 round (see Section - Data and Methodology for details).

Table S2.3 Choice of threshold and top wealth shares, 2012

p_0	Top 10%	Top 5%	Top 1%	Top 0.1%	Top 0.01%	Top 0.001%
90.0	69.5	59.4	41.3	24.4	14.2	8.1
91.0	69.7	59.6	41.4	24.4	14.2	8.1
92.0	69.7	59.6	41.4	24.4	14.2	8.1
93.0	69.7	59.6	41.4	24.4	14.2	8.1
94.0	69.5	59.5	41.3	24.4	14.2	8.1
95.0	69.3	59.2	41.2	24.4	14.2	8.1
96.0	69.2	59.1	41.1	24.4	14.2	8.1
97.5	68.4	57.9	40.4	24.2	14.3	8.2
98.0	67.9	57.3	39.8	24.0	14.3	8.3
98.5	67.3	56.5	39.0	23.8	14.2	8.3
99.0	66.6	55.6	37.8	23.3	14.2	8.4
99.5	65.2	53.7	35.2	22.1	13.8	8.4
99.9	62.8	50.5	30.7	18.3	12.4	8.1
Survey	59.9	46.7	25.4	12	6.9	—

Source: Authors' estimates combining the All India Debt and Invesment Survey 2012 round and Forbes 2012 billionaire rankings using *standard* Pareto interpolation.
Note: The wealth series presented in this paper is estimated by combining wealth surveys (AIDIS) with Forbes rich lists. The table presents how the choice of the fractile $p_0 \in (0, 1)$ in the distribution till where the survey is considered representative affects top shares for the year 2012 (last AIDIS round). Not surprisingly, we see that by assuming a lower p_0, we get higher top shares (except for at the very top—top 0.001 percent). The top 10 percent share declines from 69.5 percent with $p_0 = 90.0$ to 62.8 percent with $p_0 = 99.9$. We consider our choice of $p0$ for our benchmark series (99.99 till 2017 and 99.95 2018 onwards) as conservative given that the survey is likely to be non-representative even at lower percentiles within the top decile.

Table S2.4 Choice of threshold and top wealth shares, 2018

p_0	Top 10%	Top 5%	Top 1%	Top 0.1%	Top 0.01%	Top 0.001%
90.0	71.0	62.2	45.6	29.0	18.2	11.1
91.0	70.7	62.0	45.6	29.1	18.2	11.1
92.0	70.5	61.8	45.5	29.1	18.3	11.2
93.0	70.4	61.7	45.5	29.1	18.3	11.2
94.0	69.9	61.2	45.3	29.1	18.4	11.4
95.0	69.6	60.8	45.1	29.2	18.5	11.4
96.0	68.9	60.0	44.7	29.1	18.7	11.6
97.5	67.6	58.2	43.5	28.9	18.8	11.9
98.0	66.9	57.3	42.7	28.7	18.9	12.1
98.5	66.0	56.2	41.6	28.3	18.9	12.3
99.0	64.7	54.6	39.7	27.6	18.9	12.5
99.5	63.4	52.8	37.4	26.6	18.7	12.7
99.9	61.0	49.8	33.3	23.1	17.5	12.8
Survey	52.1	38.3	18.1	5.5	1.3	—

Source: Authors' estimates combining All India Debt and Investment Survey 2018 round and Forbes 2018 billionaire rankings using *standard* Pareto interpolation.
Note: The wealth series presented in this paper is estimated by combining wealth surveys (AIDIS) with Forbes rich lists. The table presents how the choice of the fractile $p_0 \in (0, 1)$ in the distribution till where the survey is considered representative affects top shares for the year 2018 (last AIDIS round). Not surprisingly, we see that by assuming lower p_0, we get higher top shares (except for at the very top—top 0.001 percent). The top 10 percent share declines from 71 percent with $p_0 = 90.0$ to 61 percent with $p_0 = 99.9$. We consider our choice of $p0$ for our benchmark series (99.99 till 2017 and 99.95 2018 onwards) as conservative given that the survey is likely to be non-representative even at lower percentiles within the top decile.

Table S2.5 Fraction of rich list wealth recovered using two Pareto methods

Year	Forbes		Hurun	
	Constant (%)	Log-linear (%)	Constant (%)	Log-linear (%)
2002	2	94	*	*
2003	4	97	*	*
2004	7	102	*	*
2005	5	100	*	*
2006	6	104	*	*
2007	6	105	*	*
2008	54	81	*	*
2009	39	93	*	*
2010	34	89	*	*
2011	31	94	*	*
2012	26	100	160	93
2013	18	106	160	91
2014	17	103	112	102
2015	10	118	34	130
2016	8	123	93	103
2017	9	129	25	131
2018	18	118	170	85
2019	21	114	53	107
2020	11	115	171	79
2021	20	107	20	112
2022	20	103	136	90
2023	*	*	18	109

Source: Authors' estimates based on the data from the Forbes billionaire rankings and Hurun rich lists.
Note: To top-correct the All India Debt and Investment Survey (AIDIS), we simulate wealth for the top 0.1 percent (0.5 percent, 2018 onwards) for which we need the Pareto parameter α treating average wealth at $p99.9$ ($p99.5$, 2018 onwards) in the survey as the wealth level from where the Pareto law applies. As described in wealth methodology section, we start with two approaches to recover α from rich lists: the constant inverted Pareto coefficient method and the log-linear method. We then judge the approaches based on their ability to recover the sum total wealth reported in the rich lists. Let us say the *total* net wealth of the wealthiest N persons covered in the rich list equals $\overline{W}$. This table presents the fraction of $\overline{W}$ we are able to recover with the top N individuals in our simulations based on the two approaches using both Forbes and Hurun rich lists. The constant inverted coefficient method falls far short (for Forbes mainly), whereas the log-linear method is on average quite close to the mark with both Forbes and Hurun. Hence, we pick the log-linear approach for our benchmark series. $*$ denotes rich list data not available for those years.

Table S2.6 Estimated Pareto (α) parameter, 2002–2022

Year	Forbes	Hurun
2002	1.147	$*$
2003	1.148	$*$
2004	1.104	$*$
2005	1.087	$*$
2006	1.037	$*$
2007	0.984	$*$
2008	1.164	$*$
2009	1.247	$*$
2010	1.193	$*$
2011	1.174	$*$
2012	1.166	1.180
2013	1.153	1.158
2014	1.154	1.106
2015	1.092	1.070
2016	1.097	1.090
2017	1.073	1.048
2018	1.138	1.188
2019	1.143	1.157
2020	1.163	1.189
2021	1.113	1.125
2022	1.093	1.138
2023	$*$	1.186

Source: Author's estimates based on the Forbes billionaire rankings and Hurun rich lists.
Note: To top-correct the All India Debt and Investment Survey (AIDIS) data, we simulate wealth for the top 0.1 percent (0.5 percent, 2018 onwards) for which we need the Pareto parameter α treating average wealth at $p99.9$ ($p99.5$, 2018 onwards) in the survey as the wealth level from where the Pareto law applies. This table presents the α we are able to recover with the Forbes and Hurun rich lists following the log-linear method. $*$ denotes rich list data not available for those years. Every alternate year, the Hurun rich list only releases a truncated top-100 list.

Table S2.7 Coverage of assets & liabilities in wealth surveys, 1961–2018

Type of assets/liabilities	1961	1971	1981	1991	2002	2012	2018
Physical assets							
Land	✓	✓	✓	✓	✓	✓	✓
Building	✓	✓	✓	✓	✓	✓	✓
Livestock	✓	✓	✓	✓	✓	✓	✓
Agricultural implements, machinery, etc.	✓	✓	✓	✓	✓	✓	✓
Non-farm business equipment	✓	✓	✓	✓	✓	✓	✓
Transport equipment	✓	✓	✓	✓	✓	✓	✓
Durable assets	✓	✓	✓	✓	✓	×	×
Financial assets							
Shares, debentures, mutual funds, etc.	✓	✓	✓	✓	✓	✓	✓
Deposits (company, bank, post office, etc.)	✓	✓	✓	✓	✓	✓	✓
Dues receivable—Cash	✓	✓	✓	✓	✓	✓	✓
Dues receivable—Kind	✓	✓	✓	✓	✓	✓	✓
Liabilities							
Dues payable—Cash	✓	✓	✓	✓	✓	✓	✓
Dues payable—Kind	✓	✓	✓	✓	✓	✓	✓

Source: Authors' compilation from documentation of successive round of the All India Debt and Investment Survey rounds.
Note: The table presents the coverage of various classess of assets in the AIDIS across various rounds used in this study.

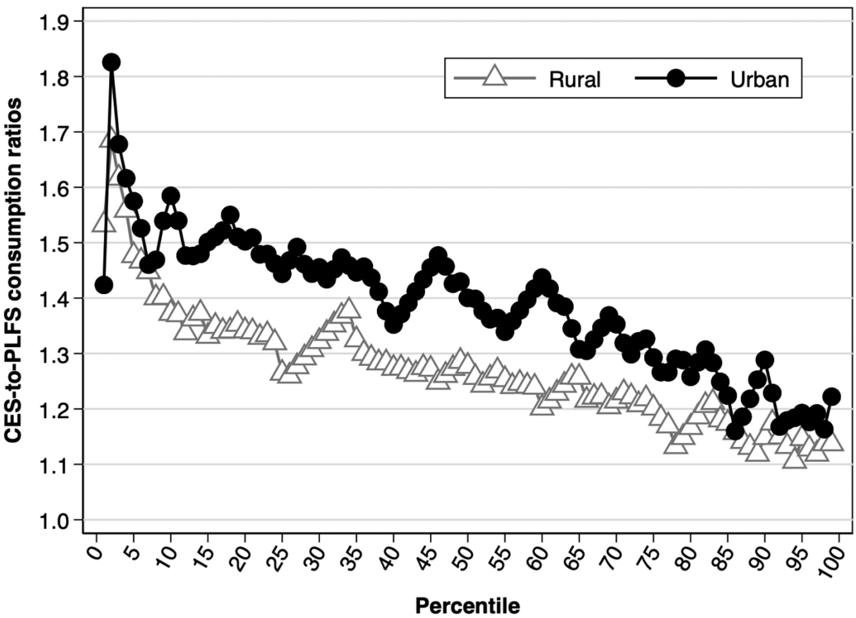
Table S2.8 Growth of very-high-net-worth individuals, 1988–2022

Year	Forbes		Hurun	
	Number of individuals	Net wealth as % of NNI	Number of individuals	Net wealth as % of NNI
1988	1	1.7	*	*
1989	1	0.5	*	*
1990	1	0.5	*	*
1991	1	0.6	*	*
1992	1	1.0	*	*
1993	1	0.7	*	*
1994	2	1.3	*	*
1995	2	1.1	*	*
1996	3	1.5	*	*
1997	4	1.6	*	*
1998	2	1.5	*	*
1999	7	2.7	*	*
2000	9	7.0	*	*
2001	4	3.4	*	*
2002	5	3.2	*	*
2003	6	3.1	*	*
2004	8	4.6	*	*
2005	9	5.1	*	*
2006	19	9.3	*	*
2007	33	16.7	*	*
2008	50	27.8	*	*
2009	21	8.3	*	*
2010	47	15.1	*	*
2011	52	14.4	*	*
2012	46	12.0	100	14.4
2013	52	11.8	141	17.4
2014	51	10.9	230	24.3
2015	90	15.5	*	*
2016	85	12.5	338	21.8
2017	101	14.0	*	*
2018	119	18.0	831	25.4
2019	106	16.1	*	*
2020	102	13.5	829	26.5
2021	140	21.5	*	*
2022	162	24.6	1103	27.5

Source: Authors' estimates combining national accounts aggregates with Forbes rankings and Hurun rich lists.
Note: Forbes billionaire rankings track all individuals with net wealth exceeding 1 billion USD MER since 1988. Hurun rich lists track all individuals with net wealth exceeding 1,000 crore INR (∼120 million USD MER on March 1, 2024) since 2012. Post-2014, Hurun has only published a full list every alternate year. NNI = Net national income.Years for which data was not available has been denoted by '∗'.

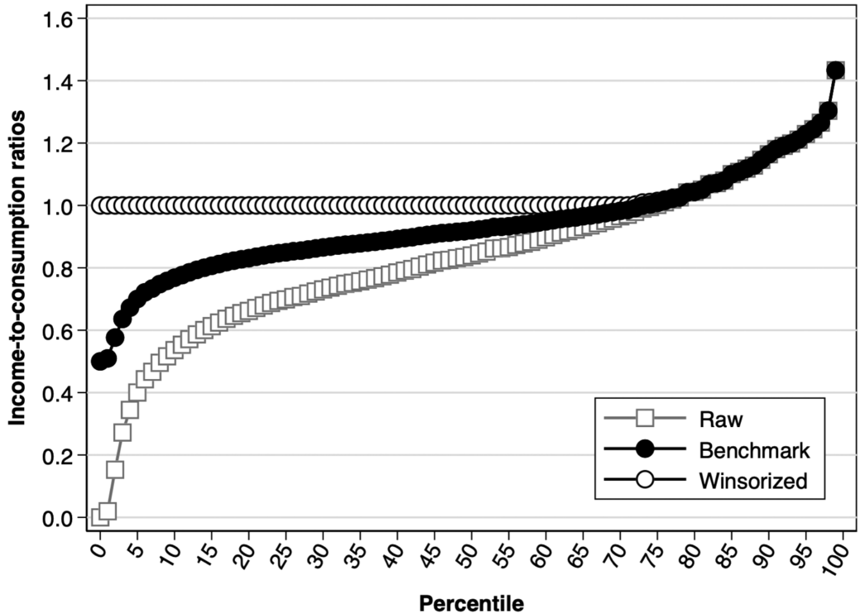
S3. Income series

Figure S3.1 PLFS-to-CES consumption ratios



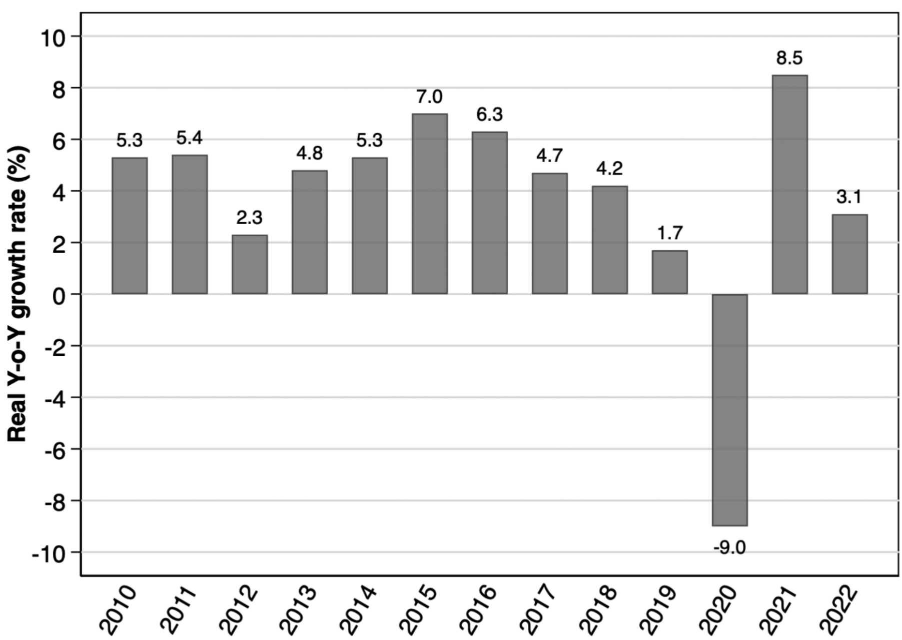
Source: Authors' estimates combining unit-level data from the 2017 Periodic Labour Force Survey (PLFS) and Consumption Expenditure Surveys (CES) conducted in for 2017–18 by the National Sample Survey Organization (NSSO).
Note: The figure presents the scaling ratios used to move from consumption observed in PLFS to a CES-comparable consumption measure. To estimate these, we use generalized Pareto interpolation to extract a full distribution of monthly per capita consumption expenditure (MPCE) for rural and urban areas available in the tabulated summary of the CES 2017–18. We then estimate the MPCE distribution from the unit-level PLFS 2017–18 data using the "usual" consumption expenditure variable in the dataset. Then we divide the CES consumption by the PLFS consumption at each percentile.

Figure S3.2 Income-to-consumption ratios



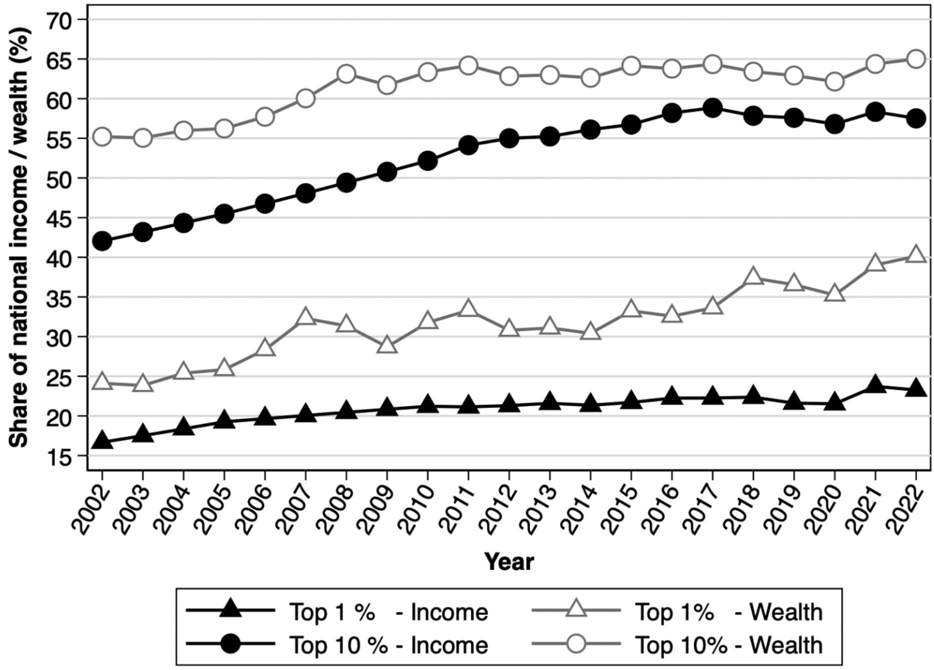
Source: Chancel and Piketty (2019) based on unit-level data from two rounds of the India Human Development Survey (IHDS).
Note: The figure presents the scaling ratios we use to move from the consumption distribution to an income distribution. These ratios are estimated as $\alpha_p = y_p/c_p$, where $p \in (0, 1)$ denotes percentiles and y and c income and consumption respectively. The "raw" variant is the ratios as observed in the data, the "winsorized" variant restricts the observed ratios to be at least as large as 1, and the "benchmark" variant (used in our series) is an average of the raw and winsorized variants.

Figure S3.3 Income growth rates as per national accounts, 2010–2022



Source: Authors' estimates based on national account statistics.
Note: The figure presents the year-on-year real growth rate of average net national income over the period 2010–2022.

Figure S3.4 Co-evolution of income & wealth inequality, 2000–2022



Source: Authors' estimates combining national income and wealth aggregates, surveys, tax tabulations, and Forbes data.
Note: The figure presents the distribution of per-adult net national income and national wealth.

Table S3.1 Per-adult pre-tax national income shares (percent), 1951–2022

Year	Bottom 50%	Middle 40%	Top 10%	Top 1%	Top 0.1%
1951	20.6	42.8	36.7	11.5	4.4
1952	20.7	43.2	36.1	11.8	4.7
1953	21.1	42.9	36.0	11.1	4.2
1954	20.4	41.7	37.9	12.6	4.8
1955	19.2	41.3	39.6	13.7	5.3
1956	19.6	41.2	39.2	13.8	5.3
1957	20.6	40.8	38.6	14.1	5.6
1958	20.1	41.2	38.8	13.6	5.2
1959	20.6	41.8	37.6	12.9	4.9
1960	21.3	41.8	36.9	13.2	5.3
1961	21.2	41.6	37.2	12.7	4.9
1962	21.7	41.3	36.9	12.6	4.6
1963	22.9	42.6	34.6	12.2	4.5
1964	22.6	41.9	35.5	12.0	4.1
1965	22.5	41.6	35.9	12.6	4.7
1966	22.5	41.3	36.2	12.9	4.7
1967	22.3	41.9	35.8	12.6	4.5
1968	22.6	42.3	35.2	12.1	4.3
1969	22.1	41.8	36.2	12.9	4.6
1970	22.0	41.5	36.5	13.0	4.5
1971	22.8	42.7	34.4	11.4	3.8
1972	23.0	42.9	34.1	11.0	3.6
1973	23.1	42.9	34.0	10.2	3.3
1974	23.0	43.0	34.0	10.1	3.1
1975	22.8	43.0	34.2	10.4	3.3
1976	22.7	43.0	34.4	10.3	3.1
1977	22.7	43.2	34.2	9.7	2.8
1978	22.7	43.6	33.7	9.3	2.6
1979	23.1	44.6	32.2	8.0	2.3
1980	23.3	45.2	31.5	7.3	2.0
1981	23.5	45.8	30.7	6.7	1.8
1982	23.6	46.3	30.1	6.1	1.7
1983	21.8	43.0	35.3	10.3	2.9
1984	22.4	44.2	33.4	8.9	2.5
1985	21.9	43.3	34.8	10.5	3.2
1986	21.8	43.1	35.1	10.8	3.3
1987	22.0	43.5	34.5	10.3	3.2
1988	21.7	42.9	35.4	11.1	3.5
1989	21.7	42.9	35.4	11.0	3.4
1990	22.4	44.1	33.5	10.5	2.9
1991	22.2	43.7	34.1	10.2	2.7
1992	21.9	43.0	35.1	10.0	2.8
1993	21.4	41.9	36.7	12.5	3.8
1994	20.9	40.9	38.2	12.4	3.8
1995	20.9	40.8	38.3	13.0	4.9
1996	21.1	40.9	37.9	13.2	4.6
1997	20.9	40.4	38.7	13.8	4.6
1998	20.8	40.0	39.2	14.4	4.6
1999	20.7	39.8	39.5	14.7	4.7

Table S3.1 Continued

Year	Bottom 50%	Middle 40%	Top 10%	Top 1%	Top 0.1%
2000	20.6	39.5	39.9	15.1	4.9
2001	20.2	38.9	41.0	16.7	5.4
2002	19.7	38.2	42.1	17.5	5.4
2003	19.3	37.5	43.2	18.4	6.1
2004	18.8	36.8	44.3	18.4	6.1
2005	18.4	36.1	45.5	19.3	6.4
2006	17.9	35.3	46.8	19.7	6.7
2007	17.5	34.5	48.1	20.1	7.1
2008	17.0	33.6	49.4	20.4	7.4
2009	16.5	32.7	50.8	20.8	7.8
2010	16.0	31.8	52.2	21.2	8.1
2011	15.3	30.5	54.1	21.1	8.3
2012	15.1	29.9	55.0	21.3	8.2
2013	15.0	29.8	55.2	21.6	8.5
2014	14.7	29.2	56.1	21.3	8.2
2015	14.5	28.7	56.7	21.7	8.2
2016	14.1	27.7	58.2	22.2	8.6
2017	13.9	27.3	58.8	22.3	8.6
2018	14.4	27.7	57.8	22.4	8.8
2019	14.7	27.7	57.6	21.6	8.3
2020	15.5	27.7	56.8	21.5	8.2
2021	15.0	26.7	58.3	23.7	9.8
2022	15.1	27.4	57.5	23.3	9.2

Source: Authors' estimates combining national income accounts aggregates, tax tabulations, and income and consumption surveys.
Note: The table presents a summary of pre-tax income inequality over the 1950-2022 period.

Table S3.2 Merge point for tax tabulations, 1953–2020

Year	Fractile	Year	Fractile
1953	0.998	1989	0.993
1954	0.998	1990	0.992
1955	0.998	1991	0.991
1956	0.997	1992	0.990
1957	0.996	1993	0.990
1958	0.996	1994	0.988
1959	0.996	1995	0.987
1960	0.996	1996	0.984
1961	0.996	1997	0.981
1962	0.995	1998	0.976
1963	0.994	1999	∗
1964	0.994	2000	∗
1965	0.994	2001	∗
1966	0.994	2002	∗
1967	0.993	2003	∗
1968	0.993	2004	∗
1969	∗	2005	∗
1970	0.993	2006	∗
1971	0.993	2007	∗
1972	∗	2008	∗
1973	0.993	2009	∗
1974	0.993	2010	∗
1975	0.993	2011	0.946
1976	0.993	2012	0.940
1977	0.995	2013	0.935
1978	0.993	2014	0.931
1979	0.997	2015	0.923
1980	0.997	2016	0.919
1981	0.997	2017	0.909
1982	0.998	2018	0.906
1983	0.996	2019	0.915
1984	0.997	2020	0.912
1985	0.996	2021	0.906
1986	0.995	2022	0.897
1987	0.995		
1988	0.994		

Source: Authors' compilation using income tax tabulations and data on adult population.
Note: This table presents the fractile $p \in (0, 1)$ in the distribution from where the tax tabulations are used. $*$ denotes years for which tax data are unavailable.

S4. Growing data challenges in recent years

During the last decade, various key data sources in India have either become unavailable or their quality has become suspect. This applies to all the key inputs that go into our inequality series: national income accounts, tax tabulations, and surveys. We briefly discuss these issues with the aim of drawing caution when interpreting the estimates for recent years.

National income accounts: Various concerns have been raised about the validity of India's national income accounts data in recent years.[7] At least two detailed empirical exercises, one by an ex-chief eco-

[7] As India's ex-chief statistician clarified recently, the issue with India's GDP estimates in recent years seems to be less about methodology and more about the severely outdated underlying data and unreliable proxies (Thapar 2023).

nomic advisor to the Government of India, point to possible overestimation of GDP in the years post-2011 (Morris and Kumari 2019; Subramanian 2019). Some concerns have also been raised regarding the possible mismeasurement of India's GDP deflator (Subramanian and Felman 2023). More generally, the dated nature of the underlying data used to estimate GDP is very concerning—key inputs like the CPI, WPI, input-output tables, industry codes, and consumption expenditure are currently based on data that might be 10–15 years old (Sapre and Bhardwaj 2023). This is especially a worry for aspects relating to the informal sector of the economy. If it is indeed the case that GDP is being overestimated in recent years, that would imply that our inequality estimates would be slightly downward biased.[8]

Tax tabulations: The British colonial administration introduced an individual income tax with the Income Tax Act, 1922. Since then, data on individual incomes began being collected and the colonial administration published these data in tabulated form on an annual basis. This practice was continued by the Indian government post-independence. Between 1922 and 1998, annual publication of these "All-India Income Tax Statistics" provided a vital source of information on top incomes, mobilizing which Banerjee and Piketty (2005) estimated the share of national income going to the top 0.01 percent, 0.1 percent, and 1 percent during this period. There were naturally improvements to the methodology used to generate these tabulations over the years (partly owing to technological and computational improvements), but systematic and regular release of these data was not disrupted. However, starting 1999 onwards, the Government of India strangely stopped publishing these tax tabulations for reasons that remain unknown. For a whole decade when India experienced strong macroeconomic growth (2000–2010), no tax tabulations are available to date. Then in 2016, the government retrospectively released data but only starting in 2011. For the next few years, data releases continued till retrospective data for 2017 was out, after which once again no tax tabulations were available. Finally, in mid-2023, the government again retrospectively released data for the years 2018–2021. In short, the release of tax data has been highly erratic and incomplete in recent decades. The reason for this remains unclear. One possibility is that the analysis and release of tax data falls low on the priority list of the Income Tax department. This stands in sharp contrast to the past when, for instance, government appointed committees specially provided recommendations on ways to better analyze and report data from income tax returns.[9] Besides releasing all-India tabulations, the income tax department also used to release state-wise tabulations till 1998. These could potentially allow going beyond all-India analysis and shed light on the evolution of top incomes and inequality at the *state level*. Given the size and population of individual states, larger than many European countries in many cases, this is an important endeavor. However, starting in 1990 (to the best of our knowledge), state-wise statistics have not been released at all, even post-2011 when all-India statistics have been released. The non-availability of state-level data in recent years is strange, not only because it used to be released regularly before, but also because computerization and digitization of records in recent decades should make disaggregation and tabulation of returns at the state level easier than before. This leaves the estimation of state-level income and wealth inequality an incomplete endeavor.

Income and consumption surveys: One of the key challenges when updating the income inequality series for the last decade is the absence of a comparable NSSO consumption survey after 2011–12. As noted earlier, NSSO has historically steered clear of measuring incomes and instead focused on consumption expenditures. Consequently, our measurement framework also relies heavily on these consumption surveys. The NSSO did conduct a round in 2017–18 but it was suppressed by the government. From 2017–18 onwards, the PLFS came to our rescue. As it turns out, even though it is primarily designed for labor-market outcomes, it collects preliminary data on "usual" consumption expenditures. By correcting these for comparability with past NSSO CES rounds, we are able to extend our income inequality series on an annual basis from 2017–18 onwards. However, this involves a correction that is bound to

[8] This is because (70 percent of) per-adult net national income serves as the "control average" for the generalized Pareto interpolation algorithm used to extract a distribution of top incomes from the tax tabulations. A lower control average would mechanically increase top income shares. To what extent this issue affects our estimates depends on the extent to which national income is being overestimated.

[9] As an example, the "Committee on Direct Tax Statistics" recommended using a part-sampling and part-census approach for generating tabulations of income tax statistics from 1974–75 onwards—all returns with incomes above INR 25,000 were to be covered by a census, while those with incomes below INR 25,000 were to be sampled, with most states assigned a 10 percent sample, some 20 percent, and a full census in some union territories like Delhi (Directorate of Inspection 1978). Incidentally, this was a time when the government of India was explicitly interested in curtailing the power of the elites.

be only imperfect at best. This creates an additional degree of uncertainty around our estimates in the recent years. More recent consumption survey rounds have been conducted in 2022–23 and 2023–24, but these have deviated from previous rounds in key methodological aspects, making temporal comparability a challenge (Ghatak and Kumar 2024; Himanshu, Lanjouw, and Schrimer 2024; Anand 2024; Subramanian 2024; Manna 2024; Sinha Roy and van der Weide 2025). The recent announcement and launch of a national household income survey by the NSSO is a welcome decision (Kundu 2025), one that we hope will contribute to better understanding the dynamics of growth in India, as well as its distributional consequences.

Wealth surveys: It is also worth mentioning a couple of concerns relating to NSSO AIDIS that forms the basis for our wealth inequality series. First, as highlighted earlier, it appears that the issue of underestimation at the top has worsened over the last three successive rounds in 2002, 2012, and 2018—the total (net) wealth of USD MER billionaires in the Forbes list as a percentage of the total survey wealth increased from 1.26 percent in 2002 to 2.74 percent in 2012 to 6.01 percent in 2018. The issue of underestimation and under-representation of the very rich and wealthy in sample surveys is not unique to India but the fact that the issue is getting worse over time deserves closer attention by the NSSO. More stratification and purposive oversampling at the top could be ways to counteract the current trend of increasing non-representativeness of the right tail. Further, with all its surveys (CES, AIDIS, PLFS, etc.), NSSO should release non-response rates by some variable like, say, the "usual" consumption expenditure variable that it could collect at the household listing stage—this would allow decomposition of the non-representativeness of surveys for the right tail more clearly into response-related and measurement-related issues. It is also worth highlighting that we are likely to be underestimating wealth at the top of the distribution due to off-shore wealth. Of the total foreign-owned off-shore real estate in Dubai, 20 percent is owned by Indians (Alstadsæter et al. 2024), amounting in total value to 1.1 percent of India's GDP (Alstadsæter et al. 2022). The second concern relating to AIDIS relates to the timing of the release of the latest round of the data. Starting in 1961–62, these surveys were meant to be decennial surveys and indeed they were conducted every 10 years, in 1971–72, 1981–82, 1991–92, 2002–03 and 2012–13. It is unclear why the last round was conducted within a shortened gap of 6 years in 2018–19. If this is part of a broader plan of more regular AIDIS rounds, then it is a welcome change. If, on the other hand, this was the result of political considerations, then there is a cause for worry. Coincidentally (or not), our estimates suggest that the top 10 percent wealth share may have been at its lowest during the last decade in 2018 (table S2.1).

S5. Generalized Pareto interpolation

To extract a distribution of top incomes from the tabulated tax data, we rely on generalized Pareto interpolation methods developed by Blanchet, Fournier, and Piketty (2022). Going back to Vilfredo Pareto's empirical observation based on income data from Swiss cantons that top incomes are well approximated by a power law (Pareto 1896), various interpolation methods relying on the property of "scale invariance" of the Pareto distribution have been deployed over the years. Consider a Pareto distributed variable with a probability density function (PDF) and complementary cumulative distribution function (CCDF) given by

$$\text{PDF:} \quad \mathbb{P}(Y \in [y, y+dy]) = f_Y(y) = \left(\frac{\alpha}{y_0}\right)\left(\frac{y_0}{y}\right)^{\alpha+1},$$

$$\text{CCDF:} \quad \mathbb{P}(Y > y) = 1 - F_Y(y) = \left(\frac{y_0}{y}\right)^{\alpha},$$

where Y is the continuously distributed random variable denoting incomes (or wealth), y a realization of it, $y_0 > 0$ some minimum income level from which the distributional form applies, and $\alpha > 0$ the tail parameter which describes the thickness of the tail of the distribution. Lower values of α imply the probability of observing extreme realizations decays slower to 0, leading to fatter tails.[10] There are two

[10] With $2 < \alpha$, both the mean and variance are finite; with $1 < \alpha \leq 2$, the mean is finite but not the variance; with $\alpha \leq 1$, both the mean and variance are infinite.

things to note: First, taking logs on the CCDF we get

$$\log(1 - F_Y(y)) = c - \alpha \log(y),$$

where $c = \alpha \log(y_0)$ is some constant given that y_0 is a constant. We can then recover the tail parameter α by regressing the log of normalized rank on the log of income (or wealth). This is what we refer to as the "log-linear" approach in the main text when describing the wealth series methodology. Second, based on the PDF and CCDF above, it is easily shown that the ratio of average incomes above a threshold divided by the threshold itself is given by

$$\frac{\mathbb{E}(y \mid y > y^*)}{y^*} = \frac{\alpha}{\alpha - 1} = \beta = \text{"inverted Pareto coefficient."}$$

That this ratio does not depend on the threshold itself (hence is scale invariant) means once β is identified (from the tax data or rich lists), average incomes above any threshold $y^* > y_0$ can be interpolated as $\mathbb{E}(y \mid y > y^*) = \beta y^*$, which in turn allows estimation of income shares at any threshold above y_0. In this context, β has a more intuitive interpretation than the tail parameter α and has come to be known as the "inverted Pareto coefficient" in the literature (Atkinson, Piketty, and Saez 2011). Higher values of β imply more concentration of incomes, i.e., fatter tails. Building on this framework, "standard" Pareto interpolation techniques have typically relied on the strict Paretian assumption that an exact power law with a constant tail parameter β holds within each income bracket to interpolate the distribution between two bracket thresholds from tabulated tax data (Pareto 1896; Kuznets 1953; Piketty and Saez 2003; Banerjee and Piketty 2005). However, these methods do not make use of all the information in the tax data, and they do not always work well, even for describing top incomes. Relaxing the strict Paretian assumption that β remains constant across the distribution, instead allowing it to vary by rank, Blanchet, Fournier, and Piketty (2022) develop *generalized* Pareto curves. Letting $p \in (0, 1)$ denote rank in the distribution and $Q(p)$ its associated quantile function, the generalized Pareto coefficient is given by

$$\beta(p) = \frac{\mathbb{E}(y \mid y > Q(p))}{Q(p)} = \frac{1}{(1-p)Q(p)} \times \int_p^1 Q(s)\,ds.$$

These yield generalized Pareto curves (typically U-shaped) summarizing the concentration of income across the distribution. Applying quintic spline interpolation to the income thresholds and averages in the tabulated tax data, the generalized Pareto interpolation algorithm is able to extract a continuous and smooth Pareto curve which is used to interpolate a full distribution from the tabulated data. As Blanchet, Fournier, and Piketty (2022) demonstrate using data from countries where tax micro-files are available, the algorithm outperforms other interpolation techniques.