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REASSESSING INDIA'S POVERTY DECLINE OVER THE MISSING DECADE: 2011-12 TO 2022-23

Abstract

This paper addresses the lack of official data on Indian poverty between 2011-12 and 2022-23, a period known as the "missing decade". It critiques two major attempts to estimate poverty during this time: one using national account growth rates and the other using a private survey. These methods are criticised for their assumptions and data limitations. The paper proposes a new method, imputing consumption from official labour force surveys using a wage-based model. The authors find that poverty reduction was not as dramatic as previously suggested, with about 20% of Indians living in poverty on the eve of the pandemic. The paper's analysis aligns with the fact that India's structural economic transformation was limited, with agriculture output stagnant and regional convergence lacking. The paper concludes that while poverty may have gone down, but its rate of decline has been slow in the decade after 2011-12.

JEL Classification: I32, O15, C81

Keywords: N/A

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Reassessing India's Poverty Decline over the Missing Decade: 2011-12 to 2022-23

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Keywords: India, extreme poverty, structural change, economic development

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1 Introduction

How many Indians live in extreme poverty would be, under normal circumstances, an easy question to answer given the periodic publication of household expenditure surveys by the National Sample Survey Organisation (NSSO). However, there is a missing decade, between 2011-12 and 2022-23, for which no official data is available. After a decade of data blackout, fresh consumer expenditure data was released for 2022-23 in 2024. According to the newly released data, the fraction of the population living in extreme poverty in 2022-23 is estimated between 2-4% using national and international (World Bank) thresholds. According to the previous release in 2011-12, India's poverty headcount was estimated at around 22-23%. A regularly scheduled release of consumer expenditure data in 2017-18 was withheld citing quality concerns. This, over the next few years, sparked a range of alternative estimates of extreme poverty for the 2012-2022 period, and debates and discussion around them, leading this to be referred to as the Great Indian Poverty Debate 2.0 (GIPD 2.0).

Our paper is a contribution to this debate by providing estimates of extreme poverty using a novel method. Two sets of authors (Bhalla et al., 2022; Roy and van der Weide, 2024) calculated India's poverty headcount by extrapolating older surveys with national account growth rates, and, using a privately produced survey, respectively. These calculations both reach the same conclusion: Between 2011 and 2020 poverty fell dramatically in India. The only difference is that while one estimate (Bhalla et al., 2022) claimed poverty was almost eliminated, the other suggested that just under 10% of the population was still in poverty on the eve of the pandemic (Roy and van der Weide, 2024). The second estimate, by Roy and van der Weide (2024), has been incorporated in the public use database of the World Bank – the Poverty and Inequality Platform[1] (PIP).

In this paper, we provide an alternative set of estimates for these intervening years. While new data suggests a near elimination of extreme poverty and has sparked a new round of debate and discussion, we feel it is important to take a careful look at India's poverty headcount in the 2010s.[2] The decline in the headcount ratio for extreme poverty from 22-23% in 2011-12 to 2-4% in 2022-23 suggests a sharp and swift decline. However, as we will argue here, there is a notable lack of structural dynamism in the Indian economy to explain improvements in the living conditions at the bottom of the income and consumption distribution. Two facts are important here: the share of output from agriculture has been stagnant for nearly two decades at 16-17% of GDP. In addition, we find precarious informal employment to also have remained stubbornly high for an economy that has otherwise grown at impressive rates since the 1990s. Ideally, one would expect more productive sectors and formal employment to overwhelm such trends in the face of a so-called sharp decline of poverty. Indeed, a more plausible explanation is that the fiscal (welfare) response to the pandemic may have played a "catch-all" role in poverty reduction by mandating the provision of basic goods and services to the vast majority of the poor (Ghatak and Kumar, 2024). This line of argument basically states that the decline in poverty was sudden and an

[1] Note that PIP replaces the World Bank's previous database (PovCalNet) by being more transparent about datasources but also shifting some of the onus on the user – the data is generated according to choice of PPP, poverty line etc

[2] See Anand (2024), Ghatak and Kumar (2024), Himanshu et al. (2024), Mohanan and Kundu (2024) and Subramanian (2024) for analysis and discussion of the latest consumption expdenditure data and what they imply about extreme poverty.

artifact of policies developed for the pandemic. To be sure, a leaked summary report of the retracted 2017-18 survey suggested that poverty had barely moved from the 2011-12 headcount (Subramanian, 2019b). Because the methods employed by (Bhalla et al., 2022) and (Roy and van der Weide, 2024) depart from the standard method of estimating poverty – calculating poverty in specific years by using that year's consumer expenditure survey published by NSO – these numbers are not yet the final word on India's poverty headcount prior to the pandemic. These studies have been subject to criticism (see Ghatak, 2022 for an overview) in terms of how comparable they are to estimates based on NSS data. For example, there are well-known problems of using national accounts statistics to project household consumption expenditure that (Bhalla et al., 2022) use. Similarly, it has been pointed out (see Drèze and Somanchi, 2023) that the sample design and geographic coverage of the private consumer expenditure data that (Roy and van der Weide, 2024) use, could lead to undercounting the extreme poor. Given this, and the discontinuous drop in extreme poverty over a decade according to the official statistics, it is worthwhile examining this issue in greater depth with other data sources. After all, the credibility of an alternative datasource should be dependent on whether their generated findings can be squared with the facts of the economy being assessed.

We first "vet" these new poverty headcounts by comparing them to what we know about India's structural transformation in the same period (2011-present). Our principal comparisons use the Roy and van der Weide (2024) estimate because of their wide adoption as the go-to source for poverty calculations in PIP. We essentially ask whether the decline in poverty, shown in these data, is consistent with India's level of development and structural composition. We then adopt a more constructive approach by calculating our own poverty estimates. We draw on the official labor force surveys which overlaps with the last (2011-12) consumption survey, but importantly, has been continuously published since then (including for more recent years). We use the overlap period to impute consumption for more recent years at the unit level. We stress: our estimates are most definitely synthetic, but they draw on nationally representative data as opposed to private consumer expenditure data, and moreover, exploits the distribution of material means of consumption (wages). Our headline numbers are consistent with the evidence in the leaked survey results of 2017-18: just under one in five Indians were living in poverty on the eve of the pandemic.

To be sure, measurement of Indian poverty has always been hotly debated (Deaton and Kozel, 2005) along issues of survey design, calorie and non-food expenditures, choice of poverty lines etc on the basis of nationally representative data collected by official authorities. However, we have confidence in our findings because they are more in line with the structural parameters of the Indian economy over the post-2011 period. In the two decades after liberalisation, high growth rates were accompanied by a sharp decline in poverty. While continued economic growth is necessary to lift people out of poverty, as Bourguignon (2003) argues, the reduction of poverty is relatively easier in the early stages and becomes progressively harder once the low-hanging fruits from the rise in average incomes are exhausted and one has to deal with structural poverty. In the decade that we call the "missing decade" the macroeconomic indicators do not suggest major structural changes. The two main structural indicators of transition from low-to-upper income status – manufacturing output and employment shares (Rodrik, 2016; Felipe et al., 2019) – remain quite underwhelming. In addition, there has been the ongoing controversy about GDP growth rates when the methodology for estimating GDP was changed in 2011-12, in which the former chief economic advisor to the Government of India (Subramanian, 2019a) has been on the side of skeptics. Going beyond the controversy over poverty in the missing decade, we hope our methodology can be used in the future as a cross-check on official statistics on consumer expenditure surveys that are published at far less frequency than annual labor force surveys.

The rest of this paper is organized as follows. In Section 2 we summarize the Great India Poverty Debate 2.0. Section 3 checks the plausibility of regional and aggregate poverty decline in India against broader stylized facts. In Section 4 we provide new calculations of poverty for recent years. Section 5 concludes.

2 Recent estimates of poverty

In principle, the calculation of poverty is straightforward. The poor can be identified by taking a consumption distribution, and isolating that part of the left tail which is below a threshold for minimum subsistence. The definition of minimum subsistence varies by country, time and even according to the standards necessary for human flourishing, or, an efficient laboring class. Most countries define national poverty lines (NPL) as a monetary amount taking into account the cost of minimum subsistence baskets adjusted for local prices. These lines vary quite substantially across the world – rich countries' poverty lines are usually higher than the GDP per capita of poor countries.The World Bank standardizes these national lines by focusing on the flat portion of a cross-country relationship between NPLs and log of per-capita consumption.[3] Recently, this line was updated to 2.15 PPP dollars per-day using 2017 prices, but since the bulk of our (and others') estimates cover the pre-2020 period, we will focus on the previous World Bank line of 1.90 PPP per-day at 2011 prices.[4]

As Ravallion (2008) notes, India's statistical authorities have historically pioneered the sample survey methods which form the basis of poverty calculations. The erstwhile National Sample Survey Organization (now NSO) published quinquennial consumer expenditure surveys which were utilized in calculation of poverty and poverty lines for redistributive policy purposes and this enables us to have a fairly continuous series for six decades starting in the 1950s until 2011-12.[5]

However, as we mentioned in the introduction, in a surprising turn of events, India's official authorities withheld the last consumer expenditure survey (for 2017-18) citing data concerns.[6] Popular and expert opinion varied – a study of leaked tabulations from this data suggested an increase in poverty, as well as a decline in real consumption per-capita between 2011-12 and 2017-18 (Subrama-

[3]The standardization of poverty lines using PPP is not without criticism. See Reddy and Lahoti (2015). An alternate method of measuring poverty, arguably superior to the World Bank's method, is provided in Allen (2017) on the basis of a linear programming model of needs. Asian poverty tends to increase as per Allen's method.

[4]Note that one obtains the same poverty headcount when using the 2.15 PPP dollar line at 2017 PPP prices as the 1.90 PPP dollar line at 2011 PPP prices

[5]See Datt, Ravallion, and Murgai (2020) for a review of trends in poverty and growth in India .

[6]https://www.thehindu.com/business/Economy/what-is-consumer-expenditure-survey-and-why-was-its-2017-2018-data-withheld/article61611662.ece

nian, 2019b). Whatever the reasons, the plain fact right now is that Indian poverty since 2011-12 until the recent publication of the 2022-23 survey results has to be calculated using "synthetic" methods which are second-best relative to estimates up to this period.

The first major update to India's poverty headcount was produced by Bhalla et al. (2022) – henceforth BBV – and ran into immediate controversy. Using the 2011-12 Consumer Expenditure Survey (CES) as a benchmark, BBV assume that each household's grew at the same rate as household consumption (nominal) in the National Accounts (NAS). The main source of variation they use is the growth of NAS consumption in different states of India. The authors argue that NAS consumption is larger and more reflective than the aggregate concept measured in household surveys (thus claiming an overestimation of poverty in prior years). The gap between NAS and NSO consumption has been previously noted in the literature. Based on these methods and the supposed superiority of the NAS, BBV conclude that by the eve of the pandemic, India had nearly eliminated poverty according to the 1.90 PPP line. Their estimates are shown in Figure 1. From 21-22% in 2011-12, the population in extreme poverty fell to 3-4% by 2019, using the Uniform Recall Period (URP).[7] Note that the World Bank's poverty estimates for India use URP. Using a Mixed Modified Recall Period (MMRP), their estimates in 2019 show between 1-2% poverty. To any specialist reader, these low poverty numbers stretch credulity. To their credit, BBV hedge for their method by suggesting India adopt a higher poverty line to accurately reflect living standards.

[7]Household surveys use different recall periods as a function of the frequency with which items are consumed

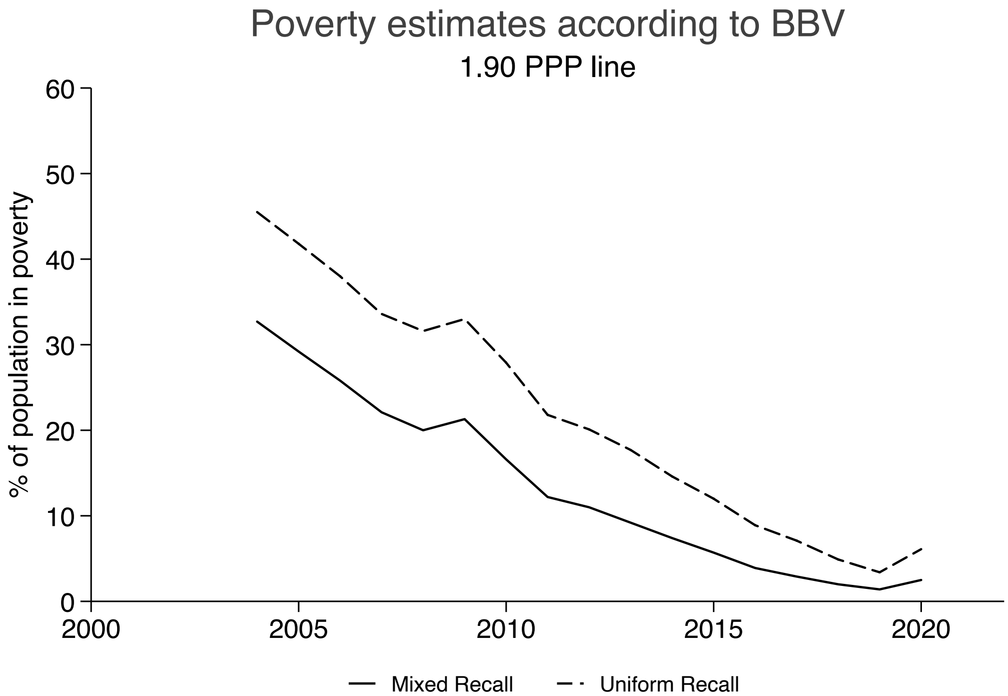

Figure 1: Poverty estimates at 1.90 PPP line in Bhalla et al. (2022)

The use of NAS to measure per-person consumption was already anticipated and critiqued long ago by experts (Minhas, 1988; Deaton and Kozel, 2005).[8] The gap between NAS and NSO, while large and growing, has been mainly attributed to the inability of sample surveys to capture the consumption of the rich (Chancel and Piketty, 2019), not the poor. In addition, the NAS consumption measure is captured residually (India's national accounts use production side methods for pri-

[8]See for example Ravallion (2008): "....it is hard to justify the practice used by some analysts of replacing the mean from the National Sample Survey by consumption per capita from the NAS, while assuming that inequality is correctly measured by the National Sample Survey..."

mary calculation) and uses several imputed items to calculate growth (such as the value of services derived from owner occupied dwellings, FISIM etc) which have no cash-flow basis in surveys. A recent attempt (Edochie et al., 2022) estimated the pass-through rate from the NAS to NSO over 2011-18 at 67%. Further, even if the pass through rate was 100%, one has to then assume that the consumption of the poor grows at the same rate as the rich, completely bypassing theoretical arguements as to why this is implausible, given poverty traps and other centrifugal forces operating in a growing economy (Ghatak, 2015) as well as evidence from growth incidence curves (see Bharti et al (2024)).

Indeed, many of these criticisms were addressed in the other synthetic estimate of poverty by Roy and van der Weide (2024) (RW henceforth) who propose an alternate solution to the data problem by using a privately produced expenditure survey. Since 2014, the Centre for Monitoring the Indian Economy (CMIE) has been publishing a household survey – the Consumer Pyramids Household Survey (CPHS). The CPHS is produced annually and thus it fills in much of the gap left by the absence of NSO data. Using machine learning methods, RW reshaped the weighting scheme on the CPHS to mimic the NSO's CES and found that poverty had declined since 2011-12, but not to the extent found by BBV (Figure 2). Between 2017-19, poverty was around 9-12%. Global estimates of poverty depend on updated data from India, thus, these calculations were internalized into the latest iteration of the World Bank's poverty website. Note that this internalization of synthetic, privately produced data marked a significant departure from the World Bank's usual practice of using official statistics for poverty calculations.

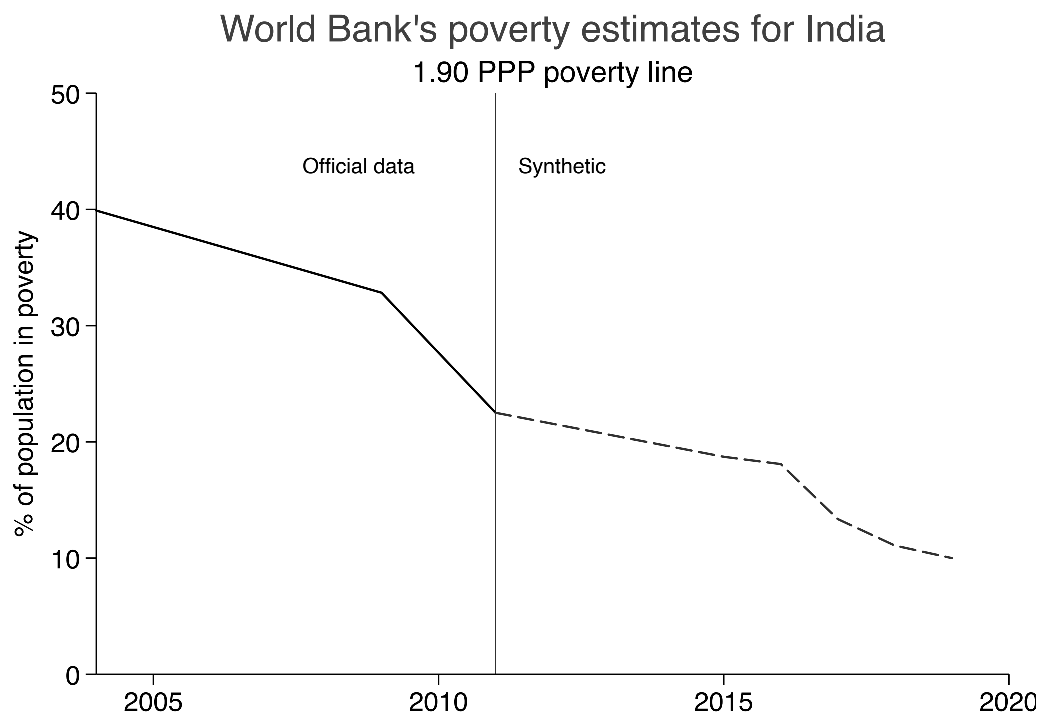

Figure 2: Poverty estimates at 1.90 PPP line in World Bank's Poverty and Inequality Platform, based on (Roy and van der Weide, 2024)

Although their approach is constructive, and perhaps necessary given the shortage of data, RW's estimates have also come under scrutiny. The main criticism is about the data used. CPHS is a privately produced dataset, but careful examination reveals that it falls well short of the nationally representative standards of NSO's surveys. Somanchi (2021) provides a clear taxonomy of issues, tracing an upward bias (which itself has been growing over time) in CPHS related to CMIE's sampling strategy. The bottom line is that CPHS undercounts the poor and its sample is biased towards well-educated Indians. In essence, no amount of re-weighting can recover the "true" left tail of the consumption distribution if the poor are *missing* in the first place.

To sum up, new estimates of Indian poverty either use uniform and unsuitable growth rates from national income statistics to extrapolate household expenditure per-capita, or, use an unrepresentative dataset with regards to India's poorest citizens. [9] Moreover, since these estimates depart from the traditional datasource based on nationally representative household surveys to estimate poverty it is important to scrutinize these estimates carefully. We now turn to the question whether they are validated by other data sources. For instance, is the decline in the poverty rate consistent with the structural transformation of the Indian economy since 2011-12? Was economic growth strong enough in regions with the highest poverty rates?

3 Indian poverty and stylized facts

3.1 The within-India perspective

We begin by addressing the spatial relationship between per-capita income and poverty within India. Namely, given the variation in per-capita income across states and we test whether economic growth was concentrated in the poorest states to justify the BBV/RW poverty reduction over 2011-19.[10] Just to fix ideas, note

[9] For a more detailed set of arguments, we encourage readers to go through a recently conducted symposium on GIPD 2.0 (Ghatak, 2022).

[10] For a cross-country comparison of spatial trends (including for India), see Lamba and Subramanian (2020)

that the ratio of per-capita income between Bihar (one of India's poorest states) and Delhi was around 12% in 2011-12; this ratio is equivalent to per-capita income comparisons of India and the richest countries in the world. At the same time, Bihar accounts for nearly 10% of the Indian population. Our question is simple: over 2011-19, did per-capita income show regional convergence?

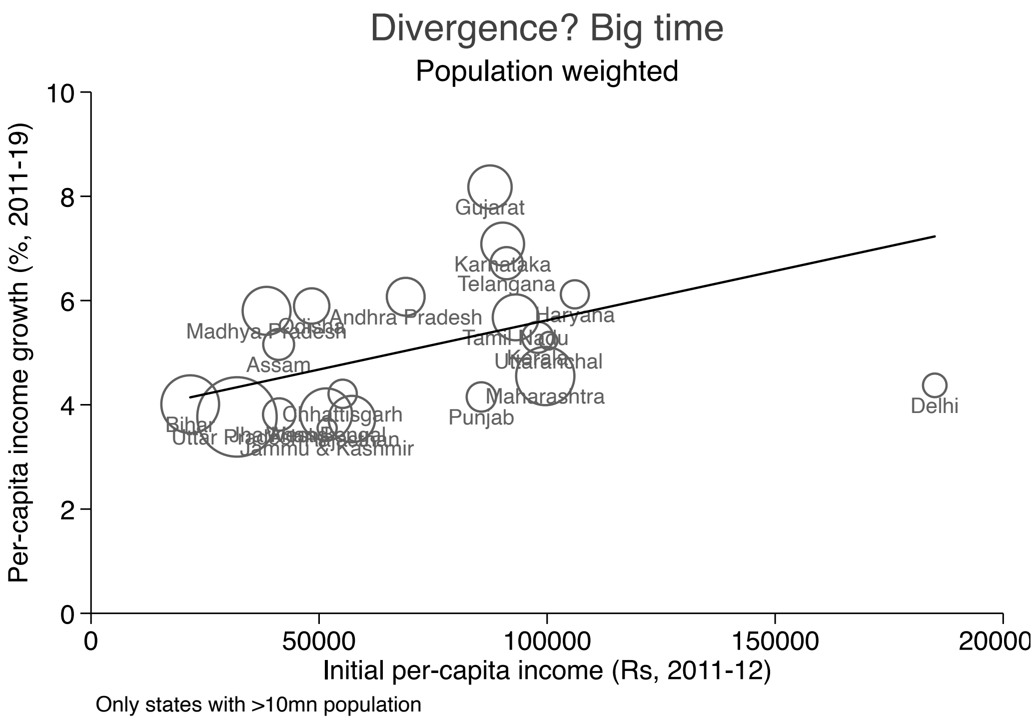

Figure 3: The relationship between initial state per-capita incomes and economic growth. Source: MOSPI national accounts.

We do not use any of the updated poverty numbers and instead rely on the growth angle alone. Basically, we are testing the statistical relationship between initial per-capita income (2011-12) and real rates of per-capita income growth.

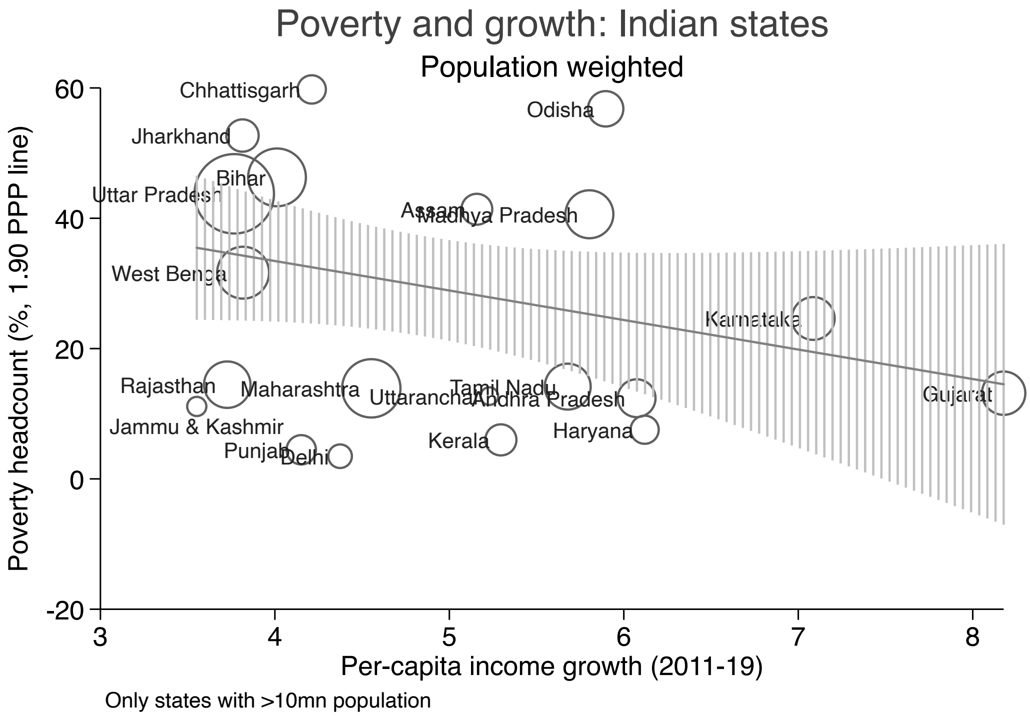

Figure 4: State level poverty and poverty headcounts at 1.90 PPP. Source: NSO CES (68th round) and MOSPI national accounts.

A negatively sloped line comparing both variables would point to convergence (poor states are catching up with faster growth). While not logically necessary, if this is not true, then finding plausible explanations of how aggregate poverty went down becomes more challenging. To this end, we use official estimates of per-capita net output and population for 33 Indian states and union territories from the website of the Ministry of Statistics and Program Implementation (MOSPI). Using state-specific GDP deflators, we calculated real growth rates over 2011 and 2019. The relationship between growth and initial per-capita income is shown in Figure

3. We note a near absence of convergence because economic growth appears positively correlated with initial per-capita income. Rich states like Gujarat and Karnataka grew at 6-8% per-capita, while populous but poor states such as UP and Bihar grew at least 2-3 percentage points less.[11] In quantitative terms, the clustering of poor states at relatively low growth rates is also important because of their weight in India's population. The six poorest states in India account for almost 40% of the population.

Up to this point, we have only considered per-capita income on a state-by-state basis. By itself, this does not shed sufficient light on the spatial concentration of poverty. In particular, at high levels of interpersonal income inequality, there is a possibility that high per-capita incomes mask the living standards of the poor.[12] We therefore extend our analysis by comparing 2011-19 growth rates to the poverty headcount of each state. Using the NSO CES for 2011-12 (68th round) and the URP method (for consistency with World Bank estimates) we computed the population living below the 1.90 PPP line for all Indian states. Our analysis (Figure 4) shows an inverse relationship between initial levels of poverty and subsequent economic growth. The poorest states (in per-capita income) and also home to a larger fraction of individuals living in below the poverty line. To be sure, the inverse relationship between poverty and growth is partly driven by population weights; among the states in the 3-4% growth range, there is significant variation in headcount poverty. However, the highest headcounts are found to be

[11] Delhi is an outlier with the highest per-capita income, but growth rates in the 4-5% range.

[12] For instance, Kumar et al. (2022) find that consumption distributions are more unequal in more prosperous states

in some of India's most populous states (Bihar, UP, West Bengal). Therefore, what we found using per capita income holds up when we take the initial level of poverty instead.

Just to recap these findings: outside of synthetically updated poverty estimates, we found little evidence from spatial growth pattern in the country over what we call the missing decade to justify a broad increase in living standards. Indian states that were poorest in 2011-12, remained so in 2019. Given that India's poverty headcount is disproportionately concentrated in these poor states, we remain skeptical about the possibility of an aggregate poverty decline over 2011-19.

3.2 The cross-country perspective

Given our findings within India, we next take the World Bank's updated (based on RW) poverty estimates for the 2011-19 period and do some cross-country comparisons. In particular, we ask whether these synthetic estimates are consistent with an economy at India's level of development in a cross-country context. At the outset, we wish to emphasize that our findings are not a final say on the quality of these estimates, but rather, they provide a simple test of plausibility to supplement our previous findings on spatial convergence.

One of the most well-known stylized facts about the process of development, as proposed by Kuznets and Lewis, is that as economic growth takes place, resources move from more traditional low-productivity sectors such as agriculture to modern and higher value-added sectors like manufacturing and services. In this respect, India's own trajectory is slightly unique. While on the growth frontier

India is part of a small subset of emerging economies that have sustained impressive growth rates over multiple decades, there is less dynamism on the structural transformation frontier (Amirapu and Subramanian, 2015; Lamba and Subramanian, 2020). Informal employment remains sticky – India is an outlier among developing economies in this aspect (Basole, 2022). Additionally, through most of its high-growth period, India has somehow skipped the manufacturing-led path to economic growth which characterized the Asian tigers (Felipe et al., 2019). These facts are well established, and hardly controversial. We focus on a related aspect which is comparatively less studied but more closely linked to poverty – stabilization of agricultural shares of output at a low level of per-capita income.

Consistent with dual-sector growth, a large class of models emphasize a continuously shrinking agriculture sector over the process of economic development. India followed this predicted path for much of its post-independence history with its share of agriculture in GDP declining from over 40% in the 1960s, to 24-25% by the 1990s. Interestingly, as economic growth accelerated further in the mid-2000s, agriculture stabilized at 16-17% – India was still classified as a low-income economy by the World Bank at this point – and remained there ever since.[13] While this persistence is important on its own, for our purposes, it highlights a puzzle when compared with poverty decline elsewhere. In Figure 5 (upper panel), we compare agricultural shares of GDP (1990-present) with headcount poverty at the 1.90 PPP line for four emerging economies (India, China, Bangladesh and Vietnam) using data from the World Bank's website. We include the World Bank's

[13] A time series of India's agricultural share of GDP is available at https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS?locations=IN

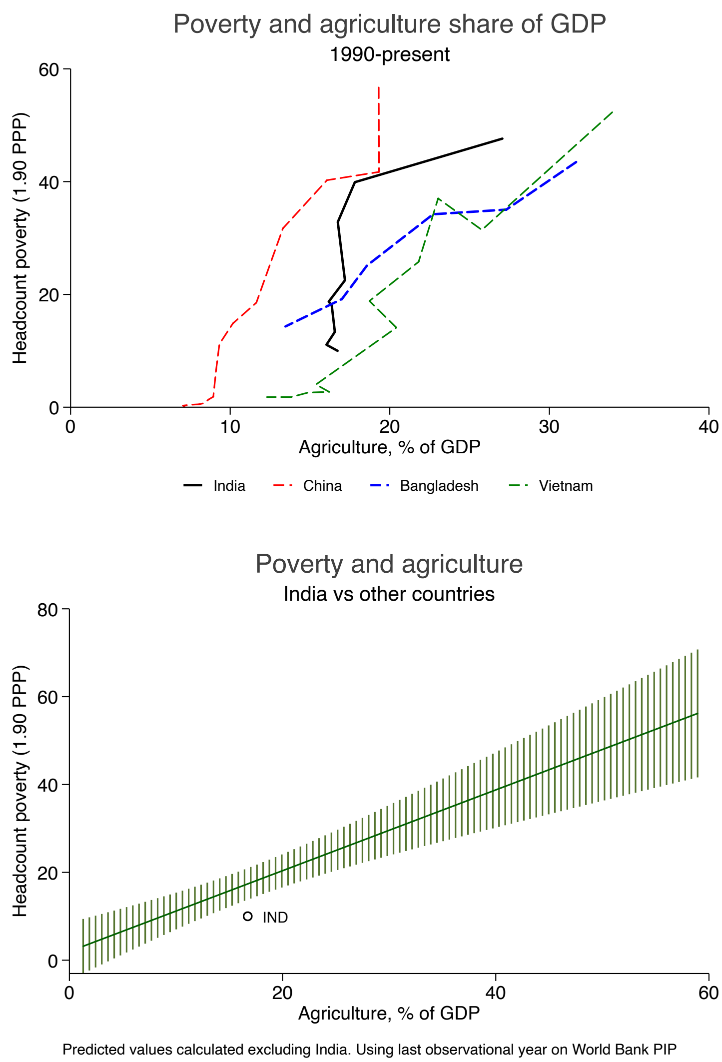

Figure 5: Agriculture share of GDP and poverty headcounts at 1.90 PPP. Source: World Bank PIP and World Development Indicators

post-2011 estimates of Indian poverty to highlight our point. As this figure shows, lower agricultural shares are associated with lower headcount poverty rates in China, Bangladesh and Vietnam. On the other hand, Indian poverty falls below

40% *at the same agricultural share of GDP*. Note that we used the World Bank's estimates (based on RW), which are themselves higher than the levels estimated by BBV. Using data on all but the high-income countries in the World Bank's database, we estimated a linear trend between agricultural shares and headcount poverty. For the sake of comparison, we excluded India entirely and only used the last year of observation for every other country. This fitted line is shown in Figure 5 (lower panel) and India's poverty headcount (for 2019) is superimposed for comparison. This exercise is exploratory at best, but it suggests that based on India's agricultural share alone, its predicted poverty headcount should be at least 5-6 percentage points higher than currently being estimated.

We have raised doubts on the plausibility of the World Bank's poverty estimate for India at the 1.90 PPP line. But they are no substitute for presenting an alternative and more credible poverty headcount. The question of what the level and trend is for Indian poverty remains unanswered. We simply show that the existing answers are not satisfactory. Now we turn to an attempt to provide a more constructive answer.

4 New estimates of poverty in India since 2011-12

In this section, we present our own calculations of poverty for the years after 2017 using other nationally representative data-sources. Our strategy is simple: we draw upon different material measures of living standards in other sample surveys that have been published by the NSO since 2011-12. Our intention is to use official data with representative coverage of the poor. We estimate the relationship between per-capita consumption in the CES and variables in these other surveys and use this to impute consumption in more recent years. In doing so, we apply a more parsimonious strategy relative to existing estimates which attempt to extend household consumption beyond 2011-12.[14]

4.1 Imputed consumption from overlapping surveys

SURVEY	Details	2011-12	2017-18	2018-19
NSO CES	Nationally representative?	Yes	Yes	NA
	Detailed Consumption Profile?	Yes	Yes	NA
	Status	Published	Redacted	NA
NSO EUS	Nationally representative?	Yes	NA	NA
	Detailed Consumption Profile?	Yes	NA	NA
	Status	NA	NA	NA
CMIE CPHS (private sector)	Nationally representative?	NA	No	No
	Detailed Consumption Profile?	NA	Yes	Yes
	Status	NA	Published	Published
NSO PLFS	Nationally representative?	NA	Yes	Yes
	Detailed Consumption Profile?	NA	No	No
	Status	NA	Published	Published

Table 1: Taxonomy of all-India surveys with data on consumption expenditure

Table 1 shows all datasets which supply information on household consumption and/or wages for the 2011-19 period. We use the overlap and continuity in these datasets, restricting our models to official datasets alone. While we have already enumerated on the NSO CES, and its redacted publication in 2017-18, we

[14]In comparison, due to their use of the CPHS, (Roy and van der Weide, 2024) spend considerable space trying to find ways to make their data "obey" household characteristics in official surveys.

now bring focus to the Employment-Unemployment Survey (EUS) of 2011-12 which is used as a base for our analysis. Conducted in sync with the CES, the EUS served as the primary indicator for labor force participation before it was eventually discontinued and replaced by a more frequent Periodic Labour Force Survey (PLFS). Published since 2017-18, the PLFS is the successor to the EUS and follows a similar sampling strategy to determine the principal employment status of each household member, estimate daily wage rates and days spent expending labor, along with their socioeconomic, educational and sectoral characteristics. There are two key differences between the two vintages of employment surveys which matter for our purposes. The EUS has a more detailed measure of household consumption – nearly as good as the CES, with listed items of consumption which are distinguished between durables and non-durables. The equivalent category on the PLFS is less informative. For every household, this survey lists a monetary aggregate representing household consumption expenditure. It is unclear whether a one-time recall satisfactorily captures "true" consumption. Moreover, the ambiguity stemming from the fact that consumption spending is commonly rounded off to the nearest thousand in most instances has to be kept in mind as well. On the other hand, the PLFS provides wage rate estimates for the self-employed (an important and large category of Indian workers), but while the EUS does not. So, both series have their pros and cons, and therefore below, we explore both.

4.1.1 Benchmark method: poverty headcount using consumption-wage profiles

Our benchmark estimation strategy draws from a simple feature across the Indian household cross section: Most households' living standards are grounded in their capacity to sell their labor in return for wages. That is, few households are capitalists and/or landlords – this is especially true for poorer households. The distribution of wages, in other words, is a good approximation of the distribution of living standards. This, in our view, provides a more robust extrapolation of consumption (and hence poverty) because wages are more reflective of on-the-ground reality compared to extrapolation of older distributions using NAS growth rates. These data are also built on NSO's sampling strategy, hence overcoming the upward bias in private datasets (as in RW). Based on these data, we develop a new method to generate synthetic consumption measures which we thereafter use to compute poverty headcounts for 2017-19. PLFS data on wages during the pandemic are sparse, so we do not extend our estimates beyond 2019. We match household consumption with wages across the CES and the EUS in 2011-12. Based on our estimated coefficients, we then project forward the consumption-wage relationship to 2017-18 and 2018-19 PLFS data, essentially using wage rates to compute household consumption.

In the EUS, we first estimate daily wage rates for every individual in every household who are in paid employment (formally or informally). Thereafter, we imputed the wages of those in self-employed status by allocating to them a mean wage *conditional* on their NSO region (a locational subdivision of their state), location (rural or urban), sector of employment, educational status and gender. This gives us a daily wage cell for every individual who was in employment or earned income from self-employment during 2011-12. On the basis of these estimates, we computed the total household wage by summing wages of every earning member of the household. with the CES, we calculated daily household consumption expenditures using both URP and MMRP methods

Note that while the EUS and CES overlap in 2011-12, we cannot match households across both surveys because they each sample different households. Thus, to create a matchable unit, we estimate average wages and consumption in the EUS and CES respectively at the level of NSO region (each state has multiple regions) and sector. This leaves us with 176 observations of mean wages and mean consumption across India, serving as our primary dataset to estimate consumption-wage profiles. We run the following regression with population weights:

$$\log cons_{ij} = a_0 + a_1 \log wage_{ij} + \delta_i + \gamma_j + u_{ij} \tag{1}$$

In equation (1) $\log cons_{ij}$ is the log of mean household consumption in NSO region i and sector j, $\log wage$ is the log of household wages, with δ_i, γ_j added to capture NSO region and sector fixed effects. $u_i j$ is the error term. We obtain highly significant estimates for a_1, which captures the wage elasticity of consumption based on both URP and MMRP methods.

Figure 6 shows that the predicted consumption does a good job of following and reproducing the two-class hump, in the actual consumption distribution. The estimates obtained using equation 1 serve as benchmark parameters. We stress that these parameters are not behavioral in any way. They simply capture the spatial relationship between wages and consumption across two official surveys. Our presumption is that if these parameters are fixed, then, we can locationally impute part of one survey using the other.

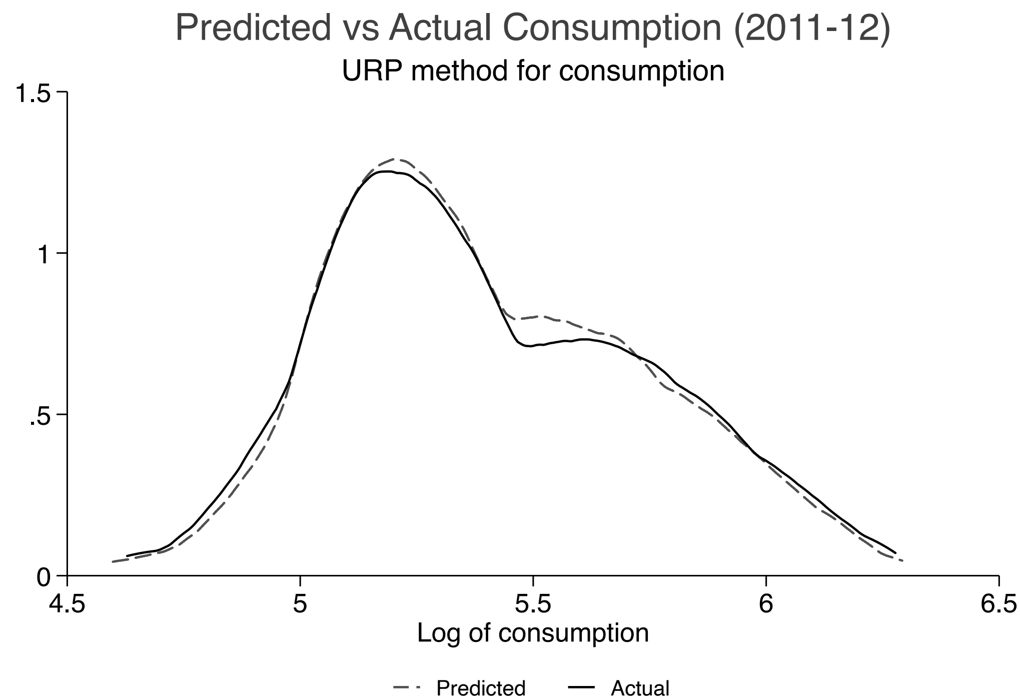

Figure 6: Using wages to predict the actual consumption distribution (2011-12).

We are now in a position to calculate consumption at the individual level by projecting our estimated model to more recent wage data. We convert the PLFS for 2017-18 and 2018-19 into comparable form, obtained each household's daily wage rate. To these wage rates, we apply our model so that each household's consumption (in log form) is:

$$\log cons_{hijt} = \hat{a_0} + \hat{a_1} \log wage_{hijt} + \hat{\delta}_i + \hat{\gamma}_j \tag{2}$$

The notation is the same as used previously, except that we estimate $\log cons$ at the level of each household (h) and year (t). From our specification, it is obvious that for households in the same NSO region (i) and sector (j), the distribution of consumption mirrors the distribution of wages. Once we obtain $\log cons_{hijt}$, we calculate per-capita consumption using household size. For only those households where no member reports a wage (for eg, retirees), we use the monthly consumption estimate directly from PLFS. From these household level estimates, we convert to per-capita using household size and translate all magnitudes from Indian Rupees to PPP dollars using the conversion factor for private consumption on the World Bank's website.

		Headcount poverty at 1.90 PPP per-day		
Year	**Recall Period**	**Total**	**Rural**	**Urban**
2017-18	URP	19.55	25.96	4.10
	MMRP	19.56	26.07	3.84
2018-19	URP	16.81	22.63	3.49
	MMRP	16.84	22.72	3.35

Table 2: Benchmark poverty calculations. Headcount for 2017-19 using consumption-wage profiles.

Essentially we now have a nationally representative dataset of per-capita consumption estimates for 2017-18 and 2018-19. We calculate poverty by considering households below the 1.90 per-day line. Our results are shown in Table 2.

For each year, we estimated equation 1 for URP and MRP consumption (resulting differences are minimal). Because these are the best distributional wage data we can possibly obtain, the estimates shown here serve as our benchmark calculations of poverty. We obtain total poverty at around 20% in 2017-18, followed by a slight decline to approximately 17% in 2018-19. Higher levels of poverty in 2017-18 indicate some hangover from the 2016 demonetization experiment.[15] Rural poverty in both years accounted for the bulk of total poverty at 25-26% and 22-23% respectively. As expected, the floor for urban living standards was higher. Less than 5% of the urban population of India was in poverty.

4.1.2 Evidence from *leaked* tables

How close are our benchmark estimate to "true" consumption? Without actual data, we cannot do a granular comparison. However, there exists one point of reference which we can use to compare the validity of our estimates. The 2017-18 NSO CES was never released in computerized format, but the controversy about its retraction arose because a journalist had obtained the leaked report (with summary tables) and published its findings online. In the summer of 2023, this journalist released his copy of the report online.[16] We obtained this report and its corresponding summary tables. For our purposes, the most important statis-

[15]In November 2016, India demonetized high denomination currency notes to combat illicit (or black) money which accounted for over 85% cash in circulation. The effect was especially pronounced on workers in informal employment with restricted access to banking. Chodorow-Reich et al. (2020) show that the contractionary effects of this policy took a few quarters to fully dissipate.

[16]See https://twitter.com/someshjha7/status/1678651674527948800

tics are listed in its state-sector level tables of monthly per-capita consumption expenditures(MPCE).[17]

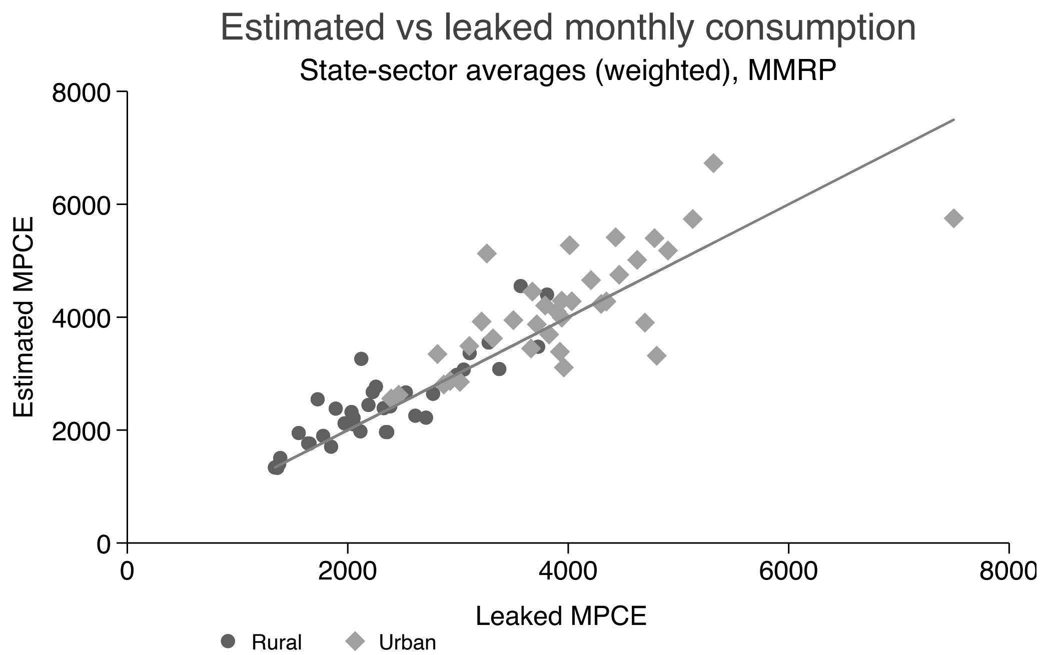

Figure 7: Consumption at the state-sector level in the leaked report versus our benchmark estimates

Figure 7 compares our own estimated consumption for 2017-18 with the leaked report. The obvious takeaway is that our model does a good job of tracking mean consumption. In fact, our model shows a slight upward bias in rural consumption for the poorest states (hence lower poverty) – the implication is that our

[17]The NSO report use the MMRP method for all estimates

benchmark poverty estimates still underestimate poverty relative to the 2017-18 redacted survey to the extent it represents "true" consumption. While the upward bias also appears in the urban sectors of rich states, these likely do not impact poverty. The region where we do worst in terms of prediction is the Union Territory of Chandigarh but given its small share of population and relatively richer living standards, the impact on the estimate of poverty is negligible. The second important takeaway is that the controversy about the quality of data in the 2017-18 redacted report may not be valid. After all, our own measure of consumption uses a completely separate dataset to estimate consumption but both datasets produce a similar pattern of consumption.

As a second estimate, we combine the insights provided by Figure 7 and rescale our benchmark estimates to the state-sector means on the leaked 2017-18 report. We calculate the ratio of predicted-leaked consumption for each sector of every state and use this as a rescaling factor for our model. We preserve this rescaling for both years of PLFS data used in our estimation. Thus, the final estimate of household consumption expenditure of household in our model is:

$$cons_{hijt} = \frac{con\hat{s}_{hijt}}{cons_{sj}/leaked_{sj}} \tag{3}$$

Once we rescale household level consumption, we obtain the same rural/urban means for every state in India for the 2017/18 PLFS as the leaked report from the NSO.[18] We use these scaling factors to also calculate consumption for 2018-19.

Table 3 shows the level changes when we rescale our benchmark estimates

[18]That is, our estimates match Table T2: "Average MPCE and rural-urban differentials for each State/Union Territory" in 2017-18 in the NSO 2017/18 redacted CES.

	Poverty headcount in India (%, URP)	
Year	Benchmark	Scaled to 2017-18 leaked tables
2017-18	19.6	22.9
2018-19	16.8	20.3

Table 3: Poverty headcounts for 2017-18 and 2018-19 before and after scaling. Note: scaling factors were derived using MMRP estimates in the denominator and numerator.

to the leaked report. Naturally, poverty is higher in the rescaled estimate with corresponding headcount of 22.9 and 20.3% for 2017-18 and 2018-19. If indeed concerns about the data quality issues of the leaked report are exaggerated, our methods suggest that poverty over 2011-18 was nearly unchanged, and fell slightly in 2018-19.

4.2 Summary of poverty estimates

Comparison of poverty estimates for the post 2011-12 period

	BBV	**World Bank-RW**	**OPHI**	**Benchmark**	**Rescaled**
Poverty line	1.90 PPP	1.90 PPP	Deprivation index	1.90 PPP	1.90 PPP
Source	NAS growth	CMIE CPHS	NFHS	NSO	Leaks
2011-12	21.8	22.5			
	Estimates below are based on synthetic consumption measures				
2012-13	20.1				
2013-14	17.7				
2014-15	14.6	18.7			
2015-16	12	18.1	27.68		
2016-17	8.9	13.4			
2017-18	7.1	11.1		**19.6**	**22.9**
2018-19	4.9	10.0		**16.8**	**20.3**
2019-20	3.4		16.39		
2020-21	6.1				

Table 4: Comparison of poverty estimates: our models vs existing headcounts in the literature. Benchmark estimate is based on consumption-wage profiles. Rescaled estimate matches state-sector means on benchmark to leaked 2017-18 tables

We are now in a position to summarize and compare our findings using newly calculated shares of the population living in extreme poverty at the 1.90 PPP line. We emphasize that our benchmark measure is the most robust – it is completely independent of the 2017-18 redacted CES, uses up-to-date distributional data on wages and is not based on the crude consumption estimate of the PLFS surveys.

The bottom line is that all of our estimates are higher than the RW and BBV estimates. Our benchmark and leak-rescaled numbers point to a poverty headcount of one in five Indians; essentially implying no change over 2011-18. The difference between our lowest (benchmark) estimate and the highest estimate (RW) for 2017-18 is almost 8 percentage points. This increases the number of the poor in India by nearly 100 million: a magnitude large enough to push up the global poverty headcount for that year. The third column lists the headcount for multidimensional poverty, estimated by the Oxford Poverty and Human Development Initiative in the 2022 Global Multidimensional Poverty Report (UNDP and OPHI, 2022). For India, this index uses data from the National Family Health Surveys which are conducted by the Ministry of Health and Family Welfare in collaboration with the International Institute for Population Studies. Poverty is calculated using ten simultaneous deprivation indices in health, education and living standards for individuals.[19] The interesting point, in relation to our arguments is that deprivation indices are likely to go down in a growing economy as access to public goods, infrastructure and education increases, even with static monetary measures

[19]Note that the use of these indices is not without critique in the economic inequality literature. This is especially important because indices with ad-hoc cutoff points and binary classification for deprivation are not strictly comparable with monetary measures of poverty. See Ravallion (2011)

of poverty. However, our poverty calculations produce numbers which are within the 17-27% multidimensional poverty range for the post-2011 period. We thus take confidence in the range of extreme poverty indicated by our estimates.

To take a broader view, it is hard to argue that India has not reduced its extraordinarily high poverty headcount since the 1980s. Also, as our alternative estimates show, poverty seems to have declined during the pandemic years but perhaps not to the extent as argued by others. However, all this does not fully capture the true reality of living standards in India. With an agricultural share of GDP gravitating around 16-17% and the continued persistence of informal, low wage, and unregulated employment, it is hard to imagine a virtual elimination of poverty. Our findings are much more in agreement with India's level of structural and economic development, pointing to a slowdown of poverty reduction and reinforcing the challenge of eliminating poverty beyond the early effects of a growth takeoff, as outlined by Bourguignon (2003).

5 Conclusion

This paper is sympathetic to synthetic exercises carried out in the absence of official data. After all, researchers and policymakers are left with no recourse but to come up with alternative estimates using different data sources to generate an up-to-date Indian poverty headcount. Given the recent publication of the new NSO consumer expenditure data after a decade, one hopes that one would not have to rely on these synthetic methods out of lack of options but as a way to verify emerging trends and how consistent they are with ohter data-sources.

Our estimates were motivated by the shortcomings of (1) uniformly applied growth rates of consumption and (2) privately conducted surveys, as well as our own analysis of the lack of regional convergence and cross-country trends. Given our findings, we followed the simplest way to cross-check India's possibly poverty rates – imputing missing surveys using the overlap of existing employment surveys and calibrating them to match consumption on leaked 2017-18 tabulations. Since employment data is much more frequently published by India's statistical authorities, our methods may also be helpful in producing more regular estimates of poverty on the basis of updated parameters. This cross-check is also useful when the underlying methodology of surveys undergo revision – for instance, the 2022-23 revises the methods used in 2011-12.

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