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Pandemic, Poverty, and Inequality: Evidence from India

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Pandemic, Poverty, and Inequality: Evidence from India

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ABSTRACT: The paper presents estimates of poverty [extreme poverty PPP$1.9 and PPP$3.2] and consumption inequality in India for each of the years 2004-5 through the pandemic year 2020-21. These estimates include, for the first time, the effect of in-kind food subsides on poverty and inequality. Extreme poverty was as low as 0.8 percent in the pre-pandemic year 2019, and food transfers were instrumental in ensuring that it remained at that low level in pandemic year 2020. Post-food subsidy inequality at .294 is now very close to its lowest level 0.284 observed in 1993/94.

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WORKING PAPERS

Pandemic, Poverty and Inequality: Evidence from India

Surjit S Bhalla, Karan Bhasin and Arvind Virmani[1]

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Section I: Introduction

In a perfect world with perfect data this paper may not have been necessary. However, the lack of reliable household consumption data has posed a problem for estimation of poverty. More so given that the pandemic has brought to the fore concerns about increases in poverty, and inequality, in rich and poor countries alike. Fiscal deficits increased around the world because of decline in tax revenues and expenditures were increased to combat effects of the pandemic on the adversely affected sectors of the economy.[1] For the first time in several decades extreme poverty (those falling below the $1.9 PPP 2011 dollars per person per day; hereafter PPP1.9) in the world increased in the pandemic year 2020. We examine the magnitude of India's contribution, *if any*, to this world increase in extreme poverty.[2]

The traditional source of poverty analysis is via household surveys. But a thorough, traditional detailed *household survey* has not been possible in the last two years, due to obvious constraints and limitations of operating in a pandemic – hence, recourse to what has been done in previous analyses (including from the World Bank, the official "bench-marker" of global poverty). The conventional method of generating poverty estimate when *no* survey has been undertaken is to take the most recent survey data and update individual consumption (or personal) income by the corresponding growth rate observed in the national accounts.[3] It is because of this assumption that the World Bank provides poverty related annual data via PovcalNet: the on-line tool for poverty measurement developed by the Development Research Group of the World Bank[4] (2021) and individual authors (including those at the World Bank) use the extrapolation technique to fill in the results for non-survey years.[5]

The pandemic has made the world rediscover this simple extrapolation technique. Using this method, World Bank (Mahler et. al. 2021) estimate an increase of 97 million extreme poor

[1] See Fiscal Tracker set up by the IMF to document the evolution of pandemic monetary and fiscal policies in over 197 economies. Available here: https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19

[2] Available here: https://blogs.worldbank.org/opendata/updated-estimates-impact-covid-19-global-poverty-turning-corner-pandemic-2021.

[3] "While awaiting household surveys, we continue our previous approach of trying to understand the poverty consequences of the pandemic by extrapolating the income and consumption from past household surveys using national accounts growth forecasts. Simple as it is, this method generally outperforms more complicated methods in nowcasting poverty." (Mahler et. al., 2021)

[4] Available here: http://iresearch.worldbank.org/PovcalNet/data.aspx

[5] See Bhalla (2002) for one of the first attempts at providing data for individual countries (and the world) when household survey data are not available. In Bhalla (2017), updated estimates of poverty and inequality in the world were presented.

worldwide in 2020 and a reduced 76 million in 2021 (that is, the number of extreme poor *decreased* by 21 million in the second pandemic year 2021). Individual country estimates of this poverty change are not provided by the World Bank authors; some (Kochhar (2021) and Basole et al (2021)) have derived poverty increase estimate for India to be in the range of 32 - 230 million in 2020.

None of the poverty estimates incorporate the effect of fiscal interventions such as those that became necessary to alleviate the worst effects of the pandemic on the poor [interventions like food subsidies and subsidized loans to the self-employed]. Unlike most studies, we consider, investigate, and document the poverty and distributional consequences of the pandemic support measures announced by the Indian government. More importantly, we stress that *any* estimate of poverty that relies on household consumption expenditure derived exclusively from survey(s) will overestimate poverty rates, unless the estimation method incorporates the effects of in-kind transfers.[6] In-kind transfers reduce the consumption expenditure of households on items supplied free or at subsidized rates and therefore such adjustments are necessary to arrive at reliable estimates of consumption expenditures and poverty. In-kind transfers of food have been an integral part of redistributive policy in India since the early 1980s.[7]

Estimation of poverty *including* in-kind subsidies is one of the primary objectives of this paper. These adjustments become important (and critical) in understanding the policy induced effects on poverty levels. Analogously, analysis of the effect of tax credits should be centered on post tax credit income (since household surveys typically report only the "pre-tax credit" income).

This paper is an extension of an earlier paper by the authors (Bhalla, Bhasin and Virmani (2020)). This paper makes several contributions to the literature besides the above-mentioned incorporation of food subsidies into the estimation of poverty and inequality. We provide a consistent time-series

[6] Survey collection techniques require interviewers to code only information supplied by the respondent. NSS CES surveys ask respondents for both cash expenditures and expenditures on state supplied (PDS) food – for each purchase, both value and quantity data are coded. However, official poverty and inequality (Gini) estimates are based exclusively on actual expenditures, and no adjustment is made for the difference between cash paid for subsidized goods like cereals, sugar and kerosene, and the market prices of these goods.

[7] See Bhalla (2015) for a detailed analysis of the effects of food subsidies, and employment support work programs. (The MGNREGA job work program)

of inequality and poverty levels for both the extreme poverty PPP$1.9, and low middle income poverty (PPP$ 3.2) levels for each of the years 2004-5 to 2020-21 (see Appendix I). Through use of state-level GDP and population data, administrative data on various consumption items, several survey based data (including NSS) we provide a verification on estimates of per capita growth provided by data on national private final consumption expenditures (PFCE). Appendix II provides an exhaustive analysis of these data as well as the non-validity of the NSS 2017-18 consumer expenditure survey, and hence its non-use.

The effect of the subsidy adjustments on poverty is striking. Real inequality, as measured by the Gini coefficient, has declined to near its lowest level reached in the last forty years – it was .284 in 1993/94 and in 2020-21 it reached .292. Possibly the more surprising result from the incorporation of food subsidies into the calculation of poverty is that extreme poverty has stayed below (or equal to) 1 % for the last three years. In the pandemic year 2020-21 extreme poverty was at its lowest level ever – 0.8 % of the population. Further, as early as 2016-17, extreme poverty had reached a low 2 % level. According to the more appropriate but 68 % higher low middle income (LMI) poverty line of PPP$3.2 a day, poverty in India registered 14.8 % in the pre-pandemic year 2019-20. This achievement is put in perspective by noting that in 2011-12, the official poverty level for the lower PPP$1.9 line was 12.2 %.

The plan of the paper is as follows. Section II surveys issues related to data, definitions, and methods involved in the estimation of poverty and inequality. Section III examines the available data on poverty according to both NSS surveys and World Bank methods, as well as alternative estimates of growth and inflation between 2004-5 and 2020-21. Section IV outlines a method to incorporate in-kind food subsidies into the estimation of poverty, with due consideration given to the possibility that the estimate of household expenditures may be contaminated due to the possibility of double counting (in-kind subsidies are also a component of household expenditures updated via PFCE). Section V concludes. Appendices 1-2 provide supplementary data, documentation of the reasons behind the non-use of the 2017-18 NSS survey (non-use officially and non-use by us). Appendix 3 contains a discussion of the non-comparability of our estimates of poverty and those reported in recent research (Basole et. al. (2021), Gupta, Malani and Woda (2021) and Kochar (2021).

Section II: Data, Definitions, Methods

Over the years, the National Statistical Organization (interchangeably NSO, NSS or NSSO) has experimented with broadly three different methods (recall periods) for collecting data on consumption. Prior to the 1983 consumer expenditure survey (CES), NSS collected all consumption data on a recall basis of 30 days (the *Uniform* Recall Period method). In 1983, for three items the recall period was extended to 365 days. Starting in 1993-94, this extension of recall was extended to a total of five major consumption items (clothing and bedding, footwear, institutional medicine, education, and durable goods (e.g., motor cars); this was termed the *Mixed* Recall Period or MRP)[8]. Purchases of perishables (vegetables and fruits) began to be experimented with in 1999-00 CES survey with a recall period of 7 days (MMRP *Modified* Mixed Recall Period).

The accuracy of the estimate of mean consumption (and therefore likely its distribution as well) is considerably increased with MMRP. This seemingly "minor" change in data collection increases the national average per capita *consumption* estimate in the 2009-10 and 2011-12 consumption by 12.6 and 10.8 %, respectively, with correspondingly large *declines* in the estimate of poverty (12.3 percentage points (ppt) and 10.9 ppt, respectively).[9] In two consecutive two-year apart surveys, with one a drought year (2009/10) and the other a normal rainfall year (2011/12), the gap between the URP and the MMRP *poverty* estimate was around 10-12 percentage points (ppt). This corresponds to a difference in the estimate of poverty of around 125 million and for an identical poverty line! The MMRP method is now the official Indian method of measuring poverty.

This movement towards MMRP across the world is a practice long recommended by the World Bank, via the results of its extensive Living Standards Measurement Surveys (LSMS)) as

[8] In its discussion about the origins of MMRP surveys, the World Bank (2018) wrongly attributes the first year of the now official method as 2011/12 – it was 1993/94.

[9] Extreme poverty measure in 2011-12 is either 21.8 % (URP) or 18.5% (MRP) and 12.2 % (MMRP); in the 2009-10 surveys, the three estimates of poverty were: 33.8 % (URP), 29.4 %(MRP) and 21.5 % (MMRP).

summarized by Deaton and Grosh (1998), and by others.[10] Deaton and Grosh discuss the use of different recall periods for consumption surveys such as in Jamaica where a seven-day and a 30-day recall periods were used. Similarly, in South Africa, food items expenditures were asked on a weekly or a monthly basis. Kyrgyz Republic, and Nicaragua use a recall period of one week while Brazil uses two weeks. Even for non-food items, many countries (like India) use separate recall periods. There are items that have a shorter recall period (a week or two) which are high-frequency or daily use categories while for others they have a recall period of monthly, quarterly, semi-annual, or annual recall periods.

With this background, experimentation, and global and domestic advice, the NSS decided to stop experimenting with recall periods and move "permanently" to the MMRP method for data on consumption and its distribution. Hence, the 2017-18 CES survey gathered information exclusively on the MMRP method. Noting this decision, World Bank (2018) summarized the history of poverty measurement in India (Box 1.3, p. 32-33) as follows:

"A longer recall period is better at encompassing expenditure on infrequently purchased items, but it can lead to underreporting if respondents forget about the past purchases. Despite lower average consumption, measured poverty might be lower under the longer recall period because it captures the purchases of low- frequency items of households in the lower parts of the distribution. Short recall periods can mitigate underreporting but can lead to telescoping, where respondents mistakenly report the consumption that took place outside of the reference period…. With the next NSS Consumption and Expenditure Survey, India is no longer enumerating consumption with the URP. *This means that the global poverty count produced by the World Bank will soon no longer be based on the URP for India and a switch to the MMRP will occur*." (emphasis added)

Methods of Measurement

Given that large-scale surveys are costly, and infrequent (the planned between survey gap in India has averaged around five years) explicit methods have been developed to estimate poverty in the

[10] One of the authors of this paper who was the Advisor heading the PPD division (in mid 2000s), of the Planning Commission, which was responsible for official estimates of poverty, recommended change-over to the modified mixed method, which was eventually accepted by the Planning Commission and the Govt. and implemented by the NSO. Also see Deaton (2003).

inter-survey years. The most common, well-known, and well-accepted procedure is to update nominal per capita consumption with the growth revealed by national accounts data (growth in Private Final Consumption Expenditure or PFCE). In the case of India, there is an additional parameter to consider – which of the *three* estimates of mean expenditure is the benchmark year (the base-year for forecasts). The NSS formally approved the MMRP method in its estimation of the distribution of consumption post the 2011-12 survey. However, despite its reasoning noted above, the World Bank continues to use the now considerably outdated uniform recall method for the estimation of poverty *in India*. This is unfortunate, because the World Bank has been the gold standard for the estimation of poverty. In the interests of transparency, we will present our results for both methods, URP and MMRP, but with a clear labelling that the URP method is no longer the official method.

Cross-Country evidence on Survey Capture

As extensively documented in Bhalla (2002), and also in NSS's own evaluation (*Sarvekshana, Expert Group on Non-Sampling Errors* (2005)) there has been a growing divergence in the estimates of expenditure as obtained from national accounts (NA) and surveys on consumption expenditure(S)[11]. The S/NA consumption ratio (also called survey capture) in India averaged between 90-95 % for twenty years 1957-58 to 1977-78. Post that survey, there was a steady deterioration to 62 % in 1993-94.

Subsequent to 1993/1994, survey capture in India has "normalized" to around 50 % in 2004-5, 2007-8 (a small-sample NSS survey), 2009-10 and 2011-12 according to the URP method; and around 55 % in 2009-10 and 2011-12 (MMRP) method. This relative constancy in the S/NA ratio (and its correspondence with a variety of survey and non-survey data) allows us to use NA nominal consumption growth rates (i.e., growth in PFCE) to relatively accurately forecast consumption growth *backwards* and *forwards* from the 2011-12 CES.

[11] Bhalla (2002) documents this phenomenon for India, and the world, developed and developing.

Meyer, Mok and Sullivan (2015) provide a review of the declining quality of household surveys. They argue that the problem of unit-non-response, item non-response and the problem of measurement errors are possible factors behind the declining quality of household surveys. They also provide an overview of the use of administrative datasets for research and policy analysis, in response to the declining quality of survey data (such as undertaken by us in this paper).

Estimating poverty in the absence of survey data

Three sets of data are needed to estimate poverty across time. First, some base year household distribution is needed. The 2011-12 consumption distribution of 100,000+ households is taken as the base-year distribution (separately) for the two different consumption estimates – URP and MMRP. Two different updating procedures (per capita nominal PFCE and nominal state domestic product per capita) are used to form four household panels for all the years 2004-5 to 2020-21. The third set of data needed is that of the poverty line for each household in the different years. CPI rural and CPI urban estimates for each State, are used to update the respective State poverty lines. State level urban and rural poverty lines are then merged with the base household data (which has information on state and urban/rural residence).

Summarizing, our forecast (or nowcast) method for estimating poverty in the absence of data is as follows. We form a synthetic *panel* of household data for the agricultural years (July-June) 2004-5 to 2020-21 with the 2011/12 household data as the base-benchmark. Per capita consumption is forecast forward (or backward) using national account consumption growth (or state per capita GDP). Combining these data, one obtains per capita level of nominal consumption expenditures for each household, and each year, as well as poverty lines based on the residence status (urban or rural). Poverty is estimated via this distribution for each year. As discussed in detail in Appendix II, very diverse data sources (NSS and surveys by other organizations, administrative data, national accounts data for individual consumption items) confirm the accuracy of using the PFCE growth rate as a very reasonable proxy for growth in survey based expenditures (post 2011-12).

In Section IV, we incorporate the role of food subsidies, in particular subsidies via the operation of the Public Distribution System (PDS). What this base forecast contains is the PFCE consumption expenditure and all its components, including wheat and rice, at market prices (as per national accounts). For those households eligible for food subsidies, the consumption expenditure is as given by the PFCE extrapolation. For those eligible for food subsidies, the expenditure is as per PFCE extrapolation and the *equivalent* cash transfer.

For 2004-5 and 2011-12 we have mean NSS consumption according to the URP recall method. This provides one test for our forecast model: the back-cast of per-capita *consumption* in 2004-5. The NSS consumption level for 2004-5, based on URP survey data, was Rs. 699 per capita per month. Our back-cast of 2004-5 from the 2011-12 survey – a level just 2.4 % lower at Rs. 682.

Consumption inequality: As stated above, we use the 2011-12 household data as the base. This means that we are assuming that the nominal distribution to remain constant, over time. How real inequality (2011-12, rural prices) has changed comes through our incorporation of three "determinants". First, the price level (poverty line) change is different for different states, and *within* a state, different for urban and rural areas. Second, the evolution of average consumption is different for different states via estimation of consumption growth via growth in state domestic product (this growth is identical for all individuals with the PFCE updation method). Third, food subsidies accrue differentially to different households because of differential access and eligibility - only the bottom 75 % of rural and the bottom 50 % of urban households were eligible for food subsidies under the 2013 Food Security Act. For all these reasons, the "extrapolation" method does provide meaningful patterns of inequality, and changes therein.

In addition, for India, real consumption inequality has changed very little for over 30 years. For the uniform recall period, real consumption inequality was 0.3272 in 1983, 0.3324 in 2004/5, 0.3389 in 2009/10 and 0.3392 in 2011-12 (sometimes, we report the Gini coefficient as a multiple of 100). The growth processes have been very different over the three decades yet there has been no discernible change in real inequality. Note that all the above reported estimates for real inequality (1983 to 2011-12) are without incorporating the effect of food subsidies, something we pointedly attempt in this paper.

Omission of NSS 2017-18 data from estimation of consumption and/or poverty

Appendix II provides exhaustive detail on the data used to test the veracity of the 2017-18 NSS consumer expenditure data, the one not made official because of its low "quality". Based on the detailed evidence presented we reach two firm conclusions. First, that the 2017-18 NSS consumer expenditure survey results did *not* correspond with most known data from very different sources – other NSS surveys, other household surveys, national accounts etc. Therefore, given this wide divergence, the 2017-18 survey cannot be used for arriving at reliable estimates of poverty. (A conclusion also reached by the government of India in 2019, and with which we concur). Poverty, and its trend, both affect and reflect policy. Hence, whether it is the World Bank, or the government of India, or individual researchers, we have to estimate poverty in the absence of the 2017/18 NSS consumer expenditure survey.

The second firm conclusion was that the *growth* in national accounts expenditures in India over the last two decades did conform closely to growth as obtained from surveys and administrative data. Hence, the method outlined above is a reliable procedure for the generation of poverty estimates.

Section III– Poverty and Growth in India 2004-2020

This section reports on estimates of (log) growth and poverty for selected years between 2004-2020. The poverty estimates are based on conventional calculations i.e. *without* the incorporation of food subsidies. Section IV reports on the more accurate poverty and inequality estimates based on the inclusion of in-kind food subsidies.

The macro data (Table 1) are a pointer to the estimates of poverty presented in Table 2. Data are presented for five different time-periods: 2004-2011, 2011-14, 2011-17, 2017-19 and 2014-19

(Appendix I provides detailed data). The data for these periods illustrate several phenomena in the Indian macro-economy. Note that GDP growth (basis for conventional back of-the-envelope forecasts about poverty trends) was the highest during 2004-11 (6.4 % per annum), and higher than the 5.4 % per annum growth experienced during 2014-19.

Some important results/inferences from a reading of Table 1:

(i) National accounts real per capita consumption growth (deflated by the PFCE deflator) has stayed relatively constant at 6.2 % per annum.

(ii) However, real per capita consumption growth (deflated by CPI) grew at 5.9 % per annum, 2014-19, higher than the 4.0 % growth experienced during the highest GDP growth period 2004-11. It is this consumption growth that is relevant for estimates of headcount poverty and inequality.

(iii) A pointer to why this poverty decline during a lower GDP growth period (2014-19 vs. 2004-11) has happened is provided by the steep decline in inflation – from a CAGR of 8.4 % in the high GDP growth period to just 3.6 % during 2014-19. Deflator inflation also falls, but not to the same degree (a decline of 3 percentage points rather than a decline of 4.8 percentage points)

(iv) Not surprisingly, poverty, regardless of whether measured by \$1.9 or \$3.2, declines the *fastest* during 2014-19. It is often assumed that inflation hurts the poor the most; there cannot be better confirmation of that intuition. Extreme poverty declines by (log) 33 % [12] compared to log 14 % in the high growth high inflation period. \$3.2 poverty declined by almost three times the rate – (log) 17 % versus log 4.6 % earlier.

(v) There is no disagreement, or controversy, related to the progress of the price level during these years. Different indicators of prices reveal different rates of inflation – the most important result and well documented for India is that CPI inflation is higher than inflation as per the price deflator. This is one of the major reasons for the divergence in consumption growth of households deflated by CPI (as done in this paper) and consumption or GDP growth as indicated by the national accounts.

[12] Unless otherwise stated, all growth rates in the paper are logarithmic growth rates.

(vi) Note that the so-called “pass-through” rate for household consumption growth is unity i.e. we assume *nominal* average household consumption growth equal to average *nominal* PFCE growth. This is a like-with-like comparison and should not be confused with the conversion of *real* per capita **GDP** growth with *real* per capita **consumption** growth. The average pass-through rate for the latter has been found to be 0.67 as cited in World Bank 2020 report on poverty. Also note the huge difference in PFCE and CPI inflation during 2004-11 (6.3 (PFCE) vs. 8.4 (CPI)) and the lack of any meaningful difference between the two inflation measures for the period 2014-19. It is the gap between the correct CPI deflator, and the inappropriate PFCE deflator, that likely gives rise to the significantly lower than unity pass-through as obtained by the World Bank.

Our conclusion was, and remains, that the NAS PFCE data (deflated by CPI) is reliable and representative of the underlying reality of real consumption growth. We now turn to the poverty estimates yielded by the different assumptions.

Table 1: Pattern of Growth and Inflation in India

	CAGR (in %)				
	2004-11	2011-14	2011-17	2017-19	2014-19
Nominal GDP	12.7	10.7	10.0	7.7	8.7
Real GDP	6.4	5.0	5.7	4.1	5.4
GDP deflator	6.3	5.7	4.3	3.6	3.3
Nominal PFCE	12.4	11.8	10.8	9.1	9.5
PFCE deflated by					
PFCE Deflator	6.2	6.1	6.4	5.5	6.2
CPI (poverty line)	4.0	3.9	4.7	6.4	5.9
Inflation as indicated by					
PFCE Deflator	6.3	5.6	4.4	3.6	3.3
CPI (poverty line)	8.4	7.9	6.1	2.6	3.6
Poverty Decline (URP)					
PPP$1.9	-14.1	-16.6	-24.0	-35.2	-32.9
PPP$3.2	-4.6	-7.1	-10.2	-22.4	-17.0

Source: Ministry of Statistics & Programme Implementation

Poverty in India, 2004-2020 – Non-inclusive of Food Transfers

Table 2 presents various estimates for poverty for the period 2004 to 2020. Perhaps the most important take-away from these estimates is that in the year prior to the pandemic, 2019, extreme poverty in India according to various methods ranged between 1.4 % (official MMRP method), PFCE growth and 5.4 % (outdated uniform recall method, state domestic product growth).

According to the "official" MMRP method, poverty in pre-pandemic 2019 was just 1.4 ppt, or a decline of 10.8 ppt since 2011-12. What deserves emphasis is that the PPP$1.9 poverty line is no longer appropriate for India[13]; nevertheless, it is accepted as the extreme poverty line around the world and used as a reference standard for claims about the elimination of extreme poverty. By

[13] In a 2003 Initiative for Policy Dialogue conference hosted by Sudhir Anand and Joe Stiglitz, whose proceedings were published in 2010, Bhalla had argued that the existing official $1 a day World Bank line was too low and that $2.16 was the appropriate poverty line (Bhalla (2010), p. 137). A few years later, the World Bank adopted PPP $ 1.9 as the absolute poverty line.

this standard, India can reasonably claim that in pre-pandemic India was on the verge of eliminating extreme poverty.

As we will show in the next section, even this low level of extreme poverty in 2019 is an incorrect, and too high, estimate of extreme poverty. This for the simple reason that the traditional estimation method (whether by us or others) ignores poverty removal because of the transfer of food rations (to now almost two-thirds of the population).

Table 2: Poverty (in %) and Gini Estimates for India -Traditional, No Food Transfers

	2004	2011	2014	2017	2019	2020
1.9$ PPP						
Updates based on Private Final Consumption Expenditure (PFCE)						
Modified Mixed Recall	32.7	12.2	7.4	2.9	1.4	2.5
Uniform Recall	45.5	21.8	14.6	7.2	3.4	6.1
Updates based on State Domestic Product (SDP)						
Modified Mixed Recall	37.1	12.2	9.4	4.2	2.2	4.1
Uniform Recall	49.7	21.8	17.8	9.4	5.4	8.8
World Bank Estimates						
Newhouse-Vyas			14.6			
Edochie et. al.				10.4		
3.2$ PPP						
Updates based on PFCE						
Modified Mixed Recall	73.8	53.6	43.3	29.0	18.5	26.5
Uniform Recall	80.8	64.0	55.4	41.7	30.4	38.9
Updates based on SDP						
Modified Mixed Recall	76.8	53.6	47.6	33.1	23.3	31.0
Uniform Recall	82.5	64.0	58.9	45.3	34.6	43.0

Source: Authors Computations using the 2011-12 NSO Consumer Expenditure Survey & National Accounts Statistics

Poverty level estimates released by World Bank authors for 2014-15 (URP method, Newhouse-Vyas via a very different survey-survey imputation of growth method) is identical (14.6 %) to our URP method based on PFCE growth rates. This is valid confirmation of the reliability of the PFCE updating growth method (though not an endorsement of uniform recall). To repeat, the evidence on the accuracy of PFCE growth during the non-*CES* survey period for the seven years 2012-19 is considerable.

More evidence on the accuracy of PFCE growth estimates for poverty calculations is provided by a just released World Bank study (Edochie et.al (2022)). The authors, after an extensive review of studies and available data (not unlike that presented in Appendix II) provide a point estimate of 10.4 % head-count poverty for 2017-18; this reveals an average decline of 11 ppt in poverty for the six years since 2011. This decline 2011-2017 is also confirmed by all the measures (trends) reported in Table 2. The authors also note, in their Abstract, a finding very close to our conclusions (Appendix II) i.e., "across a wide range of publicly available data sources, the paper *finds no evidence of an increase in poverty* between 2011/12 and 2017/18 (emphasis added).[14] The no-increase reference is to the bad quality 2017-18 CES survey which revealed an increase in poverty of almost 5 ppt between 2011-12 and 2017-18.

[14] Recall that 2017/18 survey was exclusively a MMRB method data collection, a method for which the poverty level in 2011-12 was 12.2 %; in contrast the URP method revealed a poverty level of 21.8 %.

Section IV –Food Subsidy, Consumption Expenditures, and Inequality.

Direct measures [in-kind consumption support and different from cash support which enter directly into estimates of consumption and therefore poverty] have been an integral part of Indian government policy for the last 50 odd years. The policy has primarily emphasized supplementary food rations to the poor as well as through subsidies for production of food (e.g., fertilizers) and subsidies and/or transfers for infrastructure (e.g., electricity, housing) and wages (MGNREGA employment program). The most important, and consistent, policy has been the supply of subsidized food to support the consumption of the poor.

Government food rations can be (and are) an important source of income for the consumption expenditures of the poor in India. The Public Distribution System (PDS) of food has supplied subsidized cereals, sugar, and kerosene to ration card holders. The food ration policy underwent a major expansion in 1978 as India instituted a coordinated multi-pronged strategy to produce food grains, its pricing (Minimum Support Prices, MSPs), and distribution.[15] Just seven years after the expansion of PDS policy, Indian Prime Minister, Rajiv Gandhi, described the PDS system in 1985 as corrupt and/or inefficient, and concluded that only 15 % of funds meant for redistribution to the poor reached the poor.

India announced an expansion of this already large food subsidy program in 2013. One of the differences with past policy was a decline in coverage – instead of near universal access it was now limited to support for the bottom half of the urban and bottom two-thirds of the rural population. The food support (rations) was increased during the pandemic - the food grain ration was doubled for each recipient from 5 kg of wheat (or rice) per month to 10 kg in 2020. Unit-level NSS data for the 1999-00, 2004-5, and 2011-12 surveys – all converge to the conclusion that for all total consumption quintiles 10 kg. of grain was the average monthly consumption per capita (see Table 3). In other words, in 2020, for the first time since the inception of the PDS system, the government was supplying, in full, the basic food ration needed to the bottom two-thirds of the population (coverage of PDS as per the Food Security Act).

[15] See Bhalla (2015) for a detailed analysis of the PDS (and MGNREGA) policies until 2011-12.

Total consumption of wheat and rice (PDS plus market purchases) has stayed approximately constant at 10 kgs for the entire 18-year period 1993-94 to 2011-12; in 2011-12, consumption of wheat and rice in 2011-12 was 9.73 kg. per capita with a very tight distribution – standard deviation of only 0.51[16]. The aggregate share decomposition – around 58 % rice and 42 % wheat.

Table 3: Consumption (and Leakage) in the Public Distribution System

	Quintiles					
	1	2	3	4	5	
NSS 2004 - NSS unit level data						*All*
Monthly pc consumption (Rs)	286	408	528	725	1550	699
PDS Transfers (Kg)	1.3	1.2	1.1	0.9	0.5	1
Consumption (in Kg)						
Rice	6	6.1	6.2	6	5.3	5.9
Wheat	3.4	4.1	4.4	4.6	4.6	4.2
Rice + Wheat	**9.4**	**10.2**	**10.6**	**10.6**	**9.9**	**10.1**
NSS 2011-NSS unit level data						*All*
Monthly pc consumption (Rs)	734	1053	1368	1878	3982	1803
PDS Transfers (Kg)	2.8	2.4	2.2	1.9	1.1	2.1
Consumption (in Kg)						
Rice	6	5.8	5.6	5.4	4.8	5.5
Wheat	4.1	4.3	4.2	4.3	4.1	4.2
Rice + Wheat	**10.1**	**10.1**	**9.8**	**9.7**	**8.9**	**9.7**

Source: Author's computations using NSS Consumption Expenditure Survey – various years.

The expansion of food transfers and subsidies (as a proportion of the food consumption of the bottom two-thirds) makes it an important instrument for poverty alleviation. These transfers need to be incorporated into estimates of household consumption (in rupees). How much of a difference all this makes is provided by the following example. If a household purchases 10 Kg of rice from PDS at subsidized prices (Rs. 3/kg) their recorded survey consumption expenditure is Rs 30. The same consumption of 10 Kg for a rich non-eligible for PDS household (which purchases rice in

[16] The historical constancy of 10 kg may have been partly responsible for the government's decision to increase the food ration to 10 kg. per person per month in 2020, from the previous 5 kg.

the open market at Rs. 30/kg) is recorded as Rs. 300. Note that “real” rupee expenditures are the same – the *survey recorded* expenditures are different and considerably lower for the PDS recipient. This paper is the first paper (at least known to us) to measure the direct explicit effect of in kind-transfers and subsidies on poverty in India (and perhaps elsewhere?). In turn, our results document the dramatic effect that food grain subsidies can have on poverty rates in normal years and especially during a major shock like the pandemic .

Incorporation of food subsidies in poverty calculation

There are two aspects of a subsidy scheme (in-kind or cash transfers) which are relevant for any study on poverty alleviation. The first most important aspect is the effectiveness of targeting – i.e., how much of the food subsidy is obtained, or transferred to, the targeted population. This is possible via NSS CES conducted, at least since 1983. The CES surveys have included detailed questions on the quantity and price of *both* ration food ((primarily wheat and rice and sugar) and food purchased in the market. What the NSS surveys show, for 1993-94, 1999-00 and 2004/5, is that PDS food (quantity) per person per month (pppm) consumed was in the narrow range of 0.95 to 1.02 kgs. In contrast, government food off-take data indicated that an average of 3.1 kg. of foodgrains was transferred to the “average” PDS recipient. In the 2011-12 NSS CES survey, the NSS PDS consumption more than doubled to 2.04 kgs pppm (1.40 kg of rice and 0.64 kg of wheat); off-take data indicated that 3.76 kg was “delivered”.

This divergence between what the average recipient should have got (off-take per person was 3 kg per month on 2004-5 and 3.76 kg/month in 2011-12), and what she did get, allows us to estimate the “leakage” in the distribution i.e., leakage was more than two-thirds in 2004/5. The leak was not due to administrative expenses but actual non-delivery i.e., corruption. Further, as shown in Table 3, even the *top consumption quintile* received 0.5 kg of subsidized food grains in 2004-5 and over 1 kg. in 2011-12.

Estimating Efficiency of Food Subsidy Delivery - Targeting

In 2013 a National Food Security Act was passed, which gave enhanced rations of wheat and rice, and at lower prices. We assume that this system became effective from 2014-15 based on the PDS Off-take data. During the pandemic (2020-2021) 5 kg. of wheat or rice was given free of charge; this was in *addition* to the pre-pandemic system of 5 kg. at a nominal cost of Rs. 2 per kg (wheat) and Rs. 3 per kg (rice). The market price of these two cereals in 2020-21 was Rs. 24.5 for wheat and Rs. 30.8 per kilo for rice, resulting in a weighted market food grain price of Rs. 28.1/kg in the pandemic year 2020-21.

The Food Security Act 2013 (FSA) specified that only the bottom 50 percent of urban India and bottom 75 percent of rural India was eligible to receive the food subsidy. Thus, the policy reduced the eligible population from 1280 million in 2013 to 870 million in 2014. Thus, 560 lakh tons of off-take *increased* the transfer of food grains by 38 % - from 3.9 kgs a month per person to 5.4 kgs pppm in 2014. The official stated allocation per person from 2014 onwards was 5 kgs pppm.

Household survey data from NSS are unavailable to estimate effective transfer; we assume that effective transfer increased to 86 % in 2014-15 onwards from the earlier pre-FSA 2011 level of 54 percent. We arrive at this estimate by projecting the trend in improvements in targeting as obtained during 2004-11 to be the same as in the pre FSA years. Indeed, our measure of effective transfer is very close to CMIE survey based estimates of Bhattacharya & Sinha Roy (2021) - who used the CMIE special supplementary surveys done for the World Bank to conclude that that 89.1% of rural eligible households and 77.3 per cent of urban households (All India average - 84.6%) received food transfers during the pandemic via the PDS (the Pradhan Mantri Garib Kalyan Yojana).

For poverty calculations, our objective is to estimate the subsidy obtained by individual consumer in each year 2004-5 to 2020/21. The rupee equivalent of in-kind subsidy transfer can easily be estimated as the *value* of food obtained at market prices and the value of PDS rations (quantity of food rations multiplied by the difference in market and subsidized price). When household data are not available (as post 2011-12 and intervening years between 2004-5 and 2011-12), subsidized food quantities are obtained via estimates of consumption, (inclusive of leakage) and market prices of wheat and rice. Subsidized price obtained via PDS data.

Implications of Food Subsidy and Poverty Results

Estimates of the food subsidy, and associated data, are presented in Table 4 for selected years between 2004-5 and 2020-21.[17] Note the big jump in the ratio of subsidies to the poverty line in 2020-21. What the last row in Table 4 (subsidy to poverty line) indicates is an approximation to the decline in poverty of the food subsidy for those whose consumption was below, and close to the poverty line, prior to the year in question.

Table 4: Monthly Food Transfers and Poverty Line

	2004	2011	2014	2017	2019	2020
Off-take						
Rice (lakh tons)	232.0	321.2	307.3	350.1	349.8	563.2
Wheat (lakh tons)	182.7	242.6	252.2	252.8	272.2	367.7
Total	414.7	563.8	559.5	602.8	622.0	930.9
Monthly Subsidy (Rs)	4.0	23.8	72.8	88.6	119	192.7
Poverty line (Rs. per month)	480	865	1095	1246	1312	1399
Subsidy to Poverty Line (%)	0.8	2.8	6.6	7.1	9.1	13.8

Source: Authors Computation using PDS-Offtake data from RBI's Handbook of Statistics on Indian Economy. Subsidy derived as q_s(Pm – Ps) where q_s is the food ration quantity and Pm and Ps are market and subsidized prices, respectively.*

Table 5 documents the effect of food subsidies on poverty for the two different poverty lines considered in this paper (PPP$1.9 or the PPP$3.2 poverty line). Figures 1 and 2 recount the importance of food subsidies in a more telling manner. Food subsidies have had a rather important effect in reducing poverty and inequality. First on poverty – for the last three years, and including the pandemic year, extreme poverty has been less than or equal to 1.1 % of the population. In addition, there was virtually no increase in the number of *extreme* poor(PPP$ 1.9) in the year of the pandemic, a result different than that observed for most other economies.

[17] For 2021, an additional subsidy of 1 kg. of pulses per month (chana), approximately Rs. 36 pppm, was provided free of cost.

Table 5: Poverty and Inequality in in India; Adjusted for Food Transfers

	2004	2011	2014	2017	2019	2020
1.9$ PPP Poverty Line						
Modified Mixed Recall	31.9	10.8	5.1	1.9	0.8	0.9
Uniform Recall	44.7	19.9	10.9	4.6	1.9	2.1
3.2$ PPP Poverty Line						
Modified Mixed Recall	73.5	52.2	39.7	25.2	14.8	18.1
Uniform Recall	80.1	62.9	52.0	37.7	25.5	29.9
Inequality Gini						
Consumption (Real)	31.1	30.9	30.6	30.7	30.4	29.4
$90^{th}/10^{th}$ percentile consumption	4.1	4.0	3.9	3.9	3.9	3.7

Source: Authors computation using data from 2011-12 Consumption Expenditure Survey

Notes: The inequality Gini are derived from consumption estimates obtained from the MMRP.

Figure 1: Poverty (Headcount) in India - % population

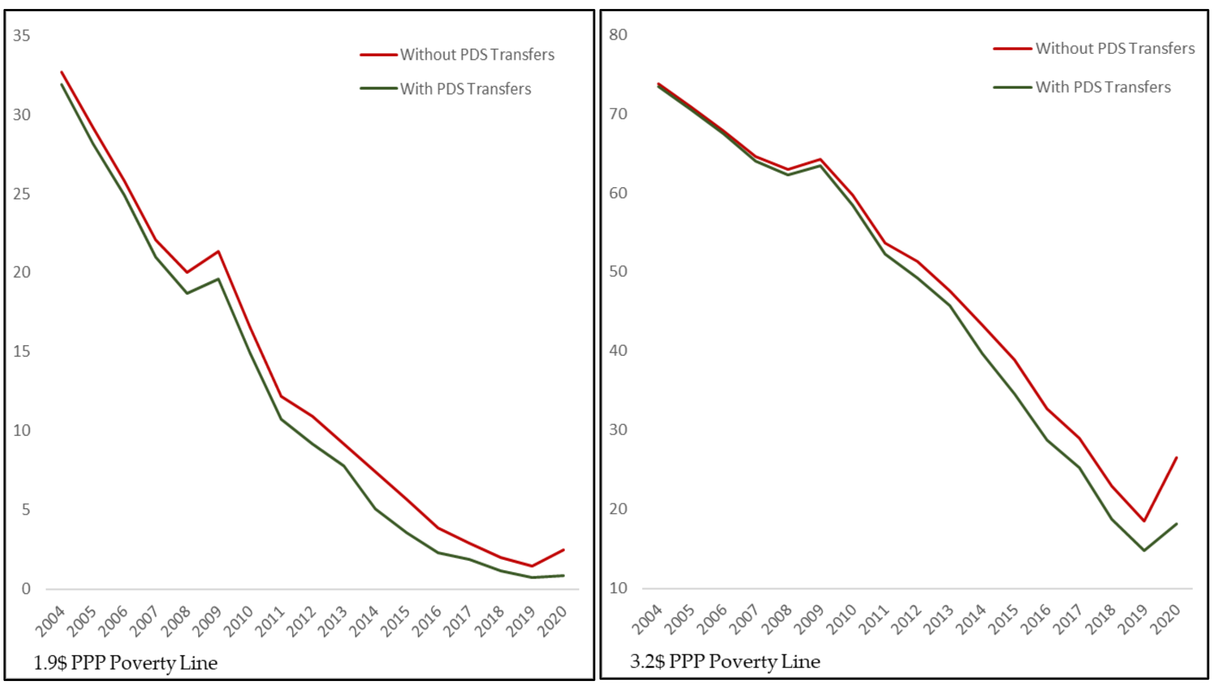
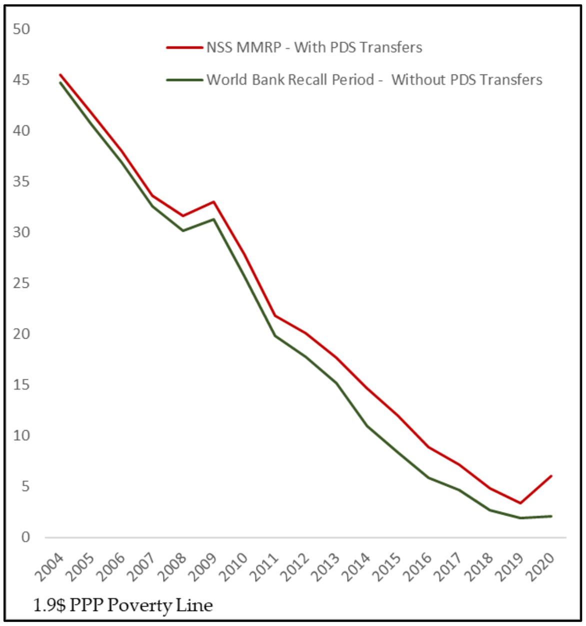


Figure 2: Impact of Food Transfers on Poverty



For the PPP3.2 poverty line, a level 68 percent higher in real terms than the PPP$1.9 line, there is an increase in the poverty rate of 3.3 percentage points (difference between a 14.8 % rate in 2019-20 and an 18.1 % rate in 2020-21), which for a population of 1340 million is an increase of 44 million. Only a cross-country comparative study can provide an answer to the question of how well the Indian government did in its policy response to the pandemic – what we do know is that for the extreme poverty line there was discussion (speculation) about the increase in poverty numbers in India to be in the hundreds of millions or 15 to 25 percent of the population. What we have documented is that with the appropriate estimation and effects of food transfers, the extreme poverty rate stayed constant at less than 1 % level for each of the two years 2019-20 and 2020-21.

Thus, effective targeting of food seems to have been the most appropriate policy response to pandemic-induced poverty. Note that the average Indian consumption basket (2011-12 CES) reports the share of food to be 46 %. For the poor, the fraction is upwards of 60 percent.

Double Counting

When household survey data are available (as in 2004-5 and 2011-12), it is a simple procedure to adjust for the implicit cash transfer (extra income) involved in the operation of food ration quantities. Extra income is equal to the quantity of food ration (in Kgs) multiplied by the difference in the market and ration price.

For an estimate of total consumption in any given year, we project from the individual household consumption estimate as reported in CES 2011-12. To this projected household consumption, we add an estimate of the food-subsidy transfer. Since the 2011-12 estimate of household consumption includes a small food subsidy component (estimated to be Rs. 23.8 or just 2.7 % of the poverty line), the possibility exists of an over-estimation of total consumption (and an under-estimate of poverty). As we show below, because of the declining share of wheat and rice expenditures, the bias is in the opposite direction i.e. PFCE growth under-estimates growth in household consumption growth inclusive of food subsidies.

The paradoxical result (negative double-counting!) occurs because consumption of food grains is very inelastic. Nominal PFCE growth is a weighted average of two growth rates.[18]

Growth in PFCE (Y) expenditures is a weighted average of two growth rates:

$$Y \ = (1 - w) * Ynf + (w) * Yf$$

or Ynf = [Y –w*Yf]/(1-w)

where;

Ynf is Growth Rate in Non – Food (wheat and rice)

w is Share of Food ((wheat and rice) in total consumption

Y is Growth Rate of consumption (as revealed by PFCE growth)

Yf is Growth Rate of wheat and rice consumption.

Table 6 documents the bias for selected years, while appendix 1 reports the "bias" for all the years 2004-5 to 2020-21. Note that the bias (over-estimate of household consumption growth via PFCE growth) is negative for all the relevant annual averages (indeed, it is negative for 12 of the 16 years

[18] Let Y represent PFCE growth and Yf and Ynf represent growth rates of nominal food and nominal non-food (rice and wheat) expenditures, and x and (1-x) the respective shares i.e. Y = x*Yf + (1-x)*Ynf. The non-double counting growth rate Ynf is then given by [(Y- x*Yf)/(1-x)].

between 2004 and 2020). Concluding, double counting is theoretically present, but empirically "absent" and when present, the bias is an under-estimate of growth.

Table 6: PFCE Growth *under-estimates* Non-food growth

Year	Market Price (Food)	Share of food (wheat and rice)	PFCE	Food	Non-Food	Over-estimate of growth
			Growth			
	(Rs Per kg)	(%)	(%)	(%)		(%)
2004	10.8	7.8	6.7	31.7	4.6	2.1
2011	20.3	6.2	16	6.3	16.6	-0.6
2014	28.5	6.1	10.5	16.8	10.1	0.4
2017	26.1	4.2	8.9	-3.7	9.4	-0.5
2019	29.4	3.9	8.5	1.4	8.8	-0.3
2020	30.8	4.2	-3.8	4.8	4.1	-7.9
Average						
2005-11			13.3		13.5	-0.2
2012-19			10.9		11.2	-0.3
2004-20			10.8		10.9	-0.1

Notes- 1) Food refers to food and rice only; market price is weighted market price for rice and wheat
2) detailed annual data (for period averages) in Annex 3.

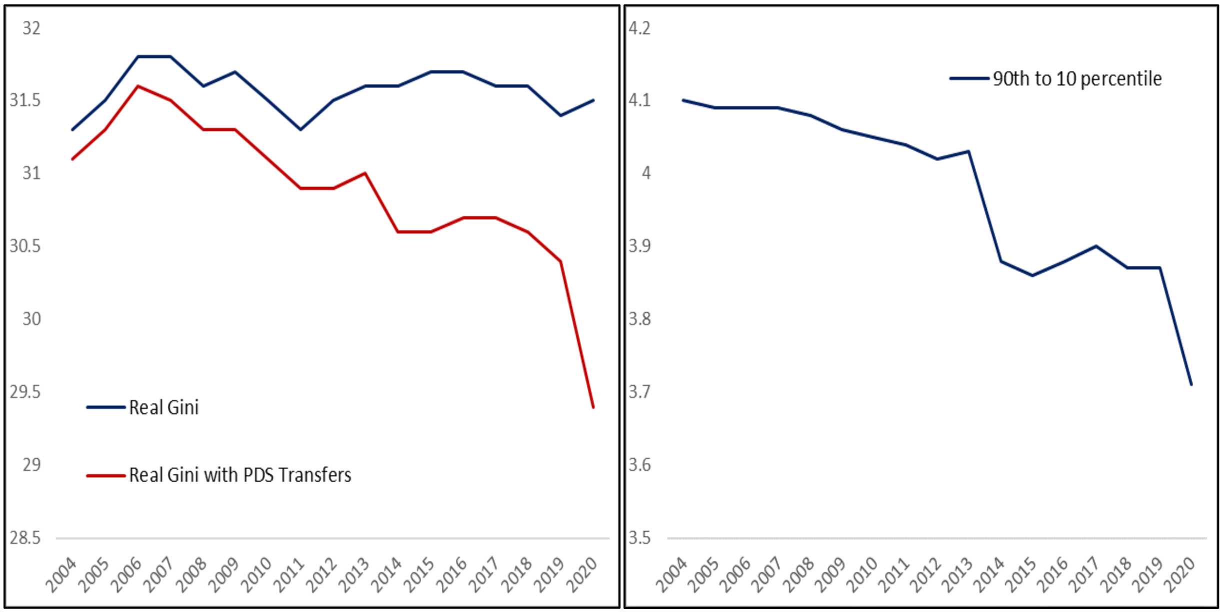
Basic Income and Targeted Transfers

Given that in kind transfers in the form of food subsidy are effective means to provide a social safety net during normal times and acting as an insurance for the poor during adverse income shocks, it is important to contrast it with the policy of Universal Basic Income (UBI). In their study of Basic Income and transfers needed to alleviate poverty, Ghatak-Muralidharan recommend a transfer, for every citizen, equal to Rs. 120 a month (2018-19) prices. The FSA has been providing this transfer to the recipients since 2014 - Rs. 109 and Rs. 200 in 2020-21 (Table 4) thus obviating the need for a universal transfer.

Bhalla (2017) had also argued that while appealing, a basic income program may not be optimal. India at present already has a universal basic income for farmers and therefore it has two distinct policy instruments for delivering welfare - Rs. 6000 a year for an approximate family of five resulting in a transfer of Rs. 120 per person per month – a policy also advocated by Bhalla-Bhasin (2019). This paper had also explored the question of universal basic income, rejected it, and instead argued for a targeted basic income policy rather than a UBI policy.

Earlier, Virmani and Bhalla (2018) had in notes/papers argued that an Aadhar based, net income transfer system is more suited to a lower middle-income country like India with relatively high fiscal deficits, high levels of tax evasion *and* high leakage in many government welfare programs. Such a system is incentive compatible and can be integrated into the existing tax system, without creating an entirely new bureaucracy to reduce leakages and evasion. The net income transfer was estimated as a lump sum (Yb) minus an implicit deduction of a fraction x of income earned (Y), i.e. the net income transfer NET was equal to (Yb - x*Y) for Y <Yb. Income taxes become applicable to those with income Y > Yo , where Yo > Yb. Those with income Y, Yo > Y > Yb do not pay taxes or receive transfers. Bhalla and Virmani (2018) showed that such a system can be financed by combining the subsidies and transfers currently allocated to anti-poverty programs. However, as illustrated in that paper, the consumption impact of targeted food subsidy is the same as that of a basic income program, and costs considerably less.

Figure 3: Impact of Transfers on Inequality



India's approach towards redistribution during the pandemic was also guided by a more cautious approach towards public finances given India's Gross Fiscal Deficit was at 4.6 per cent (with a medium term target of 3 %). The pandemic relief was provided in three forms. First was to rely on automatic stabilizers and allow them to operate fully while reducing fees and penalties on non-compliance with regulations such as tax filings etc. Second was to target new expenditures and subsidies carefully to those who were most affected by the pandemic. This was done with an iterative approach that enabled government to respond as more information became available. An outcome of this approach was a restrained spending during the lockdown restrictions which enabled the fiscal resources to have the maximum multiplier impact. The third approach was to coordinate with India's central bank and provide monetary policy support. This was augmented with providing fiscal resources for a credit guarantee program.

Based on the available evidence, we find that the second element of the fiscal response has worked remarkably well. The expansion of India's food subsidy program rather than increasing cash transfers enabled the government to provide for free food as per the average monthly requirement to all those who were entitled to purchase the same from the PDS system. The Food Security Act

(2013) and the increased use of Aadhar accelerated the declining proportion of leakage(s) in the program.

Subsequently, the *doubling* of entitlements in 2020 helped maintain extreme poverty at the low 0.8 percent level. Without any food subsidies, extreme poverty in the pandemic year would have increased by 1.05 % (from 1.43 to 2.48 %) and LMI (lower middle income poverty with a PPP$3.2 poverty line) by 8 % (18.5 % to 26.5 %).

An important implication of our results is that given that extreme poverty has been virtually eliminated, and both the Government of India and World Bank should formally switch to the LMI country poverty line of $3.2 PPP. Moreover, the World Bank should abdicate the now obsolete Uniform Recall Method and adopt the Modified Mixed Recall Method for updating their poverty estimates for India.

Our paper has illustrated the impact of the in-kind food subsidies in eliminating extreme poverty levels. There are several other in-kind transfers such as the LPG subsidy and subsidy for use of electricity. In addition, there are asset transfers in the form of financial support for construction of toilets and affordable housing. These programs are provided by both Union and State Governments in addition to providing public goods. Virmani (2021) clubbed several of these programs together and termed it as a welfare – stack. Further research is warranted to estimate the impact of the welfare stack on the incidence of poverty.

Section V: Conclusions

Estimation of poverty in the absence of an official Consumption Expenditure Survey is critical for formulation of public policy. More so in the aftermath of the pandemic which is likely to have increased the poverty rates in most countries. Several authors have attempted to answer the question regarding prevailing poverty incidence in India in the absence of the 2017-18 Consumption Expenditure Survey. However, none of the studies have incorporated the distributional implications of the expansion of the food subsidy program which is expected to have reduced the consumption expenditure on food by the beneficiaries. Improved targeting of the policy combined with an expansion in the entitlements during the pandemic should de-facto absorb a part of the consumption shock induced by the pandemic. As noted in Virmani and Bhasin (2020), the pandemic shock is largely a temporary income shock and therefore, temporary fiscal policy interventions can absorb a large part of the shock.

In this paper we explicitly make adjustments to the 2011-12 household consumption expenditure levels to arrive at the consumption distribution for all the years 2011-2020. This is achieved via use of estimates based on average per capita nominal PFCE growth. By investigating the incidence of PDS food subsidies, we derive the average rupee food subsidy transfer to each individual, and we do this for each of the years 2004-5 to 2020-21. This exercise is undertaken because any estimate solely on the basis of reported consumption expenditures will lead to an overestimation of poverty levels. Incorporation of the subsidy data allows us to conclude that pandemic support measures instituted by the government of India were critical in preventing *any* increase in the prevalence of extreme poverty. We also note and document that food subsidies have reduced poverty on a consistent basis since the enactment of the FSA in 2013 and the co-incidental increase in the efficiency of targeting via the use of Aadhar.

Differences in definitions, and methods of measurement of survey consumption have caused a huge divergence in the assessment of policy impact in general, and pandemic Covid-induced poverty in particular. We show that NSS had begun experimenting with alternatives methods of collecting consumption data as early as 1993-94 and on the basis of several iterations had formally adopted and officially switched to the Modified Mixed recall method after the 2011-12 “experiment”.

That definitions matter is illustrated by the fact that using the outdated uniform method, Kochhar (2020) concluded that 75 million Indians were pushed into extreme poverty in 2020-21. In sharp contrast, the figure yielded by the modified mixed method indicates no increase with food transfers, and only an estimated 13.4 million increase (1 % of population) without transfers. The low level of extreme poverty– around 0.8 % in both 2019 (0.76 %) and 2020 (0.86 %) – is suggestive of the need for the official poverty line to now be PPP$3.2.

These welfare implications of our work are critical given the pandemic and ongoing research into the effectiveness of various pandemic support measures in advanced and developing countries. Our work treats in-kind transfers as a transfer of income in monetary terms and therefore considers them as cash transfers. This is a reasonable assumption given that households could always sell the subsidized food grains in the open market.

Our results also demonstrate the social safety net provided by the expansion of India’s food subsidy program absorbed a major part of the pandemic shock. The program provided insurance to the poor and prevented an increase in the prevalence of extreme poverty in India. This illustrates the robustness of India’s social safety architecture as it withstood one of the world’s biggest exogenous income shocks.

Appendix I: Consumption Expenditures, Food Transfers, Poverty and Consumption Inequality in India

This section provide detailed poverty estimates for the World Bank's extreme poverty line and the lower middle income poverty line of PPP$ 1.9 and PPP$ 3.2, respectively. The estimates are for both the Modified Mixed Recall Period (MMRP) and the Uniform Recall Period (URP), with and without food-subsidy transfers.

Table A1-1: Poverty Rate (%) – Without Food Transfers

Year	PPP$ 1.9		PPP$ 3.2	
	Poverty Rate (%)			
	MMRP	URP	MMRP	URP
2004	32.7	45.5	73.8	80.3
2005	29.2	41.8	70.9	78.0
2006	25.8	38.0	67.9	75.5
2007	22.1	33.6	64.6	72.9
2008	20.0	31.6	63.0	71.7
2009	21.3	33.0	64.3	72.7
2010	16.6	27.9	59.7	69.0
2011	12.2	21.8	53.6	64.0
2012	11.0	20.1	51.3	62.0
2013	9.2	17.7	47.6	58.9
2014	7.4	14.6	43.3	55.4
2015	5.7	12.0	38.9	51.2
2016	3.9	8.9	32.7	45.8
2017	2.9	7.1	29.0	41.7
2018	2.0	4.9	23.0	35.2
2019	1.4	3.4	18.5	30.4
2020	2.5	6.1	26.5	38.9

Source: Authors Computations using the 2011-12 NSO Consumer Expenditure Survey & National Accounts Statistics

Figure A1-1: Poverty – Without Transfers

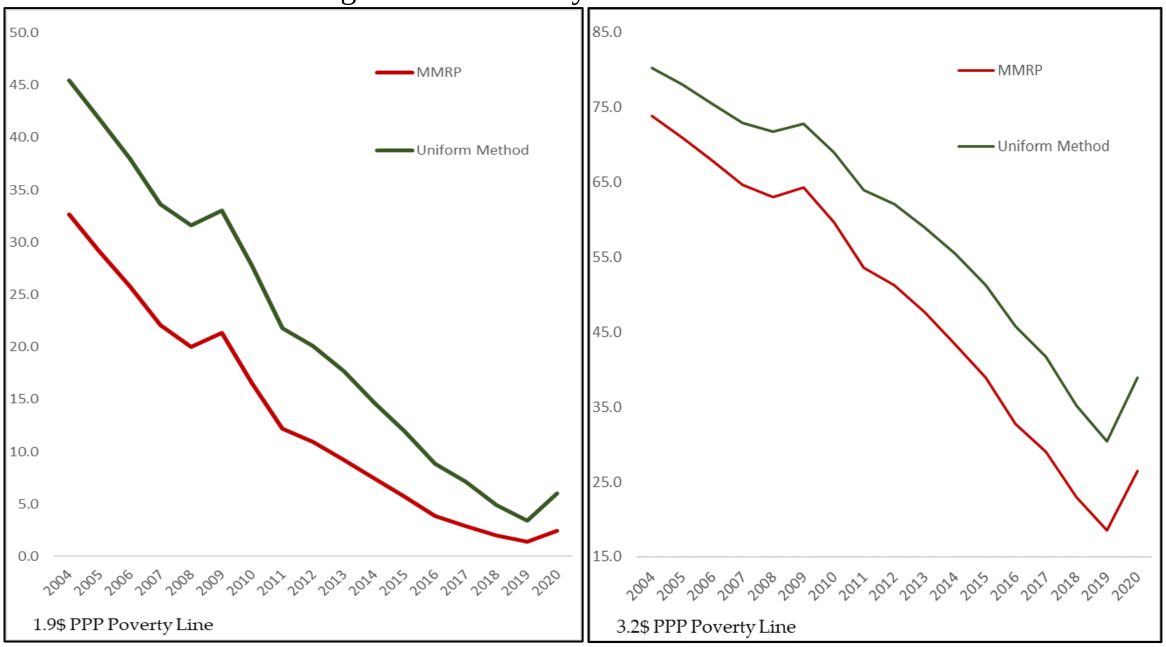


Figure A1-2: Poverty – With Transfers

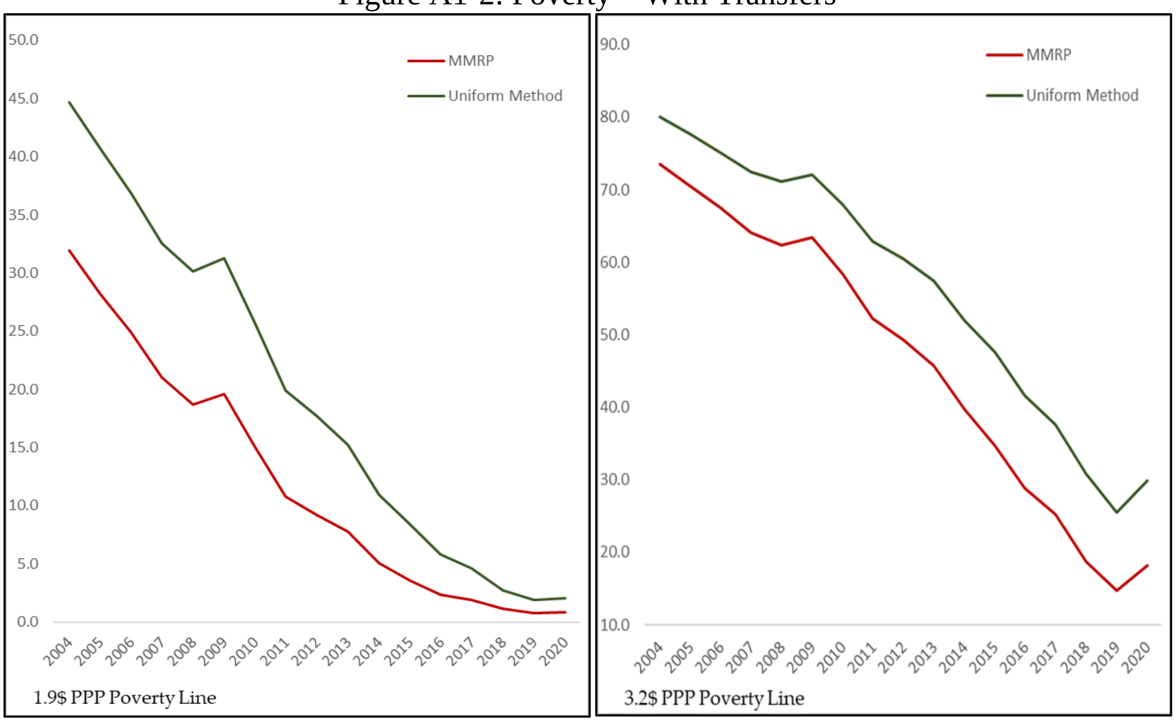


Table A1-2: Poverty Rate (%) – With Transfers

Year	1.9$ PPP		PPP $3.2	
	Recall Method			
	MMRP	URP	MMRP	URP
2004	31.9	44.7	73.5	80.1
2005	28.2	40.7	70.5	77.6
2006	24.9	36.9	67.5	75.2
2007	21.0	32.6	64.0	72.5
2008	18.7	30.1	62.3	71.2
2009	19.6	31.3	63.4	72.0
2010	15.0	25.7	58.4	67.9
2011	10.8	19.9	52.2	62.9
2012	9.2	17.7	49.3	60.4
2013	7.8	15.2	45.8	57.4
2014	5.1	10.9	39.7	52.0
2015	3.6	8.4	34.6	47.6
2016	2.3	5.8	28.8	41.6
2017	1.9	4.6	25.2	37.7
2018	1.1	2.7	18.7	30.8
2019	0.76	1.9	14.8	25.5
2020	0.86	2.1	18.1	29.9

Source: Authors Computations using the 2011-12 NSO Consumer Expenditure Survey & National Accounts Statistics

Table A1-3: Real Inequality – Gini

Year	Gini Coefficient	
	Without Transfers	With Transfers
2004	31.3	31.1
2011	31.3	30.9
2014	31.6	30.6
2015	31.7	30.6
2016	31.7	30.7
2017	31.6	30.7
2018	31.6	30.6
2019	31.4	30.4
2020	31.5	29.4

Notes – 1) For the updated consumption distribution, we used the PFCE Growth Rates for the adjustment.

2) The consumption distribution used here is the type – 2 (Modified Mixed Recall Period).

Table A1-4: Poverty based on SDP Projections – Without Transfers

Year	PPP$ 1.9		PPP$ 3.2	
	MMRP	URP	MMRP	URP
2004	37.1	49.7	76.8	82.5
2005	33.4	45.4	73.4	80.0
2006	28.4	40.2	69.4	76.7
2007	23.8	34.9	64.9	73.1
2008	20.1	31.7	62.8	71.5
2009	20.6	32.4	63.4	72.0
2010	15.3	25.8	57.6	67.3
2011	12.2	21.8	53.6	64.0
2012	11.2	20.5	51.8	62.6
2013	10.3	19.1	49.9	60.9
2014	9.4	17.8	47.6	58.9
2015	8.2	15.9	44.5	55.9
2016	5.9	12.1	38.7	50.4
2017	4.2	9.4	33.1	45.3
2018	2.9	6.9	27.0	38.9
2019	2.2	5.4	23.3	34.6
2020	4.1	8.8	31.0	43.0

Notes – SDP stands for Gross State Domestic Product. We use SDP growth rates here to adjust the 2011-12 Consumption Distribution.

Table A1-5: Poverty based on SDP Projections – With Transfers

	PPP$ 1.9		PPP$ 3.2	
Year	MMRP	URP	MMRP	URP
2004	36.3	48.9	76.5	82.3
2005	32.3	44.4	73.0	79.7
2006	27.5	39.1	69.0	76.3
2007	22.8	33.9	64.4	72.7
2008	18.9	30.3	62.0	71.0
2009	19.0	30.7	62.5	71.3
2010	13.7	23.7	56.4	66.3
2011	10.8	19.9	52.2	62.9
2012	9.4	18.0	49.8	61.0
2013	8.7	16.8	47.9	59.3
2014	6.7	13.5	44.1	55.8
2015	5.4	11.5	40.5	52.3
2016	3.7	8.6	34.6	46.6
2017	2.7	6.5	29.1	41.6
2018	1.7	4.1	22.7	34.2
2019	1.30	3.0	19.0	29.9
2020	1.42	3.3	22.8	34.2

Notes – SDP stands for Gross State Domestic Product. We use SDP growth rates here to adjust the 2011-12 Consumption Distribution.

Table A1-6: Real Inequality using SDP

Year	Gini Without Transfers	Gini With Transfers
2004	31.4	31.2
2005	32.0	31.8
2006	32.3	32.0
2007	32.4	32.2
2008	31.9	31.6
2009	32.0	31.6
2010	31.7	31.2
2011	31.3	30.9
2012	31.5	30.9
2013	31.7	31.1
2014	31.8	30.8
2015	32.2	31.1
2016	32.2	31.2
2017	32.2	31.3
2018	32.3	31.3
2019	32.4	31.3
2020	32.4	30.3

Notes – 1) We use SDP growth rates here to adjust the 2011-12 Consumption Distribution.
2) The consumption distribution used here is the type – 2 (Modified Mixed Recall Period).

Table A1-7: Underestimation of PFCE Growth (in the presence of PDS wheat and rice)

Year	Weighted Market Price	Share of Food	PFCE Growth	NSS Food Expenditures Growth Rate	Over-estimate of growth
	(Rs Per kg)	(%)	(%)	(%)	(%)
2004	10.8	7.8	6.7	31.7	2.1
2005	12.1	8.0	10.2	12.3	0.2
2006	12.4	7.2	13.0	2.1	-0.9
2007	13.6	7.0	12.5	9.7	-0.2
2008	15.5	7.1	12.6	14.1	0.1
2009	16.6	6.8	12.6	7.1	-0.4
2010	19.1	6.7	15.9	15.1	-0.1
2011	20.3	6.2	16.0	6.3	-0.6
2012	22.6	6.1	13.1	11.3	-0.1
2013	24.4	5.8	14.0	8.0	-0.4
2014	28.5	6.1	10.5	16.8	0.4
2015	28.6	5.5	11.0	0.4	-0.6
2016	27.1	4.7	11.0	-5.2	-0.8
2017	26.1	4.2	8.9	-3.7	-0.5
2018	29.0	4.2	10.5	11.1	0.0
2019	29.4	3.9	8.5	1.4	-0.3
2020	30.8	4.2	-3.8	4.8	0.4

Notes- The Weighted Market Price is for Rice and Wheat

Appendix II: Data Supplement and Accuracy of the 2017 "*Ill-Fated*" Survey

The absence of the 2017-18 Consumption Expenditure Survey poses as a challenge for estimation of poverty. Some of the results of this survey results were leaked to *Business-Standard (*Jha, Somesh (2019)*)*, and bits of the leaked survey report have analysed by several individuals, including Bhalla (2019) and Bhalla and Bhasin (2019). Later, in two articles, S. Subramaniam (2019, 2020) provides very useful information about the distribution, and decile means, in the 2017-18 survey. The source of the leaked data is referred to by Subramanian as: *Computations based on data in the 2011-12 NSO Report on Consumer Expenditure (68th Round) and Tables T3 and T4 of the 2017-18 NSO draft Report on Consumer Expenditure (75th Round")* The leaked estimates have been used by, amongst others, Ghatak and Muralidharan (2021) who derive important implications for inclusive growth in India based on the decile distributions for rural and urban India contained in the Subramanian "study".

Considering that the data was not released due to poor data quality[19], any subsequent use of the "*leaked*" data should be subject to rigorous assessments regarding its compatibility with other available data. We compile a dataset using various administrative data for the purpose of comparing them with the 2017-18 Consumption Expenditure Survey. The administrative data on televisions is from Broadcast Audience Research Council (BARC) and Census Bureau, Government of India. For fuel consumption we rely on the Annual Reports published by the Ministry of Petroleum and Natural Gas. Automobile sales data is from Society of Indian Automobile Manufacturers and the Department of Telecommunications data is used for the number of mobile users.

Annual reports released by Ministry of Railways; Government of India includes the data for railway passengers while the Ministry of Civil Aviation gives us the data on number of air travellers. The data on food items is from the Animal Husbandry Statistics along with various reports from the Ministry of Agriculture and Farmer's Welfare.

In an earlier NCAER presentation (the authors [Bhalla, Bhasin and Virmani (2020)]) began an exercise into both the quality of the 2017-18 data, and alternative estimates of expenditure,

[19] Administrative data for 2017-18 indicates support for the conclusion that the 2017-18 survey suffered from acute problems of measurement, and hence the non-release of the data. A similar judgment was made with regard to both the consumption and labor force surveys of 1989-90. More recently, the NSSO survey of 2009-10 was repeated just two years later in 2011-12 because 2009-10 was a drought year.

poverty, and consumption distribution. This section is an extension of the presentation, and we present a variety of evidence on the 2017-18 survey; all the evidence points to the same conclusion – the 2017-18 CES was, in the rich history of Indian statistics, a genuine outlier, in terms of its "quality".

Briefly, the NSS 2017-18 consumer expenditure survey (hereafter referred to as the *ill-fated* IF2017-18 survey) revealed the following:

(i) Average real rural incomes consumption declined by 8.8 % and real urban consumption increased by 2 % between 2011-12 and 2017-18. Given an urbanization ratio of approximately 33 %, this yields an average *decline* in real consumption of 5.2 % over 6 years.

(ii) Inequality Declines: Subramanian (2019) "In both rural and urban India, we have a case of Lorenz dominance of the 2017-18 distribution over the 2011-12 distribution, signaling an unambiguous decline in inequality over the reference period. This is reflected in a diminution in the Gini coefficient of inequality, from 0.2872 to 0.2581 in the rural areas, and from 0.3685 to 0.3298 in the urban areas. The move towards greater equality in the rural areas has been secured by a particularly harsh form of 'levelling down'. That is, inequality has been reduced by reducing everybody's income, but by proportionately more for the richer than the poorer sections of the population."

(iii) Never before in Indian history (at least post 1982) has such a large decline in real consumption inequality occurred. The deviation in the Gini, for both rural and urban areas, has been in a narrow 1 to 2 ppt range.

(iv) The third inference from the IF2017-18 data is that extreme poverty increased from the NSS 2011-12 estimate of 12.2 % in 2011-12 to around 17 % in 2017-18. Again, never before in the history of Indian data, 1951 to present, has CES absolute poverty increased, let alone by such an incredible margin.

(v) The inferred nominal average consumption in 2017-18 data was Rs. 1892 per capita per month (pcpm) in rural India and Rs. 3739 per capita per month in urban India leading to a nominal Rs. 2502 pcpm aggregate level (for the MMRP method). This yields a S/NA ratio of 39.8 % for India, and the lowest such level in Indian history. As comparison, the 2011-12 NSS survey/national accounts ratio of household consumption was 54.8 %.

To verify the findings of the data we subject it to a variety of smell tests. Our tests are based on the *Imagine There is No Country*, where Bhalla (2002) explored the issue the quality of household surveys and used the survey-capture as a measure for cross-country comparison. The central idea is to compare the findings of the "*Ill-Fated*" Survey with administrative datasets, national accounts and other household surveys.

i. Smell Test 1 – Growth in Food Production

Table A2-1 provides evidence on per capita food *production* growth during 2004-11 and 2011-17. It is reasonable to assume that consumption growth in food will closely parallel production trends. Annualized growth rates for several food items, plus tobacco, are provided for both the 2004-11 and the 2011-17 periods. For about 42 % of food consumption items, the average (weighted) per capita growth in 2004-11 was 1.2 % versus a marginally lower growth rate of 1 % in 2011-17.

Table A2-1: Per-Capita Log Growth Rate in Food Production

Items	**2004-11**	**2011-17**
Rice	2.8	0.6
Wheat	4	0.4
Coarse Cereals	2.7	1.4
Meat	12.5	5.1
Eggs	4.9	5.5
Milk	4	4.8
Oils	2.3	0.4
Fruits	5.2	3.5
Vegetables	4.7	3.3
Pulses	3.2	6.1
Rapeseed & Mustard	-2.6	3.6
Groundnut (as oil)	-0.2	4.2
Sugar (cane)	5.4	0.3
Spices	5.1	4.7
Tea	2.1	2.7
Tobacco	3.8	3.4

Source: Various Ministry Annual Reports *ii. Smell Test 2 - Inferences from other NSS consumer surveys*

The NSS has also conducted special social consumption surveys (health and education). Together, education (5.1 %) and health (6.2%) account for a significant share of total expenditures.[20] Between 2011-12 and 2017/18, national accounts data reveal the following per capita real annual growth rates: 7.6 % for medical care and 6.9 % per annum for education; jointly, the average growth rate for these two items is 7.3 % i.e., somewhat higher than the average real PFCE growth rate of 4.5 % per annum.

iii. Smell Test 3 - Consumption of Non-Food items

Non-food consumption data in the form of health and education are provided in Table A2-2. While in the national PFCE accounts the weight of these two expenditures is 7.4 %, it is a higher fraction in consumer expenditure surveys (11.3 %).

Table A2-2: Per Capita Log Growth Rate in Consumption of Non-Food

Items	**2004-11**	**2011-17**
PFCE	4.6	5.6
Social Consumption		
Medical - National Accounts	-0.2	7.6
Education - National Accounts	6.5	6.9
Non-Food Items		
Two wheelers	11.6	5.8
Cars	12.5	3.9
TV	4.3	7
Fuel Consumption	3.8	4.8
Electricity		5.6
Airline Passengers	31.1	10.7
Railway Passengers	5.5	-0.4
Mobile Users		5.6

Source: Various Ministry Annual Reports, Television data from BARC, automobile data from SIAM.

[20] According to the NA 2011/12 series, both education and health have an equal share in expenditures – 3.7 %.

Comparing the two periods, real social consumption rose at a 2.4 % rate 2004-11, but more than *three times* that rate (7.5 %) between 2011-17. Adding food production(consumption) and social consumption together results in reasonable direct information for a large 53 % of total consumption. The average growth rate of 2.4 % for 2011-17 is 0.9 % per annum *higher* than that during the earlier normal period, 2004-11.

iv. Smell Test 4 – Consumption Growth, 2011-12 to 2014-15

World Bank authors Newhouse-Vyas (2018) develop a method to derive per capita consumption growth from non-identical consumer surveys. Table 9 of their paper (p.31) reports real urban consumption growth between 2011-12 and 2014-15 to be 3.3 % and rural growth to be 8.6 %, for an average annual growth 2.9 % per annum. Recall that the IF2017-18 survey showed a *cumulative* growth of 2 % for urban and minus 8.8 % between the same initial year, 2011-12, and six years later 2017-18. Newhouse-Vyas use only NSS surveys to estimate growth and poverty; such a large decline 16 % in rural India in two survey years so close together (2014-15 and 2017-18) defies logic and lends support to the argument that the 2017-18 survey cannot be considered credible by any definition.[21]

v. Smell Test 5 – Pattern of real wage growth, 2017-18

Parallel to the consumption surveys the NSS also reports on trends in employment and labor force. This parallel has been consistently followed since the calendar year 1983 survey. Since 2017-18, a "new" labor survey format has been followed by the NSS, called the Periodic Labor Force survey (PLFS). This survey is being conducted on a quarterly basis in urban areas, and on an annual basis in rural areas, with the latter yielding agricultural-year (July-June) estimates of employment, education status of workers, etc. since 2017-18. The last available (all India) annual survey is for 2019-20 and the last available (urban) quarterly survey is for March-June 2021. Table A2-3

[21] All three of the present authors have gone on official record as stating that the 2017-18 CES data should be released, if only to document, as one of us put it, to document for the world how bad the NSS data was. At least one of us now firmly believes that the government made the right decision in not releasing the data. Given that the data came from a respectable and pioneering institution, the NSS, it could be misused by respected authors and credible institutions; especially with the *fait accompli* that it is so because the NSS says it is so. This paper is an elaborate example of the research required to show that the NSS data is not accurate; even with leaked data, authors e.g., Himanshu (2019), Ghatak-Muralidharan (2020) have broadly "accepted" the "results" of the 2017-18 survey.

provides with the Per Capita Log Growth Rate in Consumption from various sources such as national accounts, NSO surveys and the NCAER IHDS Survey.

Table A2-3: Per Capita Log Growth Rate in Consumption

Items	**2004-11**	**2011-17**
PFCE - National Accounts	4.3	4.5
Real Per Capita Consumption		
HCES 2017 - 18		-5.2
PLFS 2017-18		-11.5
IHDS		2.7 - 4.9

Source: NSO Surveys & NCAER IHDS Survey.

These data (Table A2-4) show real earnings increase of 9.7 % between 2011-17 for casual and salaried workers (accounting for 50 % of the work force), with females showing more than twice the increase of males (18.2 % vs. 9.7 %). Even more impressive is the real earnings gain over the subsequent two years; between 2011-2019, female workers record a cumulative increase of 29 % versus males increase of 15.2 % and a weighted increase of 16.6 %.

Table A2-4: NSS Employment Surveys - Real earnings per person month

Year	Ages 15-64 -All	Ages 15-64 -Female	Ages 15-64 -Male
2004	4288	2567	4882
2011	6383	4347	6947
2017	7005	5137	7493
2018	7248	5454	7713
2019	7445	5613	8006
Growth Rate (%)			
2011-17	9.7	18.2	7.9
2011-19	16.6	29.1	15.2

Source: NSS Employment Surveys - various phases

Wage inequality (for the casual and salaried workers) shows a large decline in Gini from 49.89 in 2011-12 to 43.04 in 2019/20 (Table A2-5). This is a very large improvement, suggestive of both inclusive growth and healthy income growth amongst a large fraction of the poor (casual daily wage workers).

Table A2-5: Wage Inequality

Year	Real Gini
1999	0.53
2004	0.52
2011	0.50
2017	0.43
2018	0.42
2019	0.43

Source: NSS Employment Surveys - various phases

vi. Smell Test 6 – Comparing consumption growth in CES and PLFS surveys

Consumption growth in the two surveys in 2017-18 (CES and PLFS) is not comparable, even though some have erroneously inferred that the consumption growth is comparable. The reason not because there were 33 questions on consumption in the 2011-12 survey, but only one in the PLFS surveys! Based on the one question, per capita consumption declines 11.5 % between 2011 and 2017, with rural areas experiencing a 12.6 % decline and urban areas almost the same (a decline of 10.4 %). Contrast this with the parallel consumer survey (the leaked one) showing a decline of 8.8 % in rural areas and an *increase* of 2 % in urban areas! (Subramaniam (2020)).

The general discussion about the accuracy of the IF 2017-18 CES data has also involved discussion about the accuracy of GDP data. Felman et. al. (2019) for instance looked at the IF2017-18 and PFCE. They concluded that the IFS 2017-18 underestimates consumption expenditures while the National Accounts overestimates it. Rangarajan and Dev (2019) looked at the increased divergence between the 2017-18 survey and pointed at the increased divergence of both estimates.

Appendix III: Comparing our results with other findings

There has been renewed interest in measurement of poverty in India in the pandemic year. The standard method for estimating poverty is the application of the World Bank's PPP $1.9 and the PPP $3.2 poverty line. The uniform application of these lines across countries enables a cross-country comparison of prevalent poverty levels and in measuring progress towards poverty alleviation. One other advantage of the PPP 1.9 poverty line (or Rs. 865 per person per month in 2011-12 prices) is that it is identical to India's official Tendulkar Poverty line making our contemporaneous estimates comparable with the previous official estimates.

In recent studies, authors have relied on the CMIE's Consumer Pyramid Household Survey to estimate consumption shock induced by the pandemic. However, these studies have not incorporated the impact of the food transfers on consumption expenditures and therefore their consumption levels are negatively biased. For instance, Gupta, Malani & Woda (2021) used the CMIE survey for their analysis and they do not mention any adjustments for the food transfers in their analysis. They provide poverty estimates for three different poverty lines – the extreme poverty PPP$1.9 line; and two higher poverty lines, one based on the national minimum *wage* and the other based on income line based on the 7th Central Pay Commission. The sensitivity analysis (and the poverty lines) yielded by these exercises is not very informative because it is difficult to compare the estimates with any other study. Wages (and income) need to be adjusted to number of earners in the household, and the poverty lines need to be adjusted to 2011 values.

A similar challenge is faced while comparing our estimates with Basole et. al. (2021) who also used the CMIE – CPHS data and wage as the appropriate metric for their poverty lines. They used a wage threshold of Rs 375 per day and argue that 230 million people fell below this wage level in 2020. For their poverty estimates, for rural areas they used a poverty line of Rs 2900 per person per month and for urban areas the corresponding poverty line is Rs 3,344 per person per month. These translate to Rs 94 per person per day for rural areas and Rs 108 per person per day for urban areas. These poverty lines are substantially higher than the PPP$ 1.9 poverty line which translates to Rs 28.5 per day.

In addition, their estimates suffer the same problem as Gupta, Malani & Woda (2021) given that wages must be translated to adjusted number of earners and consumption levels. Additionally, both Gupta, Malani & Woda (2021) and Basole et al (2021) provide estimates for a stipulated period instead of providing us with annual estimates of poverty for India. Our estimates are based on the agricultural year given that the NSO's Consumption Expenditures are based on the agricultural year, and this enables us to compare our estimates with previous poverty estimates.

In addition, our poverty lines are the standard World Bank's PPP 1.9 poverty lines and not derived from wages. Further, while both these papers mention the social security provided by various government provisions, but they do not incorporate the impact of these measures in their analysis thereby leading to a positively biased estimate of poverty. In addition, all the three poverty lines are higher than even the PPP$ 3.2 poverty line (poverty line for middle income countries).

Further, these poverty lines are also higher in PPP terms with the comparable poverty lines for countries with similar levels of per-capita income and even some advanced economies. Kochhar (2021) used the World Bank's Povcal Net data along with the national accounts data for the year 2020 to estimate prevalence of poverty in India. Using the World Bank's PPP$ 1.9 poverty, they argue that the pandemic increased poverty by 75 million due to the COVID – 19 induced recessions. However, their study does not explicitly state that the consumption distribution used was one based on the obsolete uniform recall method. In addition, the study does not poverty estimates for 2019 or any of the other preceding years. Similarly, they do not provide the corresponding poverty line in rupees for rural and urban areas.

Our historical estimates using the NSO's 2011-12 base distribution match well with similar estimates provided by the World Bank for the preceding years and are based on the standard practice of using the agricultural year and World Bank's PPP 1.9 and PPP 3.2 poverty line making our estimates comparable with previous estimates of poverty.

References:

Acs, G., & Werner, K. (2021). How a Permanent Expansion of the Child Tax Credit Could Affect Poverty. Washington, DC: Urban Institute.

Basole, A., Abraham, R., Lahoti, R., Kesar, S., Jha, M., Nath, P., ... & Narayanan, R. (2021). State of working India 2021: one year of Covid-19.

Bhalla, S. S. (2002). *Imagine there's no country: Poverty, inequality, and growth in the era of globalization*. Peterson Institute.

Bhalla, S. S. (2010). Raising the Standard – The War on Global Poverty. In Sudhir Anand, Paul Segal and Joseph Stiglitz (ed), Debates on the Measurement of Global Poverty, Oxford University Press, Oxford..

Bhalla, S. S. (2015). Food, Hunger, and Nutrition in India: A Case of Redistributive Failure.

Bhalla, S. S. (2017). The new wealth of nations. Simon and Schuster.

Bhalla, S. S., (2019, July 27). It is time we recognised that survey data cannot be interpreted in the way it used to be. Indian Express.

Bhalla, S. S., & Bhasin, K. (2019a). Towards a Targeted Basic Income Policy for India.

Bhalla, S. S., & Bhasin, K. (2019b, June 29). Rethink poverty — and policy. Indian Express.

Bhalla, S. S., & Bhasin, K. (2019c, November 28). Opinion: Is the NSO's consumption data for 2017-18 beyond salvation? Live Mint.

Bhalla, S. S., & Bhasin, K. (2020, June 25). Separating Fact from Economic Fiction: Growth Slowed beyond Expectations Starting Late 2018. Indian Express.

Bhalla, S. S., Bhasin, K. & Virmani, A. (2020). Poverty, Inequality, and Growth in India: 2011-2018. *Presented at NCAER.*

Bhalla, S. S., & Virmani, A. (2018, January 27). Smart policies for redistribution. Indian Express.

Bhattacharya, S., & Sinha Roy, S. (2021). Intent to Implementation.

Deaton, A., & Grosh, M. (1998). Designing household survey questionnaires for developing countries lessons from ten years of LSMS experience, chapter 17: Consumption (No. 218).

Deaton, A. (2003). Household surveys, consumption, and the measurement of poverty. Economic Systems Research, 15(2), 135-159.

Edochie, I. N., Freije-Rodriguez, S., Lakner, C., Moreno Herrera, L., Newhouse, D. L., Sinha Roy, S., & Yonzan, N. (2022). What do we Know about Poverty in India in 2017/18?.

Felman, J., Sandefur, J., Subramanian, A., & Duggan, J. (2019). Is India's Consumption Really Falling?'. Center for Global Development blog. Washington DC: Center for Global Development.

Ghatak, M., & Muralidharan, K. (2019). An inclusive growth dividend: Reframing the role of income transfers in India's anti-poverty strategy.

Government of India (2005) Report of the Expert Group on Cross-validation study of estimates of private consumption expenditure available from household survey and national accounts, Sarvekshana, Vol.XXV(4) and XXVI(1),Issue No.88, 1–70.

Government of India (2008) Report of the Group for Examining Discrepancy in PFCE estimates from NSSO Central Statistical Organisation, Ministry of Statistics and Programme Implementation.

Government of India (2015). The Report of Prof. A. K. Adhikari Committee on PFCE. Central Statistics Office, Ministry of Statistics and Programme Implementation.

Gupta, A., Malani, A., & Woda, B. (2021). Inequality in India Declined During COVID (No. w29597). National Bureau of Economic Research.

Hamilton, L., Roll, S., Despard, M., & Maag, E. (2021). Employment, Financial and Well-Being Effects of the 2021 Expanded Child Tax Credit: Wave 1 Executive Summary.

Himanshu. (2019, August 15). Opinion: What Happened to Poverty during the First Term of Modi? Live Mint.

Jha, S. (2019a, February 6). Unemployment rate at four-decade high of 6.1% in 2017-18: NSSO survey. Business Standard.

Jha, S. (2019b, November 15). Consumer spend sees first fall in 4 decades on weak rural demand: NSO data. Business Standard.

Kochhar, R. (2021). In the pandemic, India's middle class shrinks and poverty spreads while China sees smaller changes. *Pew Research Center*.

Lakner, C., Mahler, D. G., Negre, M., & Prydz, E. B. (2022). How much does reducing inequality matter for global poverty?. The Journal of Economic Inequality, 1-27.

Mahler D. G., Yonzan N, Lakner C, Andres Castaneda Aguilar R, Wu H. Updated estimates of the impact of COVID-19 on global poverty: turning the corner on the pandemic in 2021? World Bank Blogs. Accessed September 28, 2021. https://blogs.worldbank.org/opendata/updated-estimates-impact-covid-19-global-poverty-turning-corner-pandemic-2021

Mahler, D. G., Castaneda Aguilar, R. A., & Newhouse, D. (2021). Nowcasting Global Poverty.

Meyer, B. D., Mok, W. K., & Sullivan, J. X. (2015). Household surveys in crisis. Journal of Economic Perspectives, 29(4), 199-226.

Newhouse, D. L., & Vyas, P. (2018). *Nowcasting poverty in India for 2014-15: A survey to survey imputation approach* (No. 6). The World Bank.

Subramanian, S. (2019, November). What is happening to rural welfare, poverty and inequality in India. In The India Forum (Vol. 29).

Rangarajan. C., & Mahendra Dev., S. (2019). Mind the statistics gap. Indian Express.

Virmani, A. (2004). *Accelerating Growth and Poverty Reduction: A Policy Framework for India's Development*. Academic Foundation.

Virmani, A. (2005). *Policy regimes, growth and poverty in India: Lessons of government failure and entrepreneurial success!* (No. 170). Working Paper, ICRIER (http://icrier.org/pdf/WP170GrPov11.pdf, http://icrier.org/?s=working+papers).

Virmani, A., & Bhasin, K. (2020). Growth Implications of Pandemic: Indian Economy (Vol. 7). Working paper no 2/2020, Foundation for Economic Growth and Welfare, New Delhi.

World Bank. (2018). Poverty and shared prosperity 2018: Piecing together the poverty puzzle.

World Bank. 2020. Poverty and Shared Prosperity 2020: Reversals of Fortune. Washington, DC: World Bank.

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