Poverty at Higher Frequency*

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Abstract

National poverty rates are meant to reflect the share of households that are poor for a given year. We show how, instead, *de facto* poverty rates in many low- and middle-income countries reflect the *share of the year* that households experience poverty—including experiences of households not usually considered poor. Similarly, *de facto* poverty rates reflect households' ability to smooth consumption within the year. The outcomes arise from how household data are collected, and, with monthly panel data from India, we show how the outcomes transform empirical understandings of deprivation and expand strategies to reduce global poverty rates.

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1 Introduction

The modern concept of poverty was first defined in the late 19th century as the condition of having insufficient income relative to a poverty line (Booth 1893, Rowntree 1901, Gillie 1996, Himmelfarb 1984). Since then, the idea has been fixed in annual terms, as the condition of having insufficient yearly resources, and today this is the common understanding of the poverty rate (e.g., World Bank 2022). As Deaton and Grosh (2000) observe, "...there seems to be a general consensus that a year is a sensible reference period over which to judge people's living standards, even if this is inevitably a compromise that is too long for some purposes and too short for others" (p. 5). By this consensus, strategies to reduce poverty are effective only if they increase households' average resources for the year.

However, in low- and middle-income countries, the home of 99 percent of the world's poorest people (World Bank, 2022), the 19th-century idea has been transformed by 21st-century survey methodologies. The result is that national poverty rates are often not what they seem. We show that, when household data are collected following expert guidelines, national poverty rates reflect a different—but potentially valuable—concept of deprivation. Instead of capturing the historical idea that poverty is the share of the population whose annual resources fall below the poverty line for the year, *de facto* poverty rates approximate the average share of the year that households are poor. This notion encompasses deprivations that are experienced by households for just part of the year and episodes of poverty experienced by households that would not, historically, be considered poor.

For policy, this means that, contrary to common assumptions, the *de facto* measure of national poverty in many low- and middle-income countries is sensitive to households' exposure to shocks and their ability to smooth consumption within the year. As a result, cash transfers targeted to lean seasons can have a greater poverty-reducing impact on *de facto* poverty rates than the same value of transfers spread evenly through the year. Similarly, interventions like microfinance that have been found to have relatively small average impacts on total household consumption (Cai et al., 2021) can reduce *de facto* poverty rates if households are enabled to smooth consumption within the year (Amin et al. 2003, Islam and Maitra 2012, Somville and Vandewalle 2023).[1] It also means that targeting resources to house-

[1]The connection between consumption smoothing and poverty draws on related insights about

holds that are not conventionally "poor" can nevertheless reduce national poverty rates when the funds alleviate temporary deprivations within the year.

The transformation has happened inadvertently, without a change in the form of the poverty measures and without longitudinal data. Instead, the transformation follows from the interaction of common practices that are part of the expert consensus on household survey methodology in low-income populations (World Bank and FAO, 2019). First, household consumption is suggested as the basis of poverty measurement when collecting data on income from agriculture and self-employment is prohibitively difficult. Mancini and Vecchi (2022) report that all low-income countries measure poverty with consumption data rather than income. Ninety percent of lower-middle income countries and 62 percent of upper-middle income countries do as well.[2]

Second, to increase accuracy, survey questions about frequently-purchased items are asked with short-term recall (questions about food consumption, for example, are often asked with reference to the past week or month). Third, households are interviewed just once during the year, and the data are scaled up linearly to form annual sums.

These three practices are designed to balance the accuracy of data collection against the costs of survey collection, and the practices yield consistent estimates of a household's annual consumption only when that household completely smooths consumption during the year (so that the household's consumption in any month is the same as their consumption in any other month). But when consumption varies through the year, the practices yield estimates of "annual consumption" that are specific to the dates of interviews.[3] When plugged into conventional formulas

poverty dynamics across years. Martin Ravallion suggested this connection, and his work across years parallels our analysis within the year. See, especially, Ravallion (1988). The literature on poverty dynamics documents that households regularly move in and out of poverty from year to year, showing that much poverty is transient rather than persistent across years. Studies of poverty dynamics across years include Bane and Ellwood (1986), Morduch (1994), Jalan and Ravallion (1998), Baulch and McCulloch (2000), Addison et al. (2009), Christiaensen and Shorrocks (2012), Hoddinott (2006) and Balboni et al. (2022).

[2]Mancini and Vecchi (2022), Figure 3.2. Data are from a survey of data collection methods in 137 countries. Notable exceptions among middle-income countries outside of Latin America include the Philippines and Malaysia. Just 9 percent of high-income countries use consumption rather than income.

[3]When aggregated, these interview-date-specific estimates of annual household consumption can deliver an accurate prediction of the population average of consumption, but the values are inaccurate for any given household (Scott, 1992).

for poverty rates, these date-specific consumption measures aggregate to form indicators that are "time-sensitive" in that they register variation in household welfare within the year. The indicators are thus sensitive to households' ability to smooth consumption across months.

Accumulating evidence shows that welfare can vary substantially during the year (Chambers 1983, Collins et al. 2009). In rural areas, deprivations typically intensify in lean seasons and ease in harvest seasons (e.g., Longhurst et al. 1986, Khandker 2012, Devereux and Longhurst 2012, Dercon 2002, Christian and Dillon 2018, Dostie et al. 2002, Carter and Lybbert 2012, and Gilbert et al. 2016), with consequences that have been documented in recent randomized trials (e.g., Breza et al. 2021, Bryan et al. 2014,Pomeranz and Kast 2024, Fink et al. 2020, Casaburi and Willis 2018) and with evidence that climate change has increased seasonal variability (Santer et al., 2018). Evidence Action (2019) writes that "seasonal hunger and deprivation are perhaps the biggest obstacles to the reduction of global poverty." Similarly, Vaitla et al. (2009) note that "Most of the world's acute hunger and undernutrition occurs not in conflicts and natural disasters but in the annual 'hunger season,' the time of year when the previous year's harvest stocks have dwindled, food prices are high, and jobs are scarce."[4]

The combination of within-year variability with the three survey practices introduces time-sensitivity to poverty rates, as noted by Gibson et al. (2003) and Jolliffe and Serajuddin (2018). A fourth recommended survey methodology – collection of data from different households throughout the year (to catch the ups and downs) with stratification by period (to create a series of representative samples within the year) – directly reflects recognition of persistent seasonality (World Bank and FAO 2019, Mancini and Vecchi 2022). Adding this fourth practice yields the distinct,

[4]Evidence Action (2019) estimates that seasonal hunger affects around 600 million of the world's rural poor. Chambers (1983) argued that the ups and downs of rural poverty go "unperceived". Despite increasing urbanization globally (World Bank, 2021), Castañeda et al. (2018) find that rural residents comprised 80 percent of the world's population living in extreme poverty, and agriculture accounted for 65 percent of the employment of adults (aged 15 and above) in extreme poverty. Seasonality and poverty are thus closely linked. In cities and towns, income and consumption are often unstable as well, shaped by changing economic conditions, fluctuations in the availability of work, and shifts in seasonal demand (Collins et al. 2009, Gibson and Alimi 2020, Jolliffe and Serajuddin 2018). Even in wealthier economies like the United States, low-income populations are constrained by instability and illiquidity within the year (e.g., Ganong et al. 2020, Parker 2017, Morduch and Schneider 2017, Roll et al. 2017, Schneider and Harknett 2020, Morduch and Siwicki 2017).

interpretable concept of national deprivation that we label the "Average of Poverties." In its simplest form, this is the average share of the years that the population experiences poverty.

These practices are common in poverty measurement. Smith et al. (2014), for example, find that 42 percent of household consumption surveys in low and middle-income countries survey households throughout the year but interview each household only once. This group includes countries with a large share of households living in extreme poverty, including India, Bangladesh, Ethiopia, Azerbaijan, Mozambique, and Uganda.[5] Another 47% of household surveys analyzed by Smith et al. (2014) also interview households just once time during the year, but they collect data for just part of the year, not the full twelve months. Here, official poverty rates will be time-sensitive, but they will approximate neither the conventional poverty headcount nor the Average of Poverties.

To describe the implications of this fundamental change in poverty measurement, we use a balanced panel of household-level data from rural India that includes the income and expenditures of 945 low-income households collected monthly for at least four years. We focus on three findings.

First, we show how even with substantial consumption smoothing during the year, meaningful levels of within-year instability remain. In that context, we demonstrate that data aggregation designed to mimic expert guidelines for collecting national consumption statistics fails to yield even a noisy approximation of the conventional poverty headcount. Instead, it approximates the Average of Poverties (AoP).

Second, the within-year instability translates into large increases in measured poverty when using the headcount formula. This is largely due to including poverty experienced by households that would not conventionally be considered poor. Across our sample, the overall headcount poverty rate averages 29% when measured conventionally with yearly consumption calculated as the sum of monthly

[5]The full list of countries, which comprise 41.7 percent of the total sample, are: Afghanistan, Armenia, Bangladesh, Brazil, Burkina Faso, Cambodia, Cape Verde, Chad, Ethiopia, Gambia, Georgia, Ghana, India, Iraq, Kenya, Lao PDR, Latvia, Lesotho, Lithuania, Malawi, Mongolia, Morocco, Mozambique, Nepal, Niger, Pakistan, Romania, Rwanda, Seychelles, Sierra Leone, South Africa, Sri Lanka, Swaziland, Tanzania, Thailand, Timor-Leste, Tunisia, Uganda, Vanuatu, and Yemen. The list is from the base data accompanying Smith et al. (2014), downloaded in October 2023 from http://www.ihsn.org/food.

values. If households perfectly smoothed consumption, the Average of Poverties would also be 29%. But data aggregated in keeping with expert guidelines instead show a poverty rate of 37% when taking into account monthly movements in and out of poverty during the year (26% higher than the conventional headcount).

Two opposing forces explain the increase in measured poverty. The Average of Poverties measure is reduced by the fact that poor households (as classified by yearly consumption) are not always poor. As a group, the poor households in our rural sample spent just 86% of the year below the poverty line on average (equivalent to spending 1.7 months above the poverty line). From the other direction, the measure is increased by the fact that "non-poor" households are sometimes poor. On average, they spent 16% of their time below the poverty line.[6] Since non-poor households make up 71% of the sample, their months of poverty dominate. Just under two-thirds of households experience poverty in at least one month per year, including 47% of "non-poor" households. Altogether, 35% of all months in poverty are attributable to deprivations experienced by households that would not conventionally be considered poor.

Related results emerge when measuring deprivation with distribution-sensitive poverty measures. Here, *de facto* poverty rates (and the Average of Poverties) are sensitive to periods of worse-than-average periods of deprivation during the year, including for households who are always poor. These deprivations are fully offset by better-than-average periods (and thus removed from consideration) when poverty is measured with accurate annual data. We show that measured poverty increases by 40% and 48% when adapting the Average of Poverties to the Watts (1968) and Foster et al. (1984) squared-gap indices respectively. These results are quantitatively large and in line with related findings in national-level data analyzed by Gibson et al. (2003) in urban China, Jolliffe and Serajuddin (2018) in Jordan, and Gibson and Alimi (2020) in Nigeria.

Third, time-sensitivity adds predictive power beyond the conventional annual measure–and shows that within-year variation in the data is not mainly mea-

[6] Consistent with our findings, data from Tajikistan show that only 10% of the sample was always poor across 4 quarters while 40% of the sample was sometimes poor during the year (Azevedo and Seitz 2016). Similarly too, Dercon and Krishnan (2000) explore poverty and seasonality with three waves of data from Ethiopia in 1994-95, finding considerable movement in and out of poverty during the year due to uninsured shocks. Morduch and Schneider (2017) describe the prevalence of being "sometimes poor" in the United States.

surement error. We focus on anthropometric outcomes and use a least absolute shrinkage and selection operator (LASSO) that allows the data to determine the predictive power of alternative poverty concept. Focusing on weight and height, we show that a household-level indicator that reflects within-year variation in poverty is a stronger predictor of these health outcomes than conventional indicators of poverty based on annual consumption. In other words, household-level time-sensitive poverty metrics appear to be a stronger predictor of some development outcomes than the conventional annual lens.

The analysis builds on Deaton and Grosh (2000)'s discussion of household consumption surveys and their relation to poverty measurement. We also build on Gibson et al. (2003), Gibson and Alimi (2020), and Jolliffe and Serajuddin (2018) who recognize that the data collection methods described here lead to departures from the conventional notion of poverty, and who note that, as a result, measured poverty will move in response to within-year fluctuations. The main concern of this literature is with inaccuracy relative to conventional poverty measures. Our contribution instead centers on recognition of *de facto* measures of poverty as distinct and interpretable measures of deprivation.

The rest of this paper proceeds as follows. We first discuss some theory and practical considerations in poverty analysis in section 2. We then discuss the data we use in section 3 and the results in section 4. We conclude with broader implications and empirical strategies to improve measurement in section 5

2 Theory and practice of poverty analysis

2.1 Time-insensitive poverty: The conventional concept of poverty

There are good reasons that poverty has been historically conceived in terms of yearly resources, insensitive to the timing of consumption within the year. Maintaining a focus on total earnings and expenditure over the year highlights the challenges of overall earning capacity. But in the following sections we describe assumptions underlying the collection of household consumption data used to construct the conventional yearly measure and show how the measure transforms into the Average of Poverties (defined in section 2.2) when those assumptions fail to hold.

We start with a year split into T periods and consider the household's yearly total consumption averaged over the T periods, $\bar{c}_i$. The first of the United Nations Sustainable Development Goals, for example, calls for eradicating global poverty as measured by households' yearly average resources translated into units per person per day (United Nations, 2022). The poverty line z reflects minimum needs in each period, and the poverty mapping $P(\bar{c}_i) = 0$ if $\bar{c}_i \geq z$. The population includes N households. The generic poverty measure P has an additive form, a feature of commonly-used poverty measures including the headcount, income gap, and the distribution-sensitive measures of Watts (1968) and Foster et al. (1984). Putting the pieces together yields the conventional poverty measure:

$$P = \frac{1}{N} \sum_{i=1}^{N} P(\bar{c}_i). \tag{1}$$

Because it is based on average consumption for the year, $\bar{c}_i$, the measure is time-insensitive in that it yields the same result whether household i consumes the same amount every day of the year or if they consume more in some periods and less in others. Time-insensitivity means that policies to reduce the poverty measure are limited to policies that increase households' overall consumption—e.g., policies to increase economic growth, invest in human capital, improve jobs, and strengthen safety nets (Ravallion, 2016). This is the idea of poverty that largely occupies policymakers and experts (World Bank 2022, United Nations 2022, Deaton 1997, Ravallion 2016, and Atkinson 2019).

2.2 Time-sensitive poverty

Because the conventional poverty measure in equation 1 is insensitive to the timing of income and consumption within the year, one interpretation of the index is that it provides a measure of households' hypothetical consumption in a world of perfect within-year steadiness or complete consumption smoothing.

A simple extension of the conventional approach in equation (1) describes poverty without steadiness. The extension yields a time-sensitive poverty measure that registers the implications of instability and illiquidity. In each period t, household

i consumes c_{it}:

$$c_{i1}, c_{i2}, c_{i3}, \ldots, c_{iT}. \tag{2}$$

The period-specific consumption levels can be averaged to yield $\bar{c}_i$ for calculating the conventional time-insensitive poverty measure in equation (1). But here instead they are taken individually to determine the poverty status for each household i in each period t:

$$P(c_{i1}), P(c_{i2}), P(c_{i3}), \ldots, P(c_{iT}), \tag{3}$$

where $P(c_{it}) = 0$ if $c_{it} \geq z$.

The time-sensitive Average of Poverties (AoP) measure is this series of household-specific, period-specific poverty outcomes averaged over time and across households:

$$AoP = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{1}{T} \sum_{t=1}^{T} P(c_{it}) \right). \tag{4}$$

The specific form of the poverty mapping $P(\cdot)$ is again additive and includes the headcount, income gap, and the distribution-sensitive measures of Watts (1968) and Foster et al. (1984).[7]

When the poverty mapping is the simple headcount, time-sensitivity requires that, holding all else constant, a transfer that lifts a household out of poverty in any period must decrease the poverty measure. With a distribution-sensitive poverty mapping, time-sensitivity requires that, holding all else constant, a pure transfer of income from a household in a period where they are below the poverty line to any period where they are richer must increase the poverty measure. This second scenario is a within-household version of the Pigou-Dalton transfer axiom adapted by Sen (1976).

With a poverty line equivalent to $2.15 per person per day, if a household con-

[7] Ravallion (1988), Calvo and Dercon (2009), and Foster (2009) use a similar measure applied to longitudinal yearly data when analyzing the variability and persistence of poverty across years. To simplify notation, we ignore population weights and weights for different long periods. Adding weights would be straightforward; for example, except in a leap year, poverty in January would contribute 31/365 to the weighted annual average, poverty in February would contribute 28/365, etc.

sumes on average \$1 per person per day for each of six months and an average of \$3 per person per day for each of the other six months, they would now be counted as contributing 0.5 of a year of poverty to the headcount version of equation (4), where $P(c_{it}) = 1$ if $c_{it} < z$ and 0 otherwise. In contrast, the conventional time-insensitive approach would count them as being poor for the whole twelve months since their average consumption is just \$2 a day for the year.

The two conceptions of poverty – the time-insensitive notion in equation (1) and the time-sensitive notion in equation (4) – provide complementary, but distinct, information and are identical only in the absence of within-year instability or perfect consumption smoothing (i.e., when, for each household i, $c_{it} = \bar{c}_i$ for all months t). While, by construction, equation (1) is unaffected by consumption variability during the year, poverty measured by (4) can fall with improved consumption smoothing, even when average consumption is unchanged. As households become better able to smooth consumption during the year, the divergence decreases, and, as noted, it is eliminated when households perfectly smooth consumption.

Equation (4) requires T periods of data for each household, making calculation of the Average of Poverties seem infeasible except in a dozen or so countries with monthly or quarterly data on the same households (Smith et al., 2014). We show in section 2.5, however, that the measure can be approximated with data from just one period for each household.

The average of poverties perspective makes clear that poverty, as measured, is a combination of both overall consumption levels as well as variation in consumption throughout the year. We can make this more explicit by rewriting Equation 4, adding and subtracting mean consumption:

$$AoP = \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(P(\bar{c}_i) + [P(c_{it}) - P(\bar{c}_i)]\right), \tag{5}$$

where $P(\bar{c}_i)$ is the poverty measure using a household's *annual* mean consumption.

The notation allows analysis of how poverty is affected by changes in the economic environment – for example, the impact of the introduction of a cash transfer program, an increase in financial inclusion, or a tightening of labor markets. Taking the derivative of Equation 5 with respect to a change in an environmental factor x_t yields:

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\frac{\partial P(\bar{c}_i)}{\partial \bar{c}_i}\frac{\partial \bar{c}_i}{\partial c_{it}}\frac{\partial c_{it}}{\partial x_t}+\left[\frac{\partial P(c_{it})}{\partial c_{it}}\frac{\partial c_{it}}{\partial x_t}-\frac{\partial P(\bar{c}_i)}{\partial \bar{c}_i}\frac{\partial \bar{c}_i}{\partial c_{it}}\frac{\partial c_{it}}{\partial x_t}\right]. \tag{6}$$

The first term of the sum reflects the impact on poverty of an intervention x in period t. In each period, x may affect that period's consumption level and thus contribute to a change in average consumption, $\bar{c}_i$. An intervention that increases households' liquidity, for example, could spur investment and thereby reduce poverty by driving up average income and consumption during the year. This term captures the conventional focus of poverty analyses on totals and averages across the year. When observers say that microcredit has not reduced poverty (Banerjee et al., 2015), for example, they are implicitly saying that this term cannot be distinguished from zero.

The second term, within the square brackets, captures the impact via changes in the incidence and intensity of poverty from period to period. The term in brackets registers, for example, how increased liquidity may reduce poverty by allowing households to better protect their consumption during lean seasons by shifting resources from other seasons; how microcredit might help buffer health shocks (Berg and Emran 2020, Islam and Maitra 2012); or how saving groups might help smooth consumption within the year (Beaman et al. 2014)—even with no change in total consumption across the year.

2.3 The data collection dilemma

Designing surveys to collect data on household expenditures entails tradeoffs between accuracy and costs (De Weerdt et al., 2020). Major tradeoffs would be eliminated if (1) households had perfect recall of what they spent or (2) they perfectly smoothed their consumption within the year. In the first case there would be no loss of accuracy when asking households about their spending for the entirety of the previous year, and in the second case responses to questions with short recall periods (spending in the past week, say) could be extrapolated to construct accurate yearly consumption estimates since any given period's consumption would be similar to any other period's consumption and could thus be a good predictor of annual consumption.

The challenge for statistical agencies is that neither strategy is reliable: memories are faulty and household consumption in low-income economies typically varies substantially through the year. The consequence of faulty memories is the use of short recall periods. Asking respondents questions with shorter recall periods (a week, say) usually generates much more reliable data, especially about high-frequency purchases like food, than asking about purchases that might have taken place a month or more in the past (Beegle et al., 2012). Smith et al. (2014) judge that a recall period of two weeks or less is "reliable" for food consumption, and any length greater than that is unreliable.

As a result, survey questions on food are often asked with a short recall period, while questions about non-food purchases may be asked with longer reference periods. Questions about shelter or large durables, for example, are often asked with recall over an entire year. The ultimate measure of annual household consumption is then created by scaling up the responses in proportion to the length of the associated reference periods—e.g., by multiplying by 52 for those questions with one-week reference periods and multiplying by 12 for questions asking for recall over the past month. When food is a large share of budgets for poor households, the annualized consumption aggregate will be rooted in the experiences of the particular week of the interview.

Smith et al. (2014) analyze a global survey conducted by the International Household Survey Network and covering data sets mainly collected between 2005-9 from low- and middle-income countries, including the eight countries in South Asia (Appendix A1.3, p. 50). Smith et al. (2014) shows that of 96 household-level surveys, 41 percent employed a recall period for food of less than one week, most commonly a single day (using a diary method). Nearly a quarter used a week exactly, 5 percent used two weeks or half a month, and 7 percent used a month. Taking the data together, Smith et al. (2014) find that 70 percent thus collect food data with "reliable" recall periods of two weeks or less and 77 percent have recall periods of a month or less.

An alternative proposed by Deaton and Zaidi (2002) is to ask about consumption in "a usual month." About 10 percent of methods surveyed by Smith et al. (2014) did so. But the evidence in the past two decades has tilted against the "usual month" approach, despite its conceptual appeal.[8] Beegle et al. (2012), for example, find

[8] In principle, asking households about their consumption in a "usual month" is a way to maintain the year as a reference period and put aside concerns with seasonality, while also keeping the recall

that the "usual month" approach leads to significant underestimation of household spending on food. Asking questions about a "usual month" is complicated (what is a usual month in an unstable context?) and takes relatively long to complete. World Bank and FAO (2019) conclude that "the usual month may be a lose-lose proposition if it is less accurate and more cumbersome to implement when compared to a seven-day recall. This is possibly the most important single development in the evidence base since the publication of Deaton and Grosh (2000)" (p. 19, cited by Mancini and Vecchi 2022). The new evidence thus cements the use of short recall periods.[9]

As a consequence, surveys should then ideally be run on the same households in different periods during the year in order to account for their ups and downs of welfare (Deaton and Grosh, 2000). To calculate a conventional measure of poverty with the data from South India, for example, our calculation of household i's average monthly consumption $\bar{c}_i$ requires data on household i's consumption c_{it} in each month t:

$$\bar{c}_i = \frac{1}{12} \sum_{t=1}^{12} c_{it}. \tag{7}$$

However, panel data like those from South India are unusual in their frequency, and in general, the cost of re-visiting households makes high-frequency panel data rare in practice. As (Mancini and Vecchi, 2022) summarize in their update of (Deaton and Zaidi, 2002), "There is abundant evidence that food consumption and expenditure display systematic seasonal variation on a yearly, monthly, and weekly basis. The only way to accurately capture habitual consumption for each household is to survey them multiple times over the year, but this is also the most expensive option, and in practice, it is difficult to implement." (Appendix E, page 159.)

This outcome (using short recall periods for important budget items coupled with single-time surveys) has been recognized as being consequential for poverty measurement (Gibson et al. 2003, Jolliffe and Serajuddin 2018), but in many countries it is the only feasible option given the evidence on the relative accuracy of measurement techniques and the limited budgets available for data collection. To account for seasonal variation, experts suggest at minimum that data should be

period to one month so households are not pressed to remember spending across long horizons (Mancini and Vecchi 2022, footnote 22, p. 28).

[9] We note, however, that in an ideal world of perfect recall, the "usual month" standard collects data that reflects the traditional notion of poverty. Changing to a shorter recall period changes the notion of poverty to the "Average of Poverties" we introduced above.

collected throughout the year, with samples interviewed each month, a practice integrated in the World Bank's Living Standards Measurement Surveys (where it is typical to stratify on quarter). Another survey that followed these guidelines was India's National Sample Survey (NSS). The NSS was used for decades as the basis for official poverty estimates in India.[10]

These ideas form the basis of guidelines created by the Inter-Agency and Expert Group on Food Security, Agricultural and Rural Statistics, convened by the World Bank and UN Food and Agriculture Organization, and endorsed by the forty-ninth session of the United Nations Statistical Commission in 2018 (World Bank and FAO, 2019). The guidelines draw on the survey reported in Smith et al. (2014), and they are discussed further by Mancini and Vecchi (2022), which in turn updates Deaton and Zaidi (2002).

2.4 Recovering average consumption

One notable feature is that, under the World Bank and FAO (2019) expert guidelines, combining one-time interviews and short recall periods can nevertheless yield an unbiased estimate of average consumption in the sample. Scott (1992) shows that average consumption for the population can be estimated despite short recall periods and despite seasonal variation. This is possible if sampling is random and is carried out with equal probability through the year (if, for example, households have a 1/4 chance of being interviewed in any given quarter). This guidance for sampling is embodied in expert guidance (World Bank and FAO, 2019).

In this case, the consumption recorded for a given household will reflect the timing of their interview (so will not provide an accurate measure of their annual consumption), but the sampling process will still yield a reliable estimate of the population's yearly average consumption.

We will use the same logic when we turn to national poverty statistics in section 2.5, and illustrate it first here for average consumption. In section 2.3, we noted that, in practice, survey questions are asked with different reference periods: food and fuel over the past week, for example, but small durable goods over the past month and housing over the past year. When scaled up, the resulting "annual" consump-

[10] Interested readers can find the NSS reports on the Ministry of Statistics and Programme Implementation's website: https://www.mospi.gov.in/download-reports.

tion aggregate will reflect a mix of different reference periods, although most are short and rooted in the date of the interview.[11] Meanwhile, survey methods often stratify on quarter. Below, we assume that households can smooth consumption perfectly within a quarter, but they cannot necessarily smooth across quarters.[12] To accommodate the different reference periods for different survey questions, we focus on quarterly consumption, calculated as the "annual" consumption aggregate divided by 4, which will be a reliable measure of average consumption in the quarter of the interview.[13]

Then, to see Scott (1992)'s reasoning, start with household consumption in each quarter, as in equation (2) with $T = 4$ quarters. Since in practice it is too costly for statistical agencies to collect data in all quarters from the same households, they select a randomly-chosen quarter for each household. We refer to this quarterly value as c_i^q, where the superscript q indicates the quarter of the interview:

$$c_i{}^q = \sum_{t=1}^{4} c_{it} \cdot I_{it}, \tag{8}$$

where I_{it} is an indicator which captures the randomized sampling process; I_{it} is equal to 1 if household i was randomly chosen to be interviewed in quarter t, and it is 0 in the other three quarters. This characterization captures the spirit of the best practices for data collection in World Bank and FAO (2019) and Mancini and Vecchi (2022)

The randomly-drawn cross-section of quarters from a randomly-drawn sample of households will, when averaged, approximate the average consumption for the whole sample (Scott, 1992). Since choosing any given quarter for the interview is equi-probable with a $1/4$ chance, the expected value of c_i^q is the probability-weighted sum of the four quarterly consumption values. As a result, the expected

[11] In the VDSA rural data from India that we describe below, the food share in annual budgets is 50% for the full sample, 63% for the subsample below the poverty line, and 48% for the non-poor subsample (using yearly data and averaging across years). As we describe in section 3.2, durables and semi-durables are a small part of budgets.

[12] We could instead do the analysis at the monthly level, assuming households can smooth within months but not across them.

[13] Questions about large purchases like housing may be asked in surveys with a one-year reference period, and their associated expenditure will then be divided equally across the quarters.

value of c_i^q for household i is household i's true average consumption $\bar{c}_i$:

$$E[c_i{}^q] = \sum_{t=1}^{4} \frac{1}{4} c_{it} = \frac{1}{4} \sum_{t=1}^{4} c_{it} = \bar{c}_i. \tag{9}$$

Then, averaging the randomly sampled quarters of consumption across all households will generate, in expectation, the average annual consumption of the entire population, $\bar{c}$:

$$E[c^q] = \frac{1}{N} \sum_{i=1}^{N} E[c_i{}^q] = \frac{1}{N} \sum_{i=1}^{N} \bar{c}_i = \bar{c}. \tag{10}$$

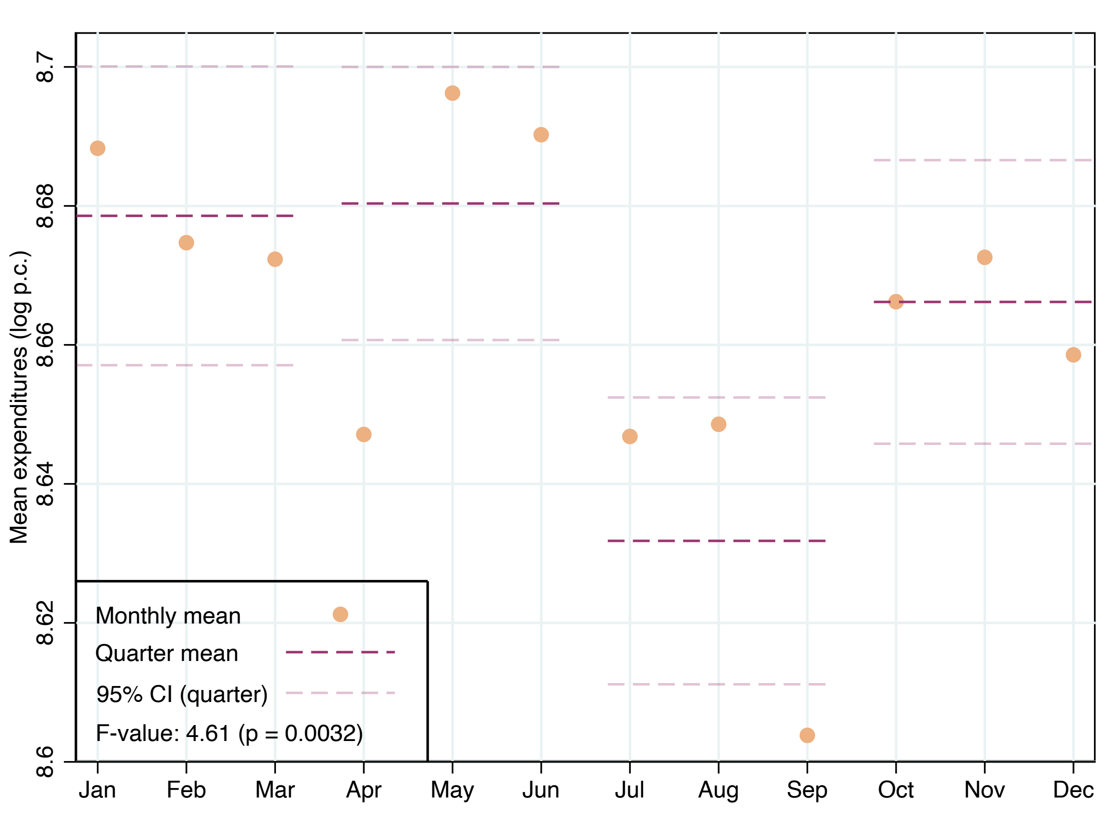
where variables without subscripts refer to population values. Some households will be surveyed in low seasons, and some in high; some households will be surveyed during idiosyncratically good or bad periods. But, taken together and averaged, the result will approximate the average consumption of the population.[14] The problem, as Deaton and Grosh (2000) note, is that analysts are also interested in estimating poverty and inequality, not just the population average of consumption. Poverty and inequality, as conventionally conceived, will not be accurately measured if the annual consumption aggregates are constructed as above and taken at face value (Scott, 1992). In other words, while the estimate of average annual consumption in the sample is indeed an accurate measure of mean annual consumption in the population, the poverty rate based on these data will not approximate the conventional poverty concept described in equation 1.

We can see the importance of collecting data throughout the year for mean expenditure estimates by examining data from India's National Sample Survey (NSS), a large nationally-representative survey. We use data from the 68th round of the NSS, which was collected from July 2011 to June 2012 – around the same time as the dataset we use below. Figure 1 shows the deviation of expenditures throughout the year. We plot both monthly mean expenditures as well as quarter

[14] Mancini and Vecchi (2022) conclude in their World Bank assessment of data collection practices, "Data collection spread over the year, but with only one interview per household, results in an accurate estimate of average consumption for the population, but with excess variability around the mean; however, it is a viable option in resource-constrained contexts. Regardless of the approach chosen, care should be exercised to ensure that enumeration is equally spread throughout the days of the week and the month..." (pp. 159-160)

means, the latter of which is considered to be nationally representative.

Figure 1: Household expenditure by date of survey
in the NSS 68 (2011-2012)



Notes: Means are calculated using person weights, which we create by multiplying the household weight by the household size. To calculate the F-test, we regress demeaned (log) expenditures on quarter dummies, using weights and clustering at the FSU, which is the primary sampling unit in the NSS. We deflate to July 2011 (the first month of the NSS 68) prices using CPI.

We note several important features of the figure. First, there is clear variability in quarter-level means throughout the year. In fact, the difference between the highest quarter (quarter 2) and the lowest quarter (quarter 3) is around 0.05, indicating a more-than-5-percent difference in mean expenditures between the lowest and highest quarters. In other words, if the survey were collected only during one of these two quarters, we would have a biased estimate of mean annual expenditures for the country as a whole.

Second, this variability means that quarters are strong predictors of expenditures.

The F-test of a regression of (log) expenditures per capita on quarter dummies yields an F-test of 4.61 ($p = 0.003$).

2.5 *De facto* time-sensitivity in national poverty statistics

We next use Scott (1992)'s logic from above to show what is actually measured when calculating poverty rates using the "annual" consumption aggregates described in 2.4 is a version of the time-sensitive Average of Poverties in equation (4).

Due to the short-recall periods and one-time surveys, each household's measured poverty status for the year will be their poverty status in the quarter in which they were randomly sampled. As above, when it is costly to collect data on each household i's average consumption, $\bar{c}_i$, an approximation is typically used, c_i^q based on data from the randomly-selected quarter. This variable is then used to estimate poverty for the sample, P^q:

$$P^q = \frac{1}{N} \sum_{i=1}^{N} P(c_i^q). \tag{11}$$

The mathematical form of the poverty measure in (11) is identical to that of the conventional time-insensitive measure in equation (1). The only change is the replacement of $\bar{c}_i$ with the approximation c_i^q defined in equation (8). In parallel to the analysis above, we define $P(c_i^q)$ as household i's poverty status in the randomly-selected quarter:

$$P(c_i^q) = \sum_{t=1}^{4} P(c_{it}) \cdot I_{it}, \tag{12}$$

where I_{it} is the indicator which captured the randomized sampling process above; I_{it} is equal to 1 if household i was randomly chosen to be interviewed in quarter t and 0 in the other three periods. Again, since choosing any given quarter is equi-probable with a probability of $1/4$, the expected value of $P(c_i^q)$ is household i's own average of poverties:

$$E[P(c_i^q)] = \sum_{t=1}^{4} \frac{1}{4} P(c_{it}) = \frac{1}{4} \sum_{t=1}^{4} P(c_{it}). \tag{13}$$

Then, averaging poverty based on the randomly-selected quarters of consumption across all households will generate the expectation of equation 11. This is what is measured as "poverty" when following expert guidelines. It turns out to be, in expectation, the average of the quarterly poverty rates of the entire population:

$$E[P^q] = \frac{1}{N}\sum_{i=1}^{N} E[P(c_i{}^q)] = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{1}{4}\sum_{t=1}^{4} P(c_{it})\right) = AoP, \tag{14}$$

which is the Average of Poverties defined in equation (4) with $T = 4$. As with the result on the population average of consumption from Scott (1992), the result holds in expectation; the data collection process does not lead to an accurate assessment of any given household's poverty across the year. In other words, while equation (11) has been seen as a measure of the conventional poverty rate based on annual consumption, it is instead an approximation of the Average of Poverties.

While mean consumption and mean poverty both approximate population parameters, the approximations reflect time in different ways due to the non-linear nature of poverty measures. As in Scott (1992), the result hinges on both (1) surveying different households through the year and (2) randomly sampling throughout. If one or both do not hold, the measure is still time-sensitive but approximates neither the Average of Poverties nor the conventional annual poverty measure.

3 Evidence from rural India

3.1 Village Dynamics in South Asia (VDSA) Survey

We show the implications of the Average of Poverties using monthly panel data. The data are from the Longitudinal Village Level Studies of the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) collected in India between 2010 and 2014. The region depends on rainfed agriculture, and the year is marked by seasonality. The data collection project, also known as Village Dynamics in South Asia (VDSA), provides statistics at the monthly level. Since the data are monthly, the analysis will shift from quarters (as in section 2.5) to months.

The VDSA data is not a random sample of rural households in India, and our final data set adds restrictions. However, the households in the sample were drawn as a random sample of the households in each area, stratified by landholdings.

We combine modules on production activities, financial transactions, and household expenditure to construct monthly aggregates of expenditures, net income, and wealth for 1,526 households over 60 months, from July 2010 to June 2015. The households come from 30 villages across 15 districts in nine states. Approximately 94% households in the full sample self-identify as Hindu and the other 6% are divided between those who self-identify as Christians, Muslims, Sarnas, and others.

Not all households are observed in all 60 months. In some regions, breaks occurred during the first quarter of 2012 and the first quarter of 2014. Additionally, households from the state of Telangana contain only yearly records from the 2014 wave. To create a panel data set with the greatest number of households possible, but with a balanced panel within each given year, we only include households for which we have four or five full years of monthly data.[15]

The demographic variables are defined yearly – they are asked in only the July survey for each year – while the income and expenditure measures are monthly. We use a simple measure of household size, aggregating across all demographic groups in the table, to calculate per capita values for income and expenditures. We deflate the monetary measures to 2011-2012 rupees. The average household in our final sample (columns two and three) includes slightly more than six individuals, with the most common demographic group being prime-aged males and females (between 15 and 59 years of age). The household head is about 50 years of age, with an average of five years of education. The probability that the household head did not complete primary education is 50 percent for the sample with five years of data and 69 percent for the sample with four years.

Net income is a combination of production activities and wages. We do not observe interest paid/received for most financial transactions, so net income is mainly earnings from production and employment. In production activities, we include all the costs and revenues originating from cultivation, employment, and livestock. We record own agricultural income based on when the crop is sold or consumed, not when it is harvested. Importantly, because net income is a combination of revenues and costs, it can be negative in some months, especially

[15] We drop villages in the state of Telangana due to this restriction. However, there are relatively few households in Telangana, making up just 1.71 percent of the original sample.

during the agricultural planting season when costs are incurred but sales are still several months away. This prevents us from taking logs and from calculating certain poverty measures for income as discussed below.

Expenditures are our main interest, and they are more straightforward. Surveys are implemented each month and consumption is divided by whether it is home-produced, purchased, or received as a gift. Thus any agricultural production that is directly consumed is given a value based on opportunity costs and aggregated in the total. We take a simple sum across these categories.

Since we use per capita variables, we weight households by household size in order to interpret results as "per person" in the population from which the sample is drawn. In line with the stratification procedure used when collecting the data, we overweight landless households, multiplying the household size by 1.5 for the final sample weights.[16]

Column 1 of Table A1 of the appendix shows summary statistics for the 581 households (24,713 household-month observations) that we drop from the analyses – those with fewer than four full years of data. The second and third columns show statistics from the sample we use. They give data from balanced panels (four full years in column two and five full years in column three). Column 2 contains 116 households and column 3 contains 829 households, and most of the analysis is with these 945 households observed for 55,308 household-months. The second and third columns do not include records from Telangana, leaving 23 villages from eight states. Comparing the first and third columns shows that the excluded households (shown in column one) are poorer (annual expenditure is 28% lower) and less wealthy (42% lower wealth) than those with four or more full years of data.[17]

While in most household surveys from low-income regions, expenditure data is more accurate than income data since income tends to be under-reported, especially in rural settings (Carletto et al., 2021), here, however, agricultural income was a main focus of survey collection and was collected monthly. The measure of median income in colums 3 is 16.7 percent higher than median expenditures, but the means are closer. When we take the weighted average across columns 2 and

[16]We thank Andrew Foster for providing us with information around the sampling design for these waves of the survey.

[17]Table A2 in the appendix shows the number of households in our final sample by year and month.

3, reflecting the full sample used in the analysis, the average difference between income and expenditure is 5 percent.

We use rural poverty lines by state reported by the Reserve Bank of India (RBI).[18] The poverty lines are in the range of the World Bank $1.90 per person per day (extreme) poverty lines using 2011 PPP prices, the global poverty line that prevailed during the study period.[19] For example, in 2011-12 the rural poverty lines in Andhra Pradesh, Madhya Pradesh, and Gujarat were 860, 771, and 932 rupees respectively. The World Bank $1.90 per person per day line is $57 per 30-day month, which, using the 2011 PPP conversion rate to rupees (15.55) is 886 rupees, just above the Madhya Pradesh line.

We integrate four decomposable poverty measures into the Average of Poverties. The four reflect different dimensions of deprivation: the poverty headcount, the poverty gap, the squared poverty gap of Foster et al. (1984), and the Watts (1968) index. When using income, we only use the headcount poverty measure, but we calculate all four measures when using expenditures.[20]

The mode of per capita expenditure is very close to the poverty line, and many households are clustered on either side of the line. Specifically, 57.6% of the poor sample (and 17.0% of the entire sample) had annual expenditures between 75% and 100% of the poverty line. On the other side, 25.5% of the non-poor sample (and 17.9% of the entire sample) had annual expenditures between 100% and 125% of the poverty line. Inspection of the density (appendix figure A1) shows how for these groups, which together comprise 35% of the sample, even modest variability in monthly expenditure can lead to movements across the poverty line.

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[18] Reserve Bank of India (2021). Handbook of Statistics on the Indian Economy, 2020-21. Table 151 : Number and Percentage of Population Below Poverty Line. https://www.rbi.org.in/scripts/PublicationsView.aspx?id=20556

[19] As of September 2022, the World Bank uses a $2.15 per day poverty line and 2017 PPP exchange rates (https://www.worldbank.org/en/news/factsheet/2022/05/02/fact-sheet-an-adjustment-to-global-poverty-lines). For comparison to the contemporaneous literature, we continue to use the $1.90 per person per day global threshold for extreme poverty (using 2011 PPP exchange rates).

[20] Since income can take negative values in some agricultural seasons, it is not possible to construct the Watts (1968) index with income on a monthly basis since it depends on logarithms. While it is technically possible to construct squared poverty gaps, the negative income values sometimes lead to very large estimates when squared. Because poverty in India is generally measured with household expenditure, and to avoid the problem of negative incomes, we focus only on expenditure-based measures (and calculate income-based headcounts for comparison).

3.2 Accounting for expenditures on durables and unusually large expenses

Durables and unusually large expenses can pose complications when measuring poverty at higher frequency than a year. Consider a household that purchases a bicycle, for example. Spending on the bicycle shows up in the data in the month it was purchased and leads to a large spike in spending. However, the actual consumption of the services of that bicycle may take place over the next several years. When measuring poverty, the ultimate interest is in consumption rather than spending, but most surveys focus on spending (Coibion et al., 2021), largely for practical reasons. The issue arises in conventional annual measures as well, but buying a bicycle is a bigger share of spending in the month of purchase than when compared to a year's worth of spending.

A related issue involves big, unusual expenses like weddings. As Mancini and Vecchi (2022) write: "If a household spends a fortune on a special celebration during the survey period, such as a marriage, the resulting spike in measured consumption is genuine enough, but unrepresentative of typical living standards for that household" (p. 24). The conventional method to address this problem is by simply excluding these kinds of lumpy and infrequent expenditures and restricting household consumption to more "regular" purchases.[21]

It turns out that these kinds of lumpy, large expenses are uncommon in our sample. Table 1 shows that expenditures on large durables and semi-durables are

[21] Mancini and Vecchi (2022) note the problem with this procedure: "The choice of excluding lumpy expenditures is not, however, entirely uncontroversial. In all likelihood, exceptional expenditures will displace other spending (that is, a household will probably cut back on some of its other expenses in order to afford the big payment). The displacement will be greater for households that are unable to draw on savings or borrow, that is, poorer families and families having to shoulder large expenses that they have not had the chance to prepare for (as in the case of a catastrophic shock). The question, then, is whether spending net of the lumpy components is more typical than total spending. Arguably, if there is displacement, neither of the two measures—net or total—is representative of long run consumption; in fact, both are noisy proxies of it. Ultimately, because we do not observe long-run consumption, and we have no way to ascertain the size of the displacement of current expenditure, we cannot know for sure which of the two proxies is, in fact, the noisiest. A pragmatic strategy is to continue to exclude the shortlist of expenditures that are usually considered lumpy (e.g., weddings, funerals, purchase of durable goods), because they are typically very large with respect to the total budget of the household (and of the likely displacement they may cause), and that, at least to some extent, they were expected. The more a certain expenditure can be anticipated or planned for, the better is the case for its exclusion, as the observed consumption pattern discounts the occurrence of that expenditure."

Table 1: Percent of expenditures on durable goods

	(1) Durables	(2) Semi-durables
Median		
Top expenditure quartile	0%	1.0%
Third quartile	0%	1.2%
Second quartile	0%	1.2%
Bottom expenditure quartile	0%	0%
90th percentile		
Top expenditure quartile	0%	14.0%
Third quartile	0%	13.8%
Second quartile	0%	12.7%
Bottom expenditure quartile	0%	9.6%

Notes: The percentages indicate the percent of monthly expenditures spent on each type of good. Expenditure quartiles divide the sample into four groups based on their total yearly expenditure per capita. Within each quartile, the columns give the median (top panel) and 90th percentile (bottom panel) of spending on durables and semi-durables (as a percent of monthly expenditures).

quite low in the sample. We define "semi-durables" as clothing (clothes, shoes, and socks) and any item classified in the VDSA as "household articles and small durables (<2 years life)" in the survey. The table breaks out the percentage of monthly expenditures spent on durables (column 1) and semi-durables (column 2) by expenditure quartiles. (Since the headcount poverty rate with annual expenditures is 29 percent in the sample, the poverty line is close to the bottom of the second quartile.) Table 1 shows that in the bottom quartile, the median month includes no spending on durables or semi-durables. Even at the 90th percentile, there is no spending on durables and less than 10 percent of total spending is on semi-durables. The second quartile shows broadly similar expenditure patterns.

As additional evidence that spending on durables and semi-durables does not drive our results, Figure A3 shows the distribution of expenditures per capita when we smooth durable spending across an entire year. To create the figure, we subtract actual durable and semi-durable expenditure from total expenditures in each month and add one-twelfth of total durables/semi-durables expenditure for the subsequent 11 months plus the current month. The distribution almost completely overlaps the original expenditure distribution in Figure A1, and monthly poverty rates with the smoothed durables/semi-durables are still 19.3 percent higher than poverty measured at the yearly level. As such, spending on durables and semi-durables does not create large differences in estimated poverty rates in our context, though this type of spending may be important in other contexts. It is less clear whether there should be similar adjustments for spending on health, and we return to that question in the final section.

We note, however, that even though these types of large purchases do not play a large role in our data, that may not necessarily be the case in other contexts.

4 Results

4.1 Income and expenditure variability

We start by establishing that within-year variability in consumption/expenditures is an important fact of economic life for the households in the sample. Figure 2 shows the data on median per capita income and expenditure over time, from 2010 to 2015. Clear seasonal ups and downs mark the income data, which is considerably more variable than the expenditure data. Expenditure data is less variable in relative terms, but it is, nonetheless, absolutely variable.

One way to summarize the data in Figure 2 is with the coefficient of variation (CV) of income and of expenditure. The coefficients of variation are calculated for each household across the months of the survey in a given year and then averaged across households. The median CV of income is 0.86 and the median CV of expenditure is 0.25. The median ratio of the latter to the former is 27%. If there were no smoothing at all, the variability of month-to-month consumption would be identical to the variability of month-to-month income, and the ratio of their coefficients of variation would be 100%. If instead households could smooth consumption perfectly, the ratio would be 0. The fact that the median of the annual ratio is 27% across all households indicates considerable but imperfect smoothing. Similarly, the median CV of expenditure is 0.25 and indicates that households still experience considerable variability in expenditure. To put the CV in context, a CV of 0.25 is roughly the number generated if a household's monthly expenditure was one quarter greater than the yearly average for half the year and one quarter less than the yearly average for the other half year.[22]

[22] An additional way to quantify variability is by regression monthly expenditure on monthly

Figure 2: Median income and expenditures, 2010-2015

Notes: The lines are simple medians for each month, weighted by sampling weights and household size. We restrict the sample to households which show up in all five years so that the sample does not change across years.

4.2 The poverty exposure (PE) curve

Figure 3 shows how the experience of poverty (measured as each household's average months in poverty in a year) compares to their household's poverty status according to yearly resources. To construct the figures, we take each household's monetary measure (average per capita household income for the left panel and average per capita household expenditures for the right panel across all months of the survey) and normalize by dividing by the poverty line. The variable y/z on the horizontal axis of the left panel is thus normalized income, with a value of one indicating that the household is exactly at the poverty line; similarly, a value of 3, say, indicates that the household's per capita income is 300% of the poverty line. The variable C/z on the horizontal axis of the right panel is the equivalent for expenditures.

income. Table A4 and Table A5 show the same patterns: household smooth imperfectly.

The y-axis gives the proportion of months that a household is in poverty. We call this the household poverty exposure (PE) rate. The scattered points give PE rates for individual households indexed by their average resources. The downward-sloping curves amid the points are local polynomial regressions of PE rates on total yearly resources. We call this mapping the PE curve. Our high frequency poverty measure in Equation 4, when defined for the headcount, is the PE curve integrated across the sample.

The PE curves provide another way to see how the evidence deviates from the assumption that poor households are always poor and non-poor households are never poor. In the simplest example of that assumption—the special case in which monthly expenditures are completely smoothed (i.e., monthly expenditures are always 1/12 of yearly expenditures)—the PE curve would be a flat line at 1 on the y-axis (poor households are always poor) until it hits 1 on the x-axis (i.e., the poverty line), after which it drops to zero and proceeds as a flat line (non-poor households are never poor). For expenditures:

$$PE\left(C/z\right)=\begin{cases}1 & \text{if } C/z<1\\ 0 & \text{if } C/z\geq 1\end{cases} \tag{15}$$

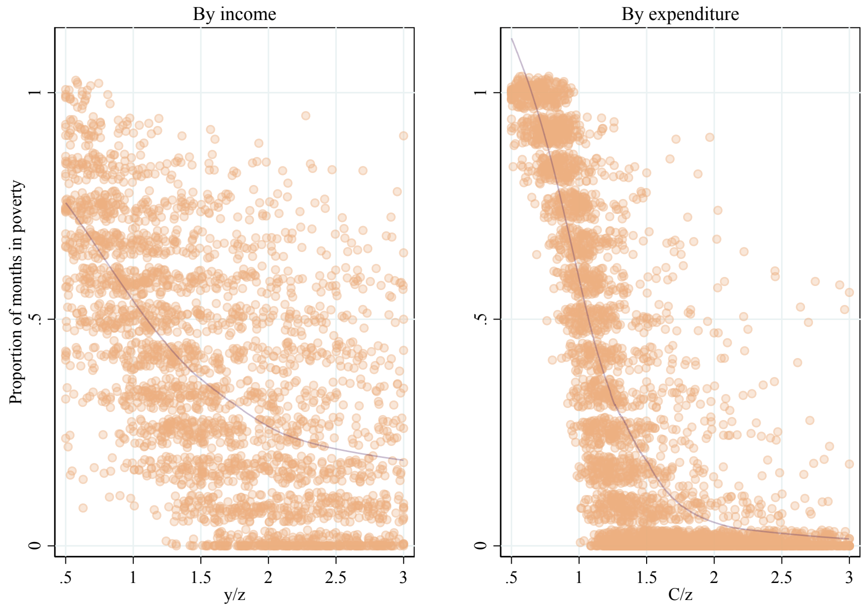
Figure 3 shows how far the data are from the pattern in equation 15. The PE curve for income is downward-sloping, indicating that poverty exposure falls as households earn more overall, but earning more does not guarantee escape from exposure to poverty even when income is greater than twice the poverty line.[23]

We can quantify this by looking at the smoothed value of poverty exposure at different ratios in the left panel. Right at the poverty line,[24] the smoothed value is 0.59, indicating that households near the line spend roughly 60 percent of the year in poverty. That decreases to 0.42 at 1.5 times the poverty line and 0.31 at twice the poverty line. In other words, poverty exposure stays quite high even when income is large relative to the poverty line. Because of seasonality, on average households with annual expenditure double the poverty line still spend roughly one third of the year in poverty.

[23]The figures are restricted to households with yearly expenditure or income below 300% of the poverty line, but the PE curve is estimated for the full sample.

[24]Since there are no values exactly equal to one, we take the mean between 0.98 and 1.02. We use identical widths for the other values in this section.

Figure 3: Months in poverty and annual income/expenditures



Notes: In both figures, the x-axis is the ratio of the monetary measure (income for the left figure and expenditures for the right figure) to the poverty line, averaged across the entire 60 months of the sample. The y-axis is the proportion of all months, across the entire sample, that a given household is in poverty. For ease of presentation, households below 0.5 and above 3 are dropped from the figure. The PE curve, shown by the smoothed curve through the middle of the scattered points, is a local polynomial regression of y on x.

The right panel shows poverty exposure by expenditures. By this measure, 53 percent of households are never expenditure-poor across the five years, and the data are distributed more compactly. All the same, many households experience months of poverty when measured by expenditure. The PE curve now slopes more steeply downward but still contrasts with the shape expected with perfect smoothing in equation 15—which is consistent with the evidence that households smooth consumption, but imperfectly.

Here, the PE curve decreases markedly as expenditures increase, at least relative to income poverty. Households are, on average, poor for slightly more than 60 percent of months right at the poverty line, but that number decreases to 23.6 percent at 1.5 times the poverty line and just 7.24 percent at twice the poverty line.

Table 2 shows related data: 63 percent of all households experience at least one month of expenditure-poverty and 47 percent of non-poor households (based on yearly expenditure) experience at least one month of poverty. When looking at poverty spells, defined as being poor for at least two months in a row, more than a quarter of non-poor households experience at least one poverty spell in any given year.

4.3 Implications of time-sensitivity

4.3.1 The extent of poverty

Table 2 presents population-weighted poverty summary statistics. The first column presents averages for the entire sample. The second column presents averages for households that are defined as poor for the entire year – in other words, using conventional poverty measures in the sense of equation (1) – while the third column presents averages for households that are (conventionally) not poor for the year.

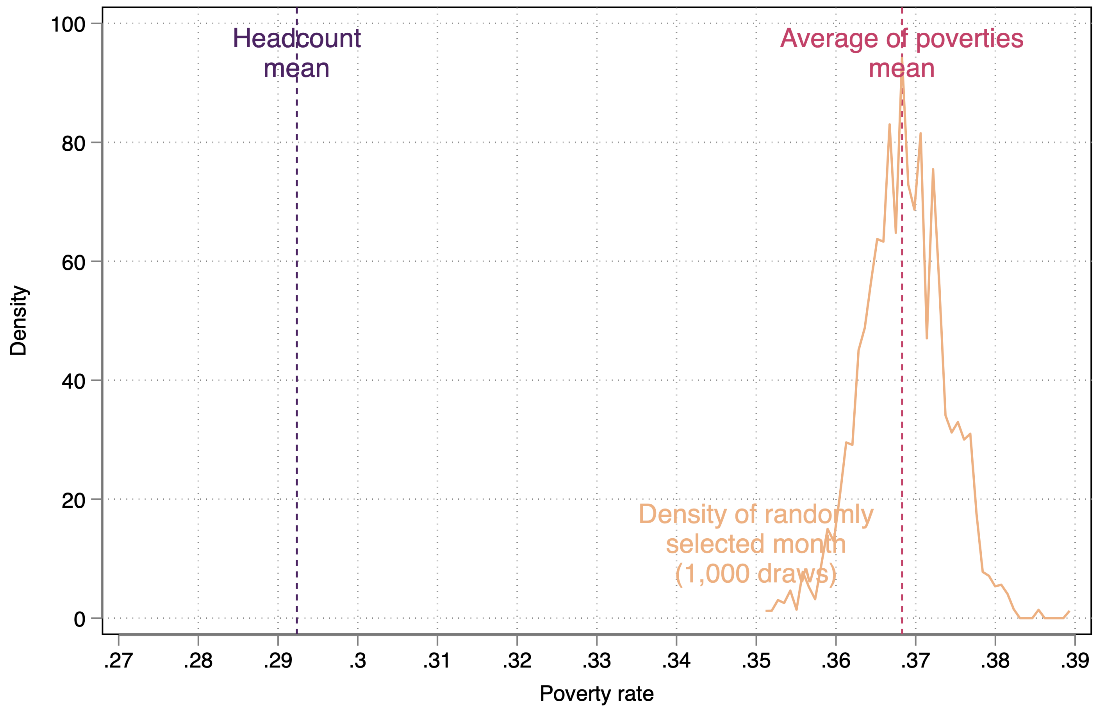
The first finding is that when measuring poverty by yearly household expenditure, poor households comprise 29% of the sample (row 2). But when recognizing movements in and out of poverty during the year, the Average of Poverties (using monthly data and a simple binary of being poor/not poor) shows that 37% of all household-months are spent in poverty, following equation 4 (row 3). This increase in the base poverty rate by more than a quarter is mainly due to the addition of people who are sometimes poor but not always poor. Since 71% of the sample lives in households defined as non-poor for the year, poverty experiences for these households add up to a substantial proportion of total poor months across all individuals (Figure A2 in the appendix).

4.3.2 Approximating the Average of Poverties measure

Figure 4 shows the difference graphically. The bar on the left is the conventional time-insensitive headcount using average expenditure for the entire year. As above, the headcount is centered just above 29 percent. To the right is the time-sensitive Average of Poverties, centered near 37 percent, showing the average number of months in poverty across the sample.

To demonstrate the logic in section 2.5, we then estimate annual poverty rates using a single, randomly selected month for each household which is used as the

Figure 4: Comparisons of poverty measures



Notes: The "time-insensitive" mean is the annual poverty rate when using average expenditure for the entire year. The "time-sensitive" mean is the annual poverty rate when using the proportion of months in the year that the household is poor. The density estimate is estimated annual poverty rates when using a single, randomly selected month, across 1,000 replications.

prediction of the household's annual average consumption. The aim is to mimic the outcomes of best practices for data collection. We then form a "headcount poverty rate" for the sample based on those household-level predictions.[25]

The figure shows the density of the "headcounts" for the 1,000 replications. As shown mathematically in section 2.5, the average of the 1,000 replications converges to the (true) time-sensitive Average of Poverties.

4.3.3 The depth of poverty

Increases are larger for the poverty measures sensitive to the distribution of income below the poverty line. When measured with yearly expenditure, the Watts (1968)

[25] Common practice in data collection is to stratify on quarter rather than month, but here we can take advantage of the ability to select random samples by month.

Table 2: Poverty summary statistics

	(1) Everyone	(2) Poor for the year	(3) Not poor for the year
Weighted proportion		0.29	0.71
Mean yearly poverty headcount	0.29	1.00	0.00
Mean Average of Poverties (headcount)	0.37	0.86	0.16
Mean yearly Watts	0.09	0.30	0.00
Mean Average of Poverties (Watts)	0.13	0.36	0.03
Mean yearly squared poverty gap	0.03	0.09	0.00
Mean Average of Poverties (squared poverty gap)	0.04	0.11	0.01
Poor at least once in year	0.63	1.00	0.47
At least one poverty spell in year	0.51	1.00	0.27
Households	945	391	893
Month observations	55,308	12,300	43,008

Notes: Poverty is based on household expenditure. The first column includes all households. The second column includes only households who are poor for the entire year, using average monthly expenditures across the 12 months. The third column includes only households who are not poor for the entire year. Spells are two or more contiguous months in poverty. All statistics are weighted with population shares.

index is 0.089 but rises by 40 percent to 0.125 in the monthly measure. The Foster et al. (1984) squared poverty gap similarly rises from 0.025 to 0.037, a 48 percent increase. The values of the two distributionally-sensitive measures are difficult to interpret, but the large changes suggest the possibility of substantial changes in relative rankings when comparing samples.[26][27]

[26]Table A3 presents the same statistics but with expenditures smoothed for spending on durables, by reallocating durable spending equally across all months. The adjustment aims to bring the measure of expenditure closer to consumption by spreading the value of durable purchases beyond the month in which they were purchased. The adjustment leads to smoother patterns of consumption, but the effect is modest in the data. The overall patterns remain similar when comparing monthly aggregates and yearly aggregates. The average monthly poverty rate without adjusting for durables is 37%, for example, and it falls to 35 percent when adjustments are made. The fraction of households that are poor at least in one month falls from 63 percent (unadjusted) to 57 percent (adjusted). Given that these differences are small, we present the figures unadjusted for durables in the main results below and provide results with adjusted data in the appendix.

[27]Table A6 in the appendix shows that these results are not driven by rising incomes over the sample period.

4.4 Evidence from China, Jordan, and Nigeria

Studies by Gibson et al. (2003), Gibson and Alimi (2020), and Jolliffe and Serajuddin (2018) take advantage of the few large household surveys with multiple observations on the consumption of the same households during the year. The three studies share the concern that different choices about data collection and extrapolation can lead to "noncomparable" poverty measurement (Jolliffe and Serajuddin, 2018). Each study shows deviations from the conventional time-insensitive notion of poverty that would result if just one of the observations were used for each household, an idea that we extend in section 2. Their data show that (1) the timing and frequency of data collection can substantially affect poverty rates, even when the form of poverty measures and the definitions of variables are standard across countries, (2) using data from one-time surveys rather than repeated surveys on the same households when measuring poverty introduces sensitivity to the timing of consumption, and (3) as a result, the poverty measures are sensitive to the within-year shocks faced by households and the ability to smooth consumption.

Our results reinforce and build on these findings. Our contribution is to introduce the Average of Poverties, both as an ethically and economically distinct concept of poverty and as a formulation that permits identification of what is *de facto* being measured by statistical agencies and reported as official poverty rates. In this context, Gibson et al. (2003), Gibson and Alimi (2020), and Jolliffe and Serajuddin (2018) provide evidence that can be interpreted in terms of our Table 2, Figure 4, and the Average of Poverties concept.

Gibson et al. (2003) use China's Household Income Expenditure Survey which is based on daily diaries for a full year, aggregated to form monthly sums. They use 1997 data from urban Hebei and Sichuan Provinces and exclude consumption of durables. They find an annual poverty rate of 30 percent when using all 12 months of data to calculate a measure of annual consumption (in the spirit of equation 7 above for monthly consumption) that can be used in the conventional headcount in equation (1). But the rate increases to 47 percent when they Gibson et al. (2003) instead choose random months and multiply by 12 to predict annual consumption (akin to equation 10 above), leading to an approximation of the Average of Poverties as in Figure 4. This is a 53 percent increase in measured poverty, and measured poverty increases 3.5 times when applied to the squared poverty gap of Foster et al.

(1984). Gibson et al. (2003) interpret the increases as being driven by measurement error, but inevitably they also reflect underlying consumption variation.

Gibson and Alimi (2020) use a similar approach with data from Nigeria in 2012/2013, where data were collected twice during the year from the same households. Using both rounds of data, they estimate that the conventional headcount was 18 percent nationally (24 percent in rural Nigeria and 4.3 percent in urban). But using just one of the rounds and extrapolating as done in China by Gibson et al. (2003), they find large increases: now they estimate poverty of 37 percent nationally (47 percent in rural Nigeria and 15 percent in urban). As above, the latter rates can be seen as a version of the Average of Poverties, and they show an increase of 54 percent. Like the data from China, the numbers show substantial increases in urban areas. Gibson and Alimi (2020) recognize the policy implications: "In terms of policy, anti-poverty interventions that offer new consumption smoothing possibilities—such as the micro-lending component of the National Social Investment Program (N-SIP)—should matter more to the urban poor than the rural poor because the transient component of poverty is larger in urban areas. Such interventions may be needed because transfers through informal networks may not fully insure against shocks." (p. 103)[28]

Jolliffe and Serajuddin (2018) use data from the 2010 round of Jordan's Household Expenditure and Income Survey, the source of official poverty statistics, which has quarterly observations of household consumption. The data show that only 45 percent of the poor population (determined by annual consumption) is poor for all four quarters. Another 37 percent are poor in all but one quarter, and 17 percent of "poor" households are poor in just two quarters. Two-thirds of the total population are "non-poor", but 22 percent of them are poor for at least one quarter. Most striking, one third of the population was exposed to poverty in at least one quarter, even though the official poverty rate was 14.4 percent.[29]

[28]Gibson and Alimi (2020) note the particular implications for urban poverty: "The 19 percentage point gap between the national headcount poverty rate from annual consumption estimates derived under naive and corrected extrapolation can be interpreted as representing the within-year transitory component of poverty in Nigeria. Thus, about half of the annual poverty is chronic and half is transient. The mix is weighted more heavily towards the transient component in urban areas, where it is about 70% of the total cross-sectional poverty." (p. 103). With the data at hand, it is not possible to distinguish measurement error from underlying variation in welfare.

[29]Jolliffe and Serajuddin (2018) suggest that one alternative welfare measure could be a Rawlsian metric that registers welfare during households' most challenging periods during the year.

The official poverty rate of 14.4 percent is calculated by summing all four quarters of data to construct annual consumption. But when Jolliffe and Serajuddin (2018) use just one of the quarters, as in our exercise in Figure 4 and in Gibson et al. (2003) and Gibson and Alimi (2020), the rate increases to 18.2 percent, a 26 percent increase. In their rural sample, the rate increases by 31 percent and in urban areas by 25 percent—again, this is not just a rural story. When turning to the squared gap of Foster et al. (1984), the overall increase is 62 percent. As Jolliffe and Serajuddin (2018) note, these numbers capture important aspects of variability that can be addressed by improving households' ability to smooth consumption during the year.

4.5 Which "poverty" best predicts health outcomes?

We approached variation in well-being within the year first as a normative concern, but within-year variability also has predictive power to explain household outcomes of practical interest. Using a least absolute shrinkage and selection operator (LASSO) procedure, we show that the proposed measure of high frequency poverty is a stronger predictor of weight (for all individuals) and of height (for children under 20) relative to the predictive power of poverty status as defined by the conventional time-insensitive headcount.[30] The finding follows earlier studies that draw connections between seasonality and health outcomes (e.g., Christian and Dillon 2018) and evidence that even short term shocks experienced by pregnant mothers can have long-term consequences for children as they age (Barker et al., 2002).

The VDSA data include anthropometrics – weight and height – once per year for each household member.[31] Weight can change in relatively short time periods, for both children and adults. Height, on the other hand, takes longer to show changes

[30]While conventional poverty measures are widely thought of as, by definition, a strong indicator of material hardship, the evidence is less clear. Mayer and Jencks (1989) find, for example, in a sample from Chicago in the 1980s, that conventionally-measured poverty explained just 24% of the material hardships reported by the households (such as being unable to afford food, housing, and medical care). Adding demographics and data on credit, health, and home ownership increased the explanatory power to 39%, leaving most material hardship unexplained in their data.

[31]There are many missing observations for the anthropometric variables, leading to concerns about selection bias. We use individual fixed effects in the regressions to absorb individual-level heterogeneity. The within-individual comparison shows the predictive ability of the high frequency poverty measure, but they are not necessarily representative given the extent of missing data.

due to changes in nutritional status and is generally applicable only to children. As such, we explore correlations of poverty measures for the previous 12 months ("current" poverty) as well as the 12 months prior to those ("lagged" poverty).

Table 3: Selecting the best predictors of anthropometrics through LASSO

	Weight		Height	
	(1)	(2)	(3)	(4)
	All	LASSO	All	LASSO
Monthly poverty	−0.118***	−0.074***	−0.410**	
	(0.027)	(0.013)	(0.197)	
Lagged monthly poverty	−0.129***	−0.103***	−0.556***	−0.518***
	(0.026)	(0.013)	(0.182)	(0.092)
Random monthly poverty	0.007		−0.027	
	(0.012)		(0.080)	
Lagged random monthly poverty	−0.007		−0.133*	
	(0.012)		(0.079)	
Annual poverty	0.019		0.082	
	(0.014)		(0.096)	
Lagged annual poverty	−0.010		−0.051	
	(0.015)		(0.103)	
Mean spell length	0.004		0.036	
	(0.004)		(0.031)	
Lagged mean spell length	0.010**		0.086***	
	(0.004)		(0.031)	
Observations	13,554	13,554	3,231	3,319

Notes: All variables are demeaned (by individual) such that LASSO is selecting covariates by mimicking individual fixed effects. Anthropometrics is only collected once each year in July. Each survey "wave" is from July to June of the following year. As such, poverty in the "current" year is actually in the future when considering anthropometrics. For this reason, the "current" poverty measure is for the previous 12 months, while the "lagged" poverty measure is for the 12 months prior to those months.
* p<0.1 ** p<0.05 *** p<0.01

Correlation matrices for weight and height with headcount poverty are presented in the first two columns of Appendix Table A7 and with the Watts poverty index in the last two columns of the sample table (the overall strength of the correlations with the Watts index is lower for both anthropometric measures). Weight, which is in log kilograms, is more strongly correlated with the high-frequency poverty measure than with annual headcount poverty. The correlation is 23 percent stronger for the one-year lag (correlation coefficient = -19.9 versus -16.2 for the one-year lag) and 18 percent larger for the two-year lag (coefficient = -20.7 versus -17.5). Height-for-age is restricted to children below 20 but shows the same pattern: the high-frequency months-in-poverty measure is more strongly correlated with height-for-age than is the conventional annual poverty measure.

The correlations take into account variation both within and across individuals. Another way to see this is to use a least absolute shrinkage and selection operator (LASSO), a method designed to choose only the most predictive covariates. In Table 3, we include a range of covariates and let LASSO select the most predictive. In addition to the poverty measures in the previous table, we also include a poverty variable related to the lengths of poverty spells, which are defined as at least two contiguous months of poverty. We estimate the LASSO in Stata using the *bic, postselection* option.

We present results for weight and height with the variables de-meaned within individuals in order to mimic individual fixed effects. For both weight and height-for-age, LASSO selects at least one of the proposed months-in-poverty measures – it selects both for weight and the lagged for height. Since height is standardized by age, the coefficients can be interpreted in standard deviations. When the lagged months-in-poverty measure increases from no months of poverty to 12 months of poverty (zero to one on the indicator), within-individual height is around 0.5 standard deviations lower. Put another way, just a one-month increase in poverty – or a change of 0.083 on the months-in-poverty measure – leads to a decrease of around 0.04 standard deviations.[32]

In other words, the evidence from LASSO aligns with our argument that measuring poverty at higher frequency reflects the experience of poverty in dimensions that are meaningfully different from poverty measured with yearly aggregates.[33]

5 Conclusions and future directions

The historical, common-sense notion of poverty ignores the timing of income and consumption during the year in order to focus on overall levels. This time-insensitive concept of poverty, elaborated in the international context by Ravallion

[32]In the appendix, Table A9 also shows that the same results hold when we use expenditures smoothed for durables over the year and Table A8 shows the results when restricting estimation to children 10 or under. We leave the child results in the appendix due to the small sample size.

[33]The finding that the monthly poverty variable is quite predictive also suggests that – at least in our context – measurement error is not driving the main results of differences across months.

(2016), Atkinson (2019) and others, fails to capture the extent and depth of households' deprivation, but its narrowness can be a strength. A large part of what makes the conventional notion of poverty actionable is its simplicity and political salience.

The reality for households living on low incomes, however, is that the overall insufficiency of resources often comes alongside instability and illiquidity within the year (Collins et al., 2009). The timing of income and consumption affects well-being, and better periods do not necessarily compensate for worse periods (Jolliffe and Serajuddin, 2018). We found, for example, that a measure sensitive to within-year poverty variability predicts health outcomes better than a measure based on overall yearly resources.

Recognizing time-sensitivity as a dimension of poverty motivated our definition of the Average of Poverties as an alternative way to understand and assess poverty. Without being recognized as such, a version of the Average of Poverties is already the *de facto* concept of poverty generated by statistical agencies in low- and middle-income countries that follow expert guidelines for data collection. This shift, visible in the details of survey methodology, shows that a coherent, distinct measure of deprivation is not only feasible but already exists.

One next step is to better catalogue global data collection practices, following the lead of Smith et al. (2014) in creating a survey of household surveys. The step would facilitate bringing together the theoretical and normative principles of poverty measurement with analyses of household survey methods, building on ideas and evidence here and in Scott (1992), Gibson et al. (2003), Jolliffe and Serajuddin (2018), Deaton and Grosh (2000), World Bank and FAO (2019), Mancini and Vecchi (2022), and studies of data collection methods including De Weerdt et al. (2020) and Beegle et al. (2012). One key implication of our argument is that changes in recall periods can have large impacts on measured poverty, even in a world of perfect recall, if expenditures vary differently based on recall length. For example, weekly expenditures may show higher variability than monthly expenditures, especially for commonly-consumed items such as food, which will in turn affect measured poverty. Documenting changes in these important survey design choices can help better understand how poverty has been changing over time.

A second step, building on the first, is to expand adherence to the expert guidelines for data collection already established in World Bank and FAO (2019) and

Mancini and Vecchi (2022). Most important, this would require following the consensus to collect data throughout the year, draw nationally-representative samples in each period, and collect data with short-term recall, especially for food. This is a call to follow expert guidelines, not to change them. This step would generate a clearer set of approximations to the Average of Poverties, following the logic in section 2. By not following expert guidelines, statistical agencies in low- and middle-income countries risk collecting data that have no ready interpretation. The measures are likely to be time-sensitive but they are neither an easily interpretable version of the Average of Poverties, nor an approximation of the conventional time-insensitive notion of poverty. The easiest step relative to current practices is to establish protocols for consistent, deliberate estimation of the Average of Poverties.

A third step is to establish feasible approaches to measure the conventional time-insensitive notion of poverty. This could take several paths. One is to use the existing data to develop statistical models that yield more accurate estimates of households' annual consumption (Scott 1992, Gibson et al. 2003). With those estimates, a poverty measure that is closer to the conventional concept could be created. The second path is to collect more data by repeatedly visiting the same households during the year to create a more accurate measure of each household's annual consumption (Deaton and Grosh, 2000)—although that path is expensive and has, so far, not been chosen by most statistical agencies in low- and middle-income countries (Smith et al., 2014). A third path would be a hybrid, where predictive tools are used to form estimates of annual consumption for all households in the sample, most of which are visited once, and data are collected repeatedly for a subsample of households to improve predictions (Scott 1992, Gibson 2001, Gibson et al. 2003). Even where the same households are not surveyed repeatedly over a year (but where waves of cross-sections are collected through the year), it would be possible in principle to model a household's predicted seasonal income or expenditure—or to map out the "poverty exposure curves" described in section 4.2.

Even with these steps, there remain empirical challenges that are generic to poverty measurement but which can have a larger impact in higher frequency data. One is measurement error which can exaggerate evidence of within-year volatility (Deaton and Grosh, 2000). The finding that within-year poverty predicts child weight and height shows that within-year variation is not just measurement error, but the broad concern remains. A second is the fact, well known to economists, that spending does not equal consumption, discussed in section 3.2. Purchases of durables and semi-durables and some expenses on health, for example, create a wedge between the timing of spending and the timing of consumption, leading spending volatility to exceed consumption volatility. Ideally, this challenge would be addressed from the start of data collection with survey questions on the consumption of durables over time so that accurate adjustments can be made.

A connected problem involves the variability of needs. We have taken the annual poverty line and applied it as the threshold for minimal consumption throughout the year. This is reasonable insofar as the fundamental material needs of life–food, shelter, healthcare–are steady across time, but there may be cases in which needs vary meaningfully. For example, an agriculturalist may need to consume extra calories to support the intense activities of the harvest season.

While we have focused on low- and moderate-income countries that measure poverty using data on household consumption, the framework raises questions about comparability to poverty rates in countries (like the United States) that use household income as the basis for assessing poverty (Atkinson, 2019). When poor households do not smooth consumption across years, basing conventional poverty measures on total annual consumption or total annual income should yield identical results. But our results show that in practice there can be large differences when households fail to smooth consumption *within* years. Our examples show that measuring poverty with household consumption data collected via one-time interviews and short-term recall yields substantially higher poverty rates than would arise when using accurate measures of total household consumption for the year. The same will hold true in comparison to poverty measured with household income data collected with a full-year reference period.

Finally, the framework raises conceptual and ethical questions which our empirical results help to frame but do not answer. Questions raised by the framework include: Should the social weight placed on particular months spent in poverty be conditioned on the broader temporal context? Are all months of poverty the same from the perspective of social welfare? How should it matter, if at all, if months in poverty are experienced by people who would not conventionally be considered poor? Does seasonal poverty deserve the same concern as other experiences of poverty? Or possibly more, as might be suggested by a Rawlsian frame (Jolliffe and Serajuddin, 2018)? Analogues to these questions have been raised in the context of poverty across years (e.g., Foster 2009, Bossert et al. 2012, Dutta et al. 2013, Hoy and Zheng 2011), and they provide a way to start thinking systematically about the variation in well-being through the year.

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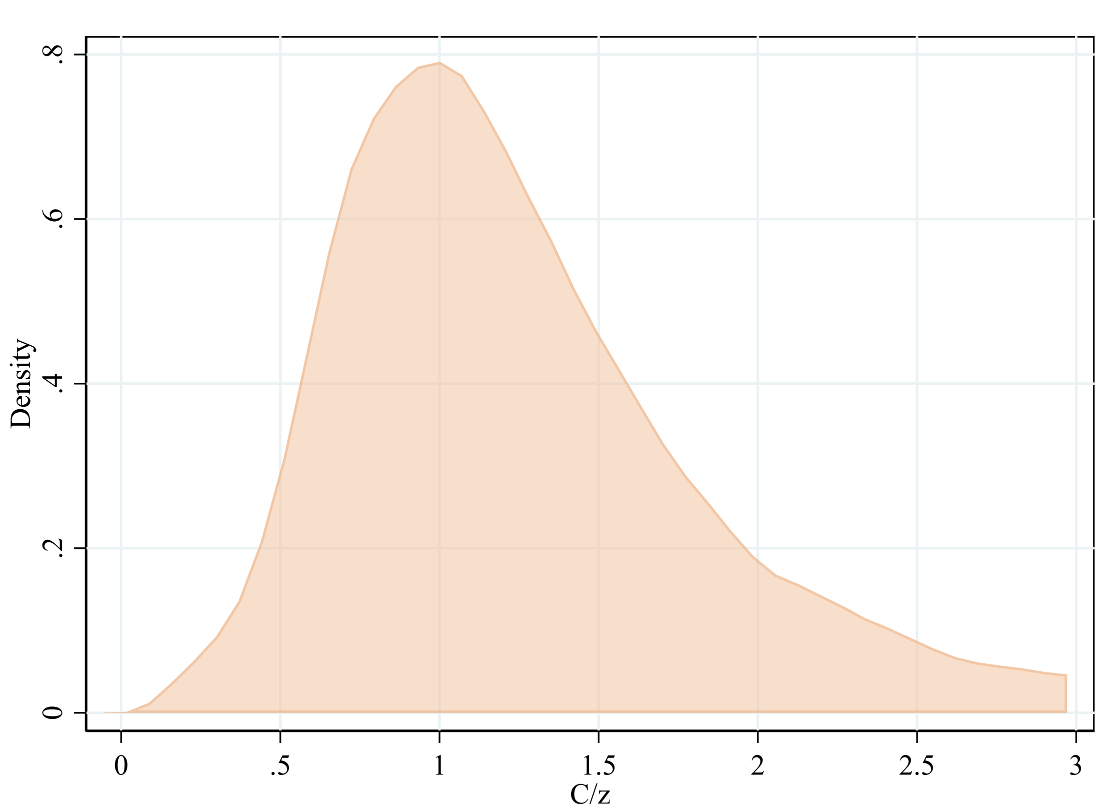
Online Appendix

A1 Density of income

Figure A1 shows the estimated density of per capita expenditure for households observed for four years or more. The horizontal axis is annual expenditure per capita of households normalized by the annual poverty line, so households at 1 are exactly at the poverty line. Those to the left, below 1, are poor according to the headcount when using annual expenditure to assess poverty. Those above 1 are not poor by this measure.

Figure A1: Density



Notes: Kernel density estimate of per capita expenditure. The unit of observation is a household-month, so a single household appears multiple times in the data. The total number of household-month observations is approximately 55,000. The horizontal axis is annual expenditure per capita of households normalized by the annual poverty line. Households below 1 are poor according to annual data. The vertical axis is the probability density function.

Table A1: Summary statistics

	(1) Fewer than four years of data mean/(median)	(2) Four full years mean/(median)	(3) Five full years mean/(median)
Prime-aged females	2.031	1.493	1.900
	(2)	(1)	(2)
Prime-aged males	2.116	1.632	2.044
	(2)	(2)	(2)
Elderly females	0.256	0.246	0.293
	(0)	(0)	(0)
Elderly males	0.290	0.201	0.366
	(0)	(0)	(0)
Girls	1.046	0.581	0.880
	(1)	(0)	(1)
Boys	1.032	0.618	0.970
	(1)	(0)	(1)
Head is male (yes==1)	0.946	0.837	0.946
	(1)	(1)	(1)
Head age	48.488	48.124	51.351
	(47)	(47)	(50)
Head graduated primary	0.278	0.153	0.251
	(0)	(0)	(0)
Head graduated lower secondary	0.236	0.159	0.254
	(0.000)	(0.000)	(0.000)
Income p.c. (Rupees)	1128.197	1057.489	1190.137
	(844.083)	(1136.160)	(1004.460)
Expenditures p.c. (Rupees)	791.014	1366.117	1094.271
	(630.786)	(1026.164)	(860.767)
Wealth p.c. ('000s Rupees)	60.380	114.549	104.400
	(37.389)	(101.104)	(68.183)
Households	581	116	829
Month observations	24,713	5,568	49,740

Notes: Means and medians correspond to household-month observations. Households in the first column are dropped from subsequent analyses. Households in the second and third columns are included in all subsequent analyses. Households in the second column have four full years of observations, while households in the third column have five full years of observations. Data are from 2010-2015.

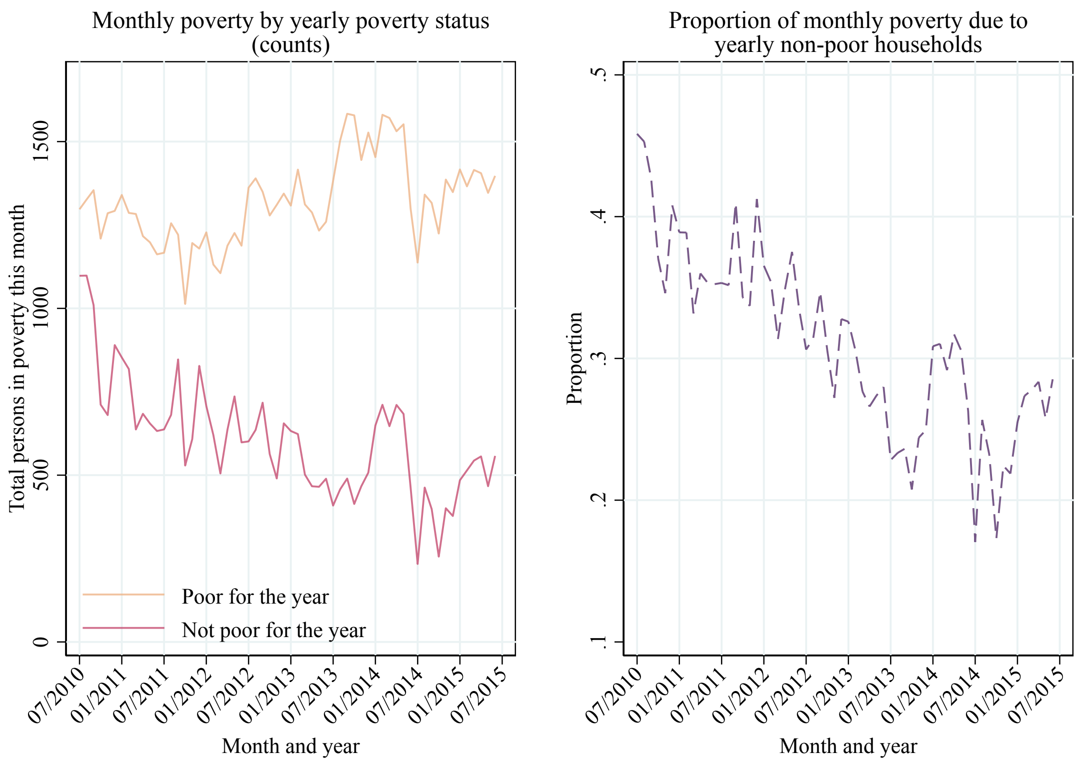
A2 Sample sizes

Table A2: Year-month sample sizes

	(1) 2010-2011	(2) 2011-2012	(3) 2012-2013	(4) 2013-2014	(5) 2014-2015
July	936	945	945	945	838
August	936	945	945	945	838
September	936	945	945	945	838
October	936	945	945	945	838
November	936	945	945	945	838
December	936	945	945	945	838
January	936	945	945	945	838
February	936	945	945	945	838
March	936	945	945	945	838
April	936	945	945	945	838
May	936	945	945	945	838
June	936	945	945	945	838

Notes: A "year" is defined as July to June of the following year. For example, column one is for 2010-2011 and include July-December of 2010 and January-June of 2011.

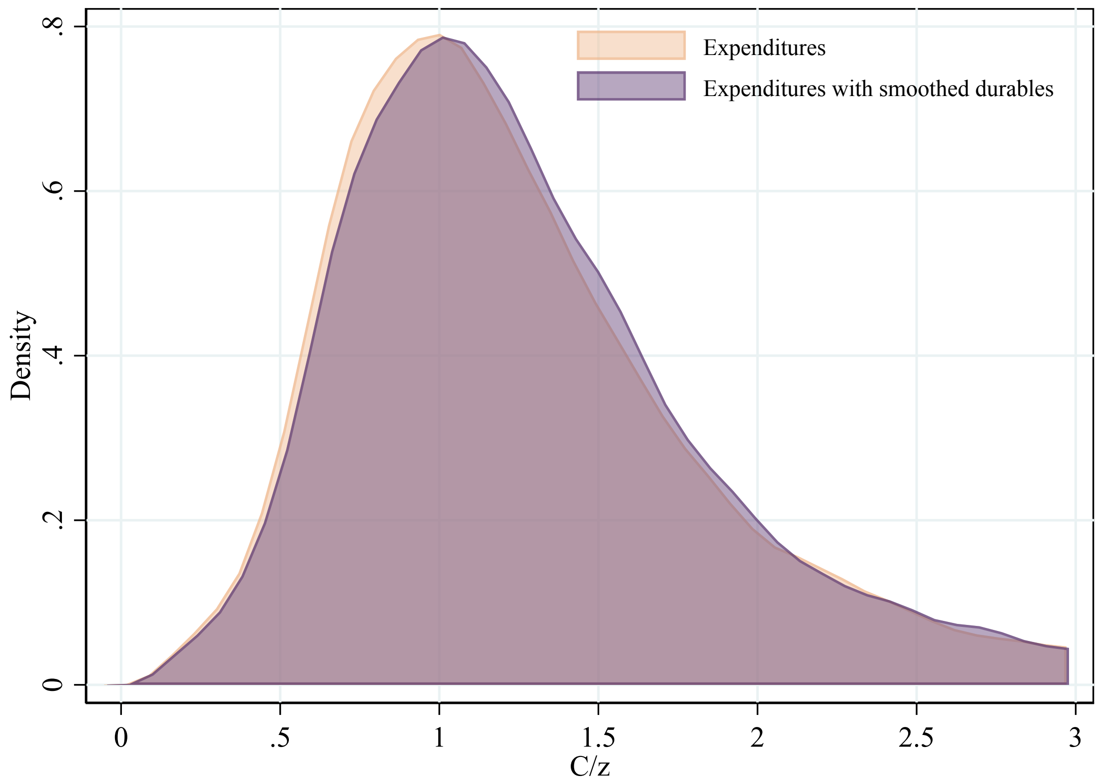
Figure A2: Total number of people in poverty,
by month and poverty status



Notes: The left panel disaggregates households into those who are poor for the year versus those who are not, based on yearly expenditures. The right panel presents the share of household-months spent in poverty that are attributable to households that are not poor based on their yearly expenditure. All counts and proportions are weighted by population shares.

A3 Adjusting for Durables

Figure A3: Density with smoothed durables



Notes: Kernel density estimate of per capita expenditure. The unit of observation is a household-month, so a single household appears multiple times in the data. The total number of household-month observations is approximately 55,000. The horizontal axis is annual expenditure per capita of households normalized by the annual poverty line. Households below 1 are poor according to annual data. The vertical axis is the probability density function.

Table A3: Poverty summary statistics, expenditures smoothed for durables

	(1) Everyone	(2) Poor for the year	(3) Not poor for the year
Panel A: Large and small durables			
Mean monthly poverty	0.347	0.873	0.129
Mean monthly watts	0.116	0.349	0.019
Mean monthly squared poverty gap	0.034	0.108	0.004
Poor at least once in year	0.570	1.000	0.392
Panel B: Large durables only			
Mean monthly poverty	0.359	0.864	0.150
Mean monthly watts	0.122	0.359	0.024
Mean monthly squared poverty gap	0.036	0.112	0.005
Poor at least once in year	0.605	1.000	0.442
Households	945	391	893
Month observations	55,308	12,300	43,008

Notes: Poverty is based on household expenditure. The first column includes all households. The second column includes only households who are poor for the entire year, using average monthly expenditures across the 12 months. The third column includes only households who are not poor for the entire year. In the first panel, expenditures on large and small durables are allocated evenly across all months in the year. In the second panel, expenditures are smoothed for large durables only. All statistics are weighted.

A4 Co-movement of monthly expenditure and income

Table A4: Co-movement of monthly expenditures and income, flexible lags and leads

	(1) Model 1	(2) Model 2	(3) Model 3
Current income	0.031***	0.032***	0.031***
	(0.004)	(0.004)	(0.005)
Household	X	X	X
Village-year-month	X	X	X
12 lags	X		X
12 leads		X	X
Observations	43,968	43,968	32,628

Notes: The dependent variable in all columns is monthly expenditures. “Current income” is monthly income. Lags and leads are for expenditures, not income. All standard errors are clustered at the household level.
* p<0.1 ** p<0.05 *** p<0.01

Table A5: Co-movement of monthly expenditures and income, by initial household wealth

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Current income	0.062***	0.045***	0.044***	0.045***
	(0.005)	(0.004)	(0.004)	(0.004)
Initial wealth (100,000k rupees)	306.336***			
	(44.349)			
Current income times initial wealth	−0.006**	−0.005***	−0.006***	−0.006***
	(0.002)	(0.001)	(0.001)	(0.001)
Fixed effects:				
Year-month	X	X	X	
Household		X		
Household-year			X	X
Village-year-month				X
Observations	55,308	55,308	55,308	55,308

Notes: The dependent variable in all columns is monthly expenditures. "Current income" is monthly income. Initial wealth is defined using the first wave of the survey and, as such, drops out of the regression when household fixed effects are included. All standard errors are clustered at the household level.
* p<0.1 ** p<0.05 *** p<0.01

A5 Expenditure growth or variable expenditure?

One possible explanation for the higher variance of monthly poverty for certain households is that their expenditures are simply growing. This would complicate the story we tell here. One way to see if growth is responsible for some of our results is to change the way we calculate the "annual" poverty measure. Instead of assuming that expenditures are identical in each month of the year, we can fit household-level trends and use the predicted values from these trends as the annual measure. We can then compare these results to the monthly expenditure results. If expenditure growth explains a large proportion of what we see here, then these new predicted poverty rates should be similar to the current monthly results.

Table A6: Expenditure growth and predicted poverty rates

	(1) Headcount	(2) Pov gap	(3) Pov gap sq.	(4) Watts
Monthly measure	0.037	0.096	0.037	0.125
Trend measure	0.021	0.058	0.021	0.076
Annual measure	0.025	0.068	0.025	0.089

Notes: The trend measure is calculated by fitting a monthly trend, separately for each household, and using the predicted values from that trend as the poverty measure.

Table A6 shows that the trend poverty measure results in lower poverty than the current annual measure we use. Our concern was that income growth could explain the higher values we see, which would lead to similar poverty rates using the trend or the monthly poverty measure. While this does not seem to be a concern in the present context, we believe our method of comparison here is one that could prove fruitful elsewhere.

Table A7: Anthropometrics and poverty measures - Correlation matrix

	Headcount		Watts	
	Weight	Height	Weight	Height
Annual (lag)	-0.162	-0.1133	-0.125	-0.051
Annual (lag x2)	-0.175	-0.134	-0.130	-0.053
Monthly (lag)	-0.199	-0.150	-0.143	-0.066
Monthly (lag x2)	-0.207	-0.166	-0.152	-0.078

Notes: Anthropometric data are only collected once each year at the start of the wave of data collection in July. (Each survey wave starts in July and ends in June of the following year.) As a result, the current year's values of income and expenditure cover a period after the anthropometric measurement, so poverty in prior years is most relevant for explaining anthropometric outcomes (so we consider lagged poverty measures only).

Table A8: Selecting the best predictors of anthropometrics through LASSO, only children (<= 10)

	Weight		Height	
	(1)	(2)	(3)	(4)
	All	LASSO	All	LASSO
Monthly poverty	−0.113*	−0.085***	0.111	
	(0.067)	(0.023)	(0.479)	
Lagged monthly poverty	−0.127**		−0.838*	−0.542***
	(0.063)		(0.448)	(0.193)
Random monthly poverty	−0.004		−0.031	
	(0.027)		(0.164)	
Lagged random monthly poverty	−0.008		−0.074	
	(0.026)		(0.152)	
Annual poverty	0.036		−0.105	
	(0.034)		(0.206)	
Lagged annual poverty	0.048*		−0.108	
	(0.029)		(0.204)	
Mean spell length	0.011		0.016	
	(0.009)		(0.062)	
Lagged mean spell length	0.014		0.096	
	(0.009)		(0.064)	
Observations	581	1,188	576	615

Notes: All variables are demeaned (by individual) such that LASSO is selecting covariates by mimicking individual fixed effects. Anthropometrics is only collected once each year in July. Each survey "wave" is from July to June of the following year. As such, poverty in the "current" year is actually in the future when considering anthropometrics. For this reason, the "current" poverty measure is for the previous 12 months, while the "lagged" poverty measure is for the 12 months prior to those months.
* p<0.1 ** p<0.05 *** p<0.01

A6 Anthropometrics and poverty

Table A9: Anthropometrics with smoothed expenditures

	Weight		Height	
	(1)	(2)	(3)	(4)
	Levels	Demeaned	Levels	Demeaned
Current monthly poverty	−0.072***	Not selected	Not selected	Not selected
	(0.011)			
Lagged monthly poverty	−0.094***	−0.014**	−0.454***	−0.223***
	(0.012)	(0.006)	(0.091)	(0.061)
Current quarterly poverty	Not selected	Not selected	Not selected	Not selected
Lagged quarterly poverty	Not selected	Not selected	Not selected	Not selected
Current annual poverty	Not selected	Not selected	Not selected	Not selected
Lagged annual poverty	Not selected	Not selected	Not selected	Not selected
Observations	13,554	13,697	3,037	3,037

Notes: Anthropometric data are only collected once each year at the start of the wave of data collection in July. (Each survey wave starts in July and ends in June of the following year.) As a result, the current year's values of income and expenditure cover a period after the anthropometric measurement, so poverty in prior years is most relevant for explaining anthropometric outcomes (so we consider lagged poverty measures only). The predictors use expenditures with durables smoothed throughout the year.
* p<0.1 ** p<0.05 *** p<0.01