Poverty at Higher Frequency*

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Abstract

One of the sharpest and most common simplifications when measuring poverty is to define poverty as a deficiency in yearly income or yearly consumption. The yearly sums approximate the experience of poverty for those households whose income is steady or who can smooth consumption through the year. Evidence shows, however, that the experience of poverty is often marked by seasonality, economic instability, and illiquidity across months. To capture this reality, we introduce a measurement framework based on a straightforward generalization of conventional poverty measures, defining annual poverty as the average of monthly poverty measures. Using monthly panel data from rural India, we explore ways that the conventional approach to measurement can underestimate and mischaracterize the experience of poverty. We show that experiences of poverty are substantially more common than annual measures suggest; entry into and exit from poverty are much less clear than typically assumed; and the proposed measure is a stronger predictor of development outcomes – child weight and height – than conventional measures. Correspondingly, the framework shows how interventions that re-distribute resources between periods can lessen the experience of poverty by smoothing consumption, even when conventional poverty measures based on yearly resources are unchanged or worsening. In considering hypothetical monthly transfers to households facing economic instability, for example, we show that targeting transfers to the most challenging months – rather than spreading them through the year as in typical cash transfer programs – can most cost-effectively reduce experiences of poverty.

Keywords: volatility, consumption smoothing, poverty measurement, seasonal poverty, liquidity, household expenditure, household income
JEL Codes: I32, G51, D14, D15

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1 Introduction

Households' experiences of poverty often change through the year. In rural areas, deprivations intensify in lean seasons and ease in harvest seasons (Longhurst et al. 1986, Khandker 2012). Incomes are often unstable for residents of cities and towns as well, shaped by the availability of work and shifts in seasonal demand (Collins et al., 2009). For many low-income households, income instability within the year is integral to the challenge of deprivation, even for households whose income and expenditures are persistently below poverty lines. Yet the way that poverty is measured eliminates evidence of the instability.

If households are sufficiently liquid—i.e., if they can get hold of the money they need when they need it—the instability of income within the year would not matter so much. Recent randomized trials in low-income areas, however, reinforce earlier evidence showing that steadiness and liquidity within the year cannot be assumed (e.g., Breza et al. 2021, Bryan et al. 2014). These RCTs echo the longer, earlier literature on the economics of seasonality (Devereux and Longhurst, 2012).

The extent and implications of within-year variability are obscured by the reliance on yearly sums as the basis for determining poverty (Christian et al., 2018). Poverty is typically measured by comparing a poverty line to yearly household income (the norm in most OECD countries and Latin America) or yearly expenditure (in most of the rest of the world). The focus on yearly resources has been in place since the late 19th century when formal frameworks to measure poverty were first developed (Himmelfarb, 1984). In relying exclusively on yearly resources, the highs and lows of deprivations through the year are averaged out. What is conventionally described as poverty is then best seen as a measure of households' potential to consume in an idealized world of within-year steadiness or perfect liquidity. Those conditions may hold approximately for richer households but do not in general hold for low-income households (e.g., Dercon 2002, Ganong et al. 2020, Parker 2017, Michael R. Carter 2012, Pomeranz and Kast 2022).

We explore the implications of measuring poverty with a framework that takes into account the combined conditions of insufficiency, instability, and illiquidity. We introduce a straightforward generalization of conventional poverty measures that defines annual poverty as the average of monthly poverty measures. With monthly panel data from rural India, we show how the conventional approach to measurement can underestimate and mischaracterize the experience of poverty.

While alternatives have been proposed for setting poverty lines (Allen 2017, Reddy and Pogge 2010, Pritchett 2006) and ways to construct composite indices to account for degrees of deprivation (Sen 1976, Foster et al. 1984, Watts 1968), there has been little inquiry into alternatives to the yearly accounting period (Atkinson, 2019). Partly this is because there are good reasons to stick with the yearly frame. Maintaining a focus on total earnings and expenditure over the year has the advantage of allowing the use of widely-available annual household-level data sets. The yearly focus also offers comparability to other annual measures like GDP and life expectancy, and it highlights the challenges of overall earning capacity, a central contributor to the experience of poverty. Moreover, since the rhythm of economic life is typically arranged around yearly cycles, aggregating to the annual level has intuitive appeal.

We build from the observation that maintaining a yearly focus does not require exclusive reliance on yearly income or yearly expenditure. We maintain the yearly frame but create a framework that builds from month-by-month measures of poverty for each household and then aggregates the monthly measures to form an aggregate for the year. We demonstrate the implications with monthly panel data on the income and expenditures of 945 households collected continuously for at least four years.

Considering within-year instability is especially relevant in the context of global poverty. Despite increasing urbanization (World Bank, 2021), rural populations like those we study in rural India remain central for understanding global poverty. Rural residents comprise

80% of the world's population living below the World Bank \$1.90 per day extreme poverty threshold, and they often face the dual challenges of low earnings and seasonality (Castañeda et al., 2018).[1] Evidence Action (2019) describes seasonal poverty as "the biggest development problem you have never heard of" and writes that "Seasonal hunger and deprivation are perhaps the biggest obstacles to the reduction of global poverty, yet they've remained largely under the radar." Similarly, Chambers (1983) argued that the ups and downs of rural poverty go "unperceived" in conventional approaches. 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." Evidence Action (2019) estimates that seasonal hunger affects around 600 million of the world's rural poor. Vulnerability to the ups and downs of resources within the year is thus both empirically important and often hidden by the aggregation of survey data to form yearly poverty statistics.

Our approach is a straightforward generalization of conventional poverty measures. For the headcount, for example, if a household's expenditure is below the poverty line for 9 months and above for 3 months, the household's contribution to our poverty headcount rate is 0.75 of a year. The conventional approach, in contrast, bases poverty on yearly expenditure and would count the household as having experienced a full year of poverty (as long as their yearly earnings are below the annual poverty threshold). We similarly incorporate distributionally-sensitive poverty measures, employing the squared poverty

[1]As of September 2022, the World Bank has switched to using 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). Castañeda et al. (2018) report that globally, of all workers living on \$1.90 or less per day (aged 15 and above), 65 percent work in agriculture. Castañeda et al. (2018) estimate that in 2013, 770 million people lived in extreme poverty, and about 1 billion were moderately poor (living on more than \$1.90 per day but less than \$3.20). Castañeda et al. (2018) find that 76 percent of the people living in "moderate poverty" as defined by the World Bank live in rural areas, and 52 percent of workers who are among the "moderate" poor work in agriculture. The \$1.90 per day poverty line (translated into local currency with 2011 Purchasing Power Parity exchange rates) was the global standard during our study period.

gap of Foster et al. (1984) and the Watts (1968) index. By bringing seasonality and other sources of volatility into yearly poverty statistics, the approach avoids the concern that transitory phenomena can cloud the interpretation of month-by-month poverty when snapshots are viewed independently (Atkinson, 2019).

Across our sample, the overall headcount poverty rate averages 29% when measured conventionally with yearly consumption. If households experience no income variability and perfectly smooth consumption, the fraction of months in which households experience poverty should also be 29% (since the panel is balanced and monthly expenditure will be a constant proportion of yearly expenditure). However, we find that the poverty rate increases to 37% (a 26% increase) when taking into account monthly movements in and out of poverty during the year. Incorporating distributionally-sensitive poverty measures into the framework reveals the varying intensity of deprivation through the year, and the gap widens relative to conventional yearly measures. Measured poverty increases by 40% and 48% when adapting the months-in-poverty measure to the Watts (1968) and Foster et al. (1984) squared-gap indices respectively. The increase is caused by sensitivity to months with particularly low consumption (which get independent weight in the aggregations rather than being averaged out as in the conventional yearly approach).

Two opposing forces explain the increase relative to the conventional headcount. Our months-in-poverty measure is reduced by the fact that poor households (as classified by yearly consumption) spent just 86% of the year below the poverty line on average (equivalent to 1.7 months above the poverty line). But the measure is increased by the fact that "non-poor" households in the sample spent 16% of their time below the poverty line.[2] Since non-poor households make up 71% of the sample, their months of poverty add up. Just under two-thirds of households experience poverty in at least one month per

[2]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 2016a). 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.

year, including 47% of "non-poor" households. Altogether, 35% of all months-in-poverty are attributable to deprivations experienced by people who would not conventionally be considered poor.

The framework shows how the ability to smooth consumption affects exposure to poverty during the year, drawing on related insights about poverty dynamics across years (Ravallion 1988, Morduch 1994, Hoddinott 2006). Exposure to poverty is greatest for households whose heads have the least education (a proxy for low socio-economic status); in 42% of months, their spending puts them below the poverty line. This is partly due to low average earning power and partly due to a limited ability to smooth income shocks. For the best educated part of the sample (those with household heads with a secondary degree or more), roughly half as much of an income shock translates into consumption shocks relative to the exposure of the least educated.

The main results use household consumption as the basis for measuring poverty, thus reflecting outcomes after households have smoothed consumption to the extent they can. With data on income, we estimate the degree of co-movement between income and consumption and relate it to the poverty measures. Like much of the cross-year literature (e.g., Skoufias and Quisumbing 2005, Townsend 1994), we find evidence consistent with substantial, but imperfect, consumption smoothing. 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. In the data we find that the annual ratio is almost 35% for households measured conventionally as being poor, indicating considerable but imperfect smoothing.[3]

The evidence relates to recent research on within-year instability and illiquidity, includ-

[3]Households with higher social status and higher yearly expenditure smooth consumption to a greater extent than other households: When limiting our sample to households with yearly expenditure above the annual poverty line, the ratio of month-to-month consumption variation to month-to-month income variation falls to 10%.

ing literatures on seasonality and illiquidity (e.g., Casaburi and Willis 2018) and seasonal hunger (e.g., Christian and Dillon 2018, Dostie et al. 2002). In a sample of agricultural communities in rural Zambia, for example, Fink et al. (2020) document the prevalence of pre-harvest lean seasons and seasonal hunger, showing that limited liquidity forces poorer households to sell more labor, putting downward pressure on wages and reinforcing inequality. Similarly, Breza et al. 2021 show clear seasonal patterns in labor market opportunities: in the lean season in Odisha, India, a quarter of workers face severe rationing of jobs in the labor market. Workers who cannot find jobs are forced to shift into (less desirable) self-employment.[4]

The approach also relates to studies of poverty dynamics across years (e.g., Bane and Ellwood 1986, Jalan and Ravallion 1998, Baulch and McCulloch 2000, Addison et al. 2009, Christiaensen and Shorrocks 2012, Balboni et al. 2022). 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. Our approach shows that households can experience regular ups and downs of poverty within the year while remaining persistently deprived across years. Thus, counter to simple assumptions about the nature of poverty, transience and persistence often exist together. As with agricultural seasonality, within-year instability can be a stable feature of people's lives.

Our evidence also shows that exits from and entrances to poverty are seldom as sharp as implied by annual snapshots. Almost half of all households which have "exited" poverty according to yearly measures nevertheless experience more than five months of poverty during the year in which they are conventionally measured as being no longer poor. Even households that are considered to have exited and are now not poor (based on yearly expenditure) for two consecutive years still experience poverty for more than a quarter of the year, on average.

[4]This relates to the relationship between wages and labor allocation documented by Jayachandran (2006).

These features open new perspectives on reducing deprivation. The results imply that interventions that re-distribute resources between periods (or that make it easier for households to do so) can lessen the experience of poverty by improving consumption smoothing, even when conventional poverty measures based on yearly resources are unchanged or worsening. In considering hypothetical monthly transfers, for example, we show that targeting transfers to the most challenging months (rather than spreading them through the year as in typical cash transfer programs; Hanna and Olken 2018) can cost-effectively reduce months-in-poverty (holding total yearly transfers constant). The framework also expands views of interventions like microfinance that have had relatively small average impacts on total household consumption or income (Cai et al., 2021). If financial interventions like these help households move money across time, they can have impacts on the experience of poverty that are missed by focusing only on total consumption (Amin et al. 2003, Islam and Maitra 2012, Beaman et al. 2014, Somville and Vandewalle 2022). Similarly, the impact that seasonal migration has on reducing exposure to acute deprivation during the lean season lean (Bryan et al., 2014) is diluted when using conventionally-measured poverty as an outcome since the impact on poverty is only reflected to the extent that total consumption for the year increases.

Taking account of within-year variability of resources may also help to narrow the gap between poverty as conventionally measured and evidence on patterns of material hardship. While poverty is 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.

In this spirit, we turn to the predictive power of conventionally-measured poverty rates versus measures that account for within-year variation. We focus on anthropometric outcomes and use a least absolute shrinkage and selection operator (lasso) to allow the data to determine the predictive power of the alternative approaches. Our data include measures of child weight and height, and we show that the high-frequency months-in-poverty measure is a stronger predictor of these physical challenges than conventional poverty measures based on yearly consumption.

The concepts here apply beyond seasonal agriculture; low-income households in non-farm settings, including the urban United States, also face notable income swings during the year. Causes include the varying availability of work through the year, changes in household composition, health shocks, and re-location (Collins et al. 2009, Maag et al. 2017, Morduch and Siwicki 2017, Schneider and Harknett 2020, Storer et al. 2020). Using the 2009-12 US Survey of Income and Program Participation (SIPP), for example, Maag et al. (2017) find that 42% of prime-working-age adults in low-income households experienced at least five months in a single year in which their household income was either 25% above or 25% below their average monthly income for that year year.

In line with our findings in rural India, most people in the United States who are counted as being poor in a given year (based on yearly income) are not poor for the full year. Others who are counted as non-poor are poor some of the time. Using the 2013-16 SIPP, for example, Mohanty (2021) estimates that 35% of all poverty spells in the United States (measured with monthly household income) lasted less than 6 months, and half lasted less than 11.1 months.[5] In the four years of the SIPP 2013-16 sample, 2.8% of U.S. households were estimated to be poor every month, while the national poverty rate averaged 15.2%. At the same time, 34% of Americans were estimated to have experienced at least one spell of poverty during the period, a strikingly high rate of exposure to poverty.[6]

[5]Spells are defined as two or more continuous months of poverty, so single months of poverty are not counted here.

[6]The prevalence of episodic poverty is not new; for example, using the 1983-86 SIPP, Ruggles and Williams (1989) found that the median poverty spell in the U.S. lasted only 4-6 months. Most poverty analyses in the United States focus on income, but swings in income translate into swings in consumption. Using

Our aim is not to elevate short-term poverty over long-term poverty. Persistent poverty remains a large challenge: the flip side of the 2013-16 SIPP finding that the median poverty spell in the United States is 11.1 months is that close to half of spells stretch a year or longer. Our aim instead is to highlight how the conventional way of measuring poverty makes it easier to lose sight of the diversity of experiences of poverty: the conventional approach undercounts both the extent and intensity of poverty.

The limited attention to within-year variation in poverty contrasts with the economic and policy literature on unemployment, which focuses on people who are persistently unemployed for the year versus those who are temporarily unemployed (International Labour Office, 2022). Economists have developed tools and data to estimate the duration and dynamics of unemployment patterns at high frequency (Moscarini and Postel-Vinay, 2018), and, unlike poverty, unemployment is conventionally measured as a rate at a given set of dates through the year—monthly in the United States. We aim to show the consequences of analyzing poverty at a similar frequency.

As higher-frequency household-level data sets become more common—including surveys collected over multiple waves within years (e.g., Azevedo and Seitz 2016a, Dercon and Krishnan 2000, Christian et al. 2018, Ligon and Schechter 2003), large-scale data from banks (e.g., Ganong et al. 2020), and financial diaries (e.g., Collins et al. 2009, Morduch and Schneider 2017)—the proposed framework will have broader application. Even without higher-frequency data, however, the framework presents a language to understand poverty that enriches standard concepts. In the final section, we raise methodological and conceptual questions that arise when using high-frequency data to measure poverty, including the possibility that household needs vary through the year.

data from a large US financial institution, Ganong et al. (2020) show that households in the United States with low liquid wealth cut their consumption far more sharply than wealthier households when exposed to the same-sized income shocks during the year. In their data, the racial wealth gap explains why Black households, on average, cut their consumption 50 percent more than white households in the face of similar income shocks.

2 Framework

Measuring poverty usually involves answering two questions: Where should the poverty line be set and how should researchers aggregate data on individuals to create a composite poverty index (Sen, 1976)? We focus on a third question that gets asked less often: How should welfare be aggregated across time for individuals?

To the extent that time is considered, the issue is often framed as the choice between measuring poverty month by month versus year by year.[7] Atkinson (2019) frames the choice as a tradeoff of intrepretation versus accuracy: Monthly "snapshots" give insight into time-specific deprivation, but transitory events can make it hard to see the larger picture. On the other hand, the year-long period has the advantage of encompassing more time, but it requires extended recall for survey respondents, which brings its own distortions (Atkinson, 2019).[8]

Our framework shifts the question. We consider poverty over a year – avoiding Atkinson's concern about interpreting snapshots – but we aggregate across experiences of poverty within the year for the same households. We thus allow for within-year variation in the experience of poverty for each household, while keeping an approach based on annual averages.

We begin with the year divided into 12 months.[9] In each month t, household i earns income y_{it} and consumes c_{it}. The household's poverty status is determined in each month by the per-month poverty line z, the household's consumption, and the poverty mapping

[7] We focus on periods within the year. A related literature considers poverty across years (e.g., Addison et al. 2009).

[8] A common alternative is to collect consumption measures for just one month in a year, but temporally adjust responses to estimate yearly consumption.

[9] An alternative approach would divide the year into quarters, seasons, or other partitions. We choose months to conform to the form of the Indian VDSA data. The data we use – which we discuss in more detail in the next section – include detailed responses on expenditures and income for each month. Rather than aggregating these to a higher level, we use the monthly set up of the data. This approach is flexible, however, and can be adapted to data collected on a different timeframe.

$P(c_{it})$:[10]

$$[P(c_{i1}), P(c_{i2}), P(c_{i3}), ..., P(c_{i12})], \tag{1}$$

where $P(c_{it}) = 0$ if $c_{it} \geq z$. The poverty levels can be aggregated across the time frame in various ways. We retain the year-long time frame and define annual poverty as poverty status measured in each month, averaged across the 12 months and N households:

$$P_{Months} = \frac{1}{12N} \sum_{t=1}^{12} \sum_{i=1}^{N} P(c_{it}), \tag{2}$$

where the poverty index is decomposable and differentiable—a property of most commonly-used poverty measures including the headcount, income gap, and the distributionally-sensitive measures of Watts (1968) and Foster et al. (1984). Calvo and Dercon (2009) and Foster (2009) use a similar approach when considering the persistence of poverty across years.[11]

We call this *high frequency poverty* to denote the high frequency (monthly) empirical lens, even though the measure is an annual aggregate. Equation 2 departs from standard practice by reflecting changes in the incidence and intensity of poverty within the time frame. As noted in the introduction, if a household is poor for 9 months of the year, their contribution to the aggregate poverty headcount is counted as 0.75 of a year of poverty.[12]

The conventional practice of measuring yearly poverty, in contrast, focuses only on each household's total consumption over a year, with no accounting for variability within the year. We call this *low frequency* poverty to denote that the data are generally collected just once a year. This corresponds to a special case of Equation 2 in which poverty status in

[10]The per-month poverty line z is assumed to be identical for all people and all periods. Poverty lines can be adjusted across space and time without changing the basic nature of the approach.

[11]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.

[12](Christian et al., 2018) suggest a related approach using daily data.

each period is determined by household i's average monthly consumption for the year, $\bar{c}_i$:

$$P_{Year} = \frac{1}{N}\sum_{i=1}^{N} P\left(\frac{1}{12}\sum_{t=1}^{12} c_{it}\right) = \frac{1}{12N}\sum_{t=1}^{12}\sum_{i=1}^{N} P(\bar{c}_i), \tag{3}$$

where $P(\bar{c}_i) = 0$ if $\bar{c}_i \geq z$. In this case, the household that is poor for 9 months would count as being poor for the whole year, or as never being poor, depending on whether $\bar{c}_i < z$ or not.

The connection between the approaches is seen by adding and subtracting Equation 3 to rewrite Equation 2:

$$P_{Months} = \frac{1}{12N}\sum_{t=1}^{12}\sum_{i=1}^{N} \left(P(\bar{c}_i) + [P(c_{it}) - P(\bar{c}_i)]\right) \tag{4}$$

The first term on the right hand side, $P(\bar{c}_i)$, reflects average consumption over the year, the focus of conventional poverty measurement. The second term, $P(c_{it}) - P(\bar{c}_i)$, reflects the contribution of the high frequency framework by capturing variation from the yearly average.

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 4 with respect to a change in an environmental factor x_t yields:

$$\frac{1}{12N}\sum_{t=1}^{12}\sum_{i=1}^{N} \frac{\partial P(\bar{c}_i)}{\partial \bar{c}_i}\frac{\partial \bar{c}_i}{\partial c_{it}}\frac{\partial c_{it}}{\partial x_t} + \left[\frac{\partial P(c_{it})}{\partial c_{it}}\frac{\partial c_{it}}{\partial x_t} - \frac{\partial P(\bar{c}_i)}{\partial \bar{c}_i}\frac{\partial \bar{c}_i}{\partial c_{it}}\frac{\partial c_{it}}{\partial x_t}\right] \tag{5}$$

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.

2.1 Implications

Measuring poverty at a higher frequency heightens the distinction between income-based measures and consumption-based measures (Atkinson 2019, Bradbury et al. 2001). The choice of income versus consumption is generally determined by data accuracy and ease of collection (Meyer and Sullivan, 2003). In most countries, especially low-income economies, consumption data are generally higher quality than income data (Deaton 1997, Carletto et al. 2021), but elsewhere income is easier to collect and thus is the favored basis for poverty comparisons.

But imagine that one only has income data but is convinced by the logic that, because of instability and illiqidity, ideally poverty should be measured using high-frequency expenditure data, P_{Months} as defined by Equation 2. However, implementing Equation 2 with monthly income rather than monthly consumption corresponds to a world in which no consumption smoothing is possible: $c_{it} = y_{it}$ for all t. In contrast, measuring poverty as P_{Year} as in Equation 3—but with monthly averages based on yearly income rather than yearly consumption—is roughly equivalent to assuming that consumption is perfectly smoothed during the time frame (as long as average monthly income is close to average monthly consumption). Neither of the two alternatives accord with the imperfect smoothing (neither fully absent nor fully complete) typically observed in low-income communities. The first alternative is too variable and the second is too smooth. Reality usually lies between the extremes but with substantial smoothing. When smoothing is extensive but imperfect, and if income is the only variable available, using yearly income to measure poverty may then be the best possible practice, despite recognition of fundamental instability and illiquidity in consumption.

This might be the most compelling rationale for the conventional practice of using yearly (rather than monthly) income to assess poverty. Because of the need for comparability across countries–some of which measure poverty with income–it also provides a rationale for using yearly expenditure in other geographies.

Still, while the outcomes are logical and practical, focusing solely on yearly sums leads to a conception of poverty that is ill-fitting in a world where insufficiency, instability, and illiquidity arise together. The framework here highlights that recognition. One aim is to distinguish between what might make sense in terms of practical measurement practice given available data versus what makes sense as a way to understand the fundamental nature of poverty.

The notation helps to show several related implications of the framework. First, the conventional approach to measuring poverty (low frequency poverty) approximates the material condition of deprivation in one of two cases: (i) the special case in which there is no instability within the year (earnings, needs, and consumption are steady across periods), or (ii) the special case in which households face instability but have ample financial mechanisms to smooth within-year instability. Equation 4 makes explicit that the standard approach to measuring poverty with yearly aggregates (reflected in Equation 3) is identical to the more general form in Equation 2 when consumption is completely smooth during the time frame; i.e., when $c_{it} = \bar{c}_i$ for all t. In this case, the term in square brackets is zero in Equation 4, but neither case (i) nor (ii) is a reliable assumption in low-income populations.[13]

Second, and similarly, because the high frequency component registers the impact of imperfect consumption smoothing during the year, Equation 5 shows that interventions that allow for re-distribution of resources between periods may reduce poverty as measured by Equation 2 even when household resources are unchanged (or possibly falling). For example, relaxing liquidity constraints can raise households' consumption in bad months even if $\bar{c}_i$ is constant.

Third, less obviously, increasing liquidity can increase aggregate poverty as measured by Equation 2. This can happen in a particular (but realistic) circumstance in which the form of $P(c_{it})$ is the headcount and $\bar{c}_i < z$. Consider a household that is poor as measured by yearly resources but whose consumption is greater than the poverty line in a peak season. Improving the ability to save may reduce consumption in the peak season but expand resources available in the subsequent lean season. It is possible that the household will then count as being poor in both peak and lean seasons, whereas previously they counted as poor in just the peak season. Still, their revealed preference suggests that their well-being has improved by being able to save and smooth consumption. Distributionally-sensitive poverty measures, in contrast, would register the poverty reduction, even though the headcount does not.[14]

[13]It is mathematically possible that Equation 2 is identical to Equation 3 even without perfect consumption smoothing, but it is unlikely. This is when, for example, the poverty mapping is completed with the headcount measure and there happen to be an identical number of months in poverty experienced by non-poor-on-average households as there are non-poor months experienced by poor-on-average households.

[14]To be more explicit: The average of per-period poverty headcounts across the year may rise, for example, if resources are transferred out of period t where initially $c_{it} > z$ and afterward $c_{it} < z$. If resources are moved to period j where $c_{jt} < z$ before and after the transfer, the average headcount in periods i and j increases from 0.5 pre-tranfer to 1.0 post-transfer. With smoother consumption, the household's well-being may be improved and the average of distributionally-sensitive measures like those of Watts (1968) and Foster et al. (1984) may fall, but the average headcount will rise in this example. Here, if a household optimally smooths consumption in the sense of Jappelli and Pistaferri (2017), the average of distributionally-sensitive measures in periods i and j always fall given the assumptions, as long as the measures conform to the transfer axiom and sub-group monotonicity. This is true of both the Watts (1968) measure and squared-FGT measure (Foster et al. 1984). For example, suppose the poverty line is 60 USD per month and the household consumes 56 USD in 11 months and 80 USD in the final month. The average expenditure across all 12 months is 58 USD. Imagine that the household gained access to a smoothing mechanism that allowed it to consume exactly 58 USD in each month. The measured months-in-poverty would actually increase (from 11 of 12 months to all 12 months). However, the distributionally-sensitive

Fourth, by relating the experience of poverty to instability and the ability to smooth consumption, researchers can identify parts of the population that face particular deprivation. In the sense of Equation 5, it becomes possible to identify a broader set of anti-poverty interventions. We show that households with the lowest average incomes and lowest average consumption over the year are also the households most exposed to intra-year volatility of expenditures relative to incomes.This also allows policymakers to identify characteristics that are distinct from average consumption but which may affect the ability to smooth consumption; households with the same average consumption may nonetheless have different consumption-smoothing capabilities depending on sector of employment, education, networks, etc.

Fifth, most analyses of poverty dynamics use multi-year panel data to quantify entry to and exit from poverty across years (Addison et al. 2009, Krishna 2016, Biewen 2014, Christiaensen and Shorrocks 2012, Valletta 2006, Baulch and McCulloch 2000, Bane and Ellwood 1986, Stevens 1999, Ravallion 2016). These multi-year analyses do not trouble conventional approaches that rely on yearly aggregates. The framework here allows a more granular examination of households' experiences of "entry" to and "exit" from poverty. "Exit" from poverty is typically defined as a transition from $\bar{c}_i < z$ in one year to $\bar{c}_i > z$ in the next year, a discontinuous break marked by the crossing of a threshold from one year to the next. Our high-frequency empirical approach shows that, empirically, the break is not necessarily discontinuous as households can continue to experience poverty, even if they are counted as having "exited" from poverty by the conventional definition (and the converse is true for those who have "entered" poverty).

Sixth, the framework adds a dimension to axiomatic derivations of poverty measures. Distributionally-sensitive measures were developed to satisfy an intuitively-appealing transfer axiom: given other things, a pure transfer of income from a person below the

Watts (1968) index would decrease by around 64 percent and the squared poverty gap would decrease by almost 75 percent. The poverty gap, which is just the total amount of money the household is short of the poverty line in each poor month, would decrease from 44 USD (4 USD short of the poverty line in 11 months) to just 24 USD (2 USD short in all 12 months).

poverty line to anyone who is richer must increase the poverty measure (Sen 1976, Foster et al. 1984). The high frequency poverty framework shows that the axiom depends on an extra assumption: that poverty is determined by the total of resources during a single period. If there are multiple periods and poverty is assessed in each of these periods and then aggregated to form an index (as in Equation 2), it is possible to transfer income from a person below the poverty line (on yearly terms) and to give the income to someone else who is richer (on yearly terms) without necessarily increasing poverty as measured by Equation 2, even when using distributionally-sensitive forms of the poverty mapping in Equation 1. This happens, for example, when transferring income from a "poor" person experiencing a non-poor period and giving it to a "non-poor" person who is experiencing a poor period. This is arguably a trivial technical clarification, but as the empirical literature shows, it is not fully obvious from a philosophical or conceptual perspective that poverty should be determined by a household's total resources during a single period, nor that that period should necessarily be a year.

2.2 Implementation

We use four decomposable poverty measures that 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. (See Appendix A.) When using income, we only use the headcount poverty measure, but calculate all four measures when using expenditures.[15]

When we calculate conventional (low frequency) poverty measures based on yearly resources, we compare the monthly poverty line z_{month} to $\bar{c}_i$, the average monthly expenditure (or income) for the year. Using the squared poverty gap (FGT) as an example and

[15] 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).

integrating it within our framework, we calculate

$$P^{FGT}_{Year} = \frac{1}{12N} \sum_{t=1}^{12} \sum_{i=1}^{N} \left[\left(\frac{z_{month} - \bar{c}_i}{z_{month}} \right)^2 \cdot 1_{\bar{c}_i < z} \right] \tag{6}$$

where the indicator $1_{\bar{c}_i<z}$ is one when households are poor based on average consumption and zero otherwise. This is equivalent to constructing a yearly poverty line and taking total yearly expenditure (or income) and redefining the sums appropriately. As in the section above, we use $P(\bar{c}_i)$ to refer to these yearly poverty measures.

We compare this to high-frequency poverty, which for the squared poverty gap is defined as

$$P^{FGT}_{Months} = \frac{1}{12N} \sum_{t=1}^{12} \sum_{i=1}^{N} \left[\left(\frac{z_{month} - c_{it}}{z_{month}} \right)^2 \cdot 1_{c_{it} < z} \right], \tag{7}$$

where c_{it} is expenditure in month t for household i and $1_{c_i<z}$ is one when household i is poor in the given period and zero otherwise. We use $P(c_{it})$ to refer to these monthly poverty measures.

3 Data

3.1 Village Dynamics in South Asia (VDSA) Survey

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 data collection project, also known as Village Dynamics in South Asia (VDSA), provides data at the monthly level. 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.[16]

[16]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.

Table 1: 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. (R's)	1128.197	1057.489	1190.137
	(844.083)	(1136.160)	(1004.460)
Expenditures p.c. (R's)	791.014	1366.117	1094.271
	(630.786)	(1026.164)	(860.767)
Wealth p.c. ('000s R's)	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.

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% for the sample with five years of data and 69% 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 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 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.[17]

Column 1 of Table 1 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.

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

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.

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% higher than median expenditures, but the means are closer. When we take the weighted average across columns 2 and 3, reflecting the full sample used in the analysis, the average difference between income and expenditure is 5%.

Importantly, 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 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. 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.

Figure 1 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

[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

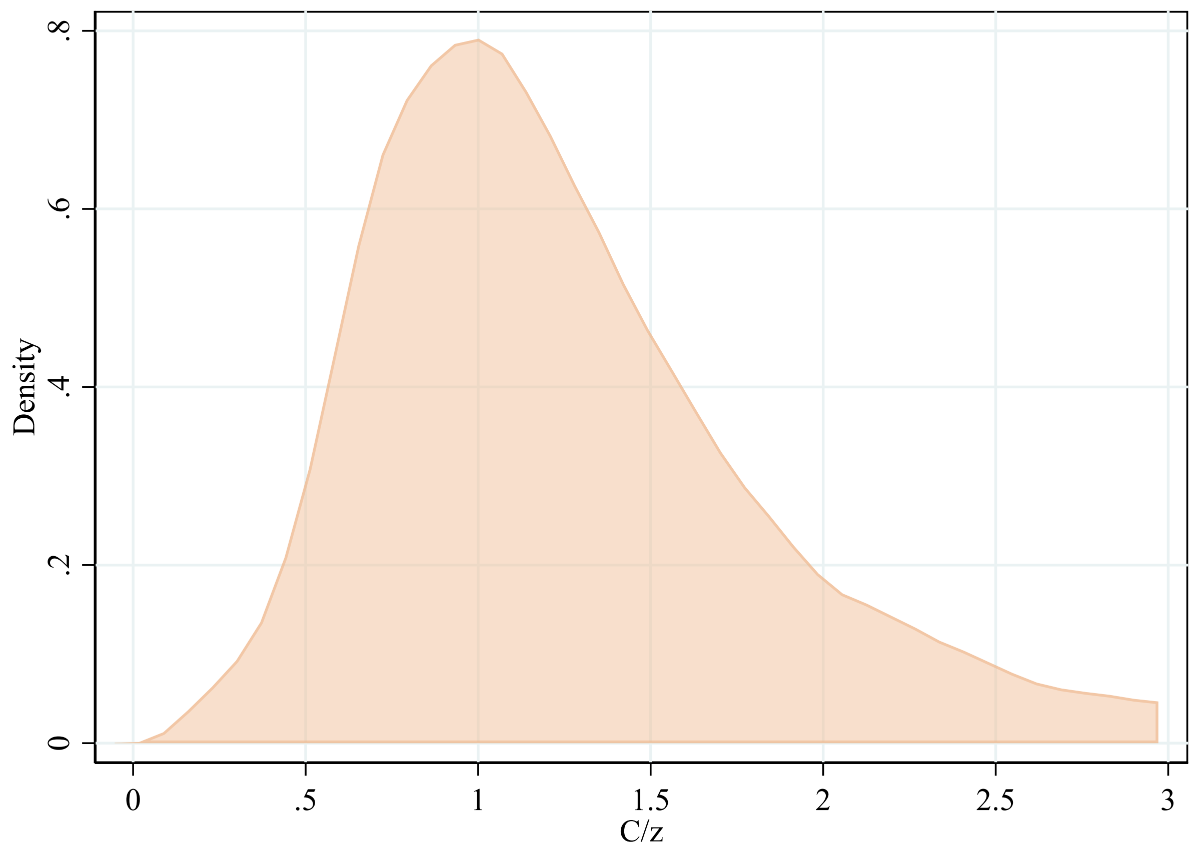
normalized by the annual poverty line, so households at 1 are exactly at the poverty line. Those to the left, below 1, are poor according to the headcount when using annual expenditure to assess poverty. Those above 1 are not poor by this measure.

The figure shows that the mode of per capita expenditure is close to 1: many households are clustered on either side of the poverty 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 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.

In poor rural areas, seeing the mode of the income distribution close to the poverty line is not surprising. For example, Figure A4 in the appendix shows the density of per capita expenditure for the Malawi 2016 Integrated Household Survey. It is a nationally representative sample and the mode for the population is below the poverty line but in the general vicinity, while the median (shown as a vertical line) is slightly above the poverty line. Similarly, Figure A5 in the appendix shows the density of household income in the United States in 2021, divided into $5,000 bins. The modal bin is $20,000 to $24,999, while in 2021 the US federal poverty threshold for a single parent with two children was $21,831 and the threshold was $27,479 for a household with two adults and two minor children.[19]

[19]Data are from the US Census, downloaded on November 1, 2022 from https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html.

Figure 1: 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.

3.2 Income and expenditure variability

The approach is motivated by the assertion that seasonality is an important fact of economic life for rural poor households. 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 relatively less variable in relative terms, but it is, nonetheless, absolutely variable.

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.

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 mean CV of income is 3.23 and the mean CV of expenditure is 0.37. The ratio of the latter to the former is 11%, consistent with substantial consumption smoothing.

But while expenditure is relatively smooth over time, it is not absolutely smooth. The fact that the mean CV of expenditure is 0.37 shows that households still experience considerable variability in expenditure. To put the CV in context, a CV of 0.35 would be generated if a household's monthly expenditure was one third greater than the mean for half the year and one third less than the mean for the other half.

3.3 Expenditures on durables

Durables pose complications when measuring poverty at high frequency. 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.

Table 2 shows that in fact expenditures on large durables and semi-durables are quite low in the sample. We define "semi-durables" as clothing and any item classified 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% in the sample, the poverty line is close to the bottom of the second quartile.) Table 2 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 is unlikely to drive our results, Figure A2 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 1, and monthly poverty rates with the smoothed durables/semi-durables are

Table 2: 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. Percentiles are defined using total yearly expenditures.

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.

4 Results

4.1 Comparing poverty measures

Table 3 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 – while the third column presents averages for households that are (conventionally) not poor for the year.

When measuring poverty by yearly household expenditure, poor households comprise 29% of the sample (row 2), but our framework shows that 37% of all household-months are spent in poverty (row 3). Focusing on months-in-poverty instead of yearly poverty shows an increase in the headcount poverty rate by more than a quarter.

The 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) index is 0.089 but rises by 40% 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% increase. The values of the two distributionally-sensitive measures are not cardinally meaningful, but the large changes suggest the possibility of substantial changes in relative rankings.

Table A6 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% when adjustments are made. The fraction of households that are poor at least in one month falls from 63% (unadjusted) to 57% (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.

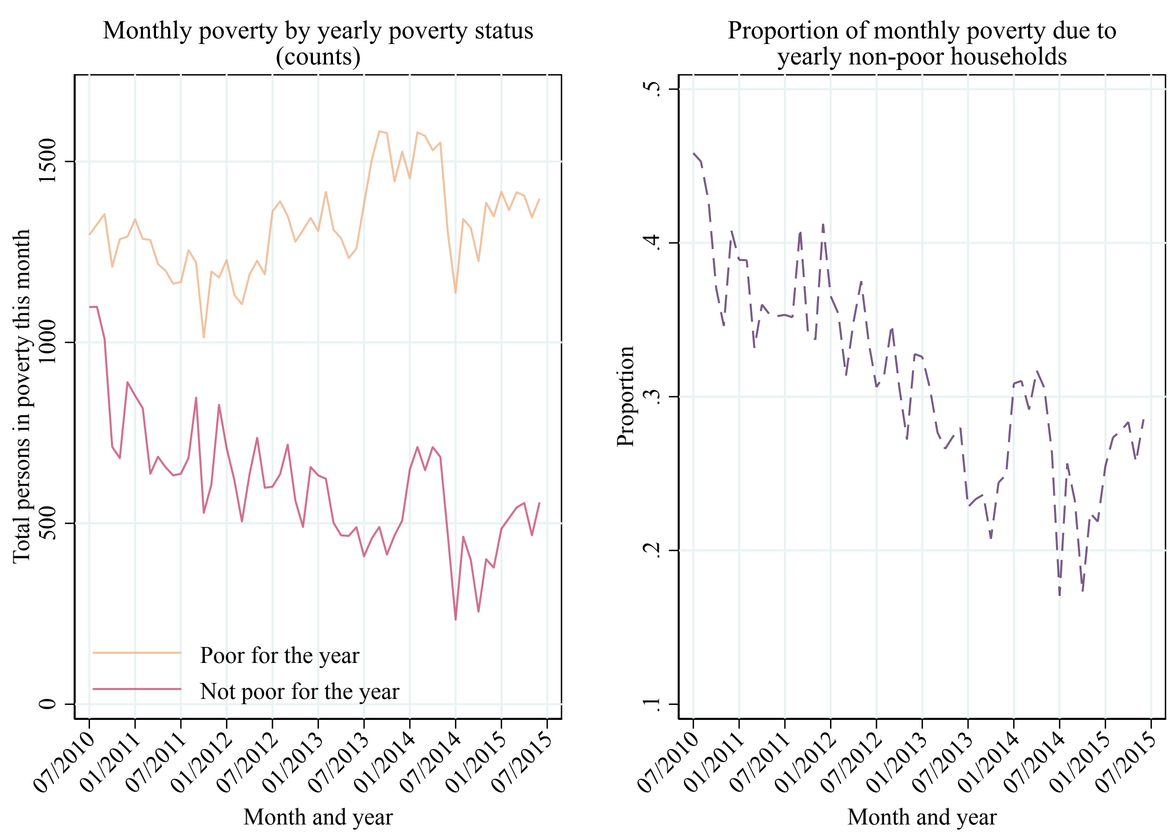
Table 3: Poverty summary statistics

	(1) Everyone	(2) Poor for the year	(3) Not poor for the year
Weighted proportion		0.292	0.708
Mean yearly poverty headcount	0.292	1.000	0.000
Mean months-in-poverty headcount	0.368	0.863	0.164
Mean yearly Watts	0.089	0.303	0.000
Mean months-in-poverty – Watts	0.125	0.361	0.028
Mean yearly squared poverty gap	0.025	0.087	0.000
Mean months-in-poverty – squared poverty gap	0.037	0.113	0.006
Poor at least once in year	0.627	1.000	0.473
At least one poverty spell in year	0.514	0.998	0.267
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.

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 3 shows the total number of people in poverty in each month across the sample using expenditures. At the beginning of the sample period in 2010, (yearly) non-poor households contribute up to 40% of total person-months of poverty. The right panel shows that this proportion decreases over the sample period, but is still between 20 and 30% of all poverty at the end of the sample period in 2015. On average, 35% of months-in-poverty are attributable to deprivations among households that would not conventionally be considered poor.

Figure 3: 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.

4.2 The poverty exposure (PE) curve

Figure 4 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.

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 2, 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:

$$PE\,(C/z) = \begin{cases} 1 & \text{if } C/z < 1 \\ 0 & \text{if } C/z \geq 1 \end{cases} \tag{8}$$

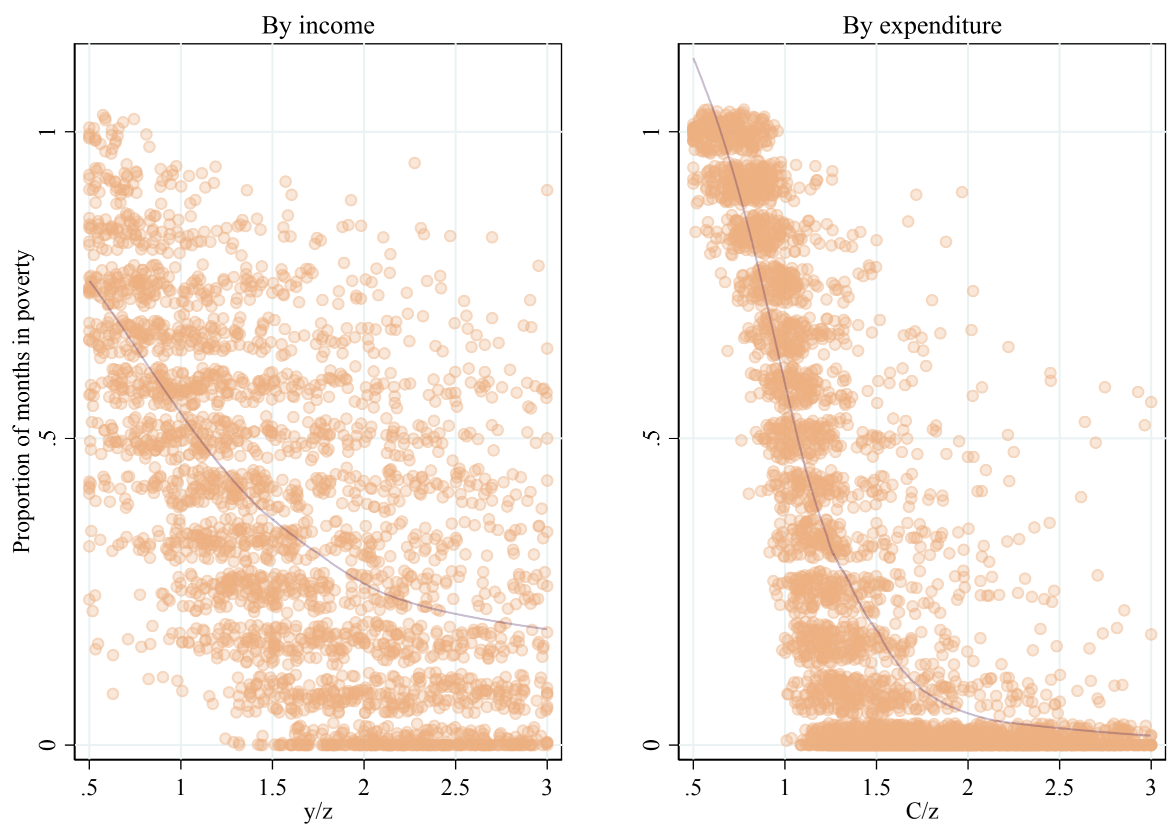
Figure 4 shows how far the data are from the pattern in equation 8. The PE curve for income is downward-sloping, indicating that poverty exposure falls as households earn more overall, but earning more does not guarantee escape from exposure to poverty even when income is greater than twice the poverty line.[20]

We can quantify this by looking at the smoothed value of poverty exposure at different

[20]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.

ratios in the left panel. Right at the poverty line,[21] the smoothed value is 0.587. That decreases to 0.416 at 1.5 times the poverty line and 0.310 at twice the poverty line. In other words, poverty exposure stays quite high even when income is large relative to the poverty line.

Figure 4: 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% 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

[21] 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.

measured by expenditure. The PE curve now slopes more steeply downward but still contrasts with the shape expected with perfect smoothing in equation 8—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 3 shows related data: 63% of all households experience at least one month of expenditure-poverty and 47% 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 Monetary comparisons of monthly and yearly poverty

Comparing conventional yearly poverty measures to months-in-poverty measures is straightforward with headcount poverty in the analyses above, since a simple comparison of rates is relatively intuitive. How does the change of temporal focus affect distributionally-sensitive poverty measures? Given the sensitivity to variation in resources below the poverty line of the squared poverty gap of Foster et al. (1984) and the Watts (1968) index, we expect even larger differences when moving from the year to the month.

However, results are less intuitive. To aid intuition, we calculate monetary comparisons using a calculation of implied equivalent yearly expenditure. Consider the monthly squared poverty gap described in Equation 6 and Equation 7. Using the monthly expenditure values, we calculate the months-in-poverty measure, P^{FGT}_{Months}. We then plug this value into the yearly definition (i.e. Equation 6), as such:

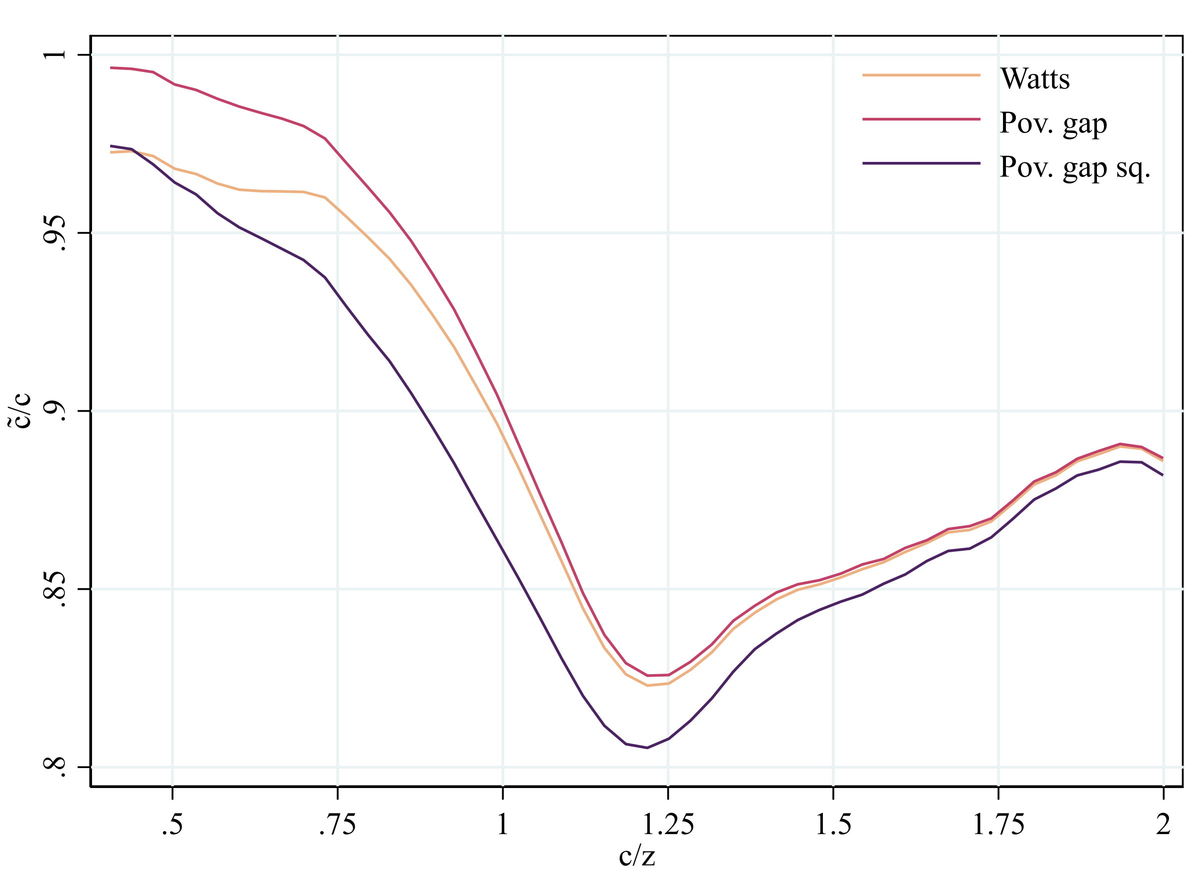
$$P^{FGT}_{Months} = \frac{1}{12N} \sum_{t=1}^{12} \sum_{i=1}^{N} \left[\left(\frac{z_{month} - \bar{c}_i}{z_{month}} \right)^2 \cdot 1_{\bar{c}_i < z} \right]. \tag{9}$$

Inverting this equation and solving for $\bar{c}_i$ gives the yearly expenditures that would yield the same poverty rate as obtained when using the monthly poverty measure, $\tilde{c}_i$. We construct a ratio of this equivalent expenditure to actual yearly expenditure and use this as a measure of the change when going from yearly to monthly poverty measures:

$$\text{implied expenditure} = \frac{\tilde{c}_i}{\bar{c}_i} \tag{10}$$

Figure 5 presents these values, mapped against monthly consumption normalized by the poverty line. The point 1 on the horizontal axis is the poverty line. From half the poverty line to twice the poverty line, this implied yearly expenditure is always lower than actual expenditure, as seen by a ratio less than one. This difference is largest just above the poverty line – around approximately 1.2 – with a ratio of implied equivalent to actual income of between 0.8 and 0.85. The difference is largest for the squared poverty gap and smallest for the poverty gap (which is not distributionally sensitive), with the Watts index falling in between. The result says that high frequency poverty measured by the squared poverty gap of FGT with each household's actual expenditure is equivalent to the rate that would be obtained if a household's average expenditure level was 15% or more smaller but smoothed across the year.

Figure 5: Implied yearly expenditures, non-headcount measures



Notes: We calculate the implied yearly expenditure by inverting the poverty measure to find the yearly expenditure that yields the same value on the poverty measure as using the monthly value.

4.4 Poverty, income variability, and consumption variability—by education level

The framework ties together material deprivation, the variability of resources, and the ability to protect consumption in the face of income shocks. We further illustrate the implications by dividing the sample into three groups defined by the education of the household head, a proxy for socio-economic status: (1) household with heads who have less than primary education; (2) those with heads who have at least primary but not secondary education; and (3) those with heads with secondary education or more. The hypothesis is that households with higher socio-economic status will be better able to smooth consumption—and that this will translate into patterns of measured poverty.

We begin with estimates of the extent to which households protect their consumption. Then we turn to poverty rates.

4.4.1 Co-movement of Income and Consumption, by education level: Regression methodology

To describe the co-movement of income and expenditure across months, we employ a series of fixed effect panel regressions of the form,

$$c_{it} = \beta_0 + \beta_{1i} * E_i y_{it} + \varepsilon_{it}, \tag{11}$$

where c_{it} is monthly expenditures, y_{it} is monthly income, ε_{it} is a mean-zero error term, and β_0 is a set of fixed effects. The variable E_i is an indicator of the education of the household head, the proxy for socio-economic status.

If households smooth consumption perfectly and permanent income does not change, for example, income and expenditure should not covary within households and $\beta_{1i} = 0$. Co-movement of income and expenditure, conditional on fixed effects, is reflected by $\beta_{1i} > 0$, and we are particularly interested whether the degree of smoothing is greater for households with higher education levels.

We vary the fixed effects across specifications, using three different fixed effect specifications. First, we include year-month and household fixed effects. Across households, monthly income and expenditures can be correlated, since higher income households tend to spend more money. However, with the household fixed effects, we restrict identification to only changes in income and expenditures over time within the household.

Income and expenditures can also covary within a household if permanent income changes. Consider, for example, if a household enters into a new type of employment that increases their expected income. Then, their income and expenditures may move together, even if they are smoothing perfectly. This motivates our second fixed effect specification, which replaces the household fixed effects with household-year fixed effects. This decreases the window across which we are identifying coefficients from 60 months to 12 months.

Finally, we replace the year-month fixed effects with village-year-month fixed effects, inspired by tests in Townsend (1994) for collective risk sharing and insurance in villages in India. Here, we are interested in partialling out covariate shocks. In other words, if the totality of the covariance between expenditures and income is driven by village-level covariate shocks, then $\beta = 0$ in this specification even if it did not equal zero in previous specifications. This is not a test for consumption smoothing *per se*, but instead is meant to better understand how covariate shocks may drive deviations from consumption smoothing.

4.4.2 Regression results

The earlier calculations of the extent of consumption and income variability are echoed in the regressions in Table 4. The dependent variable is monthly expenditures and the independent variable is monthly income disaggregated by the highest education level of the household head. If households are perfectly smoothing consumption (proxied here with expenditures), then monthly consumption should not vary with monthly income.[22]

This implication is not necessarily true in the cross section, as households with higher incomes are more likely to have higher expenditures as well. This result is shown in column 1, which includes no fixed effects and in column 2 with only year-by-month fixed effects. The coefficients show that higher monthly incomes are indeed correlated with

[22]Failure to find a significant correlation between the two does not necessarily imply that households smooth consumption perfectly. One possibility is that measurement error is so large relative to the true variation that we cannot reject zero. However, rejections of no correlation are consistent with a failure to smooth consumption across time.

Table 4: Co-movement of monthly expenditures and income, marginal effects by education of head

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Current income X less than primary	0.056***	0.057***	0.039***	0.036***	0.038***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
Current income X primary graduate	0.061***	0.063***	0.036***	0.035***	0.035***
	(0.010)	(0.011)	(0.008)	(0.007)	(0.008)
Current income X secondary graduate	0.040***	0.041***	0.023***	0.020***	0.020***
	(0.011)	(0.011)	(0.005)	(0.005)	(0.005)
Tests of equality (p):					
Income X less than primary = Inc. X prim.	0.651	0.649	0.801	0.935	0.775
Inc. X less than prim. = Inc. X secondary	0.200	0.178	0.035	0.034	0.017
Inc. X primary = Inc. X secondary	0.155	0.139	0.141	0.093	0.102
Fixed effects:					
Year-month		X	X	X	
Household			X		
Household-year-month				X	X
Village-year-month					X
R-squared	0.051	0.059	0.362061	0.458	0.492
Observations	55,308	55,308	55,308	55,308	55,308

Notes: The dependent variable in all columns is monthly expenditures. "Current income" is monthly income. Coefficients are marginal effects, not interaction terms. All standard errors are clustered at the household level.
* $p<0.1$ ** $p<0.05$ *** $p<0.01$

higher monthly expenditures. The three coefficients on income interacted with education are each statistically significant, and the size is roughly a third smaller for households headed by secondary school graduates.

Column 3 adds household fixed effects, which remove variation across households and instead focuses on changes in monthly income and monthly expenditures within households. We strongly reject the null hypothesis that there is no correlation between monthly income and monthly expenditures within households over the course of the sample. As expected, the coefficients in column 3 are smaller than the coefficients in columns 1 and 2 since they only reflects within-household variation, but it remains that better-education is associated with less sensitivity of spending to the ups and downs of income.

Column 4 takes a different approach. Instead of including household-year fixed effects, we include household fixed effects and add an additional control: average expenditures in the last 12 months. Again, the idea is to capture changes in permanent income. Results remain consistent, with the coefficient barely changing and remaining statistically significant. The coefficient on income in column 4, for example, is roughly half the size (0.020 versus 0.036) for the households with the best-educated heads versus those with the least-educated heads.

Finally, column 5 includes village-by-year-by-month fixed effects. Given the results in the first four columns, column 5 instead probes whether the failure of consumption smoothing is driven by the failure of villages to self-insure following covariate shocks as in Townsend (1994) or, more generally, whether failures of consumption smoothing are largely concurrent with other households in a village. We reject this explanation, as the coefficient is unchanged.[23]

[23]We present additional robustness checks in Table A2. First, we include 12 lags of expenditures instead of average expenditures over the previous 12 months. This increases the flexibility of the specification. Second, we instead include 12 leads. Since changes in permanent income are in the future, controlling for past expenditures may not be sufficient. Finally, we also include both 12 leads and 12 lags. All results are consistent with the results in Table 4: all three coefficients are either 0.033 or 0.034. In Table A3, we present

Taken together, the results from Table 4, shows that the ability to insulate consumption from within-year income fluctuations is weakest for households whose heads have the least education. Thus, not only do these households have less earning capacity, they also have the greatest exposure to instability.

4.4.3 Poverty by education level

Table 5 presents simple means of three types of headcount poverty: high frequency (i.e., average months-in-poverty) income-based poverty, high frequency expenditure-based poverty, and low-frequency (i.e., conventional yearly) expenditure-based poverty. The poverty measures are defined based on each survey year. We present means for each of these three poverty measures across the three education groups described in Section 4.4.

Table 5: Average poverty headcounts by education of household head

	(1) Less than primary	(2) Primary	(3) Secondary
P(month, income)	0.390	0.439	0.410
	(0.013)	(0.020)	(0.021)
P(month, expenditures)	0.416	0.360	0.251
	(0.018)	(0.026)	(0.024)
P(annual, expenditures)	0.334	0.307	0.204
	(0.020)	(0.029)	(0.027)
Tests of equality (p):			
P(m,c)=P(m,y)	0.128	0.041	0.000
P(m,c)=P(a,c)	0.000	0.000	0.000
Observations	22,560	11,201	11,152

Notes: Coefficients are simple means. Standard errors are in parentheses. Standard errors are clustered at the household level.

The first row shows that all three groups have similar levels of months-in-poverty as measured by variation in household income. Even for households that are presumably more well off (with higher levels of education), income is still quite variable.

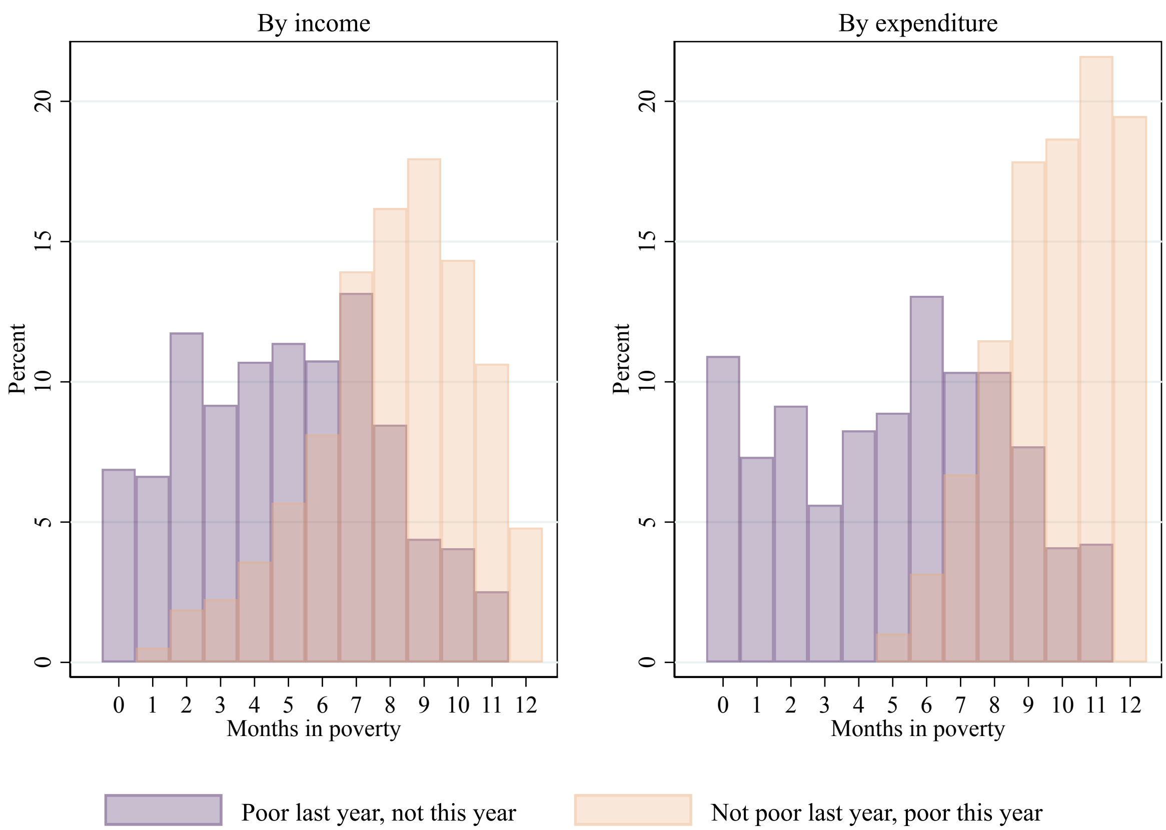
results based on initial household wealth. Higher wealth is significantly correlated with a better ability to smooth consumption. Overall, the results show that (1) households in the sample do not perfectly smooth consumption and (2) disadvantaged households struggle more in this regard than others.

The second row shows how the ability to address instability reduces poverty, especially for households with higher socio-economic status. Months-in-poverty as measured by expenditure decrease markedly from the first column to the third column. Column 1 shows that households with heads that have less than a primary education (which account for roughly half the sample) are particularly exposed to poverty: We are unable to reject that these households do not smooth their consumption at all. Their exposure to poverty in fact increases, as seen by expenditure-based months-in-poverty exceeding income-based months-in-poverty, but the difference is not statistically significant (p=0.13). In contrast, column 3 shows that households with the highest socio-economic status reduce their exposure to poverty by 39%.

If one only had income data, how well would it approximate months-in-poverty as measured by expenditure? For those with less than a primary education, months-in-poverty as measured by income is a close predictor of months-in-poverty as measured by expenditure. But that is not true for better educated household heads, who smooth consumption to a much greater degree, as in Table 4. For them, the conventional yearly measure provides a closer prediction. Even for households whose heads have primary education (but not more), we reject that months-in-poverty measured by income and expenditure are the same (column 2, rows 1 and 2).

4.5 Entry and Exit from poverty

Figure 6: Poverty entrance and exit



Notes: In both figures, the x-axis is the number of months a household is in poverty in a given year. The sample is split using the previous year's overall poverty classification and this year's poverty classification, with income for the left figure and expenditures for the right figure. All counts are weighted.

The results so far establish that "poor" people are sometimes not poor and "not poor" people are sometimes poor. What then does it mean to exit or enter poverty? Figure 6 presents what is traditionally defined as "exit" and "entrance" with respect to poverty.

We split households into those who were poor last year but are not poor this year ("exit") and those who were not poor last year but are poor this year ("entrance"). The conventional view of poverty would suggest that these are completely different states, but the two panels make clear that the terms are not as well defined as they might seem. An expectation based on strict definitions would be that people who have exited poverty last year should be free of poverty now. Similarly, people not poor last year but poor this year should experience a full 12 months of poverty. The panels should thus have a single purple spike at zero and an orange spike at 12.

The panels show something very different, with substantial overlap of the two distributions. The mode for the purple bars is at six or seven months in both panels. For households who exit poverty, a substantial proportion continue to experience poverty, regardless of whether we use income or expenditures. Households who have "exited" poverty, still experience, on average, more than five months of poverty, whether we use income or expenditures.

Almost 95% of all "exited" individuals experience at least one month of poverty with income, while the number with expenditure is almost 90%. In fact, almost half of all individuals experience at least six months of poverty despite having seemingly "exited" poverty, using either income or expenditures. Even households who are considered not poor (based on yearly expenditure) for two consecutive years still experience poverty for more than a quarter of the year on average.

The story is closer to conventional understandings for households that "enter" poverty, especially for expenditures. Almost 60% of individuals who enter expenditure poverty are poor for at least nine months, and not a single person is poor for less than five months. This is especially stark when compared with those who exited expenditure poverty. When we calculate entry and exit using expenditures smoothed for durables, similar conclusions remain (Figure A3 in the Appendix).

4.6 Predictive power

We developed the high frequency poverty framework on normative grounds, but it has predictive power to explain other household of practical interest, as well. Using a least

Table 6: Anthropometrics and poverty measures - Regressions

	Weight		Height	
	(1)	(2)	(3)	(4)
	Annual	Monthly	Annual	Monthly
	b/s	b/s	b/s	b/s
Annual poverty	0.001		−0.016	
	(0.003)		(0.037)	
Lagged annual poverty		−0.003		−0.051
		(0.003)		(0.045)
Months-in-poverty	−0.006		−0.037	
	(0.005)		(0.061)	
Lagged months-in-poverty		−0.009*		−0.177**
		(0.005)		(0.071)
Observations	18,441	13,178	4,155	2,690

Notes: 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

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 conventional headcounts. The finding follows earlier studies that draw connections between seasonality and health outcomes (e.g., Christian and Dillon 2018).

The VDSA data include anthropometrics – weight and height – once per year for each household member.[24] Weight can change in relatively short time periods, for both children and adults. Height, on the other hand, takes longer to show changes 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).

Correlation matrices for weight and height with headcount poverty are presented in

[24]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.

the first two columns of Appendix Table A4 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. Table 6 presents a set of regressions that include individual fixed effects to isolate the within-individual variation of both poverty and anthropometrics. Across all regressions, only the lagged months-in-poverty measures are significantly predictive of outcomes. Consistent with the correlation matrices, the high-frequency poverty measure is a stronger predictor of both weight and height-for-age than is the annual headcount measure. The coefficients on lags are three times as large for the high-frequency measures than for the conventional annual measures.

The correlational and regression evidence shows that monthly poverty is more highly correlated with anthropometrics than annual poverty. 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 7, 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 quarterly poverty variable that is defined similarly to monthly poverty but instead uses quarters,[25] as well as variables related to the lengths of poverty spells, which are defined as at least two contiguous months of poverty. We estimate lasso in Stata using the *bic*, *postselection* option.

[25]In other words, in a given year, the quarterly poverty variable can equal 0, 0.25, 0.5, 0.75, or 1.

Table 7: Selecting the best predictors of anthropometrics through lasso

	Weight		Height	
	(1)	(2)	(3)	(4)
	All	lasso	All	lasso
Monthly poverty	−0.141***	−0.074***	−0.303	−0.279*
	(0.040)	(0.013)	(0.323)	(0.157)
Lagged monthly poverty	−0.159***	−0.103***	−0.701**	−0.859***
	(0.041)	(0.013)	(0.276)	(0.179)
Quarterly poverty	0.067**		−0.160	
	(0.032)		(0.260)	
Lagged quarterly poverty	0.084***		0.171	
	(0.031)		(0.223)	
Annual poverty	0.000		0.137	0.126
	(0.016)		(0.119)	(0.108)
Lagged annual poverty	−0.034**		−0.082	
	(0.017)		(0.127)	
Mean spell length	0.009		0.040	
	(0.010)		(0.080)	
Lagged mean spell length	0.024**		0.203**	0.104***
	(0.011)		(0.083)	(0.036)
Max spell length	−0.004		−0.001	
	(0.006)		(0.049)	
Lagged max spell length	−0.010		−0.072	
	(0.007)		(0.050)	
Observations	13,554	13,554	2,954	2,954

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

We present results for weight and height with two separate outcomes. Columns 1 and 3 analyze data in levels, incorporating cross-sectional variation. Columns 2 and 4 present results with 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. For weight, lasso also selects two variables related to poverty spells. The coefficients are especially noteworthy 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 0.24 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 0.02 standard deviations.[26]

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.[27]

4.7 Policy experiment: Where and when to target transfers?

Since households do not smooth consumption perfectly, there may be welfare gains from improving their ability to smooth consumption, even if their average consumption does not increase. As McCulloch and Baulch (2000) write: "Anti-poverty programmes often seek to improve their impact by targeting households for assistance according to welfare measures in a single time period. However, a growing literature shows the importance to poor households of fluctuations in their welfare from month to month and year to year." Similarly, Ruggles and Williams (1989) estimate with monthly data from the United States

[26] In the appendix, Table A7 also shows that the same results hold when we use expenditures smoothed for durables over the year and Table A5 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.

[27] 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.

in the 1980s that over than one-third of all poverty spells could have been eliminated if households' financial assets were targeted to alleviating poverty in the most difficult periods. In this section, we quantify some of these possibilities. We consider alternative hypothetical transfer programs and analyze how the design affects poverty measures.

We imagine a hypothetical government transfer to households of 960 rupees per capita per annum (80 rupees per capita per month). This is approximately 7.2% of average per capita expenditures in the entire sample, or 14.8% of the average per capita expenditures of the poor. For simplicity, we design this transfer to go only to those households living below the poverty line.[28] We assume the household consumes the entirety of the transfer in the month they receive it.[29]

We vary how these 960 rupees per year are allocated across months. We compare the resulting poverty rates from four separate allocation designs: no transfer at all, a transfer of 80 rupees per month across all months, a transfer of 160 rupees per month across six months, and a transfer 320 rupees per month across three months. We assume that the totality of this transfer is consumed in the month of the transfer and then examine how estimated poverty measures change in response to these different designs. Specifically, we transfer these amounts to the lowest relevant months. In other words, for the transfer across six months, we choose the poorest six months. Similarly, for the transfer across three months, we choose the poorest three months.

Equation Equation 5 describes how overall changes in months-in-poverty respond to a change in an external factor, decomposing the effect into two parts: the effect of the external change on average expenditures and the effect of the external change on the deviation of monthly expenditures around that average. In considering the alternative

[28]In reality, such a design would present perverse incentives for households living just below the poverty line. Since we do not taper the transfer, those just below the poverty line can actually end up with a higher income than those just above the poverty line. However, we believe the simplicity of this design allows for a more straightforward elaboration of the results.

[29]Given that we were unable to reject no smoothing in Table 5, we do not think this assumption is too extreme, even if it is not perfectly accurate.

Table 8: Policy Experiment Results

	(1) Headcount	(2) Watts
No transfer	0.863	0.361
12 months (80 Rs)	0.743	0.219
Six months (160 Rs)	0.751	0.208
Three months (320 Rs)	0.699	0.234
Households	391	391
Month observations	12,300	12,300

Notes: The same total amount of 960 rupees per person per year is transferred in all designs (except "no transfer"). That money is transferred in 12 equal payments for the "all months" design, in six equal payments for the "six months" design, and in three equal payments for the "three months" design. Transfers are always made in the poorest months.

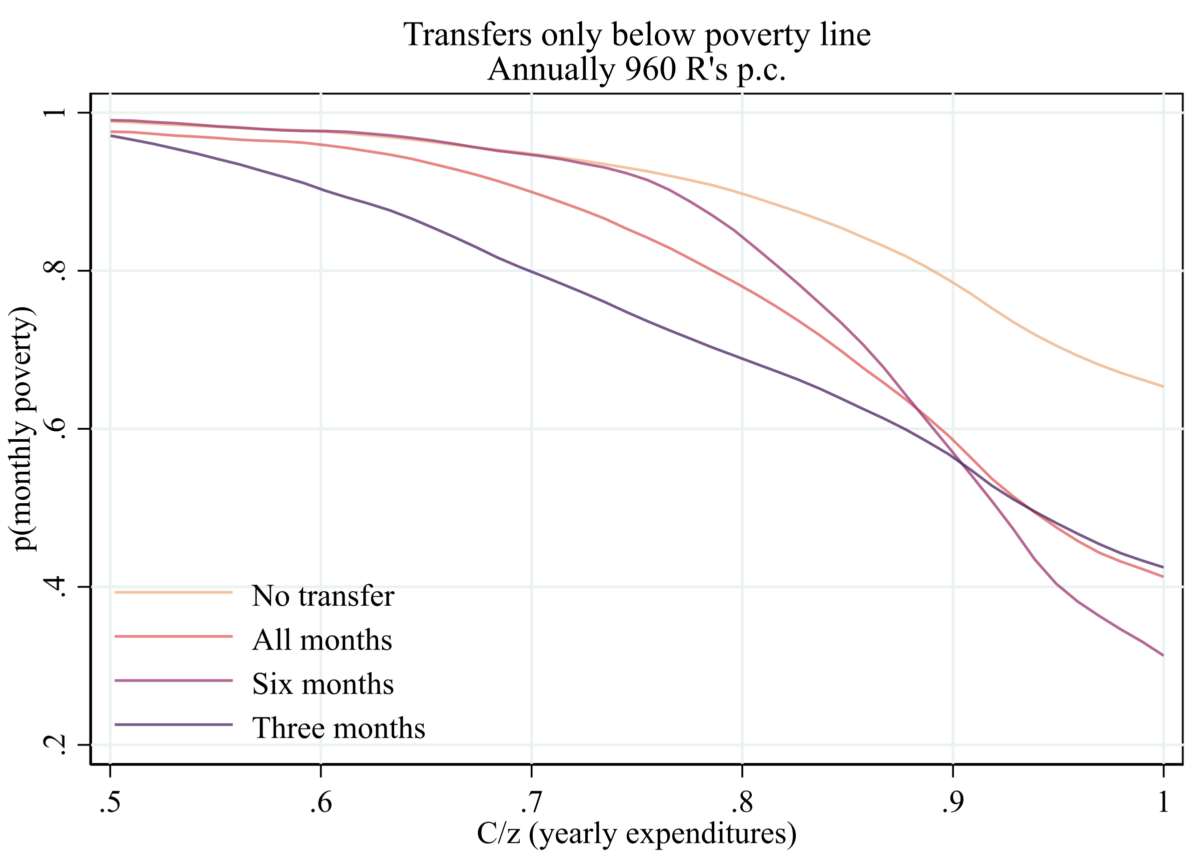
transfer policies, the total amount of the transfer is unchanged. This means that average monthly expenditures are unchanged across the three separate allocation designs and, as such, the effect on yearly poverty measures is unchanged. We thus focus on how this transfer allows households to change the distribution of resources throughout the year.

Table 8 shows the overall results for both the headcount (column one) and Watts index (column two). The transfer, unsurprisingly, has a large impact on overall poverty, relative to the no-transfer baseline. However, despite transferring the same amount of money, the three separate designs have different effects. For example, with the headcount, the monthly transfer of 80 Rs decreases poverty by 13.9 percent (12 p.p.). Transferring 320 Rs across three months per year decreases poverty by 19.1 percent. This is a 37 percent larger decrease in the poverty rate, despite transferring the same amount of money.

The results for the Watts index are not as stark given how the measure weights income more heavily farther from the poverty line. The 12 monthly transfers decrease poverty by 39.4 percent, while the transfers across six months decrease poverty by 42.4 percent, or 7.6 percent more than the monthly transfer. Interestingly, the transfer focused on the poorest three months performs worse than the other two options here, despite performing best with headcount poverty. This underlines the importance of the choice of poverty measures when evaluating government programs (Bourguignon and Fields, 1990).

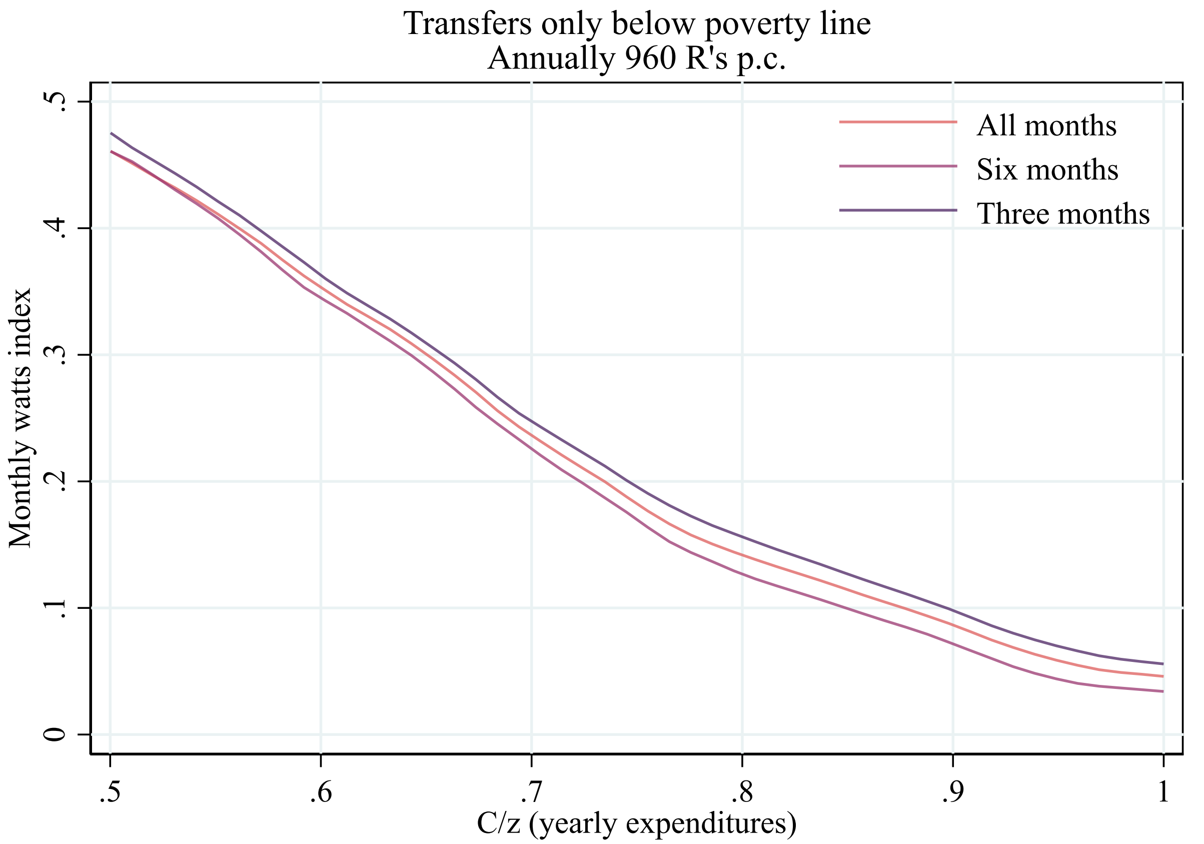
We present the results graphically for headcount poverty in Figure 7, with expenditure-based months-in-poverty on the y-axis and the (yearly) consumption to poverty line ratio on the x-axis. Across nearly all of the range, a transfer focused on the poorest three months performs better at reducing monthly headcount poverty than the other two designs. However, transferring across six months actually performs best for those closest to the poverty line.

Figure 7: Policy experiment - Headcount poverty



Notes: The same total amount of 960 rupees per person per year is transferred in all designs (except "no transfer"). That money is transferred in 12 equal payments for the "all months" design, in six equal payments for the "six months" design, and in three equal payments for the "three months" design. Transfers are always made in the poorest months.

Figure 8: Policy experiment - Watts (1968) index



Notes: The same total amount of 960 rupees per person per year is transferred in all designs (except "no transfer"). That money is transferred in 12 equal payments for the "all months" design, in six equal payments for the "six months" design, and in three equal payments for the "three months" design. Transfers are always made in the poorest months.

Figure 8 graphically presents the results using the Watts (1968) index. Here, instead, cost-effective strategies involve targeting the most disadvantaged people in their most difficult times. Overall, all three designs perform much better here than with headcount poverty. This is driven by the fact that increasing the consumption of the poorest by around 80 Rs per month (the size of the 12-month transfer) does not have much of an effect on headcount poverty – since many households are too far from the poverty line to cross it with an 80 Rs/month transfer– whereas with the Watts (1968) index, any transfer registers as a poverty reduction. The six-month transfer performs best across almost the entire range, with an exception for those households at the very bottom of the distribution (of whom there are relatively few).

The intuition is that it is helpful to concentrate effort in the poorest months, but the use of the months-in-poverty measures show that the challenges go beyond the hardest three months. In other words, the challenges go beyond a well-defined period of seasonal poverty. The hypothetical example has broader implications. For example, while a microfinance initiative may not lead to notable increases in yearly expenditure, it may allow households to move resources across time, affecting how monthly expenditures vary around the mean. The focus on yearly expenditure misses this potential reduction in poverty.

5 Conclusion

We have developed a conceptual framework that allows the experience of poverty to be captured by the interaction of insufficiency, instability, and illiquidity. Insufficiency reflects low overall earnings as seen in annual sums, the focus of conventional poverty measurement approaches. Instability reflects the variation of resources within the year. Illiquidity reflects households' challenges in coping with instability, leading to spikes and dips of within-year consumption. Together, they create conditions of material deprivation.

Poverty, as conventionally measured, approximates the experience of material deprivation best in the special case in which consumption is steady. The framework developed here, focusing on months-in-poverty during the year, instead opens a window on variance around mean levels of deprivation, not just the mean alone. The aim is to complement conventional approaches in parallel to the way that the addition of distributionally-sensitive measures and multi-dimensional measures (Alkire and Foster, 2011) have broadened understandings without fully replacing the basic headcount poverty measure.

The data are from agricultural villages in South India. They are not representative of global poverty in a statistical sense, but they represent an important setting for understanding global poverty. The evidence here shows that much of the experience of poverty in our sample goes unmeasured in the conventional approach. Next steps will involve extending the framework to other geographies.

In our framework, measured poverty is greater than in the conventional approach because we capture months of poverty experienced by all households, irrespective of whether they are poor when judged on the basis of annual resources. Many "non-poor" households are sometimes poor, and their experiences of poverty contribute 35% of the total household-months of poverty across the sample. The approach also shows that people who are said to "exit" poverty seldom fully exit poverty in the short-term. Most still experience months of poverty, just as is true for other "non-poor" households. People who enter poverty, likewise, are sometimes not poor. People who are persistently poor as measured by the headcount have highs and lows of deprivation which also go unmeasured, even in conventional applications of distributionally-sensitive measures.

These distinctions matter for how we understand poverty and the experience of poverty. They show times of greater resources and possibility, and they show times of much deeper deprivation. As a result, policy targeted to the most challenging periods can have particular impact. Helping households to smooth consumption within the year can also reduce the experience of poverty, even when total resources are unchanged.

The framework raises conceptual and ethical questions beyond the scope of the paper. Ultimately, the way that poverty is conceived shapes the way that it is measured. The reverse is also true: the way that poverty is measured can shape the way that poverty is conceived. Questions raised by the framework include: Should the social weight placed on reducing months-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 conventionally be considered not poor? Is seasonal poverty deserving of similar concern as other periods of poverty? 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 working through possibilities in the intra-year context.[30]

On practical grounds, an important limit to implementing the framework is the need for monthly data, although in principle the approach can be adapted to surveys with quarterly or seasonal waves of data collected within the year (e.g., Azevedo and Seitz 2016b).[31]

Even with monthly longitudinal data, there remain empirical challenges. One is the standard problem of measurement error which can exaggerate evidence of within-year volatility. We show that the monthly poverty measure is more predictive of important development outcomes – anthropometrics – than higher levels of aggregation, which at least suggests that measurement error is not solely responsible for the within-year volatilty we document here. A second is the fact, well known to economists, that spending does not equal consumption. A household may buy a motorcycle, say, purchasing it at the start of the year. Consumption of the motorcycle's "mobility services," however, takes place throughout the year. Spending volatility is then much greater than consumption volatility. In this case, data need to be converted into consumption equivalents for each period. This is a particular issue for durables and semi-durables and, to the extent possible, we have converted expenditure data to consumption units. Because the survey only measured spending, we rely on reasoned assumptions to do so rather than direct observations of consumption. Ideally, this challenge would be addressed from the start of data collection with survey questions on the consumption of durables over time.

A connected problem involves the variability of needs. We have taken the annual poverty

[30] One might also start by turning to the foundations of conventional poverty measures: are there compelling philosophical defenses, beyond convenience, for measuring poverty with yearly income and consumption when doing so obscures the lived experience of poverty?

[31] Even where the same households are not surveyed repeatedly over a year (but where waves of cross-sections are collected through the year), in principle it would be possible to model a household's predicted seasonal income or expenditure—or to map out the "poverty exposure curves" described above. In addition, the simple average monthly expenditure of properly collected temporally representative data can be used to calculate our monthly measure for the population as a whole.

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. This remains a topic for future research.

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Appendix

A1 Poverty measures

The most common poverty measure is headcount poverty, which is the number of poor people, N_{poor}, divided by the entire population N. The second poverty measure, the normalized poverty gap, is:

$$\frac{1}{N}\sum_{i=1}^{N}\left[\left(\frac{z-c_i}{z}\right)\cdot 1_{c_i<z}\right]. \tag{A1}$$

where z is the poverty line, and c_i is the monetary measure (one could alternatively use income y_i). The indicator $1_{c_i<z}$ is one when households are poor in the given period and zero otherwise.

Equation A1 shows the average amount of money – as a proportion of the poverty line – per person in the population needed to raise all households' consumption to the poverty line in time t. Unlike the headcount, the poverty gap registers households' deprivations relative to the poverty line, with the weight on each unit of money below the poverty line being constant. As a result, taking a unit of money from a very poor person and giving it to someone less poor does not change measured poverty.

The third poverty measure is the squared poverty gap of Foster et al. (1984):

$$FGT(2)=\frac{1}{N}\sum_{i=1}^{N}\left[\left(\frac{z-c_i}{z}\right)^2\cdot 1_{c_i<z}\right]. \tag{A2}$$

The measure is useful ordinally to rank poverty in different samples, but, unlike the headcount or poverty gap, it is not cardinally meaningful. However, it has the key of being distributionally sensitive. Here, taking a unit of money from a very poor person and giving it to someone who is less poor registers as an increase in measured poverty. Extra weight is placed on interventions that reduce extreme deprivation.

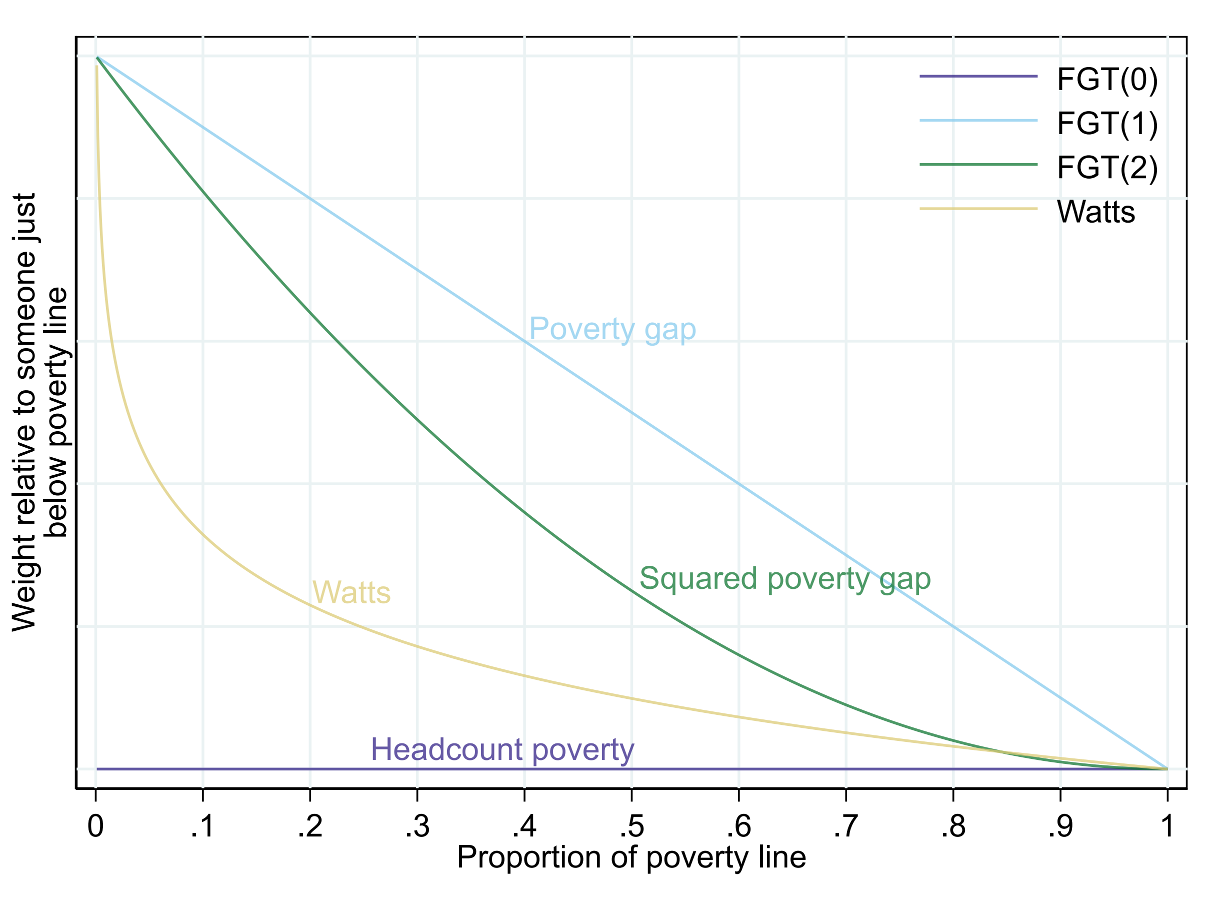
The fourth poverty measure we use is the Watts (1968) index, which is defined as

$$Watts = \frac{1}{N}\sum_{i=1}^{N}\left[\ln(z/c_i)\cdot 1_{c_i<z}\right] \tag{A3}$$

Like the squared poverty gap, the Watts (1968) index is distributionally sensitive. This sensitivity increases only slowly at first, as income decreases from the poverty line, but then increases rapidly at the lower end of the distribution.

Figure A1 compares the differences in weights across these measures. Note that the curves are scaled to allow their display on a single figure. As such, it is the relative shapes that are important, and not the levels, *per se*.

Figure A1: Relative weights of different poverty measures



A2 Panel data

Table A1: 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.

A3 Co-movement of monthly expenditure and income

Table A2: 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 A3: 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

A4 Anthropometrics and poverty

Table A4: 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).

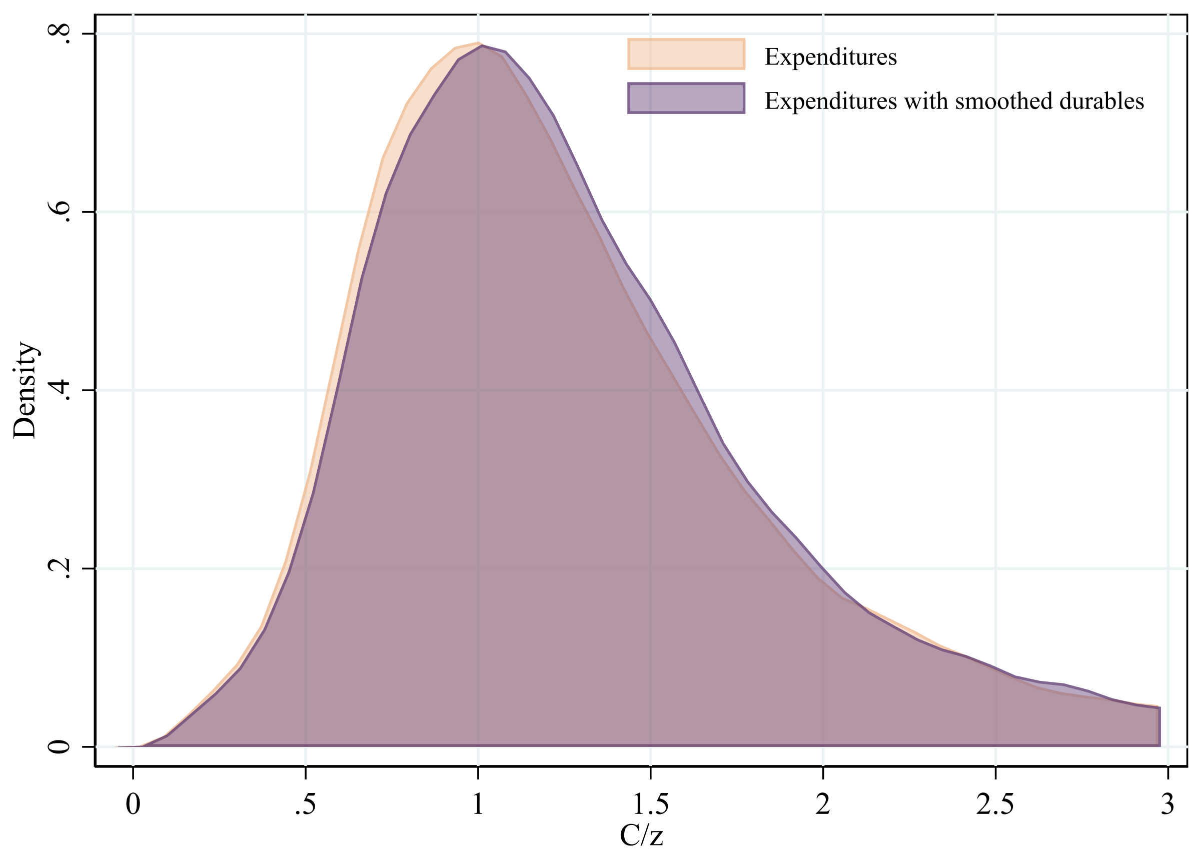
Table A5: Selecting the best predictors of anthropometrics through lasso, only children (<= 10)

	Weight		Height	
	(1)	(2)	(3)	(4)
	All	lasso	All	lasso
Monthly poverty	−0.301**		0.253	
	(0.127)		(0.346)	
Lagged monthly poverty	−0.319***	−0.131**	−0.312	−0.105
	(0.117)	(0.063)	(0.365)	(0.124)
Quarterly poverty	0.064		−0.332	
	(0.083)		(0.275)	
Lagged quarterly poverty	0.151*		−0.189	
	(0.088)		(0.267)	
Annual poverty	0.029		0.176	
	(0.038)		(0.122)	
Lagged annual poverty	−0.055	−0.036	0.053	
	(0.034)	(0.023)	(0.138)	
Mean spell length	−0.016		−0.153	
	(0.021)		(0.106)	
Lagged mean spell length	0.035	0.027***	−0.046	
	(0.026)	(0.009)	(0.107)	
Max spell length	0.025**		0.082	
	(0.012)		(0.059)	
Lagged max spell length	0.002		0.056	
	(0.017)		(0.066)	
Observations	581	623	576	617

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

A5 Adjusting for Durables

Figure A2: Density with smoothed durables



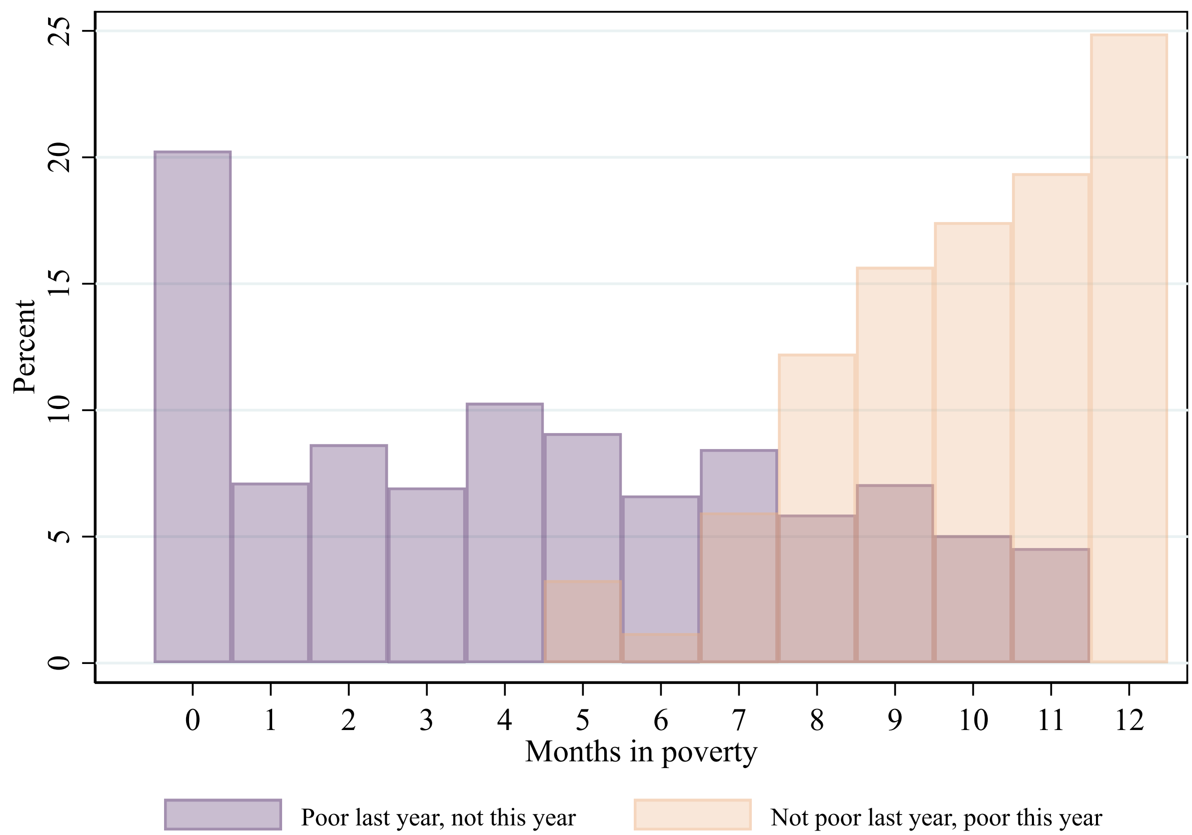
Notes: Kernel density estimate of per capita expenditure. The unit of observation is a household-month, so a single household appears multiple times in the data. The total number of household-month observations is approximately 55,000. The horizontal axis is annual expenditure per capita of households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

Table A6: 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.

Figure A3: Poverty entrance and exit, expenditure smoothed for durables



Notes: The x-axis is the number of months a household is in poverty in a given year. The sample is split using the previous year's overall poverty classification and this year's poverty classification, with income for the left figure and expenditures for the right figure. All counts are weighted. Expenditures on durables are smoothed across a year.

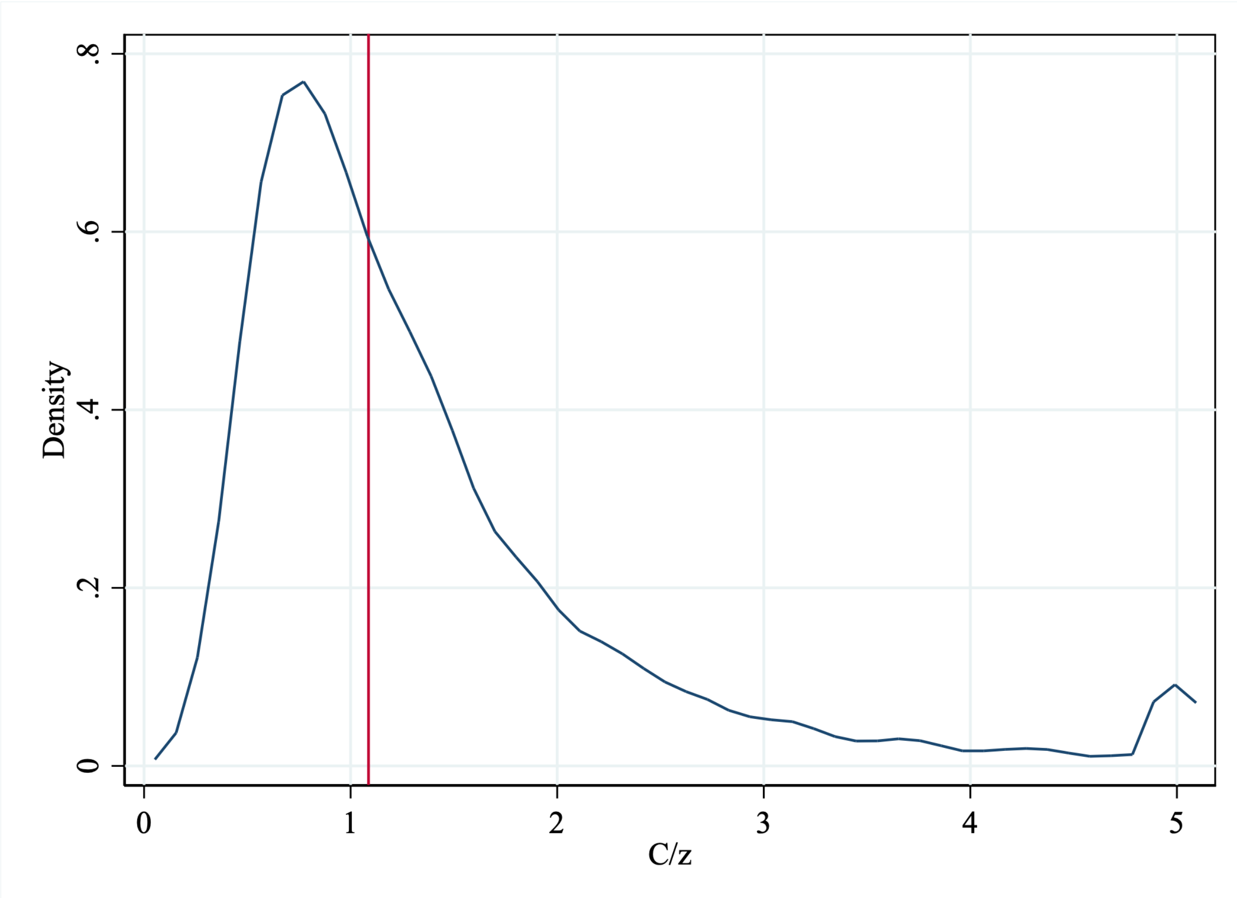
Table A7: Anthropometrics with smoothed expenditures

	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

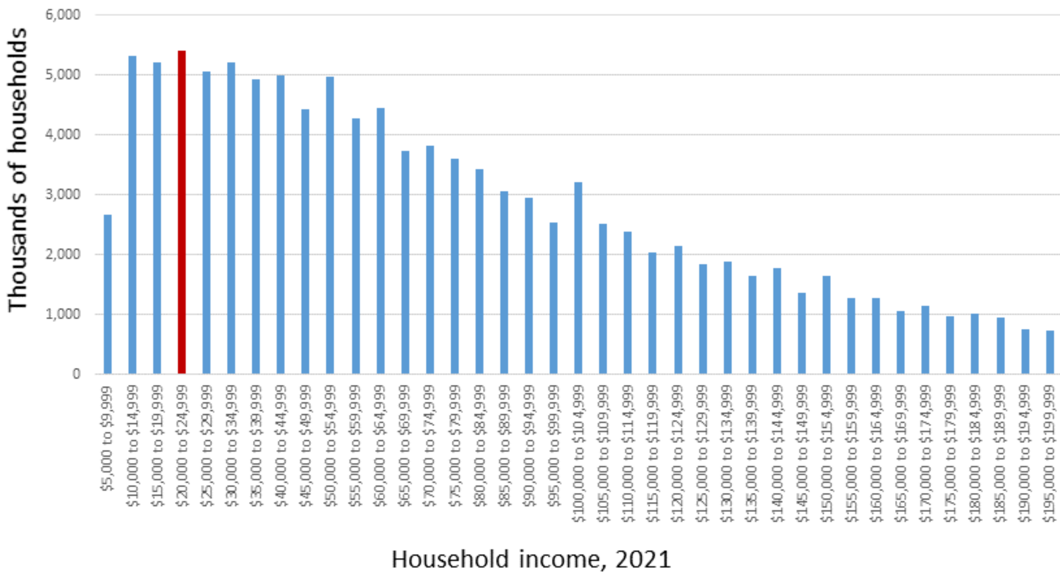
A6 Miscellaneous

Figure A4: Density of Per Capita Expenditure, Malawi IHS, 2016



Notes: Data are from the 2016 Malawi Integrated Household Survey. Kernel density estimate of per capita expenditure. 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. The red line indicates the median in the entire dataset.

Figure A5: Density of Household Income, United States, 2021



Notes: Household income in the United States. Data are from U.S. Census Bureau, Current Population Survey, 2022 Annual Social and Economic Supplement (CPS ASEC). The number of households in thousands. The red line indicates the mode among the binned income categories. The data represent 131,202,000 families. The median is $70,784, the mean is $102,316, and average per capita income is $40,857.

A7 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 A8: 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 A8 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.