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 best approximate the experience of poverty for those households whose income is steady or who can smooth consumption through the year. In reality, however, the experience of poverty is often marked by seasonality, economic instability, and illiquidity across months. To capture these elements, 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 when households face the dual challenges of low incomes and instability. 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 improving consumption smoothing, 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

The economic definition of poverty simplifies a complex set of deprivations by boiling the definition down to a lack of overall resources relative to a minimal financial threshold. The time dimension is left unspecified, but one of the sharpest and most common simplifications is to define poverty as a deficiency in yearly income or yearly consumption, a convention used since the late 19th century (Himmelfarb, 1984) and now employed globally (Atkinson, 2019). There are compelling reasons to focus on yearly resources rather than varying monthly, quarterly, or seasonal conditions. The widespread availability of annual data is a particularly big advantage, as is comparability to other annual measures like GDP and life expectancy. Moreover, poverty measured with yearly income or yearly consumption approximates the month-by-month degree of material deprivation when household income is steady during the year or when households are able to smooth consumption across months.

Recent randomized trials, however, reinforce earlier evidence showing that these conditions cannot be assumed: low yearly incomes are often accompanied by substantial swings in income and consumption during the year. For rural households, for example, illiquidity combined with agricultural seasonality creates within-year variability in consumption and pronounced periods when resources are much higher or lower than average (e.g., Breza et al. 2021, Bryan et al. 2014, Devereux and Longhurst 2012, Longhurst et al. 1986, Khandker 2012). What is conventionally described as poverty can be seen as a measure of the potential to consume in an idealized world of within-year steadiness and liquidity.

We use monthly household data from rural India to create a measure of annual poverty that is sensitive to economic ups and downs through the year. The data allow us to explore how understandings of poverty are shaped by the conventional choice to measure poverty with yearly sums versus higher frequency data. When viewed alongside conventional poverty measures, the framework shows how the condition of poverty combines insufficiency of overall resources together with instability and illiquidity. The higher-frequency data show times during the year when poor households are much poorer than their average resources suggest and other times when poor households have far greater ability to spend (Casaburi and Willis, 2018). The data show months when "poor" households are not poor, and when "non-poor" households are poor. These experiences of poverty are quantitatively substantial but uncounted in conventional poverty measures.

Our approach builds from a straightforward generalization of conventional poverty measures that defines annual poverty as the average of monthly 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, counting the household as having experienced a full year of poverty (if yearly earnings are below the annual poverty threshold). We similarly incorporate distributionally-sensitive poverty measures, like the squared poverty gap of Foster et al. (1984) and the Watts (1968) index. Since the rhythm of economic life is typically arranged around yearly cycles, aggregating to the annual level has intuitive appeal. By bringing seasonality and other sources of volatility into yearly poverty statistics, the approach also avoids the concern that transitory phenomena can cloud the interpretation of month-by-month poverty when snapshots are viewed independently (Atkinson, 2019).

Rural populations and the realities of rural life are of particular interest for understanding global poverty. Despite increasing urbanization (World Bank, 2021), rural residents comprise 80% of the world's population living below the World Bank $1.90 per day extreme poverty threshold.[1] They face the dual challenges of low earnings and seasonality.

[1] Of the population measured as poor by the World Bank's $1.90 per day per person extreme poverty measure, roughly 80 percent live in rural areas and are subject to seasonality (Castañeda et al., 2018). 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.

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) argues that the ups and downs of rural poverty have gone "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 statistics.

We estimate that in our sample the overall headcount poverty rate is 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 monthly expenditure will be a constant proportion of yearly expenditure). However, we find that the poverty rate increases by 26% (to 37%) when taking into account monthly movements in and out of poverty during the year. Increases in distributionally-sensitive measures are even larger.

Two opposing forces explain the increase relative to the conventional headcount. The months-in-poverty measure is reduced by the fact that poor households (as classified by yearly consumption) actually 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

[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

add up. Just under two-thirds of households experience poverty in at least one month per year, including 47% of "non-poor" households. Altogether, 35% of all months-in-poverty are attributable to deprivations experienced by people who would not conventionally be considered poor.

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 42% 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 heavier weight in the aggregations rather than being averaged out as in the conventional yearly approach).

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 was 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%. Instead, we estimate that the annual ratio is 31% for households measured conventionally as being poor, indicating considerable but imperfect smoothing. Better-off households (as measured by yearly expenditure) have greater ease smoothing than non-poor 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 19%.

The evidence relates to new research on within-year instability and illiquidity, including

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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 that 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 self-employment. [3]

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). 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 common intuition 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. The approach also shows that exits from and entrances to poverty are seldom as sharp as implied by annual snapshots. In our sample, almost half of all individuals who have "exited" poverty according to yearly measures nevertheless experience at least six months of poverty during the year of "exit."

These features open new perspectives on reducing deprivation. Most directly, the framework quantifies how 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

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

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 yearly transfer size 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 these interventions help households move money across time, they can have impacts on the experience of poverty that are missed by focusing only on total consumption (Islam and Maitra 2012, Beaman et al. 2014).

To further validate the approach, we use a least absolute shrinkage and selection operator (lasso) to allow the data to determine the predictive power of alternative approaches to poverty measurement. The VDSA data set includes measures of child weight and height, and using lasso we show that the higher-frequency poverty measure is a stronger predictor of these development outcomes than conventional measures

We focus on rural India and seasonal agriculture, but low-income workers in non-farm settings, including the urban United States, also cope with income swings; causes include the varying availability of work through the year, changes in household composition, health shocks, and moving to new locations (Collins et al. 2009, Maag et al. 2017, Morduch and Siwicki 2017, Schneider and Harknett 2020, Storer et al. 2020). As we find in rural India, most people in the United States who are counted as being poor in a given year (based on income) are not poor for the full year. Others who are counted as non-poor are poor some of the time. Using the 2009-11 US Survey of Income and Program Participation, Edwards (2014) finds that half of all poverty spells (measured with monthly household income) lasted less than 7 months, and 44 percent of spells lasted just 2-4 months.[4] [5]

[4]Using data from the 1983-86 U.S. Survey of Income and Program Participation, Ruggles and Williams (1989) found that the median poverty spell lasted only 4-6 months. (Spells are two or more continuous months of poverty.) The picture was similar 25 years later. When Edwards (2014) looks at only 2011, she estimates that 8.3 percent of Americans were poor every month of the year, but about one quarter of Americans spent two or more months below the poverty line.

[5]These swings in income translate into swings in consumption. Using data from a large US financial institution, Ganong et al. (2020) show that households in the United States with low liquid wealth cut their

As higher-freqency data sets become more common—including surveys collected over multiple waves within years (e.g., Azevedo and Seitz 2016a, Dercon and Krishnan 2000), administrative data (e.g., Ganong et al. 2020), and financial diaries (e.g., Collins et al. 2009)—the framework will have broader application. Beyond data availability, the framework faces other challenges. In the final section of the paper, we discuss methodological and conceptual questions that arise when using high-frequency data to measure poverty, including the need for high-frequency data, concerns regarding spending on durables, and the possibility that household needs vary through the year.

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 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 over a year. Atkinson (2019) frames the choice as a tradeoff of intrepretation versus accuracy: The month-by-month measures give insight into time-specific deprivation, but transitory events can make it hard to see the picture for the full year. 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).

Our framework shifts the question. We consider poverty over a year – avoiding Atkinson's concern about 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

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.

of poverty for each household, while keeping an approach based on annual averages.

We begin with the year divided into 12 months.[6] 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 $P(c_{it})$:[7]

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

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:

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

where the poverty index is decomposable and differentiable. Calvo and Dercon (2009) and Foster (2009) use a similar approach when considering the persistence of poverty across years. (The approach can alternatively be applied to quarters, seasons, or other periods.)[8]

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

[6] 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 – is collected monthly. There are detailed questions on expenditures and income for each month. Rather than aggregating these to some higher level, we instead choose to use the monthly set up of the data. This approach is flexible, however, and can easily be adapted to data collected on a different timeframe.

[7] 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.

[8] The most commonly used poverty measures are decomposable and differentiable, including the headcount measure, the distributionally-sensitive Watts measure (Watts, 1968), and the Foster-Greer-Thorbecke class of measures (Foster et al., 1984). 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.

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.

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

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

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:

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

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

The notation helps show several implications of the framework. First, the conventional approach to measuring poverty (low frequency poverty) reflects the actual experience of being poor in one of two cases: (i) the special case in which there is no instability within the year (earnings, needs, and consumption are unvarying across periods), or (ii) the special case in which households face instability but have ample financial mechanisms to perfectly 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.[9] As noted above, neither case (i) nor (ii) is a reliable assumption in low-income populations.

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 aggregate 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.[10]

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[9] 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.

[10] To be more explict: 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

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.The extent of their challenges with poverty (and the implications of better-than-average periods) is unaccounted for in the standard measure of average yearly poverty (Collins et al., 2009). This also allows policymakers to identify characteristics that are distinct from average consumption but which may also affect the ability to smooth consumption. For example, two households with the same average consumption may nonetheless have different consumption-smoothing capabilities depending on sector of employment, education, networks, etc.

Fifth, we assume here that poverty can be measured using data on household expenditures and consumption; in most countries, especially low-income economies, consumption data are generally higher quality than income data (Deaton 1997, Carletto et al. 2021). Those data may not be available, however, or income data may be much more reliable than consumption data. Measuring poverty at a higher frequency heightens the distinction between income-based measures and consumption-based measures (Atkinson 2019, Bradbury et al. 2001). Imagine that one only has income data but ideally wants to measure high-frequency poverty using expenditure data, $P(c_{it})$. Measuring poverty with Equation 2 with income rather than consumption is equivalent to assuming that no consumption

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 the household gained access to a smoothing mechanism that allowed it to consume exactly 58 USD in each month. The measured monthly poverty would actually increase (from 11 of 12 months to all 12 months). However, the distributionally-sensitive Watts (1968) index would actually 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).

smoothing is possible: $c_{it} = y_{it}$ for all t. In contrast, measuring poverty with Equation 3 with income rather than consumption is equivalent to assuming that there is perfect consumption smoothing during the time frame: $c_{it} = \bar{y}_i$ for all t. Neither assumption accords with the imperfect smoothing (neither fully absent nor fully complete) observed in low-income communities. If income is unsteady but consumption smoothing is fairly extensive, it may be that the conventional yearly poverty measure based on income is a better approximation to $P(c_{it})$ than is the monthly poverty measure based on income.

Sixth, 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). The 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 typically discontinuous as households often 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).

Seventh, 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 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 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 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 poverty measures that reflect different dimensions of deprivation: the poverty headcount, the poverty gap, the squared poverty gap (all three of which belong to the Foster-Greer-Thorbecke – FGT – set of measures in 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.[11]

When we calculate conventional 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 integrating it within our framework, we calculate

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

where the indicator $1_{\bar{c}_i<z}$ is one when households are poor based on average consumption

[11]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. 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).

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

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

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 and methodology

3.1 Data

The data are from the Longitudinal Village Level Studies of the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) collected in India between 2010 and 2014. The 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 are Hindu and the other 6% are divided between 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.

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 did not graduate	0.486	0.688	0.495
primary	(0)	(1)	(0)
Head graduated primary	0.278	0.153	0.251
but not lower secondary	(0)	(0)	(0)
Head graduated lower secondary	0.236	0.159	0.254
	(0)	(0)	(0)
Income p.c. (R's)	1205.167	1387.972	1466.794
	(869.173)	(1059.050)	(1025.111)
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) has slightly more than six individuals across the six demographic groups, with the most common groups 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 financial transactions. In production activities, we include all the costs and revenues originating from cultivation, employment, and livestock. In financial transactions, we include all the savings, remittances, benefits from the government, loans, and gifts that the households receive or spend on a monthly level. 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, for example, 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, which we discuss below.

Expenditures are more straightforward. Surveys are implemented each month and consumption is divided by whether is is home produced, purchased, or received as a gift. We take a simple sum across these categories.

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 mean household income in column 3 is 34% higher than mean expenditures. The measure of median income is 19% higher than median expenditures.

Wealth records include all the durables and assets (land, gold, and machinery) that the household owns. It is originally a yearly level variable, but it is expanded to the monthly level and the depreciation rate is calculated for each type of good. The wealth variable is highly right skewed, with a mean much higher than the median.

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, we overweight landless households, multiplying the household size by 1.5 for the final sample weights.[12]

Column one 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 balanced panels (four full years in column two and five full years in column three). Column two contains 116 households and column three 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.

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 are 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).[13] 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

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

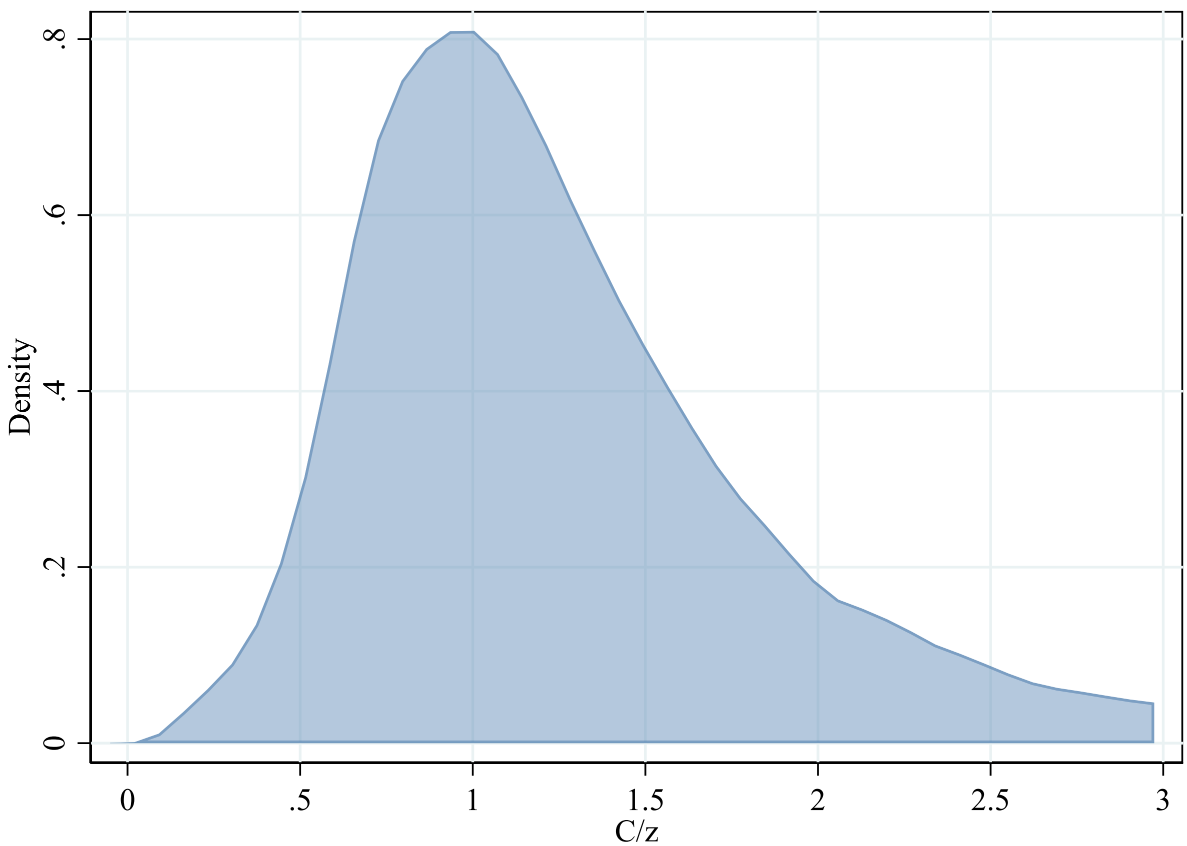
[13]Reserve Bank of India (2021). Handbook of Statistics on the Indian Economy, 2020-21. Table 151 : Number and Percentage of Population Below Poverty Line. https://www.rbi.org.in/scripts/PublicationsView.aspx?id=20556

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 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.

An important feature of the density is that the mode is roughly at 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. For these groups, which together comprise 35% of the sample, variability in monthly expenditure can lead to movements across the poverty line.

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 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. The interest is in consumption rather than spending when measuring poverty, but most surveys focus on spending (Coibion et al., 2021).

Table 2 shows that 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 one) and semi-durables (column two) 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 on semi-durables.The second quartile shows very 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. In other words, 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 that year. The distribution almost completely overlaps the original expenditure distribution in Figure 1, and monthly poverty rates with the smoothed durables/semi-durables are still 19 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.

3.3 Regression methodology

We employ a series of fixed effect panel regressions to describe the co-movement of income and expenditure across months. We investigate co-movement by estimating regressions of the form,

$$c_{it} = \beta_0 + \beta_1 y_{it} + \varepsilon_{it}, \tag{8}$$

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.

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 regressions explain differences between conventional poverty measurements based on yearly resources and the high-frequency measure. If households smooth consumption perfectly and permanent income does not change, for example, income and expenditure should not covary within households. Co-movement of income and expenditure, conditional on fixed effects, is reflected by $\beta_1 > 0$.

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 also tend to spend more money. However, with the household fixed effects, we restrict identification to only changes in income and expenditures within the household.

Of course, income and expenditures can 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. As additional robustness checks, we include flexible lags and leads of income to even better capture possible changes in expected income. We present these results in the appendix.

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, however, we are interested in partialling out covariate shocks. In other words, if the totality of the covariance between expenditures and income are 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.

After these regressions, we turn to relationships between different poverty measures in a similar spirit:

$$P(c_{it}) = \gamma_0 + \gamma_1 P(y_{it}) + \gamma_2 P(\bar{c}_i) + \mu_{it}, \tag{9}$$

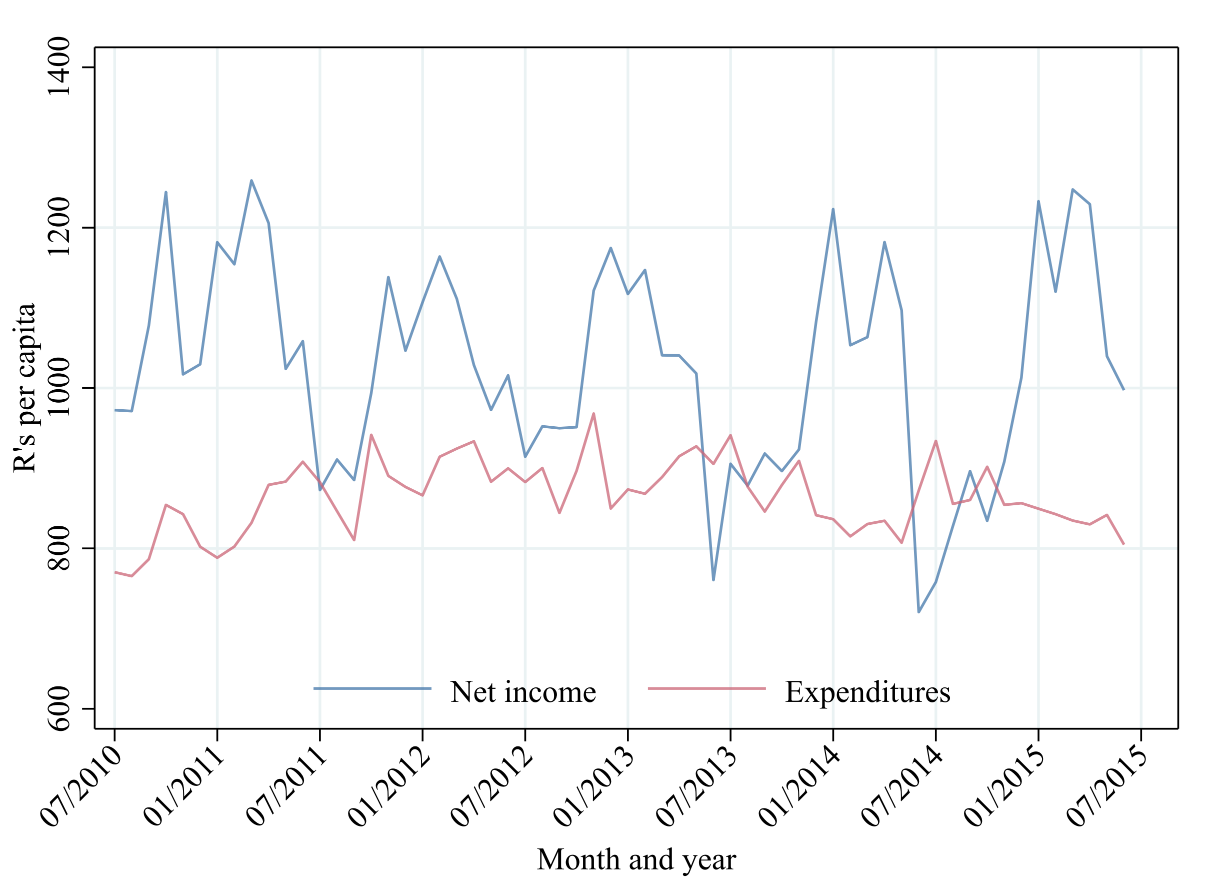
where $P(c_{it})$ is the expenditure-based months-in-poverty measure, $P(y_{it})$ is the income-based months-in-poverty measure, and $P(\bar{c}_i)$ is the expenditure-based yearly poverty measure. The aim is to show how within-year variation in expenditure translates to poverty measures. The same intuition around the fixed effects in the previous section apply here.

4 Results

4.1 Income variability and consumption variability

Figure 2 show 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.

Figure 2: Median income and expenditures



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 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 1.79 and the mean CV of expenditure is 0.37. The ratio of the latter to the former is 21%, consistent with substantial consumption smoothing. But the fact that the mean CV of expenditure is 0.37 shows that there is still considerable variability in expenditure. To put the CV in context, a CV of 0.52 would be generated if a household's monthly income was 50% above the mean for half the year and 50% below the mean for the other half.

4.2 Regressions: Income and Consumption

The simple calculations of the extent of consumption and income variability are echoed in the regressions below as well as in the high frequency poverty analysis. First, we estimate regressions to better identify the nature of their co-movement. We expect changes in poverty rates when moving from yearly values to monthly averages when consumption varies across time. As such, we first present regressions explaining movements in consumption before moving to changes in estimated poverty rates.

Table 3 presents these results. The dependent variable is monthly expenditures and the independent variable is monthly income disaggregated by the highest education level of the household head. Intuitively, if households are perfectly smoothing consumption (proxied here with expenditures), then monthly consumption should not vary with monthly income.[14]

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 higher monthly expenditures.

[14]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.

Column 3 adds household fixed effects, which remove variation across households and instead focus on changes in monthly income and monthly expenditures within households. We strongly reject no correlation between monthly income and monthly expenditures within households over the course of the sample. However, the coefficient in column two is decidedly smaller than the coefficient in column one, since it only reflects within-household variation.

Even if households are smoothing consumption, we might see a correlation between current income and current expenditures if permanent income changes. We implement two alternative specifications in Table 3 to explore this possibility. First, column three includes household-year fixed effects instead of household fixed effects. The specification limits within-household variation to just 12 months, markedly reducing the probability that changes in permanent income are driving the coefficients. Consistent with the results in column 2, the coefficient changes little.

Column 4 takes a different approach. Instead of including household-year fixed effects, we include household fixed effects and instead add an additional control: average expenditures in the last 12 months. Again, the idea is to capture changes in permanent income. Results again remain consistent, with the coefficient barely changing and remaining significant.

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 3: all three coefficients are either 0.033 or 0.034.

Finally, column 5 includes village-by-year-by-month fixed effects. Given the results in the first four columns, column 5 instead asks 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.

A key question is whether households with higher social status (a proxy for greater assets and connections) are more able to smooth consumption than others. As noted, Table 3 provides estimates by education of the household head. We present marginal effects of income for three different levels of education: less than primary, primary graduate, and secondary graduate (or higher).

Column 2 includes household fixed effects, and the results are consistent with the least-educated households being least able to smooth consumption. Specifically, the coefficient for current income for those with less than primary education is twice as large for those who are secondary graduates ($p<0.01$). Households with heads who ended their education after graduating from primary school are also less able to smooth consumption, with a coefficient more than 70% larger than those who graduated from secondary school, and this difference is marginally significant ($p=0.11$).

Results in columns 3 and 4 are consistent with the results in column 2. We strongly reject equality of the coefficient for those with less than a primary education and those who graduated secondary. In Table A3, we present 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.

4.3 Measuring high-frequency poverty

Having shown the variability in expenditure across the year, we next show how moving from yearly estimates of poverty to monthly estimates extends understandings of poverty. The results show how a yearly focus misses a substantial part of the experience of poverty.

Table 3: Co-movement of monthly expenditures and income, marginal effects by education of head

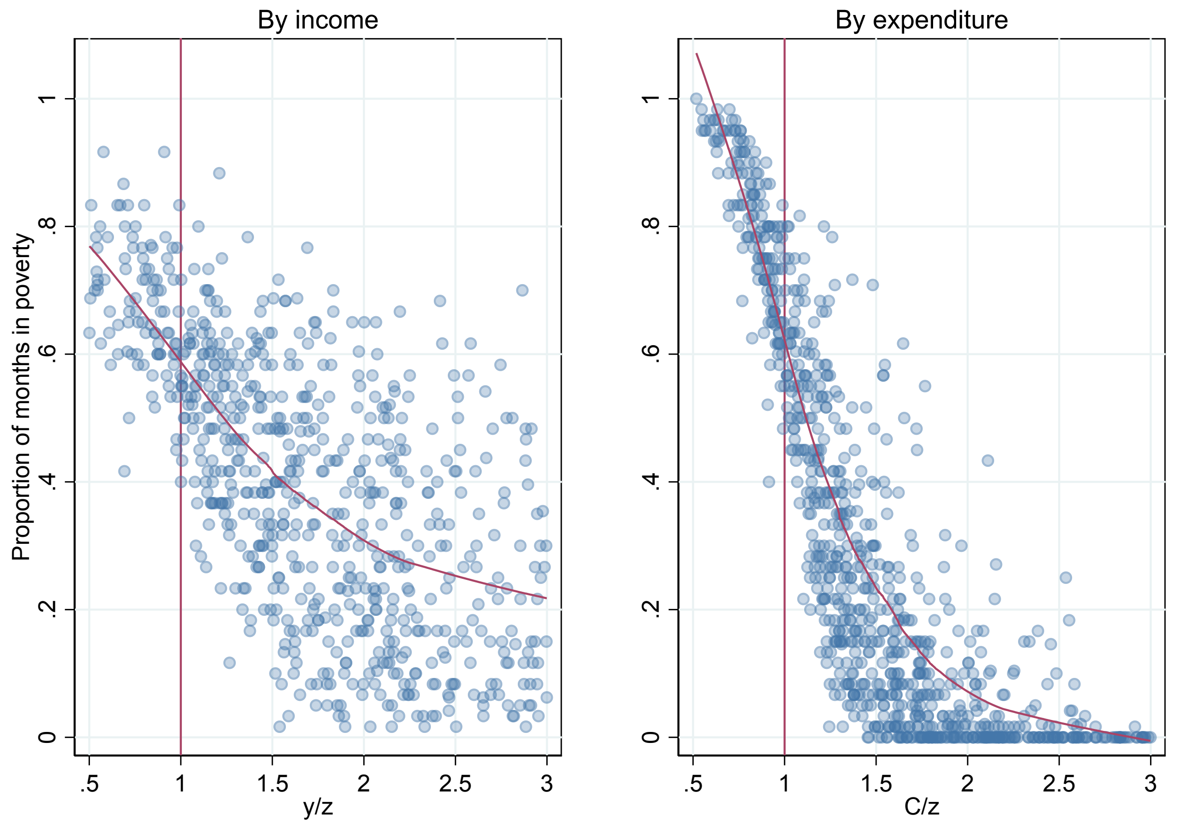
	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Current income - less than primary	0.057***	0.059***	0.044***	0.040***	0.042***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Current income - primary graduate	0.059***	0.060***	0.038***	0.037***	0.037***
	(0.010)	(0.010)	(0.009)	(0.008)	(0.008)
Current income - secondary graduate	0.050***	0.050***	0.022***	0.021***	0.021***
	(0.012)	(0.012)	(0.005)	(0.006)	(0.006)
Tests of equality (p):					
Less than prim. = Prim.	0.898	0.893	0.590	0.707	0.587
Less than prim. = Sec.	0.597	0.561	0.009	0.017	0.008
Prim. = Sec.	0.573	0.538	0.114	0.115	0.113
Fixed effects:					
Year-month		X	X	X	
Household			X		
Household-year-month				X	X
Village-year-month					X
R-squared	0.056	0.064	0.364	0.459	0.493
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

Figure 3 shows how the experience of poverty (measured as each household's average months in poverty in a year) compares to their poverty status according to yearly resources. To construct these figures, we take each household's average monetary measure (income for the left panel and expenditures for the right panel) across the entire sample and divide by the poverty line. This ratio is on the x-axis, with a value of one indicating that the household is right at the poverty line; a value of 3 indicates that the household's annual resources are 300% of the poverty line. The y-axis is the proportion of months that a household is in poverty. The red curves are smoothed estimates of the average share of months in poverty for the sample.

If there was no income instability, households would be either poor all year or not poor all year. All the dots would be lined up at 1 (=12 months in poverty) if $y/z < 1$ (the poor part of the sample) and all dots would line up at 0 (no months in poverty) if $y/z > 1$ (the not poor part of the sample). The left panel shows that most households are neither poor all year non not poor all year. The downward sloping curve is a non-parametric estimate of the average share of the year in poverty at the given average income.

Figure 3: Months in poverty and annual income/expenditures



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

Out of 692 households in the figure, not a single household has zero months of income poverty.[15] Moreover, households relatively far from the poverty line – above a ratio of two, for example – still experience a substantial amount of income poverty.

The difference when compared to expenditures is striking. There are a substantial number of households who are never expenditure poor. Similarly, the distribution of poverty for a given ratio is much smaller for expenditures than for income. All the same, many households experience months of poverty even when measured by expenditure.

[15]The figures are restricted to households with yearly expenditure or income below 300% of the poverty line, and even for households above a ratio of 300% – not shown on the graph – just five households – out of 179 – do not have a single month of income poverty.

These graphs are consistent with the evidence that households smooth consumption, but imperfectly.

Table 4 shows weighted poverty summary statistics that correspond to Figure 3. The first column is the simple average of household expenditure for the entire sample. The second column presents means for households who are defined as poor for the entire year – in other words, using conventional poverty measures – while the third column presents means for households who are (conventionally) not poor for the year.

When measuring poverty by yearly household expenditure, poor households comprise 29% of the sample, but when turning to monthly household expenditure, 37% of all household-months are spent in poverty. Focusing on months-in-poverty instead of yearly poverty shows an increase in the headcount poverty rate by more than a quarter. The increase for the distributional sensitive measures, the Watts (1968) index, and the squared poverty gap of Foster et al. (1984) are even larger, at 40% and 48%, respectively.

The data also show that most households experience poverty at least once per year: 62.7% of all households experience at least one month of poverty while 47.3% of *non-poor* households 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.

Table A5 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). Based on this, we present the unsmoothed figures in the main results below and provide results with smoothed data in the appendix.

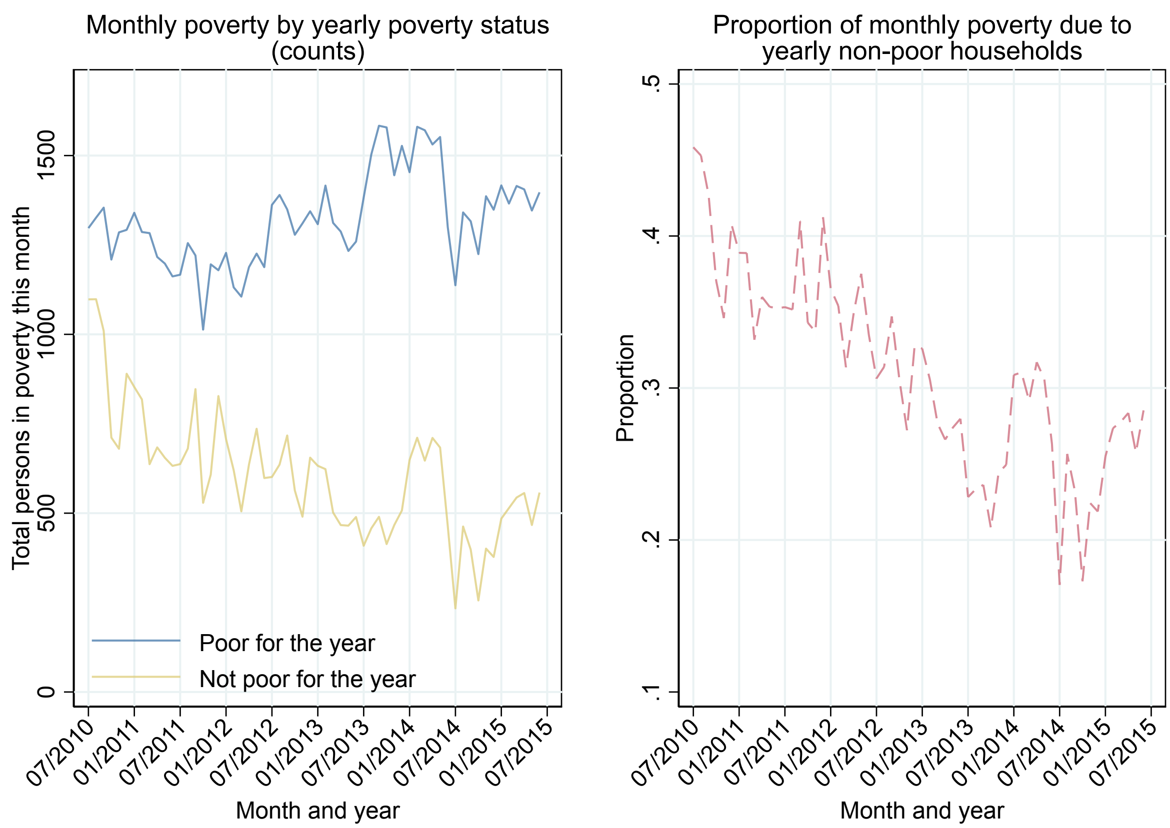
Table 4: Poverty summary statistics

	(1) Everyone	(2) Poor for the year	(3) Not poor for the year
Weighted proportion		0.292	0.708
Mean yearly poverty	0.292	1.000	0.000
Mean monthly poverty	0.368	0.863	0.164
Mean yearly watts	0.089	0.303	0.0
Mean monthly watts	0.125	0.361	0.028
Mean yearly squared poverty gap	0.025	0.087	0.0
Mean monthly 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. All statistics are weighted.

Since 71% of people live 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 4 breaks down the total number of people in poverty in each month across the sample using expenditures. Towards the beginning of the sample period, (yearly) non-poor households sometimes contribute up to 40% of total person-months of poverty. This proportion is decreasing over the sample period, but is still between 20 and 30% of all poverty by the end of the sample. In other words, focusing on yearly poverty may miss between 20 and 40% of months in poverty.

Figure 4: Total number of people in poverty,
by month and poverty status



Notes: The left figure disaggregates households into those who are poor for the entire year, using average monthly expenditures across the 12 months, and those who are not poor for the entire year. All counts and proportions are weighted.

The results above show that education is an important predictor of the ability to smooth consumption. We return to a breakdown of monthly and yearly poverty rates by education of the household head.

Table 5 presents simple means of three types of headcount poverty: monthly expenditure poverty, monthly income poverty, and annual expenditure poverty. This yearly poverty measure is defined based on each survey year, motivated by conventional yearly statistics that are defined similarly. We present means for each of these three poverty measures across three groups based on education.

Table 5: Average poverty headcounts by education of household head

	(1) Less than primary	(2) Primary	(3) Secondary
P(month, income)	0.384	0.422	0.392
	(0.013)	(0.021)	(0.020)
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)	0.131	0.053	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 linkage of poverty and household finance makes three clear predictions regarding consumption smoothing and poverty measures. First, if households smooth perfectly, the measures of expenditure-based months-in-poverty and yearly poverty should be identical. Second, if households do not smooth at all, then expenditure-based months-in-poverty should equal income-based months-in-poverty. Third, if households smooth but do so imperfectly, then expenditure-based months-in-poverty will fall somewhere between income-based months-in-poverty and expenditure-based yearly poverty.

There are several striking patterns in Table 5. 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.

But the second row shows that months-in-poverty as measured by expenditure decrease markedly from the first column to the third column. The group with the most education reduces their exposure to poverty by 36%. In contrast, 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 rises, as seen by expenditure-based months-in-poverty exceeding income-based months-in-poverty, but the difference is not statistically significant (p=0.13).

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. For them, conventional measures that use yearly income provide a closer prediction. Households whose heads have stopped after primary education fall somewhere between these two extremes. Specifically, while we cannot reject that monthly expenditure and income poverty are the same for column one, monthly expenditure poverty is approximately half way between annual expenditure and monthly income poverty for those in column two and monthly expenditure poverty is only around one quarter of the way between annual expenditure and monthly income poverty for those in column three.

4.3.1 Monetary comparisons of monthly and yearly poverty

A goal is to compare yearly poverty measures to monthly poverty measures. This 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 and Watts (1968) index, we expect even larger differences when moving from the year to the month.

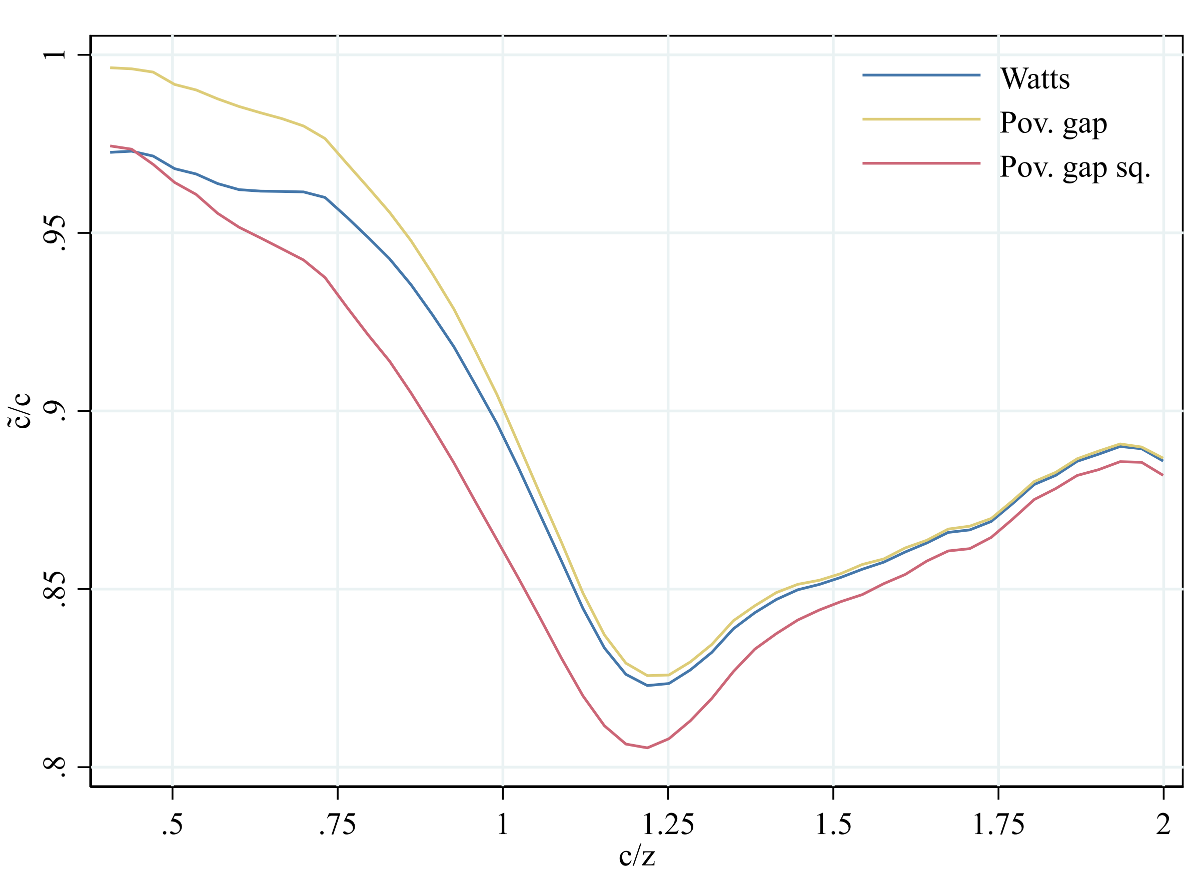
However, especially for the squared poverty gap and the Watts (1968) index, interpretation is more complicated. To aid intuition of the changes, we calculate monetary comparisons using a calculation of implied equivalent yearly expenditure. Consider the monthly squared poverty gap described in Equation 6 and Equation 7. Using the monthly expenditure values, we calculate the monthly poverty measure, $P(c_{it})$. We then plug this value into the yearly definition (i.e. Equation 6), as such:

$$P(c_{it}) = \frac{1}{12N} \sum_{t=1}^{12} \sum_{i=1}^{N} \left[\left(\frac{z_{month} - \bar{c}_i}{z_{month}} \right)^2 \cdot 1_{\bar{c}_i < z} \right]. \tag{10}$$

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:

$$\text{implied income} = \frac{\tilde{c}_i}{\bar{c}_i} \tag{11}$$

Figure 5: Implied yearly expenditures, non-headcount measures

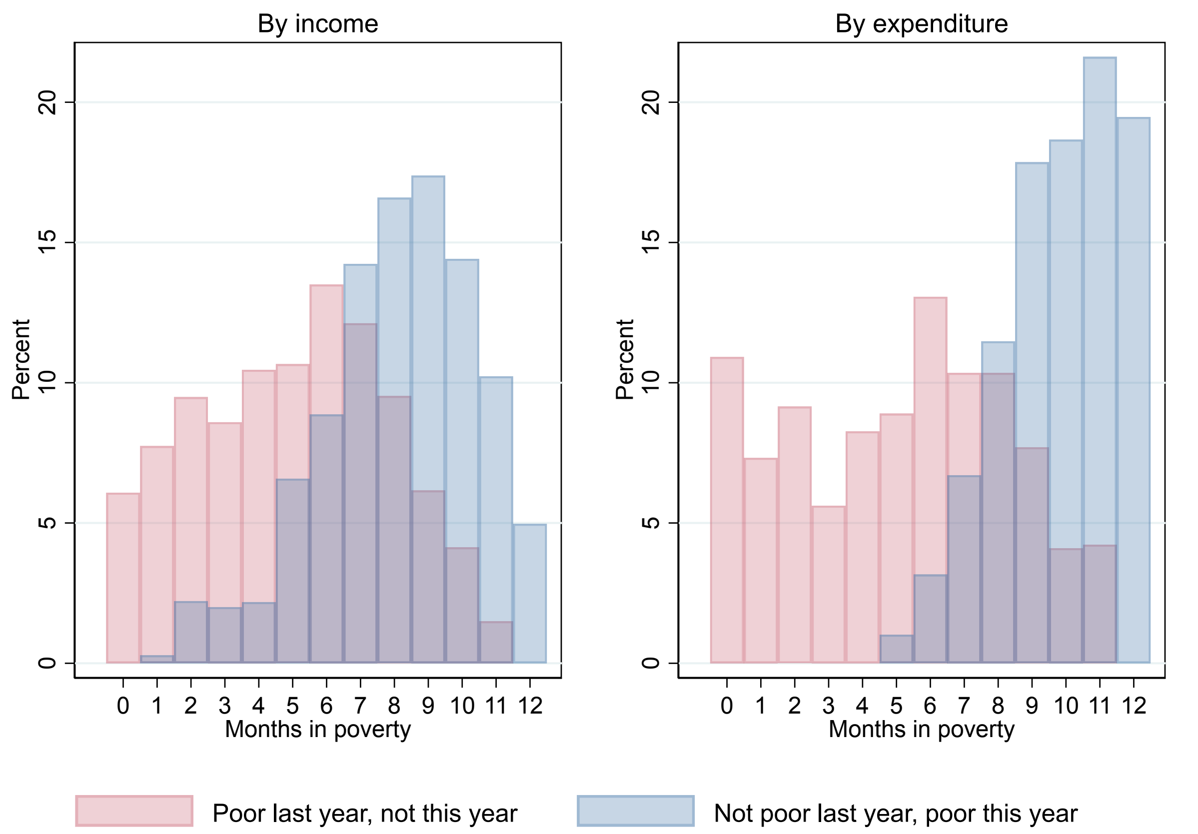


Notes: We calculate the implied yearly expenditure by inverting the poverty measure to find the yearly expenditure that yields the same value on the poverty measure as using the monthly value.

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 (1968) 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 household's average expenditure level was 15% or more smaller but smoothed across the year.

4.4 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.

Given the amount of poverty experienced by non-poor households, an important question is: what does it mean to exit or enter poverty? Figure 6 presents what we might traditionally define as "exit" and "entrance" with respect to poverty. Specifically, 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. A simple expectation would be that people who are poor last year but not this year should experience zero months 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 red spike at zero and a single blue spike at 12.

The panels show something very different, with the mode for the red bars at six months in both panels. For households who exit poverty, a substantial proportion continue to experience poverty, regardless of whether we use income or expenditures. With income, almost 95% of all individuals experience at least one month of poverty, 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.

The story is clearer for households that "enter" poverty, however, 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 durable, many of the same conclusions remain (Figure A3 in the Appendix).

4.5 Predictive power

The high frequency poverty framework was developed on normative grounds, but it has predictive power to explain household outcomes that may make the measure useful in other ways. Here, 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 collects anthropometrics – weight and height – once per year for each household.[16] 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 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 around 23 percent stronger for the one-year lag (correlation coefficient = -19.9 versus -16.2 for the one-year lag) and around 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 monthly, high-frequency poverty measure is more strongly correlated with height-for-age than is the conventional annual 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 monthly poverty measures are significantly predictive of outcomes. Consistent

[16]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.

Table 6: Anthropometrics and poverty measures - Regressions

	Weight		Height	
	(1)	(2)	(3)	(4)
	Current	Lag only	Current	Lag only
Current monthly poverty	−0.006		−0.037	
	(0.005)		(0.061)	
Lagged monthly poverty		−0.009*		−0.177**
		(0.005)		(0.071)
Current poverty	0.001		−0.016	
	(0.003)		(0.037)	
Lagged annual poverty		−0.003		−0.051
		(0.003)		(0.045)
Fixed effects:				
Individual	X	X	X	X
Year	X	X	X	X
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

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 of lags are three times as large for the high-frequency measures (aggregated to the year from monthly indices) than for the conventional measures (based on yearly resources).

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. Specifically, we include a range of covariates and let lasso select the most predictive. We do this in Table 7. 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.[17] We estimate lasso in Stata using the *bic, postselection* option.

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

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 just a single variable regardless of whether the outcome is demeaned or not: monthly poverty. The coefficients are especially noteworthy for height. Since height is standardized by age, the coefficients can be interpreted in standard deviations. When the lagged monthly 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 monthly poverty measure – leads to a decrease of around 0.02 standard deviations.[18]

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 year by year.[19]

4.6 Policy experiment

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 in the 1980s that over than one-third of all poverty spells could have been eliminated

[18]In the appendix, Table A6 also shows that the same results hold when we use expenditures smoothed for durables over the year.

[19]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.

Table 7: Selecting the best predictors of anthropometrics through lasso

	Weight		Height	
	(1)	(2)	(3)	(4)
	Levels	Demeaned	Levels	Demeaned
Current monthly poverty	−0.074***	Not	Not	Not
	(0.013)	selected	selected	selected
Lagged monthly poverty	−0.103***	−0.019***	−0.515***	−0.235***
	(0.013)	(0.006)	(0.125)	(0.096)
Current quarterly poverty	Not	Not	Not	Not
	selected	selected	selected	selected
Lagged quarterly poverty	Not	Not	Not	Not
	selected	selected	selected	selected
Current annual poverty	Not	Not	Not	Not
	selected	selected	selected	selected
Lagged annual poverty	Not	Not	Not	Not
	selected	selected	selected	selected
Observations	13,554	13,554	3,037	3,037

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

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.[20]

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.

Recall the discussion around Equation 5 of how overall changes in months-in-poverty respond to a change in an external factor can be decomposed 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. Throughout this exercise, 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, that the effect on

[20]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.

yearly poverty measures are unchanged. We focus on how this transfer allows households to change the distribution of resources throughout the year. For example, while a micro-finance initiative may not lead to increases in yearly income, it may allow households to move resources across time, affecting how monthly expenditures vary around the mean. The focus on yearly incomes (or income in a single month) misses this change, despite it being a clear increase in welfare.

In each hypothetical intervention, we transfer 960 rupees per capita per year to all households below the poverty line in a given year (as measured by yearly expenditure). However, we vary how we make the transfers: either monthly (80 Rs per month), over six months (160 Rs per month), or over three months (320 Rs per month). In the latter two cases, we make this transfer in the poorest months that the households experience in a given year. We assume the household consumes the entirety of the transfer in the month they receive it.[21]

This relates to Equation 5, which showed that any effects of changes in the policy environment can be broken down into effects on mean consumption and effects on variation around that mean. Since all three designs transfer the same amount of money, any differences are attributable purely to the latter effect.

We focus on 391 households whose total yearly income is below the poverty line. They are observed for 12,300 household months, and 86% of these are spent below the poverty line. Receiving a steady monthly transfer reduced months in poverty to 74%. If those transfers were instead transferred in the poorest six months,

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

[21]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

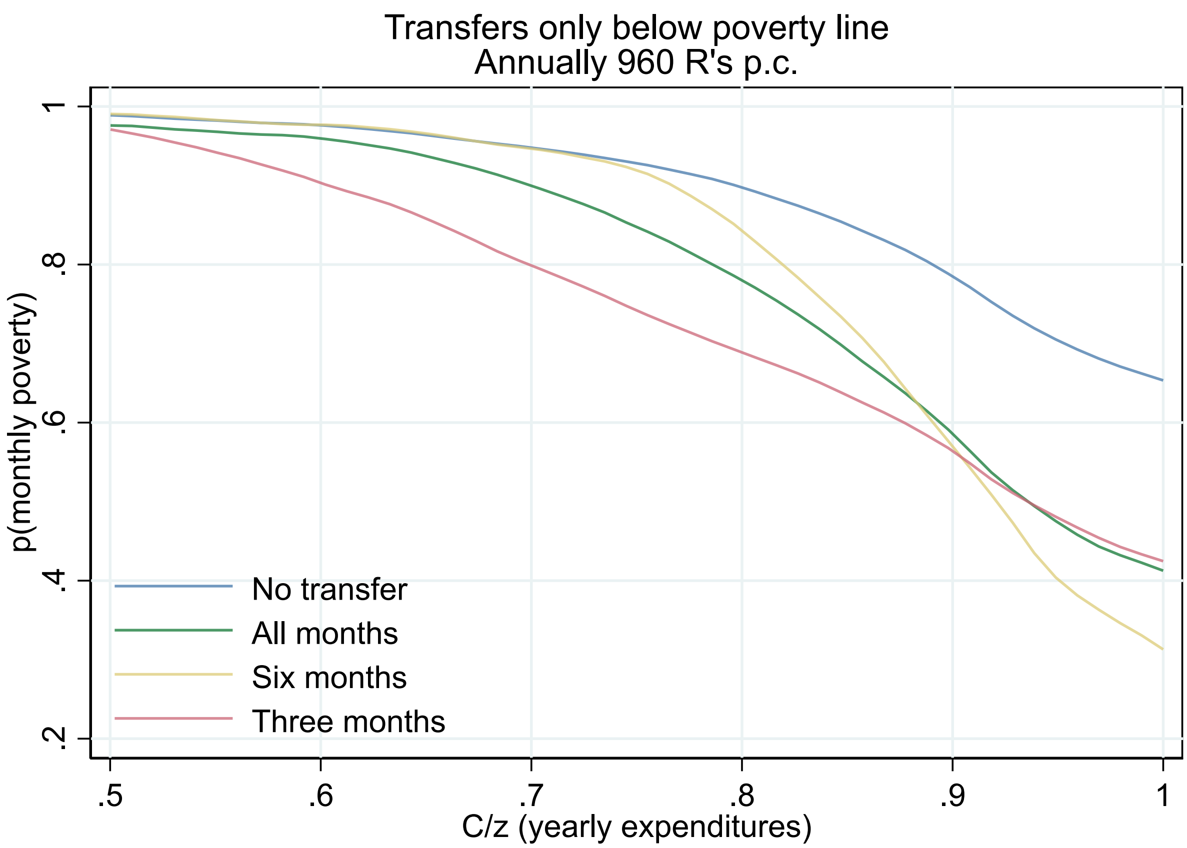
Notes: The same total amount of 960 rupees per person per year is transferred in all designs (except "no transfer"). That money is transferred in 12 equal payments for the "all months" design, in six equal payments for the "six months" design, and in three equal payments for the "three months" design.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

monthly transfer of 80 Rs decreases poverty by 13.9 percent (12 p.p.). Transferring 320 Rs every four months (or 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 monthly transfer decreases poverty by 39.4 percent, while the transfer across six months decreases poverty by 42.4 percent, or 7.6 percent more than the monthly transfer. Interestingly, the transfer across 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.

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 aa 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 that the challenges go beyond the hardest three months. In other words, the challenges go beyond a well-defined period of seasonal poverty.

5 Conclusion

Evidence from household finance shows that the experience of poverty is 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 in those earnings and in needs within the year. Illiquidity reflects households' challenges in coping with instability, leading to spikes and dips of within-year consumption.

Poverty, as conventionally measured, captures the experience of material deprivation in the special case in which consumption is steady. The framework developed here, focusing on months-in-poverty during the year, opens a window on variance around mean levels of deprivation, not just the mean alone. In this way, the framework brings instability and illiquidity into poverty measurement. The aim is to complement conventional approaches in parallel to the way that the addition of distributionally-sensitive measures has broadened understandings without replacing the still-popular 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.

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 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.

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 deeper deprivation. As a result policy targeted to the most challenging periods can have particular impact. Helping households to smooth consumption can also reduce the experience of poverty, even when total resources are unchanged.

The most practical limit to implementing the framework is the need for monthly data, although the approach can be adapted to data sets with multiple waves of data collected within the year (e.g., Azevedo and Seitz 2016b).[22] We expect that new data collection efforts will follow from the growing appreciation of within-year instability and illiquidity.

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. However, 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

[22]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. 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.

period. This is a particular issue for durables and semi-durables and, where possible, we convert 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 could 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 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 the 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.

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. In expanding the measurement framework, we inevitably open new conceptual questions. Specifically, 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 to other periods of poverty? We see value in exploring these questions, no matter how poverty is measured.[23]

[23] A parallel question arises for conventionally-measured yearly poverty when viewed across years. Turning to the ethics 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?

References

ADDISON, T., D. HULME, AND R. KANBUR, eds. (2009): *Poverty Dynamics: Interdisciplinary Perspectives*, Oxford: Oxford University Press.

ATKINSON, A. B. (2019): *Measuring Poverty Around the World*, Princeton, NJ: Princeton University Press.

AZEVEDO, J. P. AND W. SEITZ (2016a): "How Persistent is Poverty in the Short Run?" World Bank Let's Talk Development Blog.

——— (2016b): "Is Poverty Seasonal?" World Bank Let's Talk Development Blog.

BANE, M. J. AND D. ELLWOOD (1986): "Slipping Into and Out of Poverty: The Dynamics of Spells," *Journal of Human Resources*, 21, 1–23.

BANERJEE, A., D. KARLAN, AND J. ZINMAN (2015): "Six Randomized Evaluations of Microcredit: Introduction and Further Steps," *American Economic Journal: Applied Economics*, 7, 1–21.

BAULCH, B. AND N. MCCULLOCH (2000): "Economic mobility and poverty dynamics in developing countries," *Journal of Development Studies*, 36, 1–24.

BEAMAN, L., D. KARLAN, B. THUYSBAERT, , AND F. TRUFFA (2014): "Saving for a (not so) Rainy Day: A Randomized Evaluation of Savings Groups in Mali," Tech. Rep. Northwestern Department of Economics working paper.

BERG, C. AND M. S. EMRAN (2020): "Microfinance and Vulnerability to Seasonal Famine in a Rural Economy: Evidence from Monga in Bangladesh," *B.E. Journal of Economic Analysis Policy*, 20, 1–36.

BIEWEN, M. (2014): "Poverty persistence and poverty dynamics," *IZA World of Labor*.

Bradbury, B., S. Jenkins, and J. Micklewright (2001): "Conceptual and measurement issues," in *The Dynamics of Child Poverty in Industrialised Countries*, ed. by B. Bradbury, S. Jenkins, and J. Micklewright, Cambridge: Cambridge University Press, 27–61.

Breza, E., S. Kaur, and Y. Shamdasani (2021): "Labor Rationing," *American Economic Review*, 111, 3184–3224.

Bryan, G., S. Chowdhury, and A. M. Mobarak (2014): "Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh," *Econometrica*, 82, 1671–1758.

Cai, J., M. Meki, S. Quinn, E. Field, C. Kinnan, J. Morduch, J. de Quidt, and F. Said (2021): "Microfinance," *VoxDevLit*, 3.

Calvo, C. and S. Dercon (2009): "Chronic poverty and all that: The measurement of poverty over time," in *Poverty Dynamics: Interdisciplinary Perspectives*, ed. by T. Addison, D. Hulme, and R. Kanbur, Oxford: Oxford University Press.

Carletto, G., M. Tiberti, and A. Zezza (2021): "Measure for Measure: Comparing Survey Based Estimates of Income and Consumption for Rural Households," *The World Bank Research Observer*, 37, 1–38.

Casaburi, L. and J. Willis (2018): "Time versus State in Insurance: Experimental Evidence from Contract Farming in Kenya," *American Economic Review*, 108, 3778–3813.

Castañeda, A., D. Doan, D. Newhouse, M. C. Nguyen, H. Uematsu, and J. P. Azevedo (2018): "A New Profile of the Global Poor," *World Development*, 101, 250–267.

Chambers, R. (1983): *Rural Development: Putting the Last First*, Harlow, UK: Pearson/Prentice-Hall.

Christiaensen, L. and A. F. Shorrocks (2012): "Measuring Poverty Over Time [Special issue]," *Journal of Economic Inequality*, 10, 160.

Christian, P. and B. Dillon (2018): "Growing and Learning When Consumption Is Seasonal: Long-Term Evidence From Tanzania," *Demography*, 55, 1091–1118.

Coibion, O., Y. Gorodnichenko, and D. Koustas (2021): "Consumption Inequality and the Frequency of Purchases," *American Economic Journal: Macroeconomics*, 13, 449–82.

Collins, D., J. Morduch, S. Rutherford, and O. Ruthven (2009): *Portfolios of the Poor: How the World's Poor Live on $2 a Day*, Princeton, NJ: Princeton University Press.

Deaton, A. (1997): *The Analysis of Household Surveys*, Baltimore, MD: Johns Hopkins University Press.

Dercon, S. and P. Krishnan (2000): "Vulnerability, seasonality and poverty in Ethiopia," *Journal of Development Studies*, 36, 25–53.

Devereux, Stephen, S.-W. R. and R. Longhurst, eds. (2012): *Seasonality, Rural Livelihoods and Development*, London and New York: Earthscan/Routledge.

Dostie, S., J. Haggblade, and J. Randriamamonjy (2002): "Seasonal poverty in Madagascar: magnitude and solutions," *Food Policy*, 27, 493–518.

Edwards, A. (2014): "Dynamics of Economic Well-Being: Poverty, 2009–2011," Current population reports, US Census Bureau, Washington, DC.

Evidence Action (2019): "Seasonal Poverty: The Biggest Development Problem You Have Never Heard Of," Evidence Action blog.

Fink, G., B. K. Jack, and F. Masiye (2020): "Seasonal Liquidity, Rural Labor Markets, and Agricultural Production," *American Economic Review*, 110, 3351–92.

Foster, J., J. Greer, and E. Thorbecke (1984): "A Class of Decomposable Poverty Measures," *Econometrica*, 52, 761–766.

Foster, J. E. (2009): "A Class of Chronic Poverty Measures," in *Poverty Dynamics: Interdisciplinary Perspectives*, ed. by T. Addison, D. Hulme, and R. Kanbur, Oxford: Oxford University Press.

Ganong, P., D. Jones, P. J. Noel, F. E. Greig, D. Farrell, and C. Wheat (2020): "Wealth, Race, and Consumption Smoothing of Typical Income Shocks," Working Paper 27552, National Bureau of Economic Research.

Hanna, R. and B. Olken (2018): "Universal Basic Incomes versus Targeted Transfers: Anti-Poverty Programs in Developing Countries," *Journal of Economic Perspectives*, 32, 201–226.

Himmelfarb, G. (1984): *The Idea of Poverty: England in the Early Industrial Age*, New York: Knopf.

Islam, A. and P. Maitra (2012): "Health Shocks and Consumption Smoothing in Rural Households: Does Microcredit Have a Role to Play?" *Journal of Development Economics*, 97, 232–243.

Jalan, J. and M. Ravallion (1998): "Transient Poverty in Postreform Rural China," *Journal of Comparative Economics*, 26, 338–357.

Jappelli, T. and L. Pistaferri (2017): *The Economics of Consumption*, New York: Oxford University Press.

Jayachandran, S. (2006): "Selling labor low: Wage responses to productivity shocks in developing countries," *Journal of Political Economy*, 114, 538–575.

Khandker, S. (2012): "Seasonality of income and poverty in Bangladesh," *Journal of Development Economics*, 97, 244–256.

Krishna, A. (2016): "The Dynamics of Poverty," in *The Oxford Handbook of the Social Science of Poverty*, ed. by D. Brady and L. M. Burton.

Longhurst, R., R. Chambers, and J. Swift (1986): "Seasonality and Poverty: Implications for Policy and Research," *IDS Bulletin*, 17, 67–70.

Maag, E., H. E. Peters, A. Hannagan, C. Lou, and J. Siwicki (2017): "Income Volatility: New Research Results with Implications for Income Tax Filing and Liabilities," Tech. rep., Tax Policy Center / Brookings Institution and Urban Institute, Washington, DC.

McCulloch, N. and B. Baulch (2000): "Simulating the impact of policy upon chronic and transitory poverty in rural Pakistan," *Journal of Development Studies*, 36, 100–130.

Morduch, J. and R. Schneider (2017): *The Financial Diaries: How American Families Cope in a World of Uncertainty*, Princeton, NJ: Princeton University Press.

Morduch, J. and J. Siwicki (2017): "In and Out of Poverty: Poverty Spells and Income Volatility in the US Financial Diaries," *Social Service Review*, 91, 390–421.

Ravallion, M. (2016): *The Economics of Poverty: History, Measurement, and Policy*, New York, NY: Oxford University Press.

Ruggles, P. and R. Williams (1989): "Longitudinal Measures of Poverty: Accounting for Income and Assets over Time," *Review of Income and Wealth*, 35, 225–243.

Schneider, D. and K. Harknett (2020): "Hard Times: Routine Schedule Unpredictability and Material Hardship among Service Sector Workers," *Social Forces*, 99, 1682–1709.

Sen, A. (1976): "Poverty: An Ordinal Approach to Measurement," *Econometrica*, 44, 219–31.

Skoufias, E. and A. R. Quisumbing (2005): "Consumption Insurance and Vulnerability to Poverty: A Synthesis of the Evidence from Bangladesh, Ethiopia, Mali, Mexico and Russia," *European Journal of Development Research*.

Stevens, A. H. (1999): "Climbing out of poverty and falling back in," *Journal of Human Resources*, 34, 557–588.

STORER, A., D. SCHNEIDER, AND K. HARKNETT (2020): "What Explains Racial/Ethnic Inequality in Job Quality in the Service Sector?" *American Sociological Review*, 85, 537–572.

TOWNSEND, R. M. (1994): "Risk and insurance in village India," *Econometrica*, 62, 539–591.

VAITLA, B., S. DEVEREUX, AND S. H. SWAN (2009): "Seasonal Hunger: A Neglected Problem with Proven Solutions," *PLoS Med*, 6, e1000101.

VALLETTA, R. (2006): "The ins and outs of poverty in advanced economies: Government policy and poverty dynamics in Canada, Germany, Great Britain, and the United States," *Review of Income and Wealth*, 52, 261–284.

WATTS, H. W. (1968): "An Economic Definition of Poverty," in *On Understanding Poverty*, ed. by D. P. Moynihan, New York: Basic Books.

WORLD BANK (2021): *Demographic Trends and Urbanization*, Washington, DC: World Bank.

Appendix

A1 Poverty measures

z is the poverty line, and c_i is the monetary measure, either consumption or income.

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.

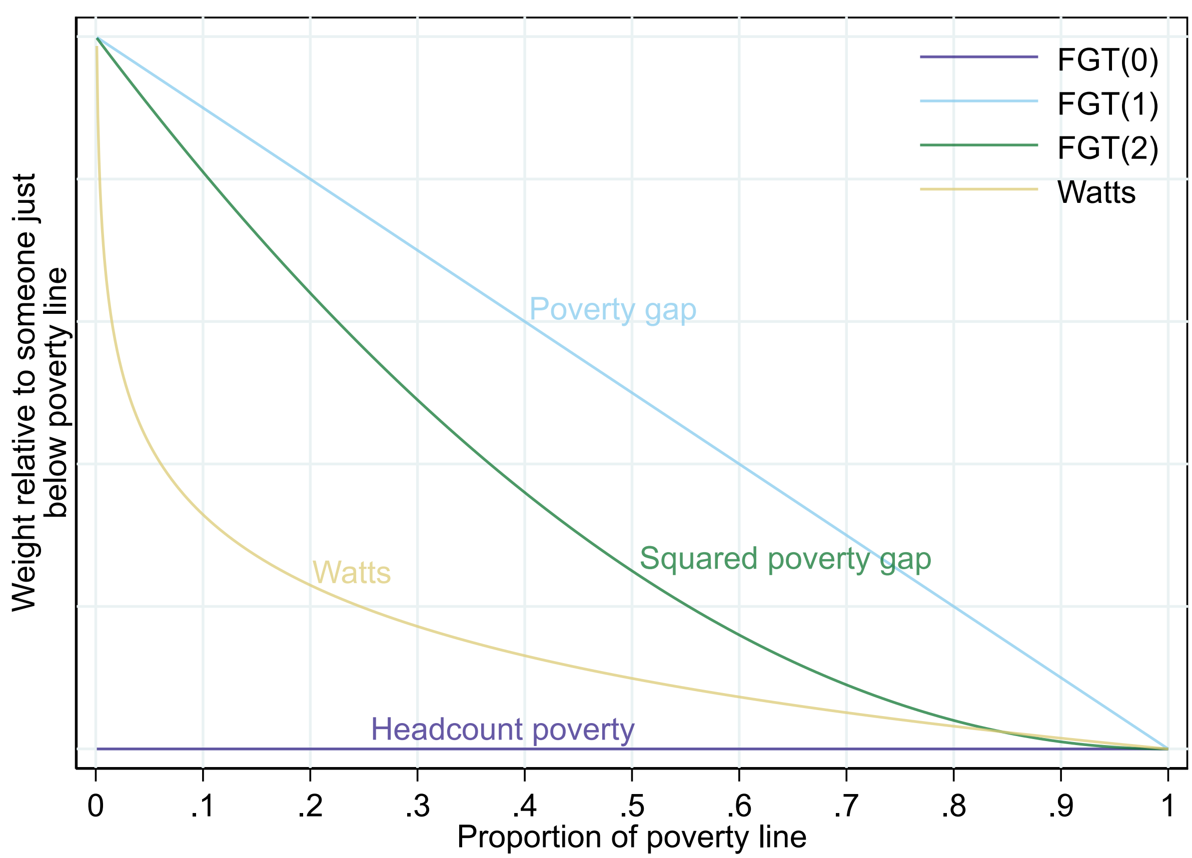
The fourth poverty measure we use is the Watts (1968) index, which is defined as

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

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	0.033***	0.034***	0.034***
	(0.004)	(0.005)	(0.005)
Fixed effects:			
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 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 A3: Co-movement of monthly expenditures and income, by initial household wealth

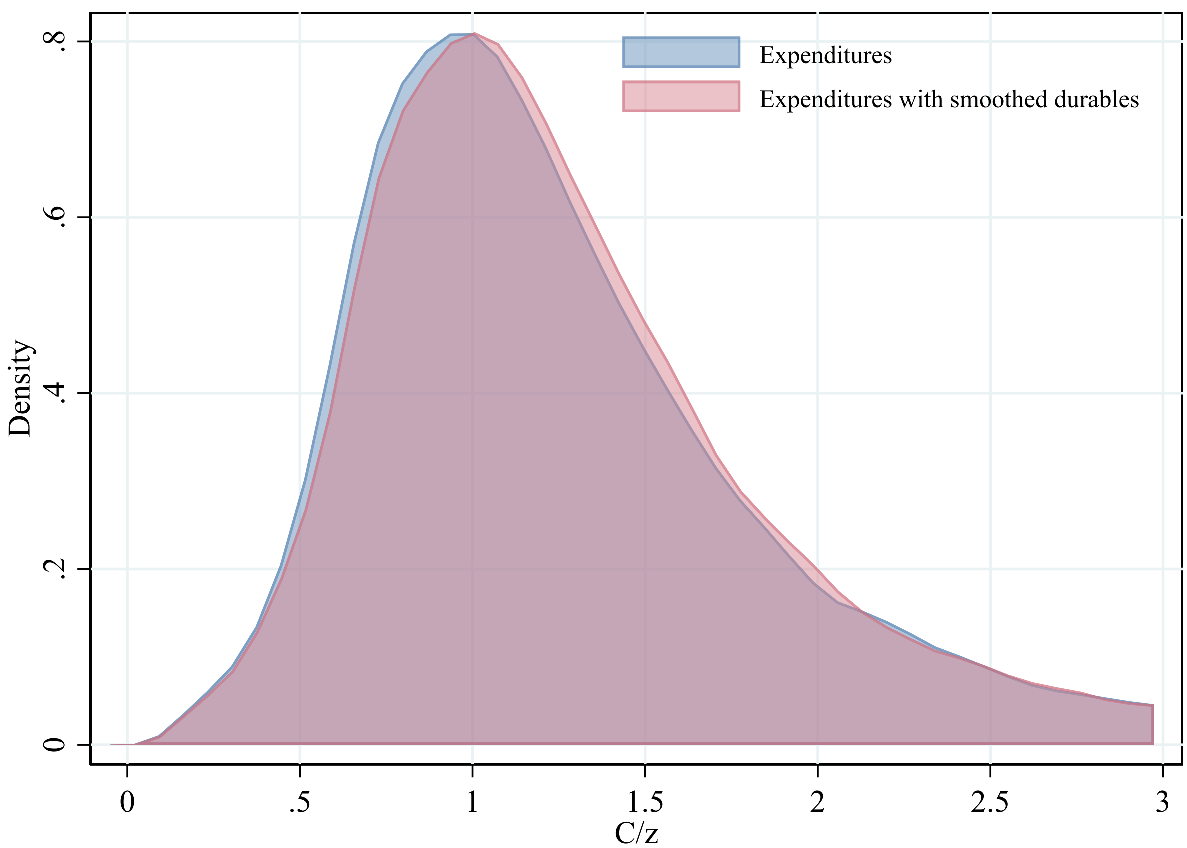
	(1)	(2)	(3)	(4)
	Model 1	Model 2	Model 3	Model 4
Current income	0.062***	0.049***	0.047***	0.049***
	(0.005)	(0.005)	(0.005)	(0.005)
Initial wealth (100,000k rupees)	305.903***			
	(41.697)			
Current income times initial wealth	−0.006**	−0.006***	−0.006***	−0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
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: Correlations

A5 Adjusting for Durables

Figure A2: Density with smoothed durables



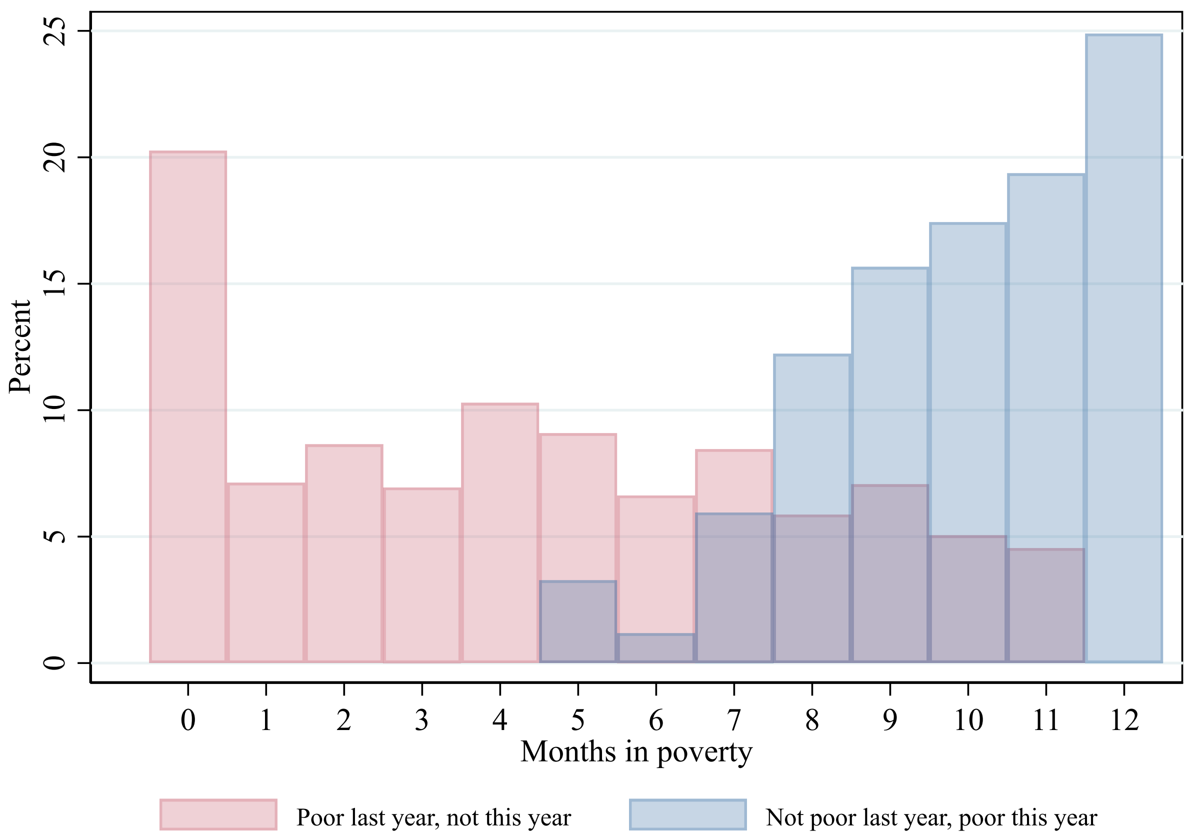
Notes: Kernel density estimate of per capita expenditure. The unit of observation is a household-month, so a single household appears multiple times in the data. The total number of household-month observations is approximately 55,000. The horizontal axis is annual expenditure per capita of households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

Table A5: 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 smooth 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 A6: Anthropometrics with smoothed expenditures

	Weight		Height	
	(1)	(2)	(3)	(4)
	Levels	Demeaned	Levels	Demeaned
Current monthly poverty	−0.072***	Not	Not	Not
	(0.011)	selected	selected	selected
Lagged monthly poverty	−0.094***	−0.014**	−0.454***	−0.223***
	(0.012)	(0.006)	(0.091)	(0.061)
Current quarterly poverty	Not	Not	Not	Not
	selected	selected	selected	selected
Lagged quarterly poverty	Not	Not	Not	Not
	selected	selected	selected	selected
Current annual poverty	Not	Not	Not	Not
	selected	selected	selected	selected
Lagged annual poverty	Not	Not	Not	Not
	selected	selected	selected	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 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 A7: 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 A7 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.