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A HIGH-FREQUENCY CASHFLOW ANALYSIS OF LOW-INCOME HOUSEHOLDS IN INDIA

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Abstract

This paper aims to document the unique characteristics of the financial lives of low-income households in India. It focuses on the intra-year fluctuations in income that are faced by these households owing to the precarity of their occupations. Contrary to the traditional view of poverty solely as an issue of insufficient resources, this paper emphasizes that poverty poses a triple whammy: *insufficiency, instability*, and *illiquidity*. These patterns are uncovered using a high-frequency measure of poverty, rendering a simplistic, annual snapshot of poverty inadequate. The paper utilizes the Centre for Monitoring Indian Economy's Consumer Pyramids Household Survey (CMIE CPHS) dataset for 2019 to perform this analysis and finds that more households qualify as poor using the high-frequency measure of poverty. It was found that 28% of households would qualify as poor according to an annual average measure of income. However, at a high-frequency level, it is observed that 50% of households spend at least three months in poverty.

Furthermore, the paper discusses how households that do not exhibit any cashflow deficit at the annual level may still face intra-year deficits when examined at a higher frequency. It finds evidence that consumption smoothing, although not fully absent, is not perfect either and discusses the possible financial strategies of saving and borrowing that households adopt during periods of cashflow surplus or deficit.

Finally, the paper argues for a nuanced understanding of poverty when designing poverty alleviation programs and financial products, such that the solutions to poverty reflect the reality of the challenge itself.

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1. Introduction

The conventional approach to measuring poverty relies on the annual income and consumption data to categorize households as poor and non-poor. In nationally representative surveys conducted by the government, households are asked to either report their total annual income and expenditure, or an average of what they typically earn or spend in a month.[3] While there are multiple definitions of poverty both at the international (World Bank[4]) and national (Tendulkar Committee[5], Anoop Satpathy Committee[6], etc.) levels, poverty classification of households conventionally happens based on annual income and consumption data, or other inclusion and exclusion criteria. Although an annualized measure of poverty better reflects a family's long-run consumption capabilities (Atkinson, 2019) it is likely to overlook the intra-year volatility that pushes people into and out of poverty during the year, hence, oversimplifying their financial lives.

If one were to examine carefully, only a proportion of households that classify as poor at an annual level, are consistently below the poverty line for all twelve months. We can refer to these households as *perennially poor*. Similarly, households that are classified as non-poor at the annual level, could spend a significant number of months in poverty during the year. For instance, an agricultural household may earn abundantly during the harvest season – thus pushing its annual income over the poverty line – but spend the rest of the year in abject poverty. Such a periodic experience of poverty for agrarian households is termed *seasonal poverty* or *seasonality* and is a well-established challenge (Longhurst et al., 1986; Devereux et al., 2012; Khandker, 2012). Longhurst et al. (1986) emphasize that seasonal poverty, which causes brief but significant financial strain and macroeconomic distress, disproportionately affects various population segments, necessitating improved, differentiated, and decentralized policy measures. The Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) is an example of a government initiative focused on providing a safety net during the lean season or when agricultural opportunities are few (Azam, 2012; Imbert & Papp, 2015). However, a few other households may find themselves above the poverty line in some periods but face episodes of

[3] The All India Debt and Investment Survey or AIDIS (2019), for instance, reports the **usual monthly consumer expenditure** for the household. This variable is calculated by using the (i) usual consumer expenditure in a month for household purposes of purchase, (ii) imputed value of usual consumption in a month from homegrown stock, (iii) imputed value of usual consumption in a month from wages in kind, free collection, gifts, etc, and (iv) expenditure on purchase of household durable during last 365 days. The full report can be accessed here.

[4] World Bank's definition of poverty is an inability to earn $1.9 per person per day. The new definition of extreme poverty raised that figure to $2.15 per person per day. It also raised the poverty line definition for a middle-income country, like India, to $3.2 per person per day. This report can be accessed here.

[5] According to the Tendulkar Committee report of 2009, the poverty line is per capita monthly income of ₹816 and ₹1,000 in rural and urban areas respectively. This report can be accessed here.

[6] The expert committee on determining the methodology for fixing the national minimum wage, headed by Anoop Satpathy, has recommended Rs. 375 and Rs. 430 as per day minimum wage in rural and urban areas respectively, in 2018, for a family comprising 3.6 consumption units. The report can be found here.

poverty due to a variety of reasons other than seasonality. Such an experience of poverty can be called *episodic poverty* (Morduch & Schneider, 2017). Unlike seasonal poverty, which is driven by agrarian cycles, *episodic poverty* is caused by various other factors that lead to income fluctuations, causing households to move in and out of poverty. These factors include but are not limited to, employment instability, losing out on work opportunities due to health emergencies, seasonal work variations, and other economic shocks. Although seasonal poverty is a widely recognized challenge, episodic poverty is not yet well-established (Morduch & Merfeld, 2023).

By obscuring such different ways in which households experience poverty, the conventional approach can exclude many poor households, thus understating both the prevalence and the complexity of poverty. The traditional approach considers insufficiency as the only indicator of poverty, although it is the triple whammy of insufficiency, instability, and illiquidity (Collins et al., 2009) that collectively shape the experience of poverty. There is thus a divergence between the way poverty is experienced and the way it is measured (Morduch, 2023). Morduch and Schneider (2017) note, temporary poverty is more prevalent than chronic poverty. To strengthen the argument that certain households may experience periods of being non-poor within a year but still be significantly affected by poverty, the authors of The U.S. Financial Diaries (2017) demonstrate that among households classified as poor based on annual income, only 8% were consistently poor throughout the year. One way to minimize this difference between "poverty as measured" and "poverty as experienced" is by employing a high-frequency lens to measure poverty (Morduch & Merfeld, 2023). Such an approach uses high-frequency (weekly, fortnightly, monthly, quarterly, etc.) data of household income and consumption, rather than yearly averages, to measure poverty which reveals the episodes of poverty that low-income households experience. This allows us to identify the different ways in which households experience poverty (perennial, seasonal, or episodic) and measure its prevalence among poor households. It also enables an enhanced understanding of how households manage their finances during their good and bad periods. This in turn helps consider measures that can be taken to ease their financial struggles during difficult periods within the year (Morduch, 2021).

Aspen Institute's Expanding Prosperity Impact Collaborative (EPIC) has attempted to examine the intra-year income volatility among American households and its impact on their lives. They highlight the various causes (such as unstable earnings, unpredictable social security transfers from governments, and changes within the households like job loss, birth, death, separation, etc.) and effects (like the inability to make ends meet, access healthcare, eat adequate food, etc.) of income volatility, especially for low-income households (The Aspen Institute, 2016a). Such households with irregular income streams from delayed payments, erratic employment, and unforeseen expenditures face significant challenges in budgeting and saving. They could also have periods of zero income. Parolin et al. (2020) highlight that the struggle caused by delays in such transfers leading to months of no cash inflow would be missed if we relied only on an annualized measure which would show an increase in income, even if that was because of a lumpsum transfer after a waiting period of months. In a country like India, where a major section of households classified as low-income are dependent on such government cash transfers[7], a high-frequency lens of cashflow analysis is crucial.

[7] As per a report issued by the Ministry of Agriculture and Farmers Welfare in February 2024, the Pradhan Mantri Kisan Samman Nidhi or PM-KISAN (the largest Direct Benefits Transfer program in the world), has benefitted more than 11 crore farmer families in India. PM-KISAN is a central government scheme in India that gives farmers up to ₹6,000 per year as minimum income support. The report can be found here.

Since this approach broadens the very definition of poverty, we hypothesize that it is likely to identify several previously non-poor households as poor, thus expanding the share of poor households needing social protection and assistance. In order to strengthen this argument for a complex understanding of poverty, this paper works to quantify and visualize the experience of poverty and its intricacies for policymakers and the larger financial system. In combination with demographic data, the paper attempts to paint a more comprehensive, heterogeneous, and hence more accurate, landscape of poverty experienced by Indian households. Although this paper uses data from India, the broader implications of using the high-frequency lens to measure poverty hold even in other geographies.

In their recent paper, Merfeld and Morduch (2023) build on the idea of episodic poverty to address the issue of how welfare for individuals should be aggregated across time. In the subsequent paragraphs, we discuss the methodology of this paper in detail as this is the latest and most quantitatively rigorous analysis of the idea of high-frequency poverty measurement. The authors utilize the ICRISAT's (International Crops Research Institute for the Semi-Arid Tropics) VDSA (Village Dynamics in South Asia) dataset from rural India, which provides five years of monthly income and expenditure data for the same households. They analyze the cashflows of 945 households for the period of July 2010 to June 2015 to perform a monthly analysis of whether a certain household shows up as poor or non-poor, for multiple years (60 months) and establish that the traditional approach is equivalent to basing poverty measurement on a household's average monthly expenditure rather than their actual expenses. The implicit assumption in poverty measures is that it renders a household either non-poor or poor in a given year, assuming perfect consumption smoothing. The authors, however, find that households classified as non-poor faced cash flow deficits for several months. If perfect consumption smoothing were happening, no households marked as non-poor based on their annual spending would qualify as poor in any month. However, that is not the case. They find that households with the lowest average incomes and consumption over the year are also the most exposed to intra-year expenditure volatility relative to their incomes.

We understand that a poverty measurement framework would calculate the average consumption of households to render them poor or non-poor. In such a scenario, a certain household can potentially assume one of two values: (i) 0 if it is deemed non-poor such that it does not contribute to the aggregate headcount of poverty, or (ii) 1 if it is deemed poor, contributing one unit to the headcount. Merfeld and Morduch (2023), however, develop a framework that aggregates the experiences of poverty within the same year for individual households. This means that a household's poverty status for every month of the year is examined, and a value of 0 is assigned to the household for the months that it is non-poor, while for the months in poverty, they are assigned a value of 1. The framework then uses these intra-year poverty measures to arrive at an annual aggregate by adding the 0s and 1s for the household for that year and dividing that by the number of months (here, 12). This way, at an aggregate level, a household can assume any value between 0 and 1 rather than being restricted to a binary choice. Such an aggregation allows them to capture changes in the incidence and intensity of poverty throughout the year. For example, a household that has been poor for nine months would contribute 0.75 of a year of poverty to the aggregate headcount, unlike the conventional method that might classify the household as entirely poor or non-poor based on annual consumption averages. It is worth noting that this framework retains a focus on annual averages; however, it calculates that in a manner that also captures the intra-year volatility faced by households.

Through such a sophisticated approach, the paper emphasizes the importance of adopting a distributionally sensitive analysis technique in poverty measurement. A distributionally sensitive measure, like the Watts index, is a way to evaluate poverty that takes into account not just the number of poor people but also the depth and severity of their poverty. Unlike simple headcount measures that only count how many people fall below the poverty line, distributionally sensitive measures give more weight to those who are further below the poverty line. The Watts index, for instance, calculates the average of the logarithms of the ratio of the poverty line to each poor person's income, which ensures that poorer individuals contribute more to the measure. This means it reflects not just the incidence but also the intensity of poverty, providing a more nuanced understanding of poverty in a given population.

Furthermore, this framework adds another dimension to some fundamental axioms or principles based on which poverty measures are developed. Specifically, understanding the transfer of income within the poor population is considered crucial to poverty indices. According to the transfer axiom, a pure transfer of income from a person below the poverty line to someone richer must increase the poverty measure (Sen, 1976; Foster et al., 1984). This is because Sen (1976) proposes that poverty measures should be sensitive to the degree of inequality between the incomes of the poor. It should rise when inequality across the income distribution increases (through a regressive transfer) and it should fall when inequality across the income distribution decreases (through a progressive transfer). Distributionally sensitive indices adhere to this axiom by ensuring that any transfer from a poorer to a less poor individual increases the total poverty measure (Foster & Greer, 2010). However, Merfeld and Morduch (2023) show that when poverty is measured over multiple period durations, this principle can be challenged. Traditionally, poverty is measured based on the total resources available in a single period (usually a year). But if multiple period lengths are considered, different dynamics could emerge. Let us take the example of two individuals: Person A is below the poverty threshold according to the annual measure but experiences some months where they are not poor, and Person B is above the threshold but experiences some months where they are poor. Now, in a given month, Person A has enough income to qualify as non-poor, while Person B has a low income and falls below the threshold. This month, Person A transfers some money to Person B. At the monthly level, this would be considered a progressive transfer and should decrease the poverty measure for that month. However, when this transfer is considered at an annual level, owing to the annual poverty statuses of both individuals, this would qualify as a regressive transfer. Thus, using traditional yearly measures, the poverty index might show an increase because Person A, who is poor annually, has less total income. The yearly measure doesn't account for the fact that the transfer happened when Person A was not poor and Person B was poor. This insight challenges the notion that poverty should be assessed based solely on total resources within a single period, typically a year. It opens new avenues for understanding and managing poverty by suggesting that the assessment period might need to be reconsidered.

In their paper, they also decompose the understanding of poverty alleviation programs into two components: (i) their effect on the annual average income of the poor, and (ii) their impact on variability or on allowing households to move money. The authors highlight that while microfinance might not have the more obvious contribution to poverty alleviation by driving up average income and consumption, it might have helped households fund cashflow deficits, which is a legitimate positive impact to consider. Such an impact can be appreciated when viewing poverty through a high-frequency lens.

In light of these insights, this paper advocates for a recalibration of poverty measurement frameworks to accommodate the temporal and contextual details of the financial lives of low-income households. We do this by applying the high-frequency framework to the Centre for Monitoring Indian Economy's Consumer Pyramids Household Survey (CMIE CPHS) dataset to establish that poor households encounter volatile income streams characterized by unpredictable timings and amounts. Given their circumstances, meeting immediate needs becomes a pressing challenge, often preceding any consideration of long-term stability. Consequently, low-income households tend to operate within short-term frameworks, making it imperative to examine their financial realities within these immediate timeframes rather than focusing solely on long-term averages.

The following sections of the paper delve into the specifics of the dataset we employ for this high-frequency analysis, the observations that the analysis presents, as well as a discussion on the relevant policy-related reformations that such an analysis points towards.

2. Data and Methodology

2.1. Dataset utilized for analysis and data cleaning

To quantify the constructs of different experiences of poverty that were discussed in the previous section, we conducted a high-frequency cash flow analysis utilizing data from the CMIE CPHS. Our initial dataset comprised 1,74,405 households; however, to ensure data completeness, we retained only those households that provided information for the entire year, that is, reported income as well as expenditure for all twelve months. This resulted in the final sample size going down to 83,638 households.

We performed the analysis on the dataset for 2019 to avoid any potential distortions in income or expenditure stemming from the COVID-19 pandemic's impact on household finances. It should be noted that all results presented from the study are for the sample, not the population. This is because CPHS assigns a different weight to each household for every month, based on the sample of households that have successfully completed the survey during that month. Therefore, the same household may have different weights during different months in the same year. This remains a potential area of exploration to arrive at a common, annual weight for each household so that these figures can be projected onto the population. Additionally, as previously mentioned, some households had to be excluded from the analysis due to incomplete data. This necessitates readjusting the weights to accurately reflect the actual population.

2.2. Choosing a suitable poverty threshold

We have chosen the minimum wage recommendations of the Expert Committee on Wages headed by Anoop Satpathy as our poverty threshold[8]. This selection was motivated by the committee's consideration of contemporary household expenses, aligning with our aim to reflect the financial realities of 21st-century households as it not only accounts for the calorific requirements of household members while fixing a minimum wage but also their other basic necessities that we believe a household should be able to afford. We acknowledge that these thresholds are substantially higher than other thresholds set by various other committees such as the Tendulkar Committee and the Rangarajan Committee.

Our definition of poverty is close to the proposed World Bank threshold, which pegs the minimum consumption at 3.2 USD per person per day for middle-income countries like India[9]. Table 1 presents the final thresholds that we used to conduct the high-frequency analysis. According to this table, any household earning below a monthly per capita income (MPCI)[10] of INR 3,393 and INR 3,882 in rural and urban geographies, respectively, is classified as poor. Therefore, any household earning an MPCI above this threshold is classified as non-poor.

Poverty Threshold (per-capita)		
Period	**Rural**	**Urban**
Monthly	INR 3,393[11]	INR 3,882
	USD 146	*USD 167*
Annual	INR 40,716	INR 46,584
	USD 1,754	*USD 2,007*

[8] The expert committee on determining the methodology for fixing the national minimum wage, headed by Anoop Satpathy, has recommended Rs. 375 and Rs. 430 as per day minimum wage in rural and urban areas respectively, in 2018, for a family comprising 3.6 consumption units. The report can be found here.

[9] World Bank's definition of poverty is an inability to earn $1.9 per person per day. The new definition of extreme poverty raised that figure to $2.15 per person per day. It also raised the poverty line definition for a middle-income country, like India, to $3.2 per person per day. This report can be accessed here.

[10] Total monthly income of the household divided by the number of members in the household.

[11] We use the Anoop Satpathy Committee's definition of poverty for rural and urban regions, that is ₹375 and ₹430 respectively. Since this poverty definition is for a household with 3.6 consumption units, we calculate the per capita poverty threshold. Furthermore, since these numbers reflect the prices for 2018, we use CPI-adjusted income figures for 2019. The CPI figures can be found here.

We use the formula: $Value\ in\ 2019 = Value\ in\ 2018 \times \frac{CPI_{2019}}{CPI_{2018}}$

Table 1: Poverty threshold definition according to the expert committee on determining the methodology for fixing the national minimum wage (Anoop Satpathy committee)

2.3. Socio-economic background of the households

As can be inferred from Figure 1, the sample for this study was primarily urban with only 32% households belonging to a rural region. To understand the occupational distribution of the households, we follow the same categories as described by the National Sample Survey Organisation (NSSO). We find that 50% of the sample households belonged to the non-agricultural occupational category (29% identified as being self-employed in non-agriculture while 21% were engaged in casual labour in non-agriculture). 22% of the households also reported being engaged in a regular, salary-earning profession. Figure 2 presents the complete breakdown of the occupational distribution.

For the entire sample, the average MPCI for a household in 2019 was 6,968 INR while its average monthly per capita expenditure (MPCE)[12] was 4,049 INR.

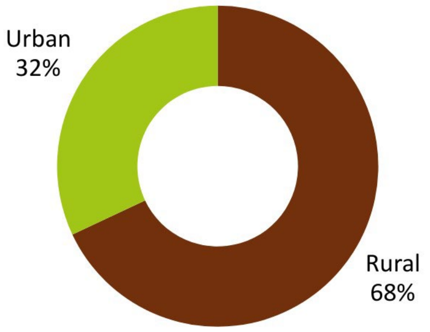

Figure 1: Regional composition of the sample

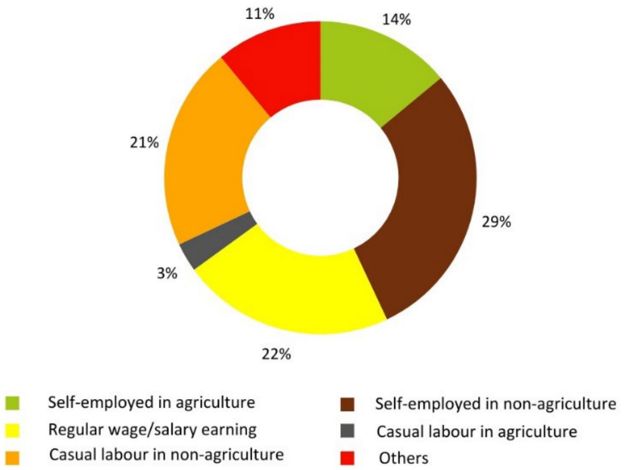

Figure 2: Occupational composition of the sample

[12] Total expenditure of the household divided by the number of members in the household.

2.4. Creating household segments for high-frequency analysis

We understand that in analyzing the cash flows of low-income households at a granular level, it becomes imperative to move beyond annualized metrics to capture the complexity of poverty. In delineating the categorization of these households, we propose three categories to classify the households (see Table 2).

- Firstly, households perennially earning below the poverty threshold across all 12 months confront the primary challenge of "insufficiency," denoting a chronic inability to meet basic financial needs.
- Secondly, households experiencing income below the threshold for at least six months, juxtaposed with periods above the threshold, encounter the issue of "instability," characterized by erratic income streams.
- Thirdly, it is essential to recognize the pervasive issue of "illiquidity" cutting across both segments, wherein households face constraints in accessing readily available funds to meet exigent expenses, regardless of their position within the aforementioned categories[13].

For the purpose of this paper, we refer to the perennially poor households (facing insufficiency) as Segment 1 and those facing instability as Segment 2 households. These two household segments will be the focus of this paper. Furthermore, the households falling outside these delineated segments, neither perennially below the poverty threshold nor exhibiting significant income volatility, are deemed non-poor for our analysis. We refer to them as “other households”. This refined classification facilitates a comprehensive examination of the multifaceted challenges besetting low-income households, thereby informing targeted policy interventions aimed at enhancing financial resilience and inclusivity.

S.No.	Household Segments	Household Classification
1	Households earning below the poverty threshold for all 12 months	**Insufficiency**
2	Households earning below the poverty threshold for at least 6 months and above the poverty threshold during other months	**Instability**
3	Other households	N/A

Table 2: Household segments created for high-frequency cashflow analysis

[13] Households that face insufficiency (Segment 1) throughout the year, might also face volatility. However, for these households persistent insufficiency is the primary problem. Whereas for Segment 2 households, insufficiency is an issue when the households are below poverty threshold for 6 months, but volatility also plays a key issue in their financial lives.

3. Findings and Insights

3.1. A high-frequency analysis shows that many households, not identified as poor by annual measures, face intra-year income volatility, qualifying them as poor in some months

We start our analysis by assessing the number of households that would qualify as poor based on an annual threshold. For the annual measure, we simply calculate the annual average of the income reported by the households and compare that with the poverty threshold. Our findings suggest that if we consider the income reported by the households, 28% of the total sample of households qualify as poor using an annual measure.

Next, we compare monthly household incomes with the poverty threshold to identify the months when households fall below the poverty line and the months when they remain above it. We categorize households into different segments based on their duration below the poverty threshold within a given year. Specifically, households are classified as falling below the poverty threshold for at least one, three, or six months in the year. 58% of the sample falls into poverty for at least a month in a given year while exactly half of the total sample of households experiences poverty for at least three months. 36% of households fall below the poverty threshold for at least six months in that year.

If we consider expenditure[14], the share of households that qualify as poor per the annual threshold increases to 54%. Overall, we find that using the expenditure level of households yields a higher share of households classifying as poor for every category. This is intuitively correct as a household's income exceeds its expenditure. Upon examining the corresponding figures utilizing expenditure data rather than income, we observe that 82%, 73%, and 59% of households would qualify as poor for at least one, three, and six months, respectively, within the given year. Notably, these proportions are significantly higher than those derived from an annualized classification.

This suggests that several households experiencing poverty for at least some portion of the year would not meet the criteria for annualized categorization.

[14] The expenditure includes all essential and non-essential expenses reported by the households, including payment towards EMIs.

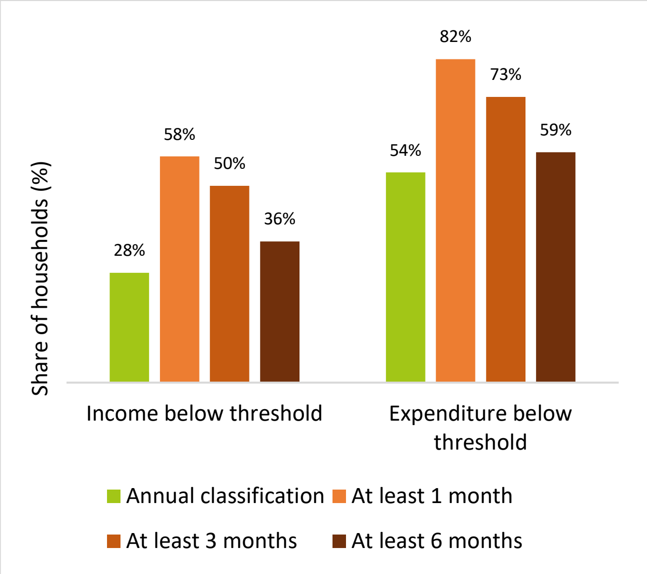

Figure 3: Percentage of households classifying as poor using the income and expenditure threshold

3.2. Self-employed agricultural households experience cashflow deficits for more than half the year

In this section we explore the occupational categories of households struggling with insufficiency and illiquidity due to episodic poverty. An understanding of the occupational categories also helps us recognize why certain households might be facing different patterns of poverty, and that is because an understanding of people's occupation tells us about the predictability and surety of their income and other cash inflows.

We find (see Figure 4) that more than half of the households self-employed in agriculture (53%) experience income dips below the poverty threshold for more than half the year. We find a similar pattern among households involved in casual labour in agriculture where 30% of the households remain below the poverty threshold for at least half the year even though there are periods of high incomes during the year. It is casual labour in non-agriculture households, however, that have the largest share struggling with insufficiency (25%).

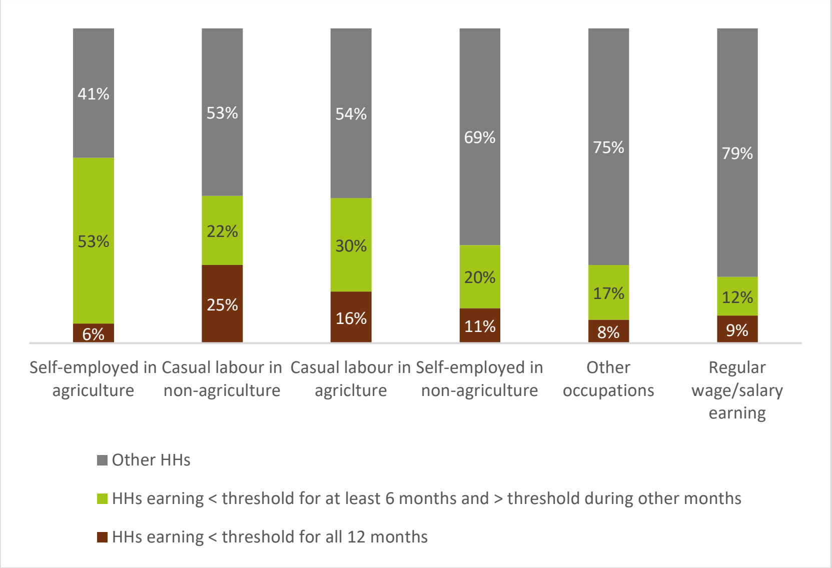

Figure 4: Distribution of experience of poverty across occupation segments

3.3. Low-income households experience significant intra-year income variability, while their consumption variability remains comparatively lower

After examining the occupational backgrounds of poor households, which display varying income volatility patterns throughout the year, we analyze income volatility in conjunction with another critical aspect of household cash flow: expenditure. We also analyze the extent of intra-year volatility in the income and expenditure levels among the households using the coefficient of variation[15].

Figures 5 and 6 illustrate how the average MPCI and MPCE values differ from the actual values on a month-to-month basis. The CMIE CPHS reports household income every month. First, we calculate the MPCI (MPCE) for every household, for every month, by dividing each household's income (expenditure) by household size. Next, we find the average MPCI (MPCE) for each month by summing the MPCI (MPCE) values for all households and dividing by the total number of households. These values are plotted as the green and red bold lines, showing the actual average income and expenditure numbers from January through December. We then calculate the average MPCI for each household for 2019 by summing their monthly MPCI values and dividing by 12. After this, we find the overall average monthly per capita income and expenditure for 2019 by summing these annual MPCI values for all households and dividing them by the total number of households. These are represented by the green and red dotted lines, respectively.

Figure 5 presents the average MPCI and MPCE over a year for Segment 1 households. While the annual averages for income and expenditure (2,393 INR and 2,297 INR, respectively) appear as bold lines, the actual monthly figures fluctuate considerably. Notably, expenditure spikes in October. Although the exact cause of this spike is not known, it could indicate a potential seasonal effect due to festivals, holidays, and other factors. This is in tune with an income hike seen in the same month; in October, average income equals average expenditure for these

[15] The coefficient of variation, defined as the ratio of the standard deviation to the mean, enables us to compare the income and expenditure volatilities of different households, regardless of differences in their mean incomes and expenditures. A lower coefficient of variation indicates less variability around the mean, signifying lower volatility, while a higher coefficient indicates greater variability around the mean, signifying higher volatility.

households. This variability suggests that consumption smoothing is not fully occurring; during low-income months, expenditure decreases, while it rises in high-income months, indicating a lack of consistent savings.

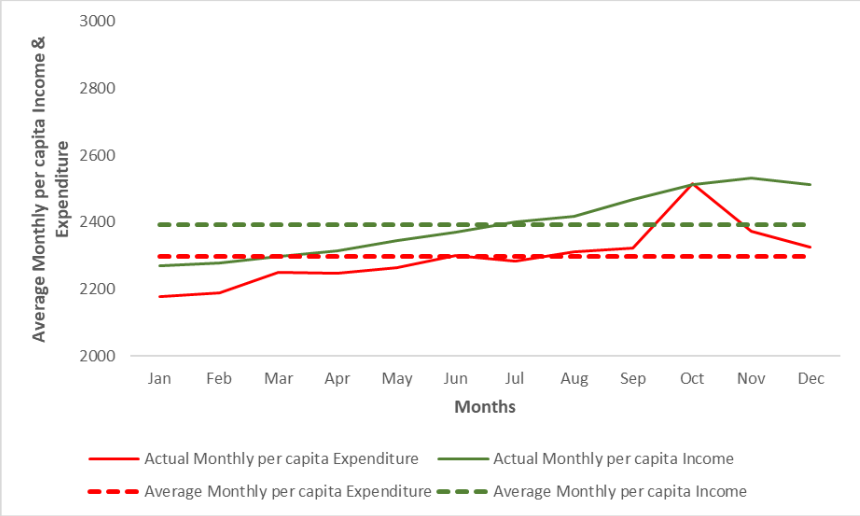

Figure 5: Month-to-Month Income and Expenditure Variation (Mean Values) for Segment 1 Households

Similarly for Segment 2 households, as can be observed in Figure 6, the annual average MPCI for Segment 1 households in 2019 was 4,343 INR while the corresponding MPCE was 2,976 INR. There is considerable fluctuation in the actual MPCI of this household segment from month to month.

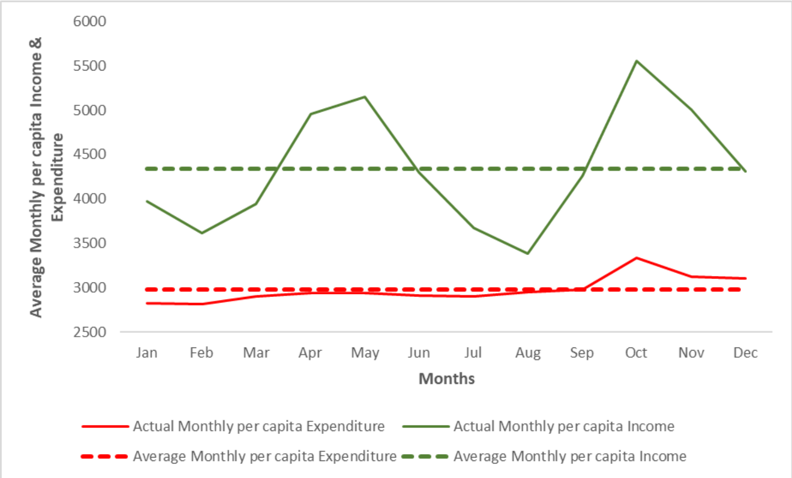

Figure 6: Month-to-Month Income and Expenditure Variation (Mean Values) for Segment 2 Households

Table 3 presents the segment-wise values of the coefficient of variation and two insights stand out. Firstly, the coefficient of variation for income is significantly higher than that for expenditure among Segment 2 households. This indicates that these households experience considerable income volatility, as shown by their fluctuating status around the poverty threshold—below it for six months and above for the remaining months. In contrast, their expenditure is relatively stable, resulting in a much lower coefficient of variation for expenditure. The second is that while there are substantial differences between the average coefficients of variation of income of different segments, the average coefficients of variation of expenditure for all three segments lie in the same range, between 19-23%. Hence, we can conclude that income is volatile, while expenditure is relatively stable.

We find that households spending the entire year in poverty have a relatively smaller coefficient of variation in income because their MPCIs fall within a relatively narrow range (₹343-₹3,232 for rural and ₹863-₹3,803 for urban households) throughout the year. It is only for these households that the coefficient of variation of expenditure (19%) is more than that of income (18%).

On the other hand, the coefficient of variation of income is high for Segment 2 households and this is because they earn high incomes for a few months and much less for the rest of the year. Their income falls in the range of ₹475-₹65,521 for rural and ₹1,331-₹65,962 for urban households throughout the year.

Household Segment	Co-efficient of variation	
	Income	Expenditure
HHs earning < threshold for all 12 months	18%	19%
HHs earning < threshold for at least 6 months and > threshold during other months	**62%**	23%
Other households	27%	23%

Table 3: Co-efficient of variation for different household segments

Due to these cashflow fluctuations, households either end up with a net positive cashflow, which is a cashflow surplus, or a negative cashflow, which is a cashflow deficit. A household is said to experience a cashflow surplus during a month if its income during that month is more than its expenditure; if its expenditure during that month is more than its income then the household is in deficit. In Figure 7, we see a representation of what this cashflow surplus or deficit could look like, on average. We find that households that are perennially poor have little cashflow surplus during peak periods and little deficit during lean periods. This is primarily because on average their income and expense evens out and they continue to struggle with insufficiency throughout the year. Their average income is almost the same as their average expenditure making it potentially challenging to achieve any significant savings. They may need supplementary inflows across the entire year to be able to meet all their consumption needs, especially in times of bulk expenditure (such as for purchasing a durable good) or for emergencies. On the other hand, Segment 2 households that earn below the threshold for at least six months and earn above the threshold for the rest of the year can experience cashflow deficits of ₹ 650 (represented by the red arrow in Figure 7) during their lean season (spanning at least six months) and surpluses of ₹ 3500 (represented by the green arrow in Figure 7) during their peak season (which last six months or lesser)[16]. The ability to move money through time is crucial for their cashflow management as their month-to-month income volatility is very high (represented by a high coefficient of variation value of 62%).

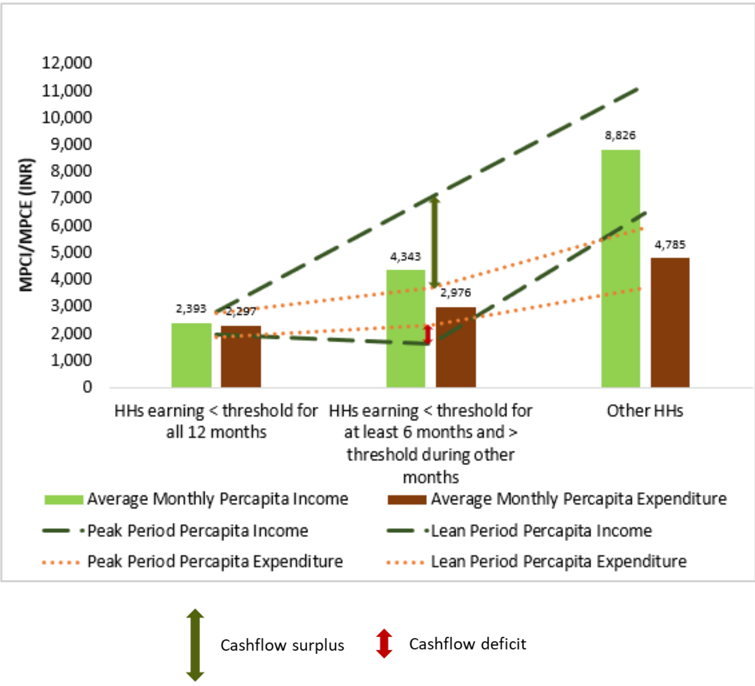

Figure 7: Intra-year variation in income and expenditure.[17]

[16] As illustrated in Figure 8, we calculate the peak period income as one standard deviation (S.D.) above the mean income and the peak period expenditure as one S.D. above the mean expenditure. Correspondingly, the lean period income and expenditure are calculated as one S.D. below their respective mean values. These calculations are performed for each household segment, and these points are plotted on the graph. This approach captures the average peak and lean period figures and reflects typical patterns of cashflow fluctuations, avoiding distortion by extreme values. The use of S.D. values helps us account for data variability around the mean and minimizes the influence of outliers, particularly for Segment 2 income values. The S.D. values are as follows: Segment 1 (S.D. for income= 430.8; S.D. for expenditure= 436.4), Segment 2 (S.D. for income= 2692.9; S.D. for expenditure= 684.5), and other households (S.D. for income= 2383.0; S.D. for expenditure= 1100.6).

[17] According to the Tendulkar Committee report of 2009, the poverty line is per capita monthly income of ₹816 and ₹1,000 in rural and urban areas respectively. This report can be accessed here.

3.4. When considering households with volatile income, more households face month-to-month cashflow deficits compared to the annual share

The previous section gives us an idea about the average cashflow surplus and deficits that households in each segment can face. To further refine our understanding, we examine how the share of households experiencing a cashflow deficit changes when transitioning from a monthly estimate to an annualized measure[18]. Specifically, we assess the prevalence of deficits among Segment 1 and Segment 2 households.

For Segment 1 households, that are persistently poor (see Figure 8), the monthly share of households in deficit (represented by the brown bars) aligns closely, although not perfectly, with the annual average. However, Figure 9 reveals an interesting insight for Segment 2 households. While the month-to-month share of households in deficit ranges from 34% to 44%, the annual share of households in deficit drops to 18%. This discrepancy occurs because Segment 2 households, characterized by volatile incomes, may experience several months of deficit. Yet, when their total annual income (and total expenditure) is considered, this volatility is masked, making it appear as though they do not face a deficit. This observation is critical; in the absence of perfect consumption smoothing, these households may struggle significantly during months of cashflow deficit, a struggle that is obscured when viewed from an annual perspective.

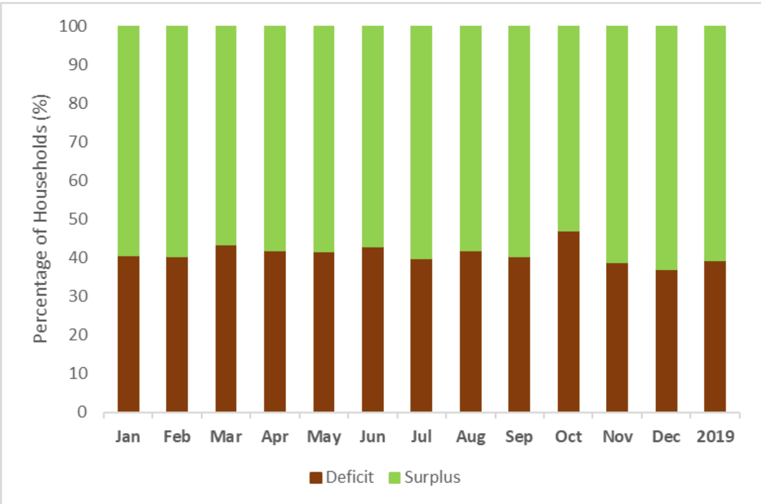

Figure 8: Surplus state for households earning below the threshold for all 12 months (month-to-month and annual average)

[18] We calculate the household surplus or deficit for each wave by subtracting their total expenditure (as reported for the four months in a given wave) from their total income (for the same wave). We calculate the annual surplus or deficit values by using the income and expenditure values for all twelve months.

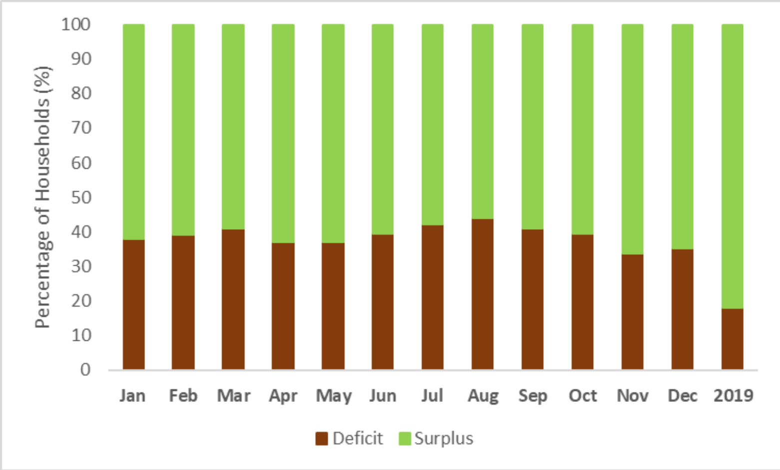

Figure 9: Surplus state for households earning below threshold for at least 6 months and above the threshold for other months (month-to-month and annual average)

We further investigate the prevalence of monthly cashflow deficits among households that have an annual surplus. Figure 10 presents these values for the different household segments.

Among the persistently poor (Segment 1) households with an annual surplus, we find that 78% experience at least one month of cashflow deficit. Additionally, 50% of these households spend at least three months, and 11% spend at least six months in deficit. As expected, these numbers are higher for households experiencing income volatility (Segment 2). In this segment, 83% of households with an annual surplus spend at least one month in cashflow deficit. Furthermore, 63% of these households experience at least three months of deficit, and 33% face at least six months of deficit. The graph also illustrates the situation for "other households," showing that only 3% of those with an annual surplus encounter at least six months of deficit. This is attributed to the relatively stable and predictable income of this segment.

This shows that even among households that have a surplus when the whole year's income and expenditure are considered, there are quite a few that struggle to match their income to their consumption needs for several months within that year.

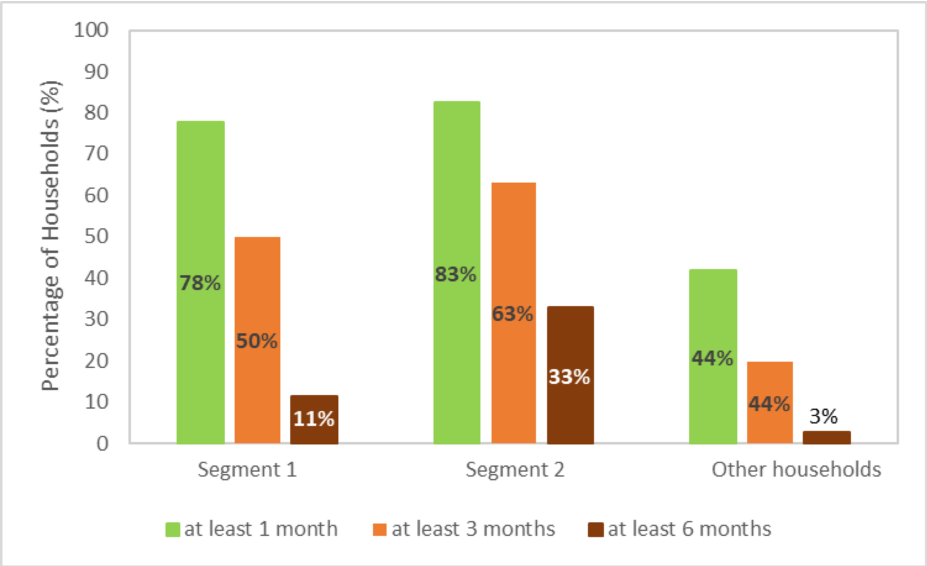

Figure 10: Percentage of households facing cashflow deficits during the year despite having a positive surplus at an annual level

Next, we calculate the share of households with a surplus or deficit on a wave[19]-level. Also, having looked at the cashflow surplus and deficits of households, we now delve into understanding their financial management strategies, specifically their saving[20] and borrowing[21] behaviour during the year[22]. Across household segments, whether characterized by cash flow deficits or surpluses, a significant proportion of households report saving as well as borrowing. Figures 11 and 12 report the savings and borrowing patterns of households that fall below the poverty line throughout the year. In Figure 11, the brown bars show the number of households (in Segment 1) that have a cashflow deficit in each wave. The last bar shows the number of households in this segment that have a deficit at an annual level. As represented by the green dots, we see that even among these households, between 29% to 32% of households save in each wave. We consider the household to have saved annually, in case it has saved in even one of the waves. We, hence, find that among the households that are found to be in a cashflow deficit at an annual level, 42% still report saving at least once in the year. The red dots represent the percentage of households that have borrowed during the different waves in the year. Between 53% to 61% of households borrow in different waves. We find that 76% report borrowing at least once in the year.

[19] The CMIE CPHS collects data in waves, where each wave spans four months. Each wave is part of a continuous data collection process that captures longitudinal data.

[20] The Aspirational India dataset of the CMIE CPHS, which reports data at a wave-level, i.e. once every four months, captures whether the household has saved in any financial instrument in a given wave. If the household reports saving in any of the thirteen listed instruments, they are considered to have saved in that wave. If a household reports saving in any wave of 2019, they are considered to have saved for that year.

[21] The Aspirational India dataset of the CMIE CPHS also captures whether the household has an outstanding borrowing. This is the information that was utilised to understand if a particular household borrowed during a wave or not. If a certain household reports borrowing in any wave, they are considered to have borrowed in 2019.

[22] The dataset contains information only on household participation in assets and liabilities but not allocation.

Figure 12 can be interpreted in a similar manner. Among the Segment 1 households classified as having a cashflow surplus at the annual level, 61% report borrowing at least once in the year, despite the positive surplus, while 39% have reported saving at least once.

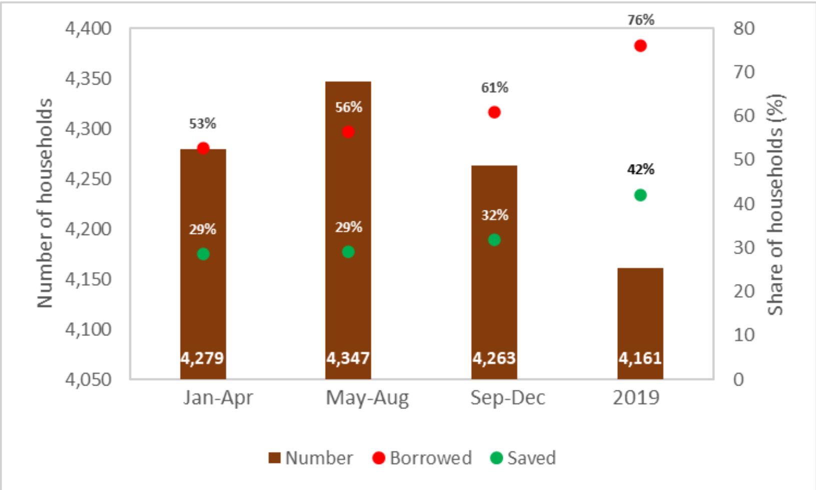

Figure 11: Borrowing and Savings behaviour among households with a cashflow deficit (for households earning below the threshold for all 12 months)

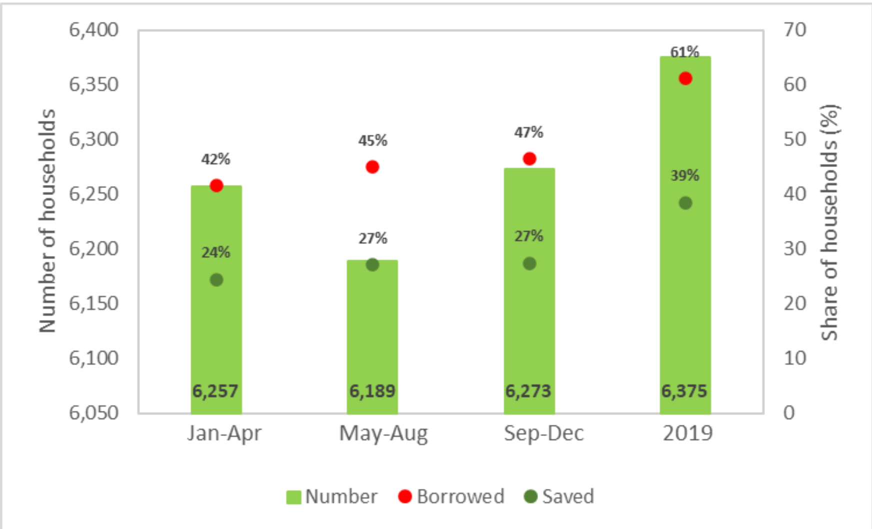

Figure 12: Borrowing and Savings behaviour among households with a cashflow surplus (for households earning below the threshold for all 12 months)

Figures 13 and 14 present the corresponding values for households that are below the poverty threshold for at least six months and above for the rest of the year. We find that despite having a negative annual surplus, 47% of households report saving at least once in the year. Additionally, 66% of households with a positive annual surplus report borrowing at least once in the year.

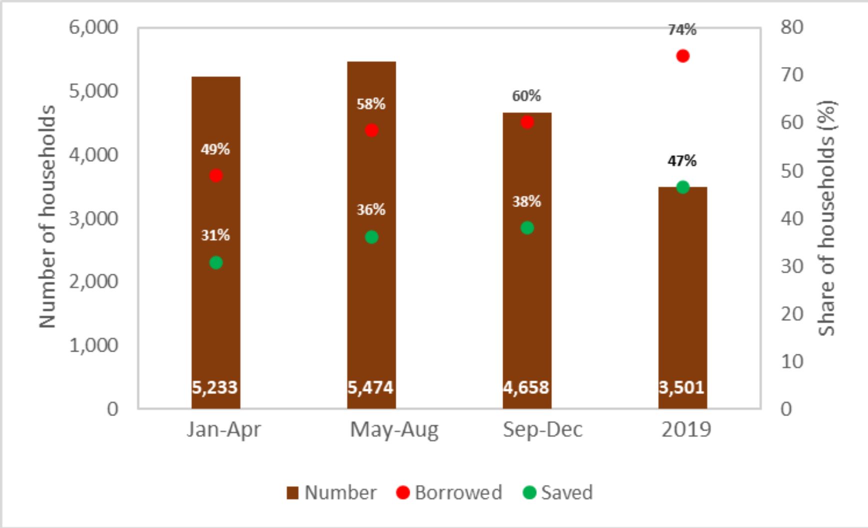

Figure 13: Borrowing and Savings behaviour among households with a cashflow deficit (for households earning below the threshold for at least 6 months and above the threshold for other months)

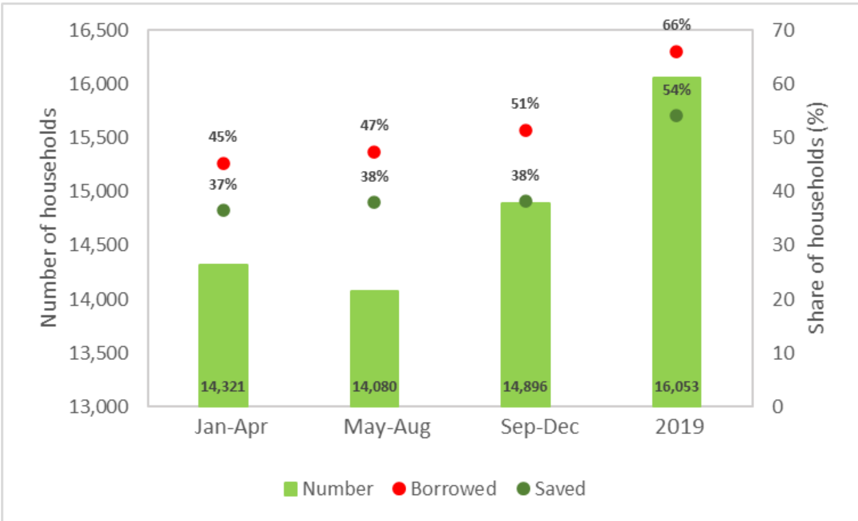

Figure 14: Borrowing and Savings behaviour among households with a cashflow surplus (for households earning below the threshold for at least 6 months and above the threshold for other months)

Since certain households, specifically in Segment 2, earn relatively higher incomes for a few months, their cashflow surpluses during these months can be used to manage cashflow deficits during the other months. But we find that 74% of households (see Figure 13) that face a cashflow deficit annually, report borrowing at some point. This could indicate an inadequacy of the surplus income from periods of income spikes to meet the total consumption needs of households. Moreover, only about half (54%) of the households with a positive annual surplus reported saving money at least once a year. What also stands out is that in every case, the percentage of households that borrow is higher than the percentage of households that save.

Later, in the *Discussion* section of this paper, we examine these findings further to comprehend the financial strategies of the households in question.

3.5. Illiquidity is an experience common between both segments of households, that is, households facing insufficiency or instability

The previous analyses have shown how the experience of poverty can be different for households that are poor throughout the year, facing insufficiency, and those who struggle with instability and move in and out of poverty throughout the year. However, the experience of illiquidity is a struggle that both segments of households face for large parts of the year. From Figure 15, we infer that 43% of the households face a cashflow deficit for at least half the year among the Segment 1 households. Additionally, among the Segment 2 households, 15% of households face cashflow deficits for at least nine months in a given year. In such situations of cashflow deficits, households may rely on their social network or resort to adverse coping strategies such as cutting back consumption, drawing down on their savings, selling assets, etc., as discussed in the following paragraphs.

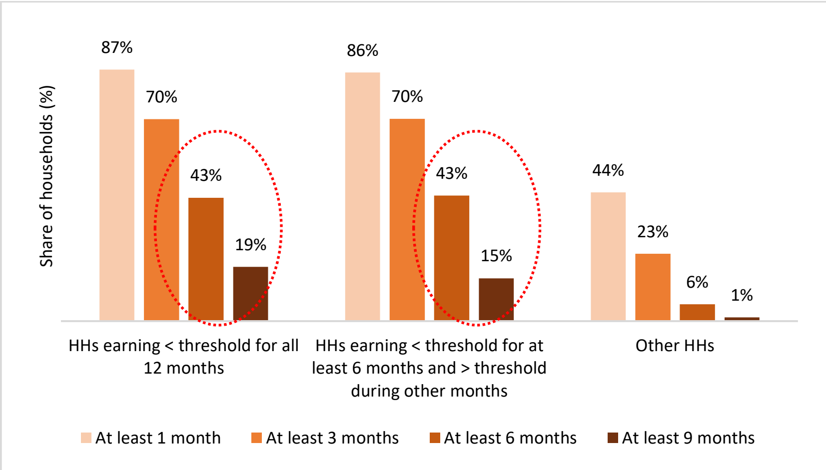

Figure 15: Number of months for which different household segments experience a cashflow deficit

4. Discussion

The traditional approach to measuring poverty primarily focuses on insufficiency, or low income, as the defining characteristic. However, this paper argues for a broader definition of poverty that includes not only insufficiency but also instability, and illiquidity. Instability is caused by the volatile income patterns prevalent among low-income households, and it signals an area of potential intervention to design financial products that enable households to better manage these fluctuations and meet their consumption needs. A lack of access to suitable formal financial tools that could help households work around these spikes and dips in their income causes illiquidity among these households. Such a comprehensive understanding of the experience of poverty can lead to strategies that address both the mitigation and prevention of poverty. This can enable the creation of policies that do not merely respond to the effects of poverty but also aim to prevent its occurrence by providing timely and well-suited social protection. To allow for such a holistic measure of poverty, the first step would be for the government to collect and report consumption and income-related variables for the same households, at a high frequency. Although the CMIE CPHS provides high-frequency data on the financial lives of low-income households in India, it is crucial to acknowledge its key limitation. This dataset primarily captures reported incomes and expenses rather than providing a comprehensive view of financial inflows and outflows. This distinction is important as reported figures may not encompass all financial transactions, thereby potentially limiting the dataset's ability to provide a complete financial overview of the household.

Now, to reflect on the results presented in Section 3, we attempt to comprehend the money management strategies of poor households by applying existing frameworks. It is well-established that low-income households do not perceive saving and borrowing as distinct strategies; rather, they view them as interconnected methods for managing their financial priorities, including day-to-day money management, raising lump sums, and coping with financial shocks. As described in the money management framework created by Mas and Murthy (2017), low-income households adopt three strategies to effectively manage their money. The first is termed *income shaping* and refers to cashflow management that strives to match volatile income patterns with consistent expenditure. The second strategy is referred to as *liquidity farming* which, essentially, highlights the importance of nurturing social and business relationships to act as a source of emergency funds or buffers. And the third strategy is called *animating money*. This strategy can be understood as mentally compartmentalizing different stores of money for different uses so as to avoid unwarranted spending of designated savings, which could lead to the household following a strict saving routine.

As mentioned in the previous sections, we observe the phenomenon of *income shaping* (Mas & Murthy, 2017) in our analysis as we see income levels continuously show up as more variable than expenses. Our sample households may save despite having a deficit by using money from an unreported source. However, they could also potentially use their monthly income to fund their consumption and seek loans to save money (a common phenomenon observed among low-income households) (Collins et al., 2009). Conversely, they could be funding their routinized saving through their monthly income and borrowing money for their consumption expenditure. Such a desire or discipline to continue to save despite facing financial struggles could be understood as *'animating money'* (Mas & Murthy, 2017). These households could also be selling assets or drawing down on savings to fund their consumption needs. In an adverse scenario, they could also be cutting back on consumption to survive a cashflow deficit (Basole, 2019). However, it is important to bear in mind the dataset's limitations, as mentioned earlier, which may temper the completeness of our insights into their financial behaviours.

Aspen Institute's EPIC also explores the perceptions among researchers and policy experts about the causes and implications of intra-year income volatility and the role that different actors and institutions should play in addressing these issues (The Aspen Institute, 2016b). They advocate for a solution framework aimed at mitigating the effects of poverty and enhancing the capacity of households to manage intra-year income volatility. This framework entails a call for a collaborative effort involving employers (tasked with enhancing employment stability by fostering predictability in work arrangements and earnings), governments (encouraged to enforce labor regulations and fortify social safety nets), financial institutions (tasked with facilitating simpler and quicker access to liquidity for low-income households through innovative financial products and processes) and philanthropists (encouraged to promote such innovation, The Aspen Institute, 2016c). Thus, appropriate assistance can be delivered to poor households through targeted financial products and social protection measures that help them manage episodic poverty.

All of the above underscores the unique challenge of effectively addressing episodic poverty. Episodic poverty can be unpredictable and sporadic, which makes it essential to identify reliable indicators such as the socio-economic background of households, other household characteristics, financial practices and/ or choices, and other indicators that might make households susceptible to certain patterns of episodic poverty. Classifying these households according to such indicators could be an initial step in identifying specific instability patterns. This understanding can then inform the design of timely assistance programs aimed at helping them stabilize consumption during income downturns and save during upswings. Furthermore, contextual considerations could be paramount in understanding and addressing episodic poverty. By adopting a decentralized approach to poverty alleviation, policymakers can account for the diverse cultural and regional factors that influence household financial dynamics. One such example is recognizing region-specific festivals or events that impact expenditure levels and can inform the design and implementation of direct benefit transfer programs. This localized approach ensures that an intervention is tailored to the unique circumstances of each community, maximizing its relevance and impact. For instance, the MGNREGS authorizes the *Gram Panchayats* (village councils) to choose the nature of projects based on regional requirements such as drought-proofing, irrigation, or land development. *Gram panchayats* have the sole authority to initiate projects within their jurisdiction. This is decided through *gram sabhas,* which consist of all villagers listed as voters, forming the village's legislative body. They determine which projects to prioritize, regardless of the scheme's predetermined list, thus allowing the program to align with agricultural cycles and regional climatic conditions, customized to local needs. (The Hindu, 2016) This flexibility can help address local unemployment during non-peak agricultural periods.

By broadening our understanding and response mechanisms, we can foster more inclusive and effective strategies that support poor households and work towards more suitable and sustainable poverty alleviation strategies.

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