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An empirical evaluation of the performance of financial protection indicators for UHC monitoring: Evidence from Burkina Faso

Benjamin Sas Trakinsky [a], Bridget R. Irwin [a], Hervé J.-L. Guéné [b], Karen A. Grépin [a,c,*]

[a] Wilfrid Laurier University, Canada
[b] Institut National de la Statistique et de la Démographie, Burkina Faso
[c] The University of Hong Kong, Hong Kong SAR, China

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ABSTRACT

Achieving Universal Health Coverage (UHC) has been recognized as one of the Sustainable Development Goals (SDGs) and includes both ensuring access to health services and providing financial protection (FP) against using these services. Currently, progress towards achieving the FP component of UHC is assessed using the catastrophic health expenditure budget share indicator, which estimates the proportion of the population with health expenditures exceeding 10% of total income or consumption. Other indicators exist, however, and are widely used in the literature, yet few studies have compared the usefulness of these indicators for UHC monitoring. Using panel data from Burkina Faso, this paper seeks to evaluate the performance of common FP indicators based on three properties: (1) their ability to identify those most at risk of financial hardship (i.e. the poor), (2) their ability to detect households with health shocks, and (3) their sensitivity to seasonal variation. Our results indicate that, while some indicators perform better in certain conditions than others, none are without limitation. Indeed, despite being the best able to differentiate households who have experienced a health shock, the official SDG indicator performs the worst at identifying the poorest group of the population and is the most sensitive to seasonal variation. As such, more research is needed in order to improve the measurement of FP such that progress towards achieving UHC can be accurately monitored.

1. Introduction

Universal Health Coverage (UHC) has emerged as a global health priority and is considered necessary for strengthening health systems, reducing health inequalities, and improving access to primary health care [1]. Indeed, achieving UHC for all has been selected as target 3.8 of the United Nations' Sustainable Development Goals (SDGs), and includes ensuring both access to health services (SDG 3.8.1) and financial protection against using these services (SDG 3.8.2). According to the World Health Organization (WHO), financial protection (FP) can be defined as the state wherein "direct payments made to obtain health services do not expose people to financial hardship and do not threaten living standards" [2]. Also known as out-of-pocket health expenditures (OOPs), direct payments are relied upon to finance health systems in contexts in which there exist few risk pooling or other social protection mechanisms to protect households against the economic effects of illness, and thus disproportionately affect low- and middle-income countries (LMICs) [3]. Those who can't afford to pay may also avoid seeking healthcare altogether, potentially exacerbating their condition and further reducing their living standards [3,4]. As a result, improving financial protection is a key objective of many LMICs [5].

While the importance of improving FP is universally agreed upon, how best to measure and monitor progress at achieving this target is less clear [6–9]. At present, there exist two primary forms of indicators used to measure FP from OOPs: incidence of catastrophic health expenditures (CHEs) and incidence of impoverishing health expenditures (IHEs). CHEs identify the proportion of households in a population for whom OOP health spending exceeds a predefined threshold of their available resources, where thresholds can range from 5 to 40% and available resources can be defined as either total household consumption (the budget share approach) or total household consumption after food or subsistence expenditures have been subtracted (the capacity to pay approach). The use of non-food or non-subsistence consumption as a proxy for available resources has been advocated in order to account for poorer households' lower capacity to pay for health services, as a larger share of their household budget must be allocated to food and other basic necessities [10]. IHEs, on the other hand, identify households that are above a defined poverty line when OOPs are included in total household consumption, but would be below it if OOPs were subtracted. The choice of poverty line used to calculate IHEs varies across studies.

The Inter-Agency Expert Group on SDG Indicators (IAEG SDG), which is composed of United Nations Member States and is responsible for developing

* Corresponding author at: 7 Sassoon Road, Pokfulam, Hongkong.
E-mail address: kgrepin@hku.hk. (K.A. Grépin).

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and implementing the global indicator framework for the SDGs, has selected the CHE budget share indicator as the official indicator for monitoring global progress towards achieving SDG target 3.8.2, defining it as OOPs exceeding 10% of total household consumption or income (CHE10%). The choice of this indicator, however, remains controversial [11], and there is substantial debate in the literature surrounding which indicators are best suited to track and monitor progress towards UHC [6,7,12–14]. As such, despite the adoption of CHE10% as the official SDG indicator, other indicators continue to see widespread use in the literature, and authors often employ multiple indicators at once, each yielding different estimates of FP.

A recent study of FP in 133 countries, for example, found that the global incidence of CHEs varied greatly depending on the indicator selected: from 11.7% when using the official SDG indicator, to 2.6% when using the CHE budget share indicator with a 25% threshold, to 3.0% when using the CHE capacity to pay non-food consumption indicator with a 40% threshold [5]. Similarly, a study in Kenya reported that between 1.5% and 28.3% of households experienced CHEs, depending on the threshold and definition of available resources used [15], while a multi-country study observed that country rankings based on the prevalence of CHEs varied according to which threshold was used [16]. The lack of consistency in the use of indicators makes it difficult to make comparisons across studies and has important implications regarding the estimated level of FP across countries, as well as which aspects of FP are being captured [17,18].

Previous studies have identified a number of potential limitations of widely used FP indicators, which could affect their ability to measure FP and may explain the varied use of indicators by different researchers. For example, CHE10%, the official SDG indicator, may be insufficient for identifying the poorest group of a population, who are theoretically the most financially vulnerable. Indeed, while one study in Bangladesh found that CHEs were generally concentrated among the poor using CHE10% as well as other indicators [19], several others have identified more pro-rich patterns [20–23], with one finding that, in 10 out of 14 Asian countries investigated, the prevalence of catastrophic spending was higher among wealthier households than among poorer households [24]. Part of the challenge may result from the fact that none of the current FP indicators are able to distinguish between low utilization of health services due to lack of affordability as opposed to lack of need. As a result, the vulnerability of lower income households to health expenditures may be underestimated [4]. In addition, the official indicator does not adjust to account for differences in more discretionary health spending among wealthier households [7], particularly because wealthier households are more likely to use more expensive, private health services [25]. Given the cross-cutting goals of equity that are embedded in the SDGs, in particular the focus on promoting the economic well-being of the poor, indicators used to monitor UHC should be sensitive to equity considerations.

The validity of the current FP indicators, including their ability to measure true financial hardship, has also been questioned, primarily due to their failure to account for the severity and riskiness of OOPs [18]. The FP indicators, after all, make use of total aggregate household health expenditures, including both predictable and less predictable health spending, however they are not able to distinguish between the severity of health events. Given that studies have shown that large and unexpected health events, or health shocks, can lead to very high levels of spending, this is an important limitation of all of the indicators. In Vietnam, for instance, Wagstaff and Lindelow observed that households that had recently experienced a health shock spent on average 250% of their annual per capita food consumption on health [26]. Similarly, using panel data from Indonesia, Gertler and Gruber found that households were not able to fully insure their non-medical consumption after a health shock to the household head, but that households were able to insure against less severe shocks, suggesting that more severe health shocks may expose households to higher levels of financial hardship [27]. In rural Burkina Faso, Bocoum et al. found that monthly per capita non-medical consumption dropped by approximately 4.3% following a severe illness or accident of a household member [28]. In addition to the severity of health shocks, the current CHE indicators do not account for the ways in which households finance OOPs, for example through borrowing or selling productive assets, which could lead to an underestimation of the true impact of OOPs on households [29–31].

Seasonality is another factor that may influence the measurement of CHEs, as both health expenditures and available resources can fluctuate over the course of a year. Indeed, health expenditures have been shown to vary throughout the year due to seasonal differences in the prevalence of disease, income, and the opportunity costs associated with seeking health services [32–34], while total household consumption fluctuates as a result of changes in household preferences (e.g. the products and services they choose to consume), prices, and different opportunity costs relative to labour supply [34–36]. Among households residing in rural areas, where agriculture plays a major role in the economy and where the harvest season is associated with increased income and variation in food prices, these effects are likely to be more pronounced [37–39]. Estimates of FP may therefore vary seasonally, even when the same indicator is used, which could limit their ability to monitor progress towards UHC, but there has been little investigation of these effects to date. Such seasonality effects have been demonstrated for health service utilization in other contexts, including a recent article by Ataguba [34], but have not been investigated in the conext of FP measurement.

Burkina Faso is amongst the poorest and least developed countries in the world. In 2018, it ranked 183 out of 189 countries on the Human Development Index [40], and its gross domestic product was estimated at roughly $700 USD per capita in 2014. The country also has a relatively weak health system and, as a result, some of the worst health indicators on record. A previous study investigating the determinants of OOPs in Nouna District, Burkina Faso found that between 6 and 15% of households experienced CHEs, and poorer households and those that had used modern medical care, had a sick adult, or had someone with a chronic illness were more likely to experience catastrophic health expenditures [41]. While health insurance coverage has historically been very low in Burkina Faso [42], meaning that most health expenditures by households were likely to be OOPs, efforts are being made to expand access, and a number of health financing reforms have been proposed. A program offering free health care for pregnant women and children under five years old was expanded to the whole country in 2016 [43], for instance, and in 2019 the country is planning to implement a new UHC scheme [44,45]. The effects of the former program have been evaluated in pilot locations and it is believed to have increased institutional delivery rates, antenatal care visits, and health service utilization [46–50]. Burkina Faso has a primarily tropical climate that is characterized by 2 distinct seasons: a rainy season that runs from approximately May through September and a dry season than runs from approximately October–April. Additional details concerning the climate in Burkina Faso are included in Appendix A.

The following paper evaluates the performance of a range of commonly used FP indicators among Burkinabe households, looking specifically at their ability to identify the most theoretically financially vulnerable in the population, their ability to detect large and severe health shocks, and their sensitivity to seasonal variation. From a UHC monitoring perspective, we argue that a robust FP indicator should be able to detect greater financial hardship among the poor and among households that have experienced a health shock, and should not be sensitive to short term fluctuations that are unlikely to be due to changes in the level of FP. The availability of a recent and relatively unique household survey in Burkina Faso, as well and the high proportion of health services financed by OOPs, makes the country the ideal setting in which to explore the short-term dynamics of health spending. The results of this study will inform ongoing discussions about the most appropriate indicators for monitoring progress towards UHC.

2. Materials and methods

2.1. Data source

Data for this study were obtained from the 2014 Burkina Faso *Enquête Multisectorielle Continue* (EMC), which was conducted by the Institut

National de la Statistique et de la Démographie (INSD) in collaboration with the government of Burkina Faso [51]. A two-stage stratified sampling strategy was used. In the first stage, primary units or enumeration areas (EAs) were selected with a probability proportional to the number of households in each EA. In the second stage, 12 households were sampled with equal probability from each EA. A total of 900 EAs were sampled in the survey.

The EMC is based on a standard Living Standards Measurement Survey (LSMS) questionnaire, but was implemented as a panel survey, something that is unusual for studies of this nature. Households were interviewed by trained enumerators in four rounds, at least once per quarter, from January to December 2014. The first round of data collection took place between January 19th and March 17th; the second round between April 27th and June 26th; the third round between July 15th and September 30th; and the final round between October 15th and December 15th 2014. In Burkina Faso, the rainy season occurs from May to and September, and as such would correspond with data collected in rounds 2 and 3.

In each round, data on household composition, education, employment, and financial transfers were collected, and households were asked to complete a full consumption module, which included information on household assets and durables, expenditures on goods and services in the previous three months, and food consumption in the previous seven days. Data on health shocks was only collected in the third round. All data on expenditures were collected in CFA Francs (CFA), but for ease of interpretation, a conversion rate of 1 USD = 526 CFA, the rough exchange rate in December 2014, was used to translate our findings.

Only data from the subsample of households that completed the questionnaire in all four rounds were analyzed in this study. To be included, households were required to have declared positive (i.e. greater than zero) food and non-food consumption in each round. Of the original 10,800 households that completed the first round of the survey, 90.3% completed all four rounds. More information on the survey, as well as code to replicate the entire study, are provided in Appendix B.

2.2. Indicator and variable construction

For each household in each round, EMC data were used to calculate the most commonly used indicators of financial protection, identified based on a review of the literature. These indicators were: (1) CHE 10% of total consumption, where households with OOPs exceeding 10% of their total consumption were considered to have CHEs; (2) CHE 40% of non-food consumption, where households with OOPs exceeding 40% of their non-food consumption, defined as their total consumption minus their food consumption, were considered to have CHEs; (3) CHE 40% of non-subsistence consumption, where households with OOPs exceeding 40% of their non-subsistence consumption, defined as their total consumption minus a poverty line reflecting the cost of satisfying the basic subsistence needs of all household members, were considered to have CHEs; (4) IHE using the World Bank's USD 1.90 per person per day poverty line, where households who fall below this poverty line after subtracting their OOPs from their total consumption were considered to have IHEs; and (5) the Poverty Gap measure using the World's Bank USD 1.90 per person per day poverty line; an intensity measure that captures the average overshoot of households, which is defined as the monetary amount by which households are pushed further into poverty due to OOPs and is calculated as the average of the sum of: (i) the monetary amount spent by households living below the poverty line on OOPs, and (ii) the monetary amount households with IHEs are pushed below the poverty line after paying for OOPs. Appendix C describes the methods used to construct these indicators.

2.2.1. Out-of-pocket health expenditures

Household OOPs were aggregated using data from the household consumption module, which consisted of nine questions with a 3-month recall period relating to modern drugs, traditional drugs, medical devices, other medical products, lab and radiology services, hospital services, and other medical services. Additional details regarding the calculation of OOPs are provided in Appendix D.

2.2.2. Consumption

Consumption estimates, including food consumption, non-food consumption, and medical consumption, were calculated from the microdata as in described in Appendix E, using the methods outlined by Deaton and Zaidi [52]. A broad definition of consumption was used, and included the cost of use of consumer durables (cellphones, computers, appliances, etc.), as well as imputed rent for households who lived rent-free. Imputations of the cost of rent were performed using a RIDGE regression on a wide range of property characteristics, based on information from those who pay rent. The cost of use of consumer durables and the imputed rent values for households calculated in round 1 were used in all rounds to calculate non-food consumption, as the house characteristics module necessary for these calculations was only implemented in round 1.

2.2.3. Wealth index

Wealth quintiles were constructed using round 1 data from the house characteristics module, which included information about the construction of the house, the conditions of the bathroom and kitchen, and the energy sources of the home. Principal component analysis was performed for all households using all available variables [53], and each was assigned a wealth score. In order to accurately capture wealth in both urban and rural settings, we also computed wealth scores for the urban and rural samples separately, the process for which is explained in detail in Appendix F.

In accordance with Rutstein & Johnson [54], we then used the three calculated wealth scores (full sample, urban sample, and rural sample) to create a unique wealth score for all households, taking into account the different characteristics of urban and rural households. This unique score was used to generate the wealth quintiles employed throughout the study.

2.2.4. Poverty line

In order to construct the IHE indicator, we used the USD 1.90 per person, per day poverty line, adjusted for inflation and purchase power parity (PPP) and converted to local currency using the equation presented in Appendix G. For the purpose of this study, an exchange rate of 526 CFA = 1 USD was used. The PPP conversion between the US and Burkina Faso was obtained from the International Comparison Program Database, an international organization that is in charge of calculating PPP for the world. Given that PPP was calculated in 2011, we updated the prices according to inflation to reflect those of 2014, when the data was collected, using the consumer price index (CPI) of Burkina Faso. The CPI information was extracted from the World Development Indicators Database.

2.3. Analytical methods

Each of the four indicators of financial protection was assessed according to the three criteria described previously: (1) their ability to identify the most financially vulnerable households in a population (e.g. the poor), (2) their ability to detect households with large and severe health shocks, and (3) their sensitivity to seasonal variation.

Criteria 1 was evaluated by estimating the incidence of each indicator by wealth index quintile. It was expected that a strong indicator would demonstrate higher levels of CHEs or IHEs among households in the lowest wealth quintiles. Criteria 2 was evaluated by estimating the incidence of each indicator according to whether households had reported being affected by an important adverse event or “shock” over the past 12 months or not. Adverse events were defined as shocks to household income, such as the loss of employment of a household member or a bad harvest season, or health shocks, including severe health events or a death in the household, and exposure to these shocks was measured using a shock module, which was administered during the third round of the survey. The proportion of households experiencing each type of shock are provided in Appendix Table 2. It was expected that a strong indicator would demonstrate higher levels of CHEs and IHEs among households who had experienced a shock, compared to those who did not. Criteria 3 was evaluated by estimating the incidence of each indicator for each of the four survey rounds separately. It was expected that a strong indicator would demonstrate minimal variation in the proportion of households experiencing CHEs and IHEs from season to season.

3. Results

Table 1 summarizes the characteristics of our sample. A total of 10,800 households participated in round 1 of the survey, of which 9750 (90.3%) completed all four rounds and were included in this study. Households were large, containing between 7.6 and 8.2 members on average, and only a small proportion (about 13%) were headed by a female. Approximately 63.2% of households resided in rural areas. Poverty in Burkina Faso was widespread: around 44% of households lived below the $1.90 USD per person per day poverty line, and this was more heavily concentrated in rural areas. Total household consumption ranged from approximately $740 to $823 USD per quarter, averaging to about $3053 USD per year. Food represented roughly 37% of total household consumption over 12 months, while health expenditures represented about 3%. Substantial variation in consumption was observed across the four survey rounds, with the highest levels reported in round one, and the lowest reported in round 4.

Out-of-pocket spending, including total OOPs, OOPs conditional on any spending, share of OOPs over total consumption, and households reporting zero OOPs, are presented by wealth quintile and survey round in Fig. 1, Panel A. Total OOPs were found to increase as wealth quintile increased in all rounds, with households in the highest quintile spending significantly more on health than those in the lowest quintile. Across all wealth quintiles, OOPs were highest in round 1, and decreased with each subsequent round. When restricting the sample to just the households who had reported any positive health spending (i.e. greater than zero), OOPs were higher for

Table 1
Sample summary statistics.

	Round 1	Round 2	Round 3	Round 4	Average over rounds
Number of households	9750	9750	9750	9750	9750
Number of individuals	74,328	76,545	78,805	79,747	77,356
Response rate[a]	90.3%	90.3%	90.3%	90.3%	90.3%
Household characteristics	**Round 1**	**Round 2**	**Round 3**	**Round 4**	**Average over rounds**
Mean household size	7.6	7.8	8.1	8.2	7.9
Urban	36.8%	36.8%	36.8%	36.8%	36.8%
Head of household is female	13.0%	13.0%	13.0%	13.0%	13.0%

Wealth quintiles[b] (Calculated using round 1 data)	All households	Rural households	Urban households
	Percent	Percent	Percent
Q1	20.1%	27.1%	7.9%
Q2	19.4%	28.9%	3.1%
Q3	20.6%	29.2%	5.8%
Q4	25.5%	13.7%	45.7%
Q5	14.5%	1.1%	37.4%
Total	100.0%	100.0%	100.0%

Household consumption (USD, 2014)[d]	Round 1	Round 2	Round 3	Round 4	Average over rounds
Total	823.2	730.0	760.2	740.3	763.5
	(1009.49)	(922.07)	(949.48)	(891.91)	
Food	299.1	257.2	299.0	278.3	283.4
	(287.85)	(201.29)	(267.3)	(236.47)	
Non-food (including health)	524.1	472.8	461.3	461.9	480.0
	(896.59)	(840.71)	(847.61)	(806.46)	
Health	28.8	19.4	19.5	15.7	20.9
	(78.75)	(72.26)	(61.88)	(44.58)	
Modern drugs	22.4	15.7	16.2	13.4	16.9
	(55.95)	(52.91)	(39.9)	(36.64)	
Traditional drugs	2.0	1.5	1.1	0.8	1.4
	(10.88)	(14.72)	(5.56)	(4.96)	
Medical consultations	0.3	0.04	0.1	0.1	0.1
	(11.06)	(1.47)	(2.48)	(2.85)	
Hospital services	1.2	0.7	0.4	0.5	0.7
	(23.18)	(14.41)	(7.62)	(7.96)	
Insurance premiums	0.5	0.1	0.5	0.1	0.3
	(21.49)	(2.56)	(31.23)	(9.65)	
Other health related	2.4	1.4	1.3	0.8	1.5
	(26.22)	(22.56)	(21.67)	(9.68)	
Poverty	**Round 1**	**Round 2**	**Round 3**	**Round 4**	**Average over rounds**
% of households below the poverty line[c]	38.5%	46.6%	45.2%	46.3%	44.2%
% of rural households	46.1%	55.1%	54.2%	56.8%	53.1%
% of urban households	15.3%	21.3%	19.0%	17.4%	18.2%

[a] Descriptive statistics were calculated only for households that answered all four rounds of the survey and reported positive values of consumption (both food and non-food) in all rounds.

[b] The wealth quintile cutoffs were calculated using household survey weights as recommended by Rutstein, S. O., & Staveteig, S. [53] at the level of the household in Burkina Faso. This table reports the proportion of the households in our sample in each wealth quintile, which explains why the estimates vary from 20%.

[c] Poverty Line = World's Bank USD 1.90 PPP.

[d] All amounts are in USD using an exchange rate of 526 CFA to 1 USD, the prevailing market rate at the end of the data collection for the EMC. Standard deviations are in parenthesis.

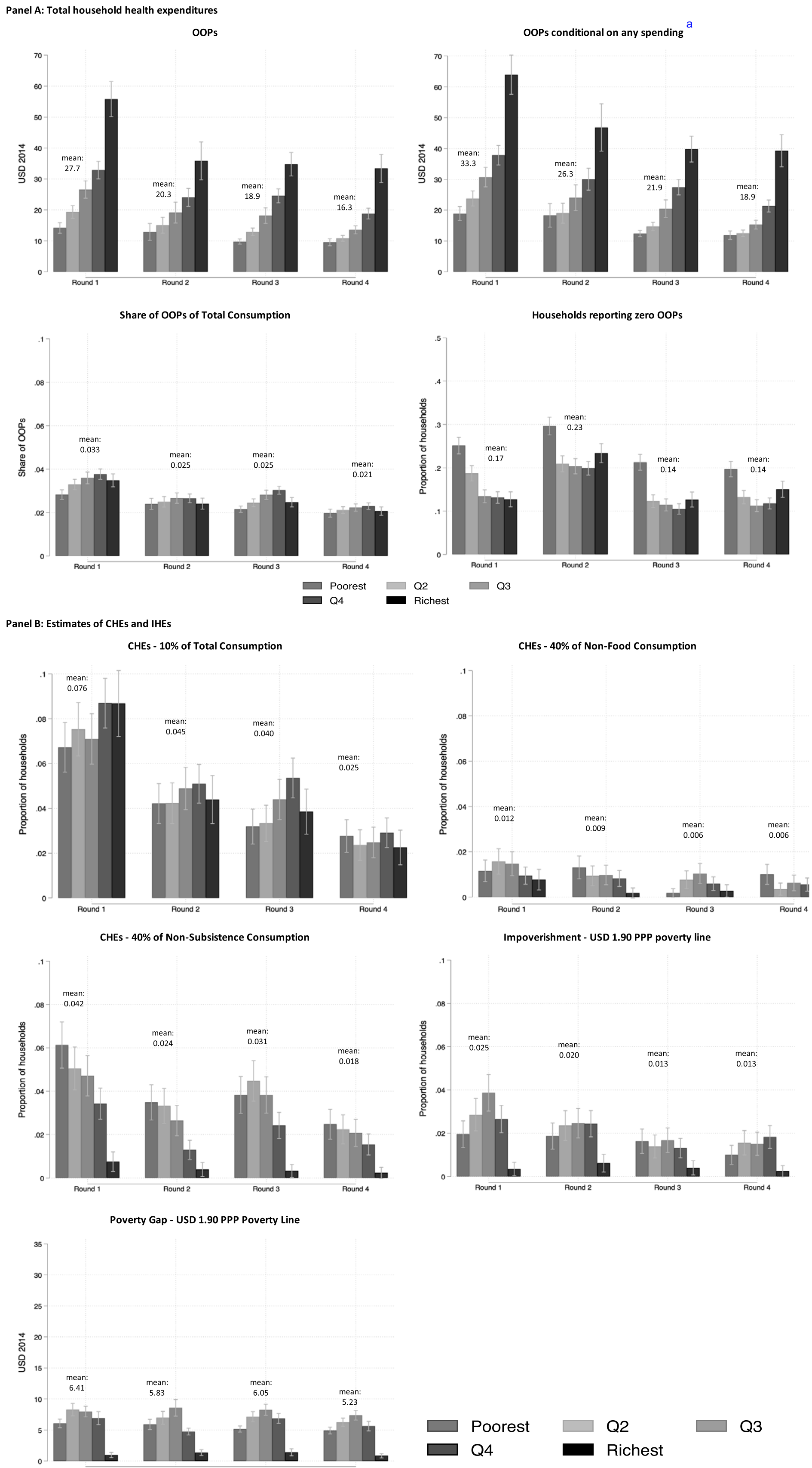

Fig. 1. Measures of high out-of-pocket health expenditures. Notes: Panel A and B include 95% confidence intervals for the mean incidence of each group. Values were calculated using survey sampling weights and are representative at the national level. (a) OOPs conditional on any spending represents the mean OOP among only those households that reported a positive (i.e. greater than zero) health expenditure.

every round and wealth quintile, however the distribution did not appear to change. In examining the share of OOPs over total consumption, we found that it remained relatively stable across all four rounds, averaging between 2 and 3%, and all wealth quintiles appeared to spend a similar proportion on health (except in round 1). The percentage of households reporting zero OOPs in each round varied from 14 to 17% depending on the round, and a similar proportion of households reported zero spending in all wealth quintiles, with the exception of the poorest (Q1), who were significantly more likely to spend zero on health. In Appendix Fig. 1, we present similar data, for both households that did and did not also report illnesses in the household, and show that conditional on some illness, poor households were still less likely to report health expenditures than wealthier households.

Fig. 1, Panel B displays the incidence of high OOPs for each of the selected financial protection indicators by wealth quintile and survey round. As is demonstrated from the graphs, the choice of indicator greatly influences the estimates of FP both across round and by wealth quintile. In comparing the three CHE indicators, for instance, CHE10% generates the highest rates of CHEs, varying from about 7.6% to about 2.7% depending on the round, and rates generally increase by wealth quintile. The 40% non-food and non-subsistence indicators, on the other hand, produce results in the opposite direction, with households in the poorest wealth quintile generally having the highest rates of CHEs and households in the richest quintile having the lowest. Interestingly, when using the 40% of non-food consumption CHE indicator, the incidence of CHEs is very low across all wealth quintiles and survey rounds, with an almost negligible proportion of households exceeding this threshold, varying from 0.6% to 1.2%. Using the 40% of non-subsistence consumption CHE indicator yields an incidence of CHEs ranging from approximately 1.5% to 4%, depending on the survey round. The ratio of the highest to the lowest estimate for each indicator across rounds is substantial: 2.81 times for CHE10%, 2.0 times for CHE 40% non-food consumption, and 2.7 times for CHE 40% non-subsistence consumption, however for all indicators, rates of CHEs are almost always the highest in survey round 1, regardless of the wealth quintile. In looking at the impoverishment FP indicator, the proportion of households experiencing IHEs is relatively low in the sample overall (~2%) and exhibits no clear pattern across wealth quantiles, with the exception of the wealthiest quintile (Q5), for whom rates of IHEs are substantially lower. The poverty gap indicator shows a similar pattern, with households in the richest wealth quintile experiencing a substantially lower poverty gap than those in the poorer quintiles. Within each quintile, the poverty gap remains relatively stable across all of the survey rounds.

Fig. 2, Panel A displays the conditional relative frequency of high OOPs by different types of shocks for each FP indicator. Rates of high OOPs are generally highest among households reporting health shocks, followed by those with a recent death, regardless of the indicator used, while households declaring no shock or an income shock generally have the lowest incidence of high OOPs. Among the indicators, CHE10% appears to be the most sensitive to health shocks and recent deaths, and CHE 40% non-food consumption appears to be the least. While at most only 15% of those households that have reported a health shock are classified has having high OOP using one of the FP indicators, this difference may be partially explained by the difference in reporting rates for the health shocks (12 months) and OOPs (3 months). Fig. 2, Panel B shows the poverty gap among households reporting each type of shock. Again, the poverty gap is generally highest for households who experienced a health shock, followed by those who experienced a recent death in the household.

4. Discussion

In this paper we assess the performance of the most commonly used FP indicators based on three properties that we argue are important for UHC monitoring: (1) their ability to identify the most financially vulnerable households in a population, (2) their ability to detect households with recent health shocks, and (3) their sensitivity to seasonal variation. Our findings reveal that, while none are perfect, certain indicators perform better than others for specific criteria.

In assessing their ability to detect greater financial hardship among the most vulnerable groups of the population, we observed large differences in rates of CHEs and IHEs by wealth quintile within indicators, as well as differences in the distribution of high OOPs across wealth quintiles between indicators. The official SDG indicator (CHE10%) for example, exhibited a pro-rich gradient, with wealthier households found to experience higher rates of CHEs than other households, including those in the poorest wealth quintile. While the differences between wealth quintiles were not all statistically significant, these findings suggest that wealthier households have a greater prevalence of financial hardship than poorer households, which is counter intuitive and goes against the equity goals of the SDGs. The other CHE indicators, on the other hand, yielded wealth gradients more in line with the equity goal, generally showing a decreasing incidence of CHEs with increasing wealth quintile. The 40% non-subsistence indicator was particularly effective at differentiating the poor, showing wide variation in the proportion of households experiencing CHEs between the richest and poorest wealth quintiles, while the 40% non-food consumption CHE indicator was less useful, demonstrating just small differences. The IHE indicator produced no clear wealth gradients across any of the rounds, with the proportion of households experiencing IHEs generally similar across the first four quintiles, but substantially lower for the fifth. Similar patterns were observed for the poverty gap indicator.

An important limitation of all of the indicators investigated in this study is that they do not account for the fact that some households may report no or low OOPs due to their inability to afford health services, arguably the most devastating consequence of a lack of FP, rather than a lack of need for these services. Indeed, as is demonstrated in Fig. 1, Panel A, households in the poorest wealth quintile report zero OOPs at higher rates than those in the other quintiles, which is not likely to be only explained by differences in health needs by income level, suggesting that all of the indicators may overestimate the level of FP experienced by these households. To further investigate this possibility, we also calculated the proportion of households with zero OOPs among households that reported having a sick household member and those that did not. The results, which are presented in Panel A of Appendix Fig. 1, demonstrate that households who did not report a sick member had higher rates of zero OOPs than those who did, and that, among households who did report a sick member, households in the poorest wealth quintile had higher rates of zero OOPs than those in the richer quintiles. This supports the idea that it is likely a lack of affordability, rather than just a lack of need, that explains the higher rates of zero OOPs observed among poor households. Ideally indicators should be able to distinguish between these two scenarios but current indicators do not do a good job at measuring these differences.

In assessing their ability to identify households who had experienced a recent health shock or death, the two adverse events most likely to drive OOPs [55], we found that the CHE10% indicator yielded the highest rates of CHEs among this group, followed distantly by the CHE 40% non-subsistence consumption indicator. Almost 15% of households who reported a large health shock over the past year were identified as having CHEs using the CHE10% indicator, while the CHE 40% non-food consumption, CHE 40% non-subsistence consumption, and IHE indicators identified just 2.5%, 6%, and 3.5% of households, respectively. For the poverty gap, the highest average spending was observed in those experiencing a health shock, followed by those with a recent death in the family. Given that households had been explicitly asked if they had experienced a severe health shock or a death in the household, it is surprising how low the overall rates are among all the indicators in identifying households with these shocks.

Finally, in assessing their sensitivity to seasonal variations, large differences in CHE and IHE estimates were observed depending on the survey round, as well as the choice of indicator used. The official SDG indicator, CHE10%, yielded the largest fluctuations, with a nearly 3-fold difference in the proportion of households experiencing CHEs

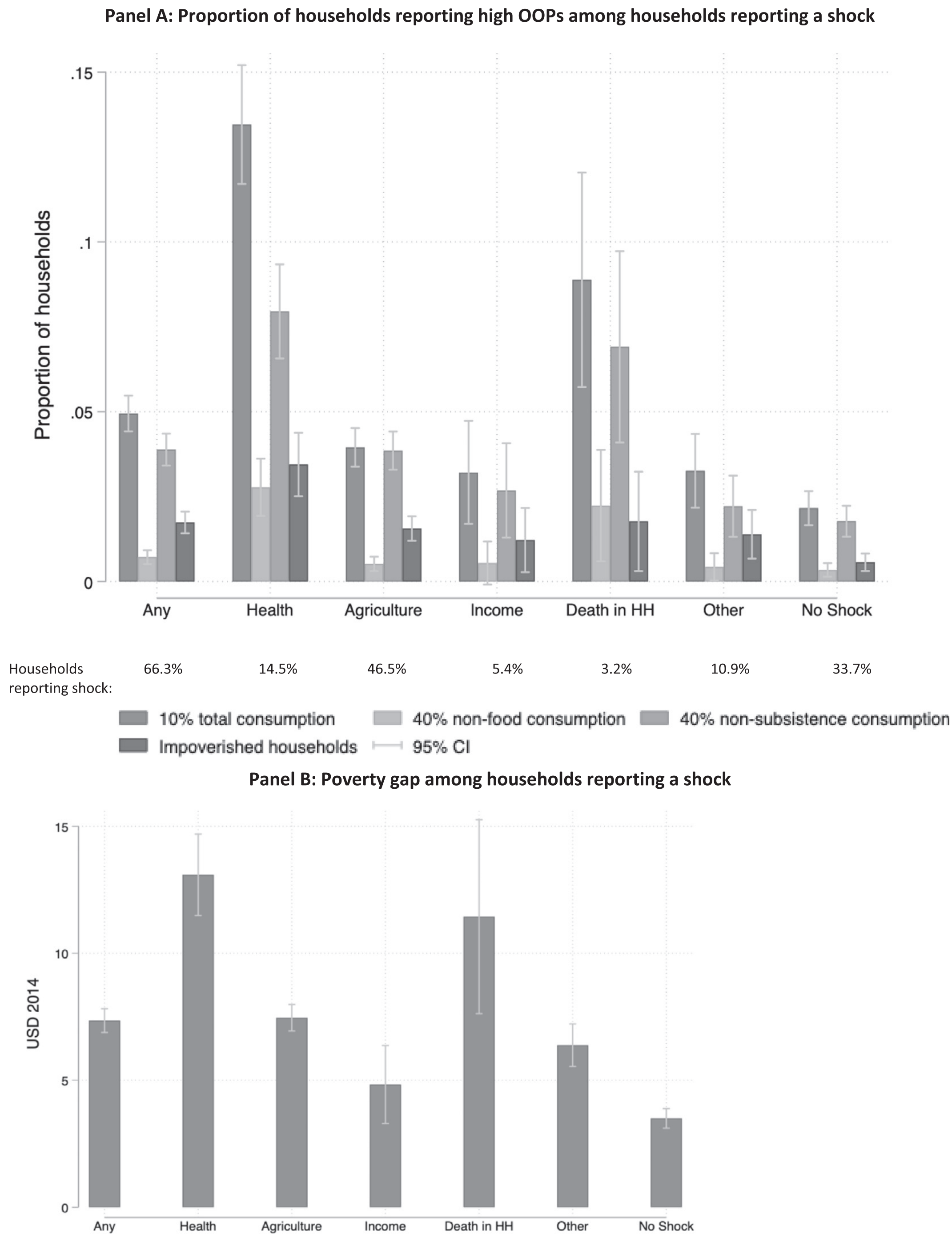

Fig. 2. Incidence of high Out-of-Pocket health expenditures among households reporting a recent shock. Notes: Only round 3 collected data on household shocks, and all calculations are therefore based on round 3 data exclusively. The incidence rates shown are for households who reported having each shock. Households could select up to three of the most important shocks to have affected their household in the past 12 months.

between round 1, generally collected in the dry season, and round 4, generally collected in the wet season (7.6% vs 2.7%). Variation was also observed across rounds when using the other indicators, however, suggesting that seasonality is an important challenge in the measurement of FP. The poverty gap appears to be the most stable indicator over time. In line with this, previous work by Sauerborn, Nougtara, Hien, & Diesfeld in Burkina Faso found that approximately 79% of health expenditures among households were concentrated in the dry season (October–April) compared to only 21% during the rainy season (May–September) [32]. Indeed, the incidence of illness was perceived to be lower in the rainy season compared to the dry season and, among those who did get sick, many chose not to seek treatment at all, or else sought a low-cost treatment, such as home remedies [32], likely due to reduced availability of cash during the rainy season as well as increased opportunity costs [32]. These seasonal differences may be problematic, however, given that most studies are carried out during the dry season for logistical reasons, and thus may result in an over-estimation of health expenditures if generalized to the rest of the year [34,32].

Alternatively, the higher rates of OOPs, as well as of CHEs and IHEs, that were consistently observed in survey round 1 in our study could be due to telescoping, a well-known bias in households surveys wherein respondents perceive distant events as being more recent than they actually were, which can result in their inappropriate inclusion or exclusion depending on the recall period [56,57]. Regardless of the cause of the discrepancies, our results suggest that the time of year in which a survey is conducted strongly influences the resulting estimates of FP for all indicators, calling into question the validity of changes in FP observed over time.

4.1. Implications

Taken together, our findings reveal serious limitations with the current official SDG indicator, as well as the alternatives, which have important implications for the measurement of FP. The official SDG indicator performed the worst at identifying the households that were theoretically most vulnerable to the high costs of health services, namely those in the poorest wealth quintile. The pro-rich gradient of this indicator strongly questions its suitability as the official SDG indicator – particularly in light of the cross-cutting equity goals that are built into the SDGs. Indictors that adjust the denominator to account for essential spending, such as the CHE 40% non-food and non-subsistence consumption indicators, were more sensitive to equity, and thus preferable for this criterion. However, none of the indicators were able to adequately differentiate between households with low or no OOPs due to a lack of use versus a lack of affordability (unmet need), which likely caused all to underestimate the number of people in the population who suffered due to high healthcare costs, particularly among the poor.

The official indicator also demonstrated the largest fluctuations in levels of CHEs across survey rounds, indicating that it is highly sensitive to seasonal differences in health expenditures and available resources, although again, all of the indicators exhibited some variation. The poverty gap intensity measure emerged as the most stable over time. These between-round differences were likely the result of a combination of both true seasonal variation, as well as measurement error, as data sourced from surveys are subject to biases, such as telescoping bias. As a result, it is difficult to discern whether differences in the estimates of FP over time can be attributed to actual changes in FP, for example resulting from policy changes such as the expansion of health insurance, which limits our ability to monitor progress towards UHC.

Importantly, the official SDG indicator was the best suited to identifying households that had reported a recent health shock, which have been found in previous studies to have an increased likelihood of experiencing OOPs compared to other households [55]. Despite being the best indicator for this criterion, however, even the CHE10% indicator classified just 15% of households who had reported a health shock as having CHEs, which is far lower than what was expected. This may be due in part to measurement error, however there is an urgent need to better understand this relationship and researchers may wish to include additional questions relating to shocks in future surveys to better understand their associations with financial hardship and financial protection.

Rather than finding that one indicator performs better than all others, we therefore conclude that all of the indicators have important limitations. As such, in addition to research into the development of new indicators, we encourage researchers to make use of multiple indicators in future studies of FP in order to gain a more accurate idea of the level of financial hardship caused by OOPs in a population. Given the substantial seasonal variation that was observed across all FP indicators, we also recommend data be collected during both the wet and dry seasons so that estimates of FP can be averaged over a single year. Alternatively, a small subsample can be resurveyed following the completion of the ordinary cross-sectional survey to allow for seasonal adjustments in consumption and health service usage [58]. At the very least, when comparing levels of FP in a single country over time, care should be taken to collect data from the same time period in order to ensure that true variations in financial protection, as opposed to regular seasonal differences, are captured [34].

4.2. Limitations

As with all research, this study has a few limitations which must be considered when interpreting the results. For one thing, our estimates of FP indicators are all subject to measurement error due to the reliance on self-reported data and the subjective nature of the survey instrument. A particular concern in our data is telescoping bias, in which events are perceived as having occurred earlier (backward telescoping) or later (forward telescoping) than they really did, resulting in temporal displacement. This is most likely to have occurred in survey round one, as the recall period boundary is more abstract, whereas in later rounds respondents are able to use their response to the previous survey as a reference, allowing them to more accurately estimate events [56]. Similarly, given that these are no gold standards for measuring FP, we developed our own criteria using logic to assess the performance of the FP indicators rather than a strong theoretical framework to evaluate their performance.

5. Conclusions

UHC is an important goal for all countries, however robust indicators are needed in order to monitor progress towards achieving this target. This study evaluated the performance of four commonly used FP indicators, including that selected as the official SDG indicator, according to three criteria. Our results suggest that, while each of the indicators performed well in different areas, no one indicator emerged as superior to the others for measuring the FP component of UHC, and all exhibited important limitations. Given that the current indicator, however, was the least effective at identifying those most vulnerable to high health costs, demonstrating a pro-rich bias, and showed the most seasonal variation in FP estimates, more research is urgently needed to improve the measurement of SDG 3.8.2 such that any progress is adequately captured. This could involve the use of multiple existing indicators in combination or the development of new indicators.

Author credit statement

BST: cleaned and analyzed data, generated figures and graphs, and contributed to the manuscript preparation.

BRI: contributed to the manuscript preparation.

HG: assisted with the analysis of the data, including the construction of the consumption estimates.

KG: conceptualized paper, acquired funding, and contributed to manuscript preparation.

Declaration of competing interest

None declared.

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Appendix A

Appendix Table 1
Distribution of OOPS, CHEs and IHEs.

Panel A: Total household health expenditures

	OOPs				OOPs conditional on any spending[a]				Share of OOPs over total consumption				Households reporting zero OOPs			
	Round 1	Round 2	Round 3	Round 4	Round 1	Round 2	Round 3	Round 4	Round 1	Round 2	Round 3	Round 4	Round 1	Round 2	Round 3	Round 4
All households	27.8	20.3	19.6	16.3	33.6	26.3	22.7	19.1	3.4%	2.5%	2.5%	2.1%	17.0%	22.8%	13.7%	14.2%
Q1	14.2	12.9	9.8	9.5	18.9	18.3	12.4	11.9	2.8%	2.4%	2.1%	1.9%	25.2%	29.6%	21.2%	19.8%
Q2	19.3	15.0	12.9	10.8	23.8	19.0	14.7	12.5	3.3%	2.5%	2.4%	2.0%	18.7%	21.0%	12.3%	13.3%
Q3	26.6	19.1	18.1	13.6	30.8	24.0	20.5	15.3	3.6%	2.7%	2.7%	2.1%	13.4%	20.4%	11.4%	11.3%
Q4	32.9	24.1	24.6	18.8	37.9	30.0	27.4	21.3	3.8%	2.7%	3.0%	2.2%	13.2%	19.9%	10.5%	11.8%
Q5	56.9	36.2	39.3	33.9	65.1	47.0	45.0	39.8	3.5%	2.4%	2.6%	2.1%	12.6%	22.9%	12.7%	15.0%

Panel B: Estimates of CHEs and IHEs

	CHE10%				CHE 40% non-food consumption				CHE 40% non-subsistence consumption				Impoverishment			
	Round 1	Round 2	Round 3	Round 4	Round 1	Round 2	Round 3	Round 4	Round 1	Round 2	Round 3	Round 4	Round 1	Round 2	Round 3	Round 4
All households	7.68%	4.56%	4.15%	2.77%	1.22%	0.89%	0.56%	0.59%	4.27%	2.38%	2.67%	1.52%	2.48%	2.04%	1.45%	1.74%
Q1	6.72%	4.22%	3.10%	2.45%	1.16%	1.31%	0.16%	1.11%	6.13%	3.48%	2.88%	2.68%	1.95%	1.87%	1.06%	2.09%
Q2	7.52%	4.23%	3.34%	2.52%	1.57%	0.94%	0.68%	0.55%	5.05%	3.31%	3.63%	2.02%	2.85%	2.36%	1.63%	2.11%
Q3	7.18%	4.89%	3.98%	2.17%	1.47%	0.97%	0.92%	0.49%	4.71%	2.64%	3.57%	1.25%	3.87%	2.46%	2.13%	2.09%
Q4	8.70%	5.10%	5.63%	3.17%	0.95%	0.82%	0.58%	0.46%	3.42%	1.29%	2.15%	1.08%	2.65%	2.44%	1.80%	1.52%
Q5	8.75%	4.39%	5.20%	3.90%	0.78%	0.18%	0.39%	0.22%	0.75%	0.39%	0.32%	0.18%	0.35%	0.62%	0.30%	0.53%
Concentration index	0.06	0.03	0.08	− 0.02	− 0.09	− 0.19	0.04	− 0.20	− 0.21	− 0.26	− 0.22	− 0.22	− 0.05	− 0.07	− 0.14	− 0.07
p-Value	0.03	0.39	0.00	0.12	0.12	0.01	0.26	0.00	0.00	0.00	0.00	0.00	0.20	0.09	0.21	0.00

	Poverty gap			
	Round 1	Round 2	Round 3	Round 4
All households	6.4	5.8	6.1	5.2
Q1	6.1	5.9	5.2	4.9
Q2	8.3	7.0	7.2	6.2
Q3	8.0	8.6	8.3	7.4
Q4	6.9	4.7	6.9	5.6
Q5	1.0	1.4	1.4	0.9
Concentration index	− 0.68	− 0.73	− 0.45	− 0.59
p-Value	0.00	0.00	0.00	0.00

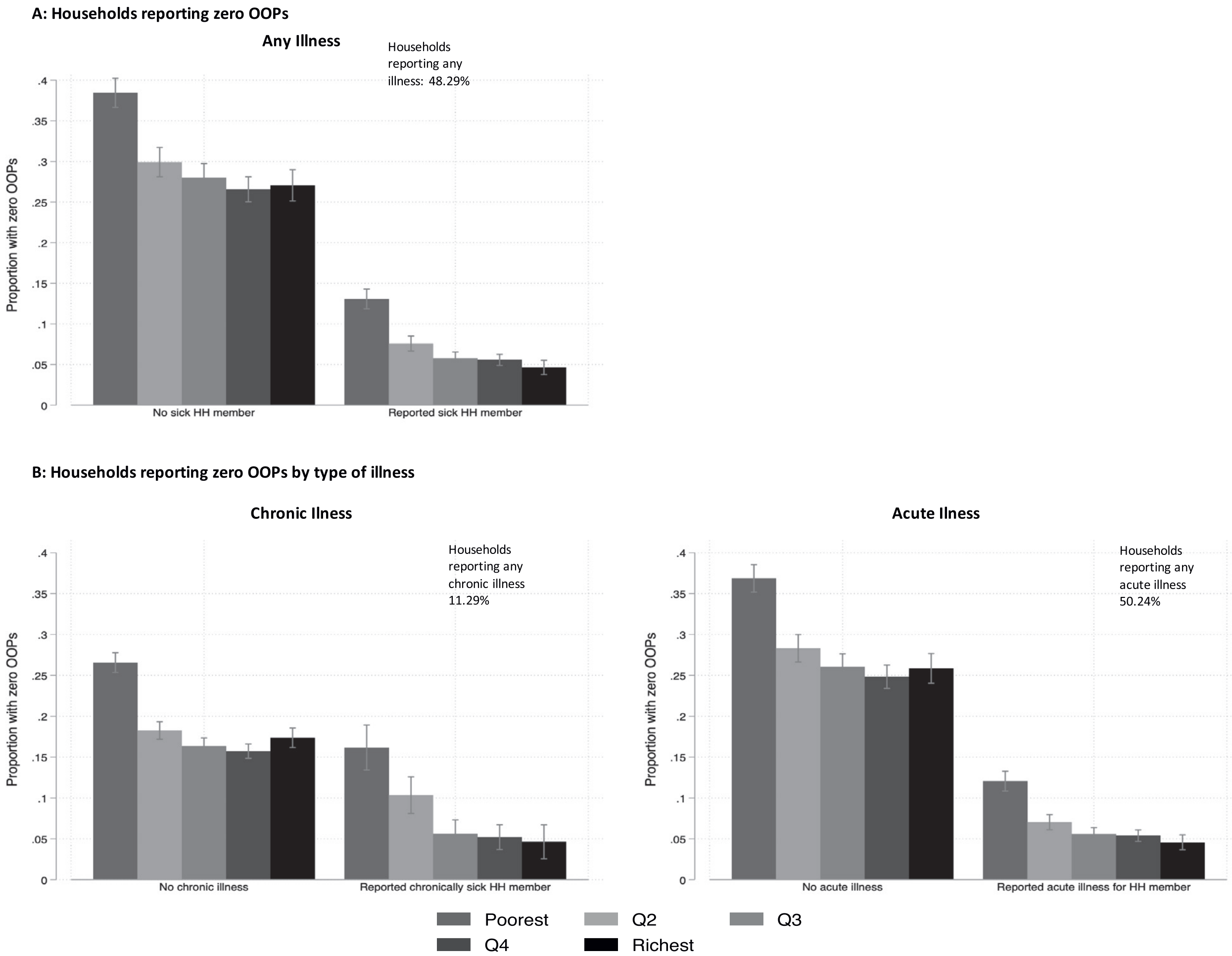
Notes: All values were calculated using survey sampling weights and are representative at the national level.
The concentration index is a measure of inequality, ranging from − 1 to 1. In our case positive and larger values of the concentration index imply that the incidence of the indicator is more concentrated in richer households, while negative values and lower values imply that the incidence of the indicator is more concentrated in poorer households.

[a] OOPs conditional on any spending represents the mean OOP among only those households that reported a positive (i.e. greater than zero) health expenditure.

Appendix Table 2
Catastrophic health expenditures given reported shocks.

	No shocks	Any shock	Health shock	Agricultural shock	Income shock	Death in household	Other shock
Percentage of households declaring shocks							
All households	33.7%	66.3%	14.5%	46.5%	5.4%	3.2%	10.9%
Q1	21.0%	79.0%	13.4%	66.3%	4.6%	3.7%	12.9%
Q2	25.0%	75.0%	15.9%	59.9%	4.9%	3.4%	12.1%
Q3	27.5%	72.5%	16.6%	55.9%	2.9%	3.2%	12.5%
Q4	40.2%	59.8%	15.7%	31.6%	7.5%	3.8%	10.4%
Q5	65.7%	34.3%	9.8%	3.4%	8.2%	1.3%	4.5%
Households with catastrophic health expenditures using 10% of total consumption threshold, given declared shock							
All households	2.4%	5.1%	14.1%	4.0%	3.6%	8.6%	3.7%
Q1	0.9%	3.7%	11.2%	3.3%	4.3%	2.5%	3.0%
Q2	1.5%	4.0%	11.6%	3.4%	0.9%	8.1%	2.2%
Q3	2.4%	4.6%	13.8%	3.4%	2.8%	10.4%	4.2%
Q4	2.8%	7.6%	16.9%	6.8%	2.8%	11.7%	6.3%
Q5	3.3%	8.9%	18.6%	15.0%	5.6%	10.6%	0.4%
Households with catastrophic health expenditures using 40% of non-food consumption threshold given declared shock							
All households with CHE	0.3%	0.7%	2.8%	0.4%	0.5%	2.3%	0.4%
Q1	0.0%	0.2%	0.8%	0.2%	1.1%	0.0%	0.7%
Q2	0.1%	0.9%	3.5%	0.6%	0.9%	1.7%	0.2%
Q3	1.1%	0.8%	3.5%	0.5%	0.0%	4.0%	0.5%
Q4	0.0%	1.0%	3.4%	0.6%	0.3%	4.0%	0.3%
Q5	0.4%	0.3%	1.0%	0.9%	0.3%	0.0%	0.0%
Households with catastrophic health expenditures using 40% of subsistence consumption threshold given declared shock							
All households with CHE	1.7%	3.2%	6.7%	3.0%	2.3%	5.1%	2.6%
Q1	1.4%	3.3%	6.9%	3.3%	2.5%	6.1%	1.6%
Q2	2.2%	4.1%	8.1%	3.4%	3.9%	6.3%	4.3%
Q3	3.5%	3.6%	8.0%	3.0%	2.1%	3.9%	3.4%
Q4	1.9%	2.3%	6.0%	2.0%	1.9%	4.0%	1.3%
Q5	0.3%	0.5%	0.9%	0.9%	1.0%	0.9%	0.0%
Households with impoverishing OOPs given declared shock							
All households with IMPOV OOPs	1.1%	1.7%	3.6%	1.6%	1.5%	2.5%	0.8%
Q1	1.5%	0.9%	2.3%	0.9%	0.0%	1.9%	0.9%
Q2	1.5%	1.7%	3.5%	1.7%	1.7%	3.2%	0.0%
Q3	1.5%	2.4%	5.0%	2.0%	0.0%	2.5%	1.3%
Q4	1.2%	2.2%	4.7%	2.7%	2.8%	4.4%	1.3%
Q5	0.2%	0.6%	1.1%	0.9%	1.2%	0.9%	0.0%

Notes: In round 3 households were asked whether they had recently, in the past 12 months, been affected by a shock. Households had the choice to pick up to three different adverse events, which we categorized in the above categories. All estimates were calculated using survey sampling weights and are representative at the national level.



Appendix Fig. 1. Zero OOPs by reported illness in household. Notes: Panel A and B include 95% confidence intervals for the mean incidence of each group. Estimates were calculated using survey sampling weights and are representative at the national level. Households reported any ill or injured members in last 15 days in the health module, and we consider households to have any illness, an acute illness, or chronic illness if at least one of its members declares one of these. The above graphs represent the pooled data from round 1 to 3 when the health module was collected. Chronic illnesses considered included tension problems, skin illnesses, and articulation problems. Acute illnesses considered included malaria, diarrhea, cough, ENT problems, eye problems, dental problems, injuries, stomach pain, and others.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.hpopen.2019.100001.

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