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Frequent and timely monitoring of poverty, inequality, and poverty profiles using SWIFT during the COVID-19 Pandemic

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Abstract

This paper shows the results of a pilot using the Survey of Well-being via Instant and Frequent Tracking (SWIFT) with the World Bank's COVID-19 High-Frequency Phone Surveys to produce frequent and timely updates on poverty during the COVID-19 Pandemic. SWIFT is a rapid poverty monitoring tool engineered by machine learning and multiple imputation techniques. But producing reliable poverty estimates from phone surveys during a big crisis is difficult because the phone ownership has a rich bias, and a big crisis like the Pandemic makes imputation models outdated. This paper shows these issues can be overcome by introducing a sample reweighting procedure proposed by Zhang et al. (2022) and using a new variable selection procedure proposed by Yoshida et al. (2022). We conducted a pilot for tracking poverty in the COVID-19 HFPS using this modified SWIFT approach. Results show that all countries in this pilot experienced substantial poverty increases during the Pandemic, followed by a gradual recovery. The impact on inequality varies – rising in some countries and declining in others. Comparisons of poverty profiles show that the poor suffered from food insecurity and employment losses but did not always fare far worse than the national average.

Poverty projections and profiling using a SWIFT-COVID19 package during the COVID-19 pandemic[1]

[1] This report was prepared by Nobuo Yoshida, Shinya Takamatsu, Danielle Aron and Kexin Zhang based on inputs from J. Campbell, X. Li, J. Upton, K. Yoshimura, C. Wieser, M. Asai, J. C. Parra Osorio, E. B. Perge, R. C. Behal, A. B. Uulu, X. Chen, F. Fatima, U. Gray, Xueqi Li, S. C. Mathurin, A. L. Paffhausen, A. Kotikula, W. Karamba, H. S. Suh, D. Sharma, R. Swinkels, and J. A. Ramos Morales.

Abstract

This report is the first in a series on the estimation of poverty and inequality trends and profiling of the poor during the COVID-19 pandemic from an ongoing pilot where a SWIFT-COVID19 package is applied to data from a COVID-19 High Frequency Phone Surveys (HFPS) or a Rapid and Frequency Monitoring System (RFMS). This report includes results from the following six countries: Saint Lucia, Ethiopia, Malawi (southern rural region only), Somalia, Rwanda, and Zimbabwe. The SWIFT-COVID19 package includes the imputation of household expenditures using SWIFT Plus, a new poverty projection method, and adjustments for sampling weights to address the sampling bias in phone surveys and RFMS. The package shows that all countries in this report likely experienced sizeable increases in poverty from the pre-COVID era to the COVID era. Changes in inequality, however, are limited, and even declined in some countries. This indicates that the pandemic has hit not only the poor but also the middle class and the rich. This report also compares the impact of the pandemic between the poor and the overall population in each country. The poor suffered more with regards to food security, but there is no clear difference in job stoppage and access to social assistance between the poor and the overall population. This report shows some evidence that governments have been slow to identify and distribute aid to those who have become newly poor since the start of the COVID-19 pandemic, although further research is needed to reach a clear conclusion. The first results of this SWIFT pilot program, showcased in this report, show promise for the future of frequently monitoring poverty in even the poorest countries using the SWIFT-COVID19 package with HFPS or RFMS, not only during the pandemic, but also in the future. This report also includes the results of some empirical tests to show reliability of estimation of poverty profiling and inequality using the SWIFT methodology.

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Overview

Across the world, evidence is mounting that COVID-19 and the associated economic fall-out may have high social costs, including declining welfare and rising poverty levels. The poor and those subsisting near the poverty line tend to be heavily dependent on income from casual daily labor or subsistence farming. The restrictions that COVID-19 lockdowns have had on non-remote daily labor, combined with a general lack of savings among the poor, might have put the poor at the greatest risk of experiencing these negative economic shocks. Timely and reliable data are instrumental in determining who is being affected by the crisis, how they are being affected, and how effective policy can be designed as a remedy — but this data is missing.

Because there is a need for frequently and quickly collected data to reflect the changing economic conditions, the World Bank launched the COVID-19 High Frequency Phone Survey (HFPS) series around the world. Phone interviews were adopted because face-to-face interviews have not been possible in many countries where nationwide lockdowns have been implemented. HFPS collects data on a wide variety of socio-economic conditions, including food security, employment, social assistance, health, education, and access to markets, etc. However, household expenditure/income is not collected due to the long interview time required, which is not feasible via phone interviews. As a result, there are no direct measures of monetary poverty and inequality included in HFPS.

To address the lack of direct poverty and inequality measures in HFPS, a pilot using Survey of Well-being via Instant and Frequent Tracking (SWIFT) was launched in March 2020 to provide estimates of monetary poverty and inequality. The SWIFT methodology is a rapid poverty monitoring tool which applies machine learning and multiple imputations techniques to project household expenditure/income and poverty using the data from 10 to 15 simple questions from household surveys. Due to the challenges the COVID-19 pandemic presented for the standard SWIFT methodology, a modified approach, the SWIFT-COVID19 package, was created. The SWIFT-COVID19 package includes (i) a refined SWIFT poverty projection model, SWIFT-Plus, which is more sensitive to sudden economic downturns and (ii) adjustment of sampling weights (reweighting) to address the biases towards more well-off phone owners in phone survey data (see Table 0.1). This report describes how the SWIFT-COVID19 package has been implemented during the COVID-19 pandemic and discusses key results from analysis using SWIFT-based poverty projections.

Table 0.1. Comparison between SWIFT and SWIFT-COVID19

	Standard SWIFT	**SWIFT-COVID19**
Projection method	Standard SWIFT modeling	SWIFT-Plus modeling
Weight	No adjustment	Adjustment using Zhang and Yoshida (2021)

The SWIFT pilot is being conducted in around 20 countries. This report is the first in a series on the findings of SWIFT-based poverty projections and includes the results of six countries: Saint Lucia, Ethiopia, Malawi (southern rural region only), Somalia, Rwanda, and Zimbabwe. For each of these countries, companion papers have also been prepared separately to include further details on country-specific SWIFT models and results.

It should be noted that unlike the other five countries in this report, the results for Malawi (rural south) are not based on HFPS data, but instead on data from a Rapid and Frequent Monitoring System (RFMS), which is a continuous data collection system based on local enumerators' face-to-face interview. The Malawi RFMS also includes the COVID-19-specific questions included in HFPS and have been collected during the pandemic (see more details in Part III – country specific results).

This report includes the following sections: Part I covers the methodology of the SWIFT-COVID19 package, Part II presents an overview of some findings in the context of a cross-country analysis, and Part III reviews the results of each country individually in more detail. The report ends with concluding remarks.

Part I: Methodology

Poverty projections using the SWIFT-COVID19 package

Survey of Well-being via Instant and Frequent Tracking (SWIFT) is used to estimate poverty rates from COVID-19 HFPS and RFMS data. The SWIFT methodology combines machine learning techniques and the latest ICT technology to estimate household consumption expenditure and produce poverty statistics. SWIFT makes it possible for users to obtain reliable poverty data and profile the poor at low cost. Only 10 to 15 questions on poverty correlates, such as ownership of assets, housing conditions, and household demographics, are needed for the statistical model to project household income/expenditure and then estimate poverty and inequality. SWIFT has proved its usefulness in over 50 countries on more than 100 projects.

Reliability of SWIFT in the COVID-19 pandemic

That being said, Yoshida et al. (2020) found that SWIFT does not perform well during a large negative economic shock. Afghanistan (2011 – 2016) and Gaza (2011 – 2016) both experienced severe economic downturns where the poor population increased by 16 and 14 percentage points, respectively. However, the standard SWIFT approach underestimated the poverty rate increases, estimating increases of only 5 and 6 percentage points in Afghanistan and Gaza, respectively (see Table 1.1). This presents a challenge for using the traditional SWIFT methodology during the COVID-19 pandemic, which has caused sharp and severe negative economic shocks in many countries.

Yoshida et al. (2020) showed that underestimating a surge of poverty during economic downturns is due to the inclusion of slow-changing indicators, like asset ownership, in the standard SWIFT models. While asset ownership is highly correlated with household expenditure/income during times of stable economic growth, the correlation weakens during times of crisis when poverty surges. Due to the lack of active second-hand markets, households cannot easily sell many of their assets during a crisis, even when household income declines substantially. Therefore, households may own items that are correlated with a higher expenditure than their current lived poverty. This leads to the standard SWIFT model producing underestimates of poverty during economic downturns.

Table 1.1. Comparison of standard SWIFT and SWIFT Plus modeling

	Afghanistan (2011 - 2016)			Gaza (2011-2016)		
	Official Estimates	Standard SWIFT	SWIFT Plus	Official Estimates	Standard SWIFT	SWIFT Plus
2011	38.3%			38.8%	46.7%	41.3%
2016	54.5%	39.4%	53.5%	53.0%		

Source: Yoshida et al. (2020)

Creation of SWIFT Plus for estimating poverty during the COVID-19 pandemic

A modified approach, SWIFT Plus, was developed to overcome the standard SWIFT model's underestimation of poverty during severe economic downturns. While a standard SWIFT model selects only slow-changing indicators that are highly correlated with household expenditure/income, SWIFT Plus adds fast-changing indicators that quickly reflect current economic conditions, even though they are only

moderately correlated with household expenditure/income. Specifically, SWIFT Plus includes dummies for consumption of specific items, like meat or shirts. Households tend to stop purchasing these items when their income declines, but resume purchasing them once their income recovers. SWIFT Plus also includes economic sentiments, food security indicators, and employment conditions — all of which change quickly depending on the economic conditions. In sum, SWIFT Plus bolsters the slow-changing poverty correlates in the standard SWIFT model with the above-mentioned fast-changing poverty correlates, making SWIFT Plus more sensitive to short-term changes. In some cases, slow-changing indicators may be removed from the SWIFT Plus model, but this is not always necessary to make the model more responsive to quickly changing economic conditions.

Yoshida et al. (2020) provided evidence for SWIFT Plus. For Afghanistan, SWIFT Plus produced a poverty estimate of 53.5 percent for 2016, only one percentage point away from the official poverty rate (see Table 1.1). For Gaza, the SWIFT estimation was done backwards – models were developed using the 2016 data to estimate poverty rates in 2011. Official poverty rates showed a significant increase in poverty between 2011 and 2016 for the Gaza region. However, standard SWIFT estimates showed almost no change in poverty over this period, while SWIFT Plus estimates showed a significant increase in poverty (see Table 1.1).

For the purpose of the models in this paper, slow-changing indicators are the set of variables that have shown to change very little before and after the outbreak of the COVID-19 pandemic. Likewise, fast-changing indicators here refer to the set of variables that have continued to change quickly in the time periods both before and after the outbreak of COVID-19 pandemic.

The SWIFT Plus approach is adopted to estimate poverty rates during the COVID-19 pandemic using COVID-19 HFPS data in Saint Lucia, Ethiopia, Somalia, Rwanda, and Zimbabwe and RFMS data in Malawi. As the severity of the pandemic and government containment measures have and continue to fluctuate over the course of the pandemic, including fast-changing indicators into the SWIFT models allows for more accurate and up-to-date poverty estimates on a month by month or quarter by quarter basis. To run SWIFT Plus, fast-changing indicators like consumption of specific items, food security, employment conditions, and economic sentiment are added into the COVID-19 HFPS and RFMS questionnaires.

Poverty projections for the Pre-COVID era

As discussed above, SWIFT Plus is used to estimate poverty rates during the COVID-19 era. That being said, in order to estimate the impact of the COVID-19 pandemic on poverty, both the *pre-COVID* (just before the pandemic) and *COVID-era* (during the pandemic) poverty rate estimates are needed. If the latest household survey was conducted just before the COVID-19 outbreak, that survey's poverty rates can be treated as pre-COVID poverty rates. However, if the latest household budget survey was conducted even one year prior to the COVID-19 outbreak, the true pre-COVID poverty rate could be different from the poverty rate of that survey. Therefore, if there is no recent household survey, the pre-COVID poverty rate must be estimated using data collected after the COVID-19 outbreak.

This subsection describes how pre-COVID poverty rates are estimated using data collected during the pandemic. As previously stated, slow-changing indicators are those that have shown to change little between the pre-COVID and COVID-era time periods. Therefore, data collected on slow-changing indicators *during the pandemic* can be used to estimate poverty rates for the period of time directly *prior to the start of the pandemic.* For example, housing conditions cannot be changed unless households move to different houses or make significant renovations, both of which would be unusual during a global pandemic. Ownership of assets is also unlikely to change significantly from the pre-COVID era because many developing countries do not have efficient second-hand markets for consumer durables, making it difficult for households to sell their assets. Consequently, the current status of many indicators used in a standard SWIFT model, despite being collected post-COVID-19 outbreak, can be used to estimate the pre-COVID poverty rates. After estimating the pre-COVID poverty rates, the COVID-era poverty rates can be

estimated using the SWIFT Plus approach (as discussed in the previous subsection), replacing some slow-changing indicators with fast-changing indicators.

Table 1.2 illustrates how pre-COVID and COVID-era poverty rates are estimated, showing an example of data from two rounds of high frequency COVID-19 surveys. First, a standard SWIFT model (f_s) is estimated using a full set of slow-changing indicators (X) and a SWIFT Plus model (f_{sp}) is estimated using a subset of slow-changing indicators (X') and fast-changing indicators (Z) from the latest household budget survey.

A full set of slow-changing indicators from the round one COVID-19 survey is inserted into the standard SWIFT model (f_s) to estimate pre-COVID household expenditure ($\boldsymbol{Y_0}$) and the poverty rate ($\boldsymbol{P_0}$). Slow-changing indicators collected during round one of the COVID-19 survey (X_1) are assumed to be no different from those indicators just prior to the COVID-19 outbreak (X_0). Therefore, predictions based on X_1 will be a good approximation of those based on X_0.

To estimate poverty rates for the round one survey time period, a subset of round one COVID-19 survey slow-changing variables (X'_1) and fast-changing variables (Z_1) are inserted into the SWIFT Plus model (f_{sp}) to estimate household expenditures ($\boldsymbol{Y_1}$) and poverty rate ($\boldsymbol{P_1}$). For round two estimations, fast-changing variables (Z_2) are collected during round two of the COVID-19 survey. It is not necessary to collect round two slow-changing variables (X'_2) because they are unlikely to have changed from the previous round (in other words, $X'_1 \approx X'_2$). Still, if there is room in the round two questionnaire, it is good to add questions on the slow-changing variables to check. Round two household expenditure and poverty rates are estimated by inserting both round two slow- and fast-changing variables (X'_2 and Z_2) into the SWIFT Plus model (f_{sp}).

Whether the pre-COVID poverty rates are estimated by SWIFT or through consumption data in the latest household survey differs across countries. Details are available in each country-specific section.

Table 1.2. Illustration of SWIFT COVID-19 projections

	Pre-COVID (Round 0)	Round 1	Round 2
Slow-changing variables: $\boldsymbol{X_0 \approx X_1 \approx X_2}$ $\boldsymbol{X'_0 \approx X'_1 \approx X'_2}$	X_0, X'_0 (unavailable)	X_1, X'_1	X'_2
Fast-changing variables: Variables strongly correlated with real-time welfare level	Z_0 (unavailable)	Z_1	Z_2
Household expenditures	$\boldsymbol{Y_0} = f_s(X_1)$	$\boldsymbol{Y_1} = f_{sp}(X'_1, Z_1)$	$\boldsymbol{Y_2} = f_{sp}(X'_2, Z_2)$
Poverty rates	$\boldsymbol{P_0}$	$\boldsymbol{P_1}$	$\boldsymbol{P_2}$

Note: X_t refers to a full set of slow-changing indicators in period t, and X'_t refers to a short set of slow-changing indicators in period t. "Unavailable" means that these characteristics were not observed at time 0 if there was no pre-COVID survey.

Evidence of slow-changing indicators for pre-COVID estimations from Uganda and Comoros

Data from Uganda and Comoros provide support for the assumption of slow-changing indicators during the COVID-19 pandemic. In 2019/20, Uganda collected their National Household Survey using traditional, in-person data collection methods, resulting in samples before and after the COVID-19 outbreak. The

comparison between the two groups shows that there are very small changes in ownership of key consumer durables (except for livestock), which can be seen in Table 1.3.

Table 1.3. Asset ownership before and after COVID-19 outbreak in Uganda

	pre-COVID	COVID-era	Total in 2019/20
Mobile phone	73.0	74.3	73.7
Television	16.8	21.0	19.0
Radio	32.8	30.4	31.6
Car	2.7	3.0	2.9
Motorcycle	9.7	7.4	8.5
Generator	0.2	0.1	0.2
Solar	33.1	32.0	32.6
Computer	2.0	1.9	2.0
Agricultural land	65.4	62.4	63.9
Cattle	43.9	40.0	41.9

Source: Uganda National Household Survey 2019-20

Data from Comoros also supports the assumption of asset ownership and housing conditions as slow-changing during the COVID-19 pandemic. Comoros collected data for its 2020 Harmonized Survey on Living Conditions of Households (EHCVM) from January to September 2020 using traditional, in-person data collection methods. Since the first cases of COVID-19 were not recorded in Comoros until May 2020, but the island was still affected by the pandemic due to the economic impacts of border closures and government restrictions, Mendiratta et al. use the announcement date of lockdowns (March 23, 2020) as a cutoff date to divide households into pre-COVID and COVID-era groups, depending on when their interviews took place. Mendiratta et al. found no significant difference in housing conditions (water, sanitation, electricity, flooring, roof, walls) between the two groups. There was a decrease in the value of asset ownership from the pre-COVID group to the COVID-era group, however this difference was still relatively small and primarily concentrated among small appliances.

Advantages of SWIFT over other poverty projections

The reliability of poverty estimates using the SWIFT methodology has several advantages over those from other published poverty projection methods.

First, SWIFT poverty projections are based on data collected on the ground, which is not always the case for poverty projections from other methods. Poverty is often estimated based on other projections, such as growth projections. If the inputs are also projections, the end poverty projection is subject to both errors in the projected inputs and errors in the poverty projection model. If the initial inputs are wrong, then even if the poverty projection models are correct, the poverty estimate will be biased. The SWIFT-COVID19 package does not have this issue because all inputs are collected during the COVID-19 pandemic, rather than projected from other data sources.

Second, the SWIFT poverty projection methodology continues to be evaluated empirically and theoretically. The SWIFT program evaluates the performance of existing approaches and, if needed, refines them (see Yoshida et al. 2022). The SWIFT Plus approach was created as a result of this continuous performance assessment, which identified the need for adaptations to the original methodology to more quickly capture economic conditions during negative economic shocks.

Third, for all pilot countries, SWIFT poverty projections are conducted in close collaboration with country poverty economists in the World Bank. Country poverty economists are familiar with country-specific conditions and household surveys. The selection of indicators for the pre-COVID and post-COVID SWIFT models require deep knowledge of each country and its household survey data, making consultation with

country poverty economists highly valuable. The need for knowledge of subjects and data is also acknowledged in the recent Machine Learning literature (see Rudin 2019).

Fourth, SWIFT poverty projections can be interpreted as signals of changes in socio-economic conditions. SWIFT poverty projections are a multidimensional poverty measure, in other words, a weighted average of non-expenditure indicators. Although multidimensional poverty measures often draw debate because their weighting can be arbitrary (discretionarily and manually set), the weights for SWIFT poverty projection models are assigned based on a regression of household expenditure on the selected non-expenditure variables. As a result, if SWIFT poverty projections show an increase in poverty, then it must be that some key poverty correlates included in the SWIFT projection model are also getting worse. Therefore, SWIFT poverty projections can be used as a reflection of the current status of the socio-economic environment in a country.

Presentation of poverty and inequality projections in this report

Official poverty estimates are often very sensitive and require multiple rounds of consultation with stakeholders and experts before publications. All the projections included in this report were prepared with country poverty economists who are very familiar with the country context and technical experts who are familiar with the SWIFT methodology. However, due to the sensitivity of the matter, this report does not include direct poverty estimates, but instead measures poverty with a *poverty trend score*.

A poverty trend score measures changes in poverty for a period of time relative to a reference period. In this case, the poverty trend score indicates the rate of change in the poverty rate since the pre-COVID era. For example, if the score is 1.1, the poverty headcount rate is estimated to have increased 10 percent compared to the baseline (pre-COVID era). If the population size between the pre-COVID era and the survey period remains the same, the score implies the growth rate of the poor population as well. For example, a score of 1.1 implies a 10 percent increase in the poor population.[2] This measure has been used in Latin America to show monthly fluctuations in poverty.

Additionally, the probability of the poverty rate increase is estimated. The poverty trend score is calculated using point estimates. However, all estimates involve noise (measured by standard errors), and thus, even if there is an apparent increase in the point estimate of the poverty rate, that increase may be due to noise, and there may be no high likelihood of real change. The probability of the poverty increase from the pre-COVID era to the COVID-19 period is calculated to measure the certainty in the increase in poverty. This measure is presented alongside the poverty trend score for each country in this report.

Lastly, this report includes an annex that shows empirical evidence for the estimation of Gini coefficients by the SWIFT method. Yoshida et al. (2022) show the series of empirical evidence for poverty projections by the SWIFT method, but does not include the analysis on the reliabilty of inequality estimates by the SWIFT method. Since this report includes the projections of Gini coefficients, it includes an annex that shows how well the SWIFT method can estimate Gini coefficients and also report some caveats (annex 2).

Reweighting to obtain nationally representative poverty estimates

One shortcoming of the COVID-19 HFPS is its lack of national representativeness in key statistics. People who respond to phone interviews may have systematically different characteristics compared to people who do not respond to phone interviews. For example, many poor households and those living in rural areas do not have a phone, while most rich households and those in urban areas do. Since phone ownership is essential for phone interviews, an unbalanced distribution of phone ownership makes the collection of nationally representative data challenging.

[2] If the population growth between the pro-COVID period and the RFMS survey round is x and the poverty trend score is y, then the growth of the poor population is xy.

The following section will outline how the sample bias of HFPS is addressed by adjusting sampling weights, called "reweighting." Country-specific details for reweighting are provided in each country section and more details on the process can be found in the companion papers prepared for each country participating in this pilot.

To address the sampling limitations of a phone survey, sampling weights are adjusted so that the weighted averages of key statistics become nationally representative. The reweighting process has two major steps: (i) Propensity Score Weighting and (ii) Maxentropy or Raking.

Propensity Score Weighting (PSW)

Propensity Score Weighting (PSW) is designed to adjust a phone survey's sampling weights by comparing a nationally representative household survey (the reference survey), with the phone survey. PSW appends the phone survey to the reference survey and estimates each sample household's probability of being included in the phone survey. PSW then ranks all households in the phone and reference surveys based on the predicted probability and creates quintiles. The weights of households in the phone survey are adjusted so that each quintile's share of households in the phone survey exactly resembles that of the reference survey. More specifically, the weights of households in the phone survey are adjusted so that the sum of their weights in each quintile becomes identical to that of households in the reference survey included in the same quintile.

Maxentropy and Raking

Maxentropy or raking is executed to refine the weights further. Even after PSW, summary statistics in the phone survey could still differ largely from those in the reference survey. Such differences can be real, particularly when a long time has passed between the reference and phone surveys. Still, it is unlikely that summary statistics of slow-changing indicators like household size, dependency ratios, household head's educational attainment, or population shares of districts would change significantly within a relatively short time span. Maxentropy or raking adjusts weights to match the summary statistics of selected slow-changing variables between the reference and phone survey in an exact (or very close) manner. The following information boxes briefly explain maxentropy and raking.

Box 1.1. Maxentropy

Maxentropy is a Stata command that selects weights that maximize entropy while matching averages of pre-selected indicators between the reference and phone surveys. The selection of indicators is important — only slow-changing variables should be considered as candidates for such indicators. For variables that changed to a large extent over the time period between the reference and phone surveys, ignoring the real changes and forcing averages to be the same between the two surveys can bias all statistics estimated from the phone survey. Therefore, it is important to select indicators that are slow-changing. This identification of slow-changing variables is also important when running SWIFT Plus. Indicators like household size, dependency ratio, highest educational attainment of the household head, and population shares of subnational units are such examples. However, since these indicators can also change over time and the speed of the change varies by country, it is always useful to look at trends of these indicators using multiple rounds of past comparable household before selecting the indicators for matching.

Box 1.2. Raking

Raking, also known as "iterative proportional fitting," is an algorithm consisting of an outer cycle that checks convergence criteria and an inner cycle that iterates over the control variables. Once the phone survey with an updated weight shows convergence along a certain control variable, the algorithm moves to the next control variable, and adjusts the weights until there is convergence on that variable, and so on. The process continues until the weights achieve convergence along all specified variables. More information on raking can be found from Kolenikov (2014).

For some countries, maxentropy is conducted at the subnational level. By doing this, summary statistics of target indicators are matched at the subnational level, but the new weights might not be consistent with the population share of subnational unit in the reference survey. If so, one more step to adjust the weights – post-stratification – is needed to ensure that the population share of subnational units are consistent with the reference survey.

More details on all of the above-mentioned reweighting steps, in particular, Propensity Score Weighting, maxentropy, and post-stratification, can be found in Zhang and Yoshida (2021).

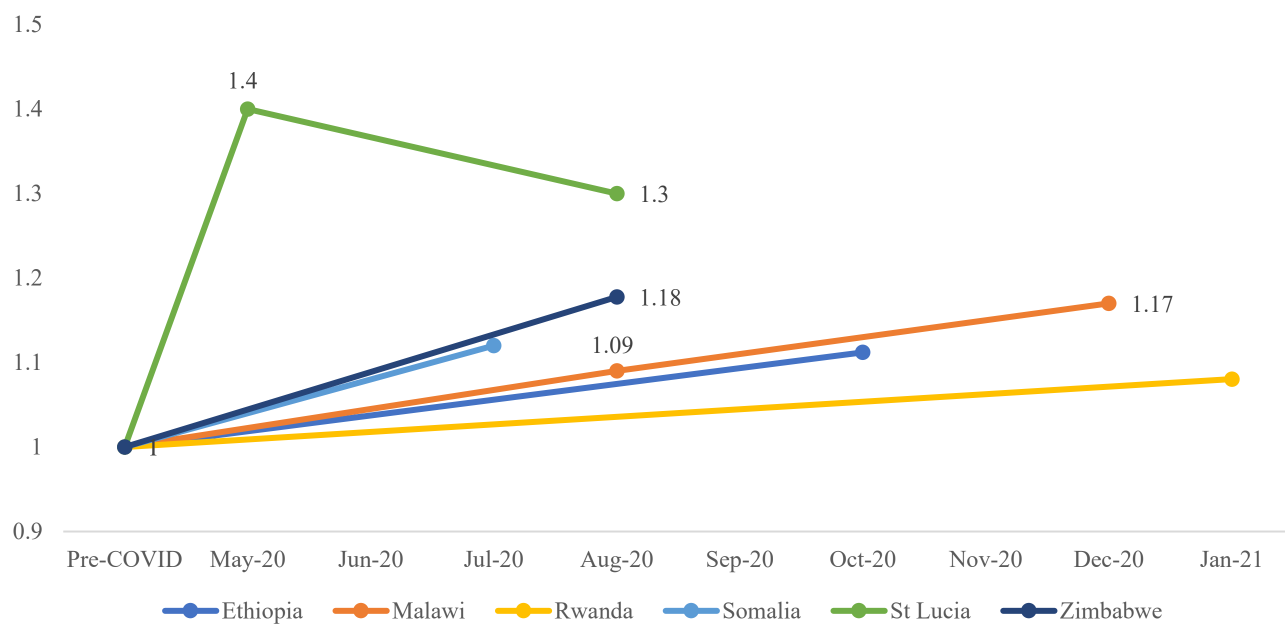
Part II: Cross-Country Analysis

This section highlights some key findings from cross-country comparisons. The following section covers the results for each country individually and in more depth.

Poverty and Inequality

A cross-country comparison shows that poverty has increased compared to the pre-COVID era in all countries included in this report. Saint Lucia is the only country in this report which includes poverty projections within three months of the COVID-19 outbreak (March 2020), revealing that poverty increased rapidly in this short period and then slowed. Although other countries included in this report do not have poverty projections in the early stage of the pandemic, it is likely they experienced a similar spike and plateau in poverty.

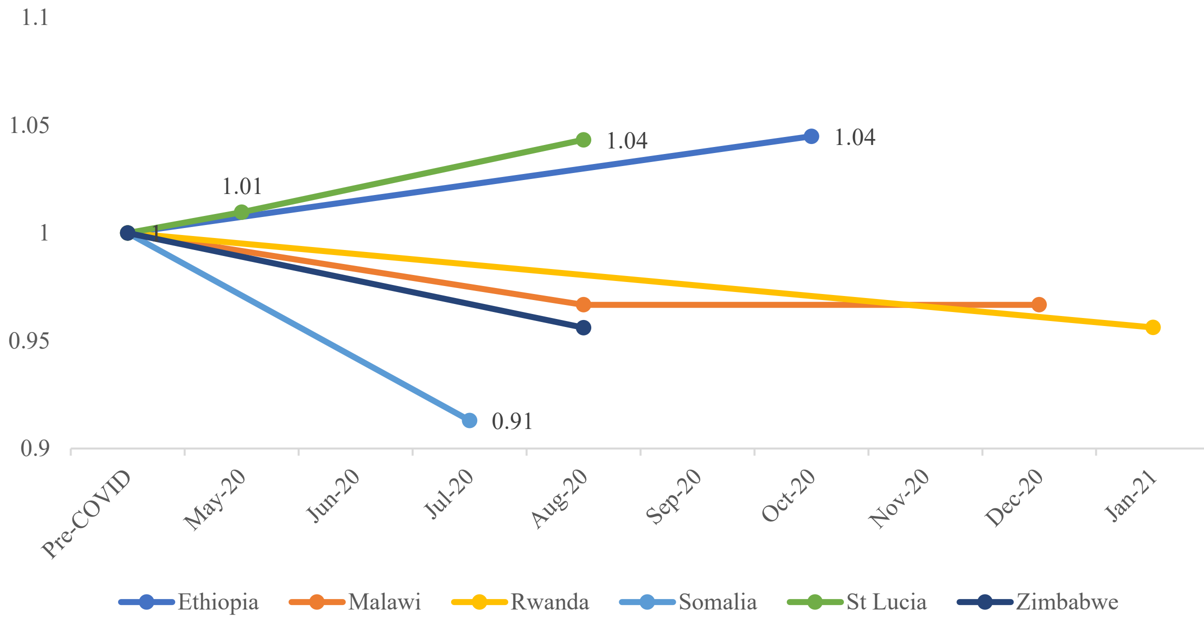
Figure 2.1 Poverty trend scores



In contrast, inequality trends show the more complex nature of how COVID-19 has impacted populations.[3] In Saint Lucia, both poverty and inequality increased in the first round (May 2020), but in the next round, poverty decreased while inequality continued to increase. Ethiopia shows both poverty and inequality increased for all survey rounds. Lastly, inequality appears to have declined for all survey rounds in Rwanda, Malawi (rural south), Zimbabwe, and Somalia.

[3] Annex 2 shows evidence that SWIFT methodology can estimate Gini coefficients accurately.

Figure 2.2 Inequality trend scores

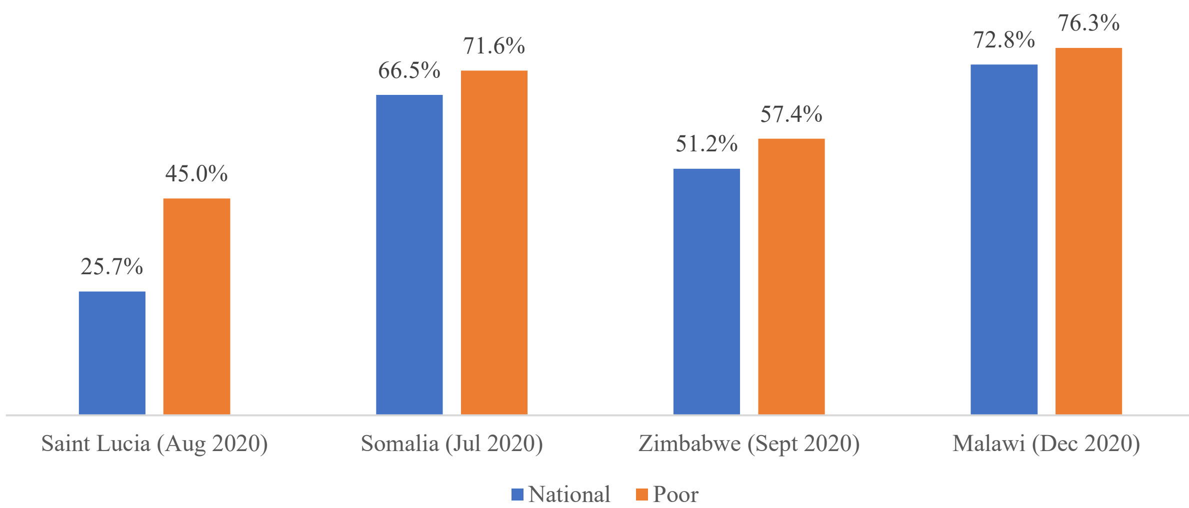


SWIFT enables us to estimate profiles of the poor. Annex 3 shows the results of empirical evaluations on how accurately we can estimate the means of variables for the poor identified by household expenditures imputed by SWIFT models. Using SWIFT, the next sections show comparisons of key variables between the poor and other segments of the population.

Food Security

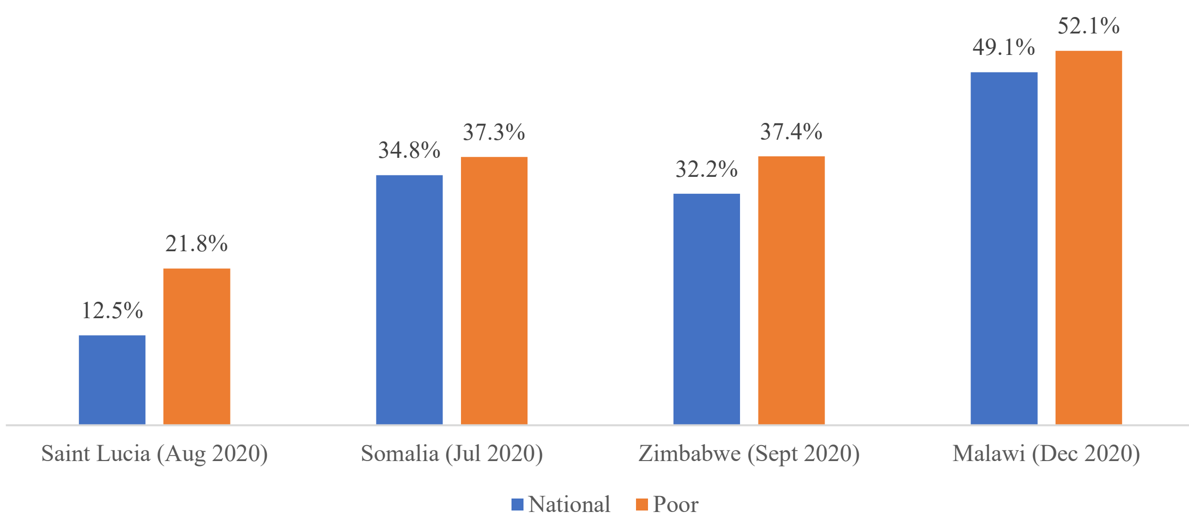
Throughout the COVID-19 pandemic, the poor have experienced higher rates of food insecurity. Figures 2.3 and 2.4 show the results of two of the primary food security questions for four of the countries included in this report. On both of these indicators and in every country, the poor fare worse compared to the national average. This is true for countries with high rates of food insecurity at the national level, like Somalia and Malawi, as well as countries with relatively lower rates of food insecurity at the national level, like Saint Lucia and Zimbabwe.

Figure 2.3. Comparison of food security indicators — household member ran out of food



Note: In this figure, Malawi refers to only southern rural Malawi

Figure 2.4. Comparison of food security — household member went a day without eating

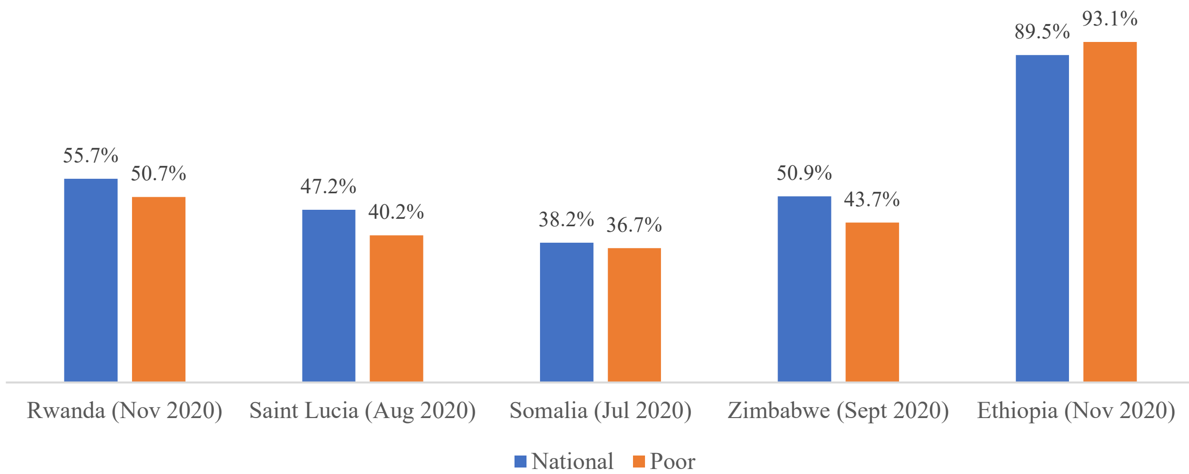


Note: In this figure, Malawi refers to only southern rural Malawi

Employment Status

Similar to food security, the poor have experienced harsher employment conditions compared to the national average, with some exceptions. The poor had slightly lower levels of employment (as measured by the household head having worked in the past week) compared to the national average in all countries except Ethiopia, where the poor had slightly higher rates of employment. It should be noted, however, that this finding has no relation to the relative employment status of the poor in the pre-COVID era.

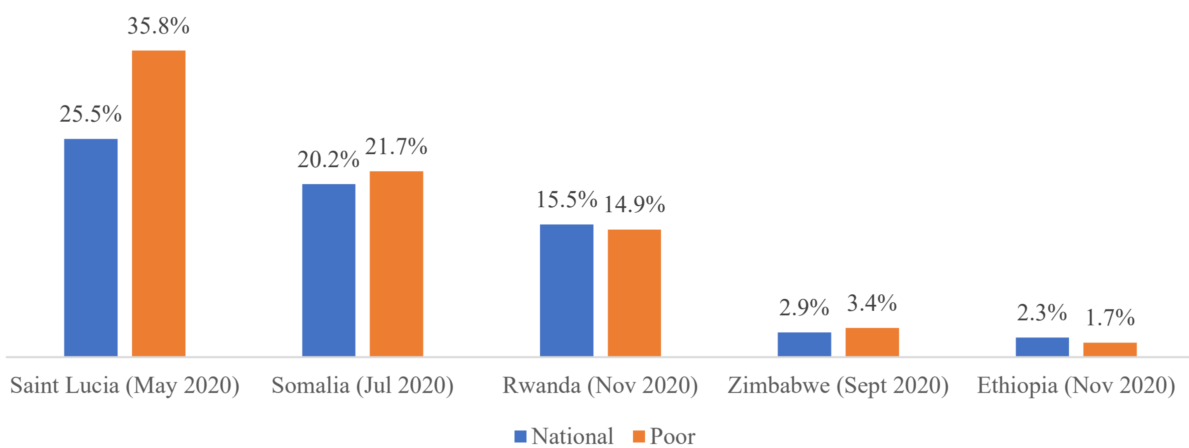
Figure 2.5. Comparison of household heads who worked in the past week (at time of survey)



Note: In this figure, Malawi refers to only southern rural Malawi

Looking at job stoppage (if the household head was working prior to the pandemic but not at the time of the survey), there is no clear trend when comparing the poor and the national average. In Somalia, Rwanda, Zimbabwe, and Ethiopia, the rates of job stoppage among the poor are nearly identical to the national average and are actually slightly lower in Rwanda and Ethiopia. The exception is Saint Lucia, where the poor experienced job stoppage at a rate 20 percentage points higher than the national average.

Figure 2.6. Comparison of household heads who were working before the COVID-19 outbreak but not at the time of survey (job stoppage)



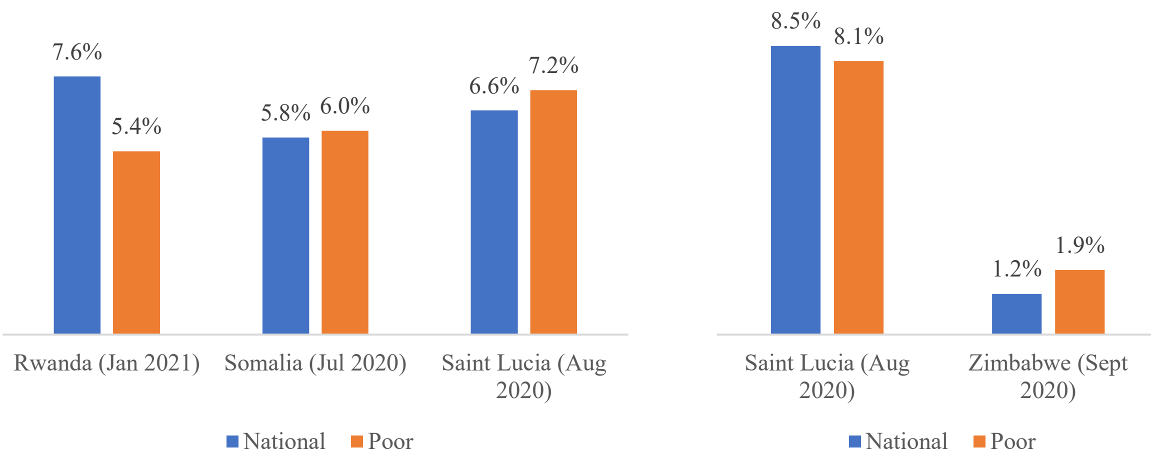
Note: In this figure, Malawi refers to only southern rural Malawi

Government Assistance

Where data is available, government assistance in most countries appears pro-poor for both cash transfers and food assistance, but only marginally in most cases. The poor have received cash transfers at rates slightly higher than the national average in Somalia and Saint Lucia, but at lower rates in Rwanda. Food assistance has been mostly even between the national population and the poor in Saint Lucia and in Zimbabwe.

Figure 2.7. Comparison of government assistance between the national average and poor

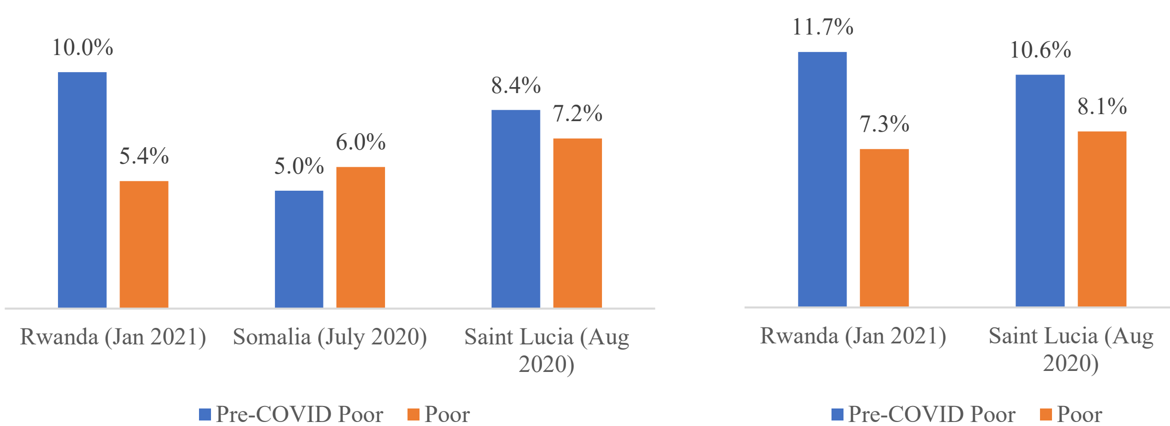
(a) Cash transfers (b) Food



To see if government assistance has been successful at reaching the newly poor, estimates for Rwanda, Somalia, and Saint Lucia include government assistance rates for the pre-COVID poor and the current poor. Results of this analysis show that government assistance has been slow to accurately target the current poor during the pandemic. In Rwanda, the current poor received cash assistance at a rate almost half that of the pre-COVID poor. Somalia, however, was more successful at targeting cash transfers to the current poor compared to the pre-COVID poor. With regards to food assistance, both Saint Lucia and Rwanda were less successful at distributing aid to the current poor as compared to the pre-COVID poor.

Figure 2.8. Comparison of government assistance between the pre-COVID poor and the current poor

(a) Cash transfers (b) Food



Part III: Country-Specific Results

I. Saint Lucia

This section shows country specific information for Saint Lucia SWIFT poverty projections and profiling. Further details on the following subsections (data, reweighting, and results), as well as descriptions of the SWIFT models and estimates for Saint Lucia, can be found in the companion paper, Chen et al. (2021).

Data and Reweighting

Round one of the Saint Lucia COVID-19 HFPS drew its sample from a database of telephone numbers from 179 out of 582 Enumeration Districts (EDs) spread across the eleven regions in Saint Lucia. The database was collected as part of the listing for a Saint Lucia Disaster Risk Management (DRM) & Poverty survey. After removing phone numbers that were no longer active and households that did not want to participate, the survey's final sample contained 1,093 phone numbers across 141 EDs.

The first round of HFPS was collected between May 5 and May 18, 2020 and the second round between July 27 and August 20, 2020. All respondents from the first round of HFPS were contacted for interviews in the second round, but due to nonresponses, the second round's final sample was 900. The Household Budget Survey 2016 was used for developing the poverty projection models.

The reweighting procedure for the Saint Lucia HFPS consisted of three steps: (i) propensity score weighting, (ii) subnational maxentropy, and (iii) post-stratification at the national level. The reference survey is the Household Budget Survey 2016.

Results: Poverty projections and profiles

Poverty and inequality in the pre-COVID era are estimated from Saint Lucia HFPS round one data using the pre-COVID model in the SWIFT-COVID19 package. Poverty and inequality in the COVID-19 era are estimated from HFPS round one and two data using the COVID-era model.

The following section shows the trends in poverty and inequality from 2016 to August 2020, including estimates for the periods of time directly before and after the COVID-19 outbreak. This section also compares profiles on food security, employment status, and the coverage of social protection for several key groups: the pre-COVID poor, the poor in the first round of the HFPS, the poor in the second round of the HFPS, and the overall national population. In the following discussion and figures, the "pre-COVID poor" refers to the group of individuals who would have been considered poor prior to the COVID-19 outbreak and who are identified by the pre-COVID model.

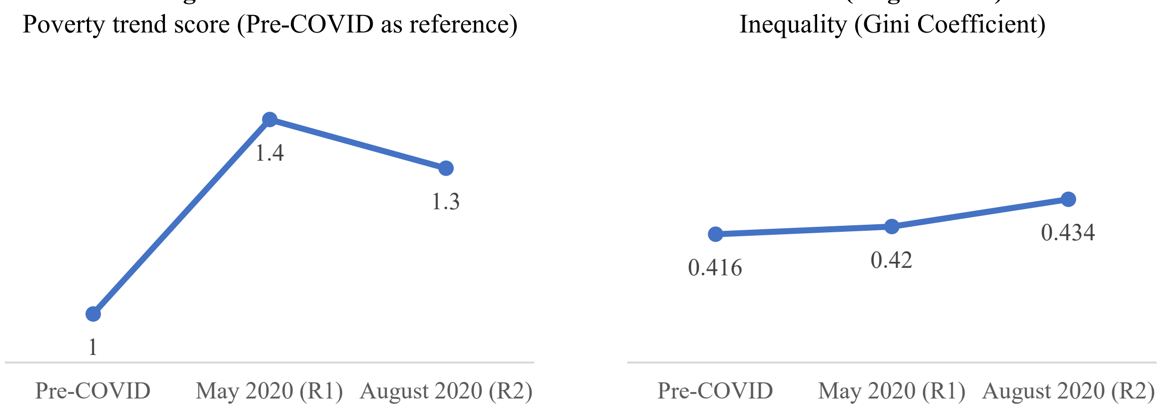
A. Poverty

Figure 3.1.1 shows the poverty trend score, a ratio of poverty rates with the pre-COVID rate as reference. According to this measure, poverty incidence increased 40 percent (not 40 percentage points) between the pre-COVID era and May 2020 (round one COVID-19 HFPS). The incidence of poverty then started to decline 10 percent from May to August 2020 (between HFPS rounds one and two). The probability that the poverty rate increased by 5 or more percentage points between the pre-COVID era and May 2020 is 85 percent. The same probability declines significantly to 64 percent when looking at the period of time from May to August 2020.

B. Inequality

Based on the imputed consumption expenditures, the Gini coefficient was estimated for the pre-COVID era, round one data, and round two data. All of the Gini coefficients are above 0.4, indicating a sizeable income gap in Saint Lucia, even before the COVID-19 outbreak. After the COVID-19 outbreak, the Gini coefficient increased slightly to 0.42 in May 2020 (round one) and then to 0.43 in August 2020 (round two). The upward trend shows that the recovery from the COVID-19 pandemic has not been uniform and may have increased income inequality further.

Figure 3.1.1. Trends between HBS 2016 and HFPS Round 2 (August 2020)

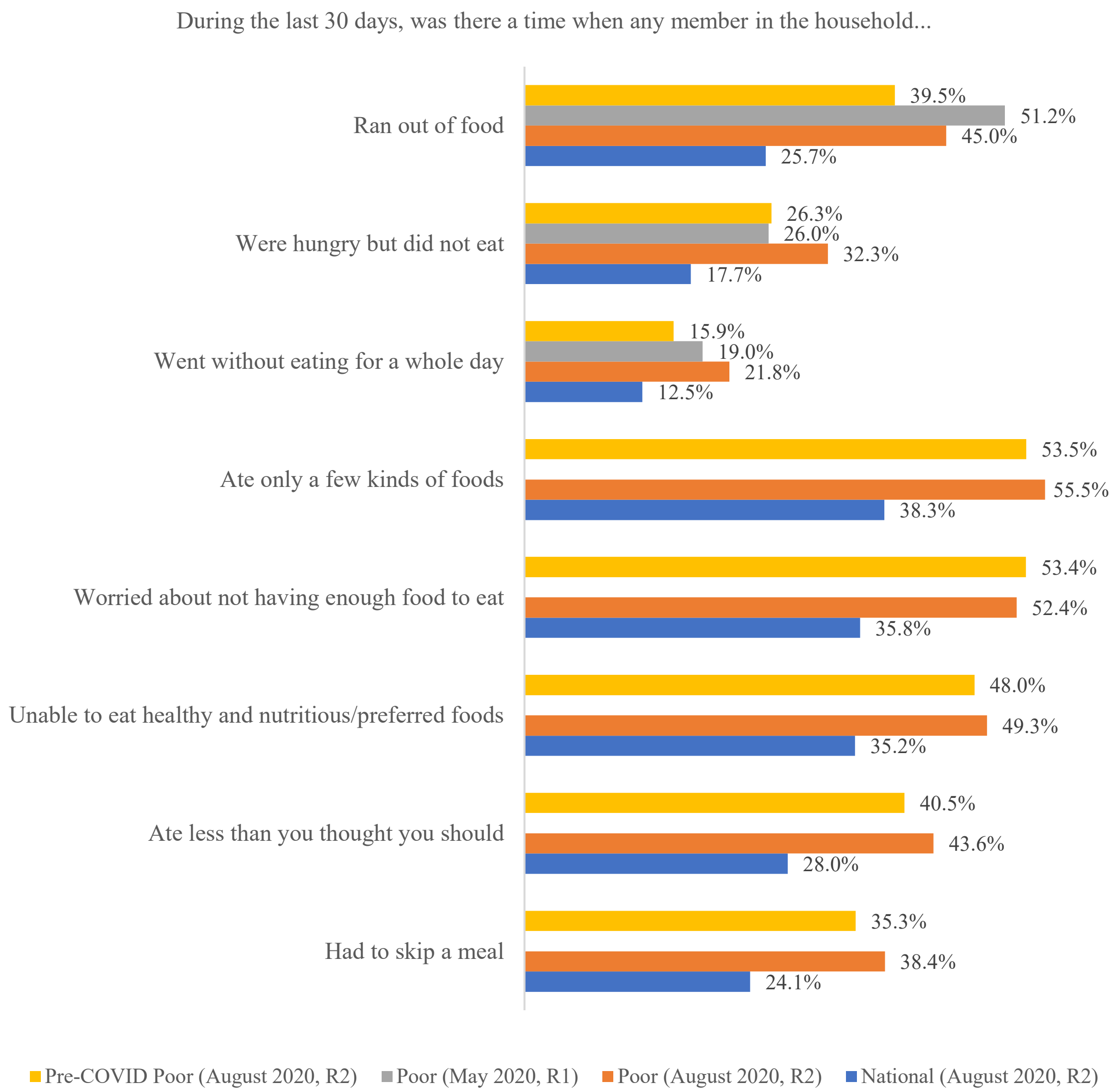


Source: Authors' estimation using data from HBS 2016 and HFPS round 1 and round 2

C. Food security

Food security is measured by eight questions included in the Food and Agriculture Organization (FAO)'s food security measurement. Round one included only three questions, while round two included all eight questions. The surveys yielded two major findings. First, the poor's food security conditions were far worse than the national average. In almost one-third of poor households surveyed in round two, at least one adult member experienced hunger but did not eat anything during one or more days in the last 30 days, as compared to only 18 percent of all households. Second, the poor's food security has worsened severely since the COVID-19 outbreak. That being said, the trend from round one is mixed — two out of three indicators show a significant deterioration in food security between rounds one and two, but one indicator shows some improvement.

Figure 3.1.2. Comparison of food security indicators across different groups

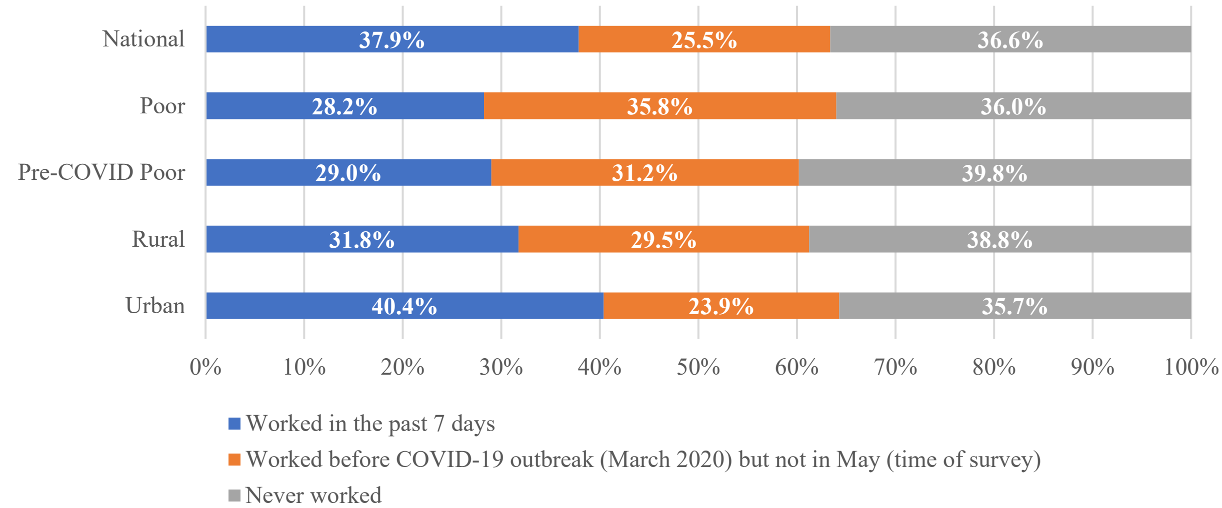


Source: Authors' estimation using data from HBS 2016 and HFPS round 1 and round 2

D. Employment status

In round one, all respondents were asked whether they were working last week and, if not, whether they were working before the COVID-19 outbreak (i.e., before March 20, 2020). According to the round one data, only 29 percent of the pre-COVID poor were working in May 2020 (during the round one HFPS) and 31 percent reported to have worked prior to the COVID-19 outbreak but not in May 2020. The percentage of job stoppage among the pre-COVID poor was significantly higher than the national average (31 versus 26 percent). The poor in round one faced an even worse situation, with 36 percent experiencing job stoppage.

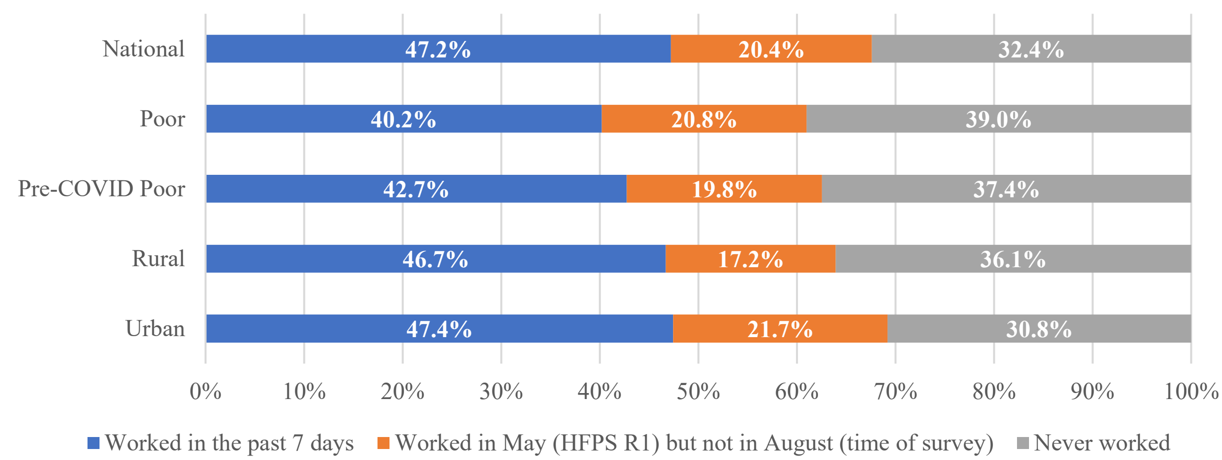
Figure 3.1.3. Comparison of employment status across different groups during May 2020 (HFPS R1)



Source: Authors' estimation using data from HBS 2016 and HFPS round 1 and round 2

Employment status appears to have improved between rounds one and two of the COVID-19 HFPS. However, the improvement is not uniform. Around 43 percent of the pre-COVID poor worked in August 2020 (during the round two HFPS), compared to 29 percent in May 2020. However, the employment status of the pre-COVID poor still remained worse than the national average (43 versus 47 percent). The poor in August 2020 faced an even lower employment rate than the pre-COVID poor.

Figure 3.1.4. Comparison of employment status across different groups during August 2020 (HFPS R2)



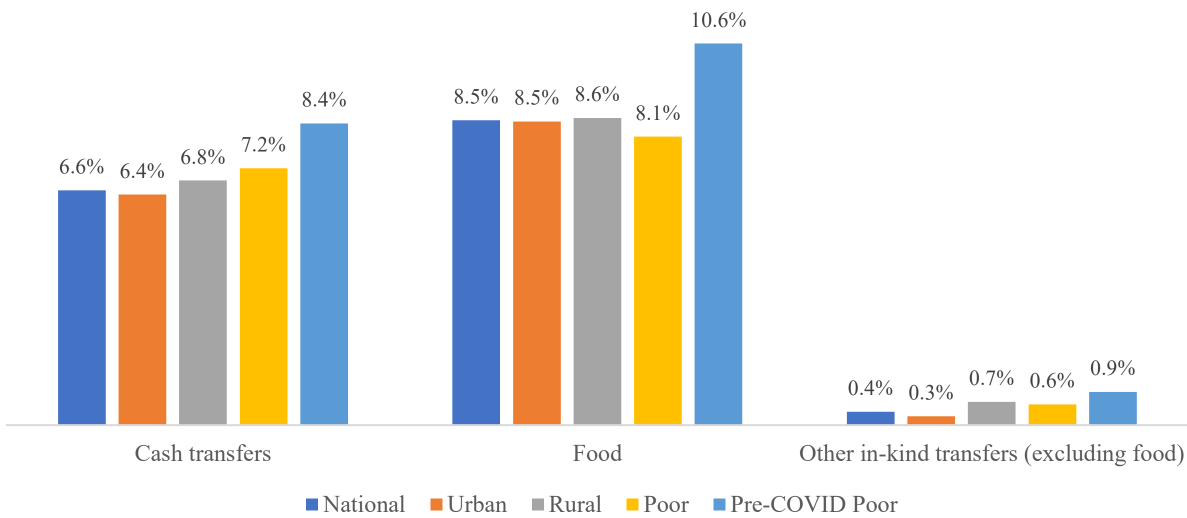
Source: Authors' estimation using data from HBS 2016 and HFPS round 1 and round 2

E. <u>Coverage of government assistance</u>

In Saint Lucia, the coverage of government assistance was pro-poor, meaning those who were already poor before the COVID-19 outbreak had higher rates of assistance than that of the national average. However, government assistance was less pro-poor in round two. In round two, the coverage of cash transfers and other in-kind assistance was higher among the poor than the national average, but the coverage of food assistance was lower. It should be noted that round two data was collected before the government expanded

the social assistance program. In future work, it will be beneficial to estimate the coverage of the poor and the national average in the newly expanded program to evaluate its pro-poorness.

Figure 3.1.5. Comparison of government assistance across different groups as of August 2020 (HFPS R2)



Source: Authors' estimation using data from HBS 2016 and HFPS round 1 and round 2

Summary

Since the beginning of the pandemic, Saint Lucia has collected two rounds of COVID-19 High-Frequency Phone Survey (COVID-19 HFPS), the first in May and the second in August of 2020.

Estimates show a spike in poverty in May 2020 compared to before the COVID-19 outbreak – the relative poverty score increased from 1 to 1.4 and the probability that poverty increased more than 5 percentage points is 85 percent. This increase is a sharp reversal of the trend in poverty before the COVID-19 outbreak. Subsequently, poverty decreased slightly between May and August 2020. Inequality did not change much in May but started to increase slightly between May and August.

Most food security indicators show that the poor have experienced increased food insecurity and fared worse than the national average during the pandemic. The poor have also experienced worse employment conditions than the national average, including higher rates of job stoppage — though this has improved slightly between May and August of 2020, even among the poor. Lastly, government assistance remains pro-poor, but was less so in round two (though this is likely due to the fact that the round two data was collected before the government expanded the social assistance program).

II. Ethiopia

This section shows country specific information for Ethiopia's SWIFT poverty projections and profiling. Further details on the following subsections (data, reweighting, and results) as well as descriptions of the SWIFT models and estimates for Ethiopia can be found in the companion paper, Wiser et al. (2021).

Data and Reweighting

The Ethiopia COVID-19 HFPS drew its sample from the database of telephone numbers from the 2018/19 Ethiopia Socioeconomic Survey (ESS4). At least one valid phone number was obtained for 5,374 households (4,626 owning a phone and 995 with a reference phone number). This database is the sampling frame for the HFPS. ESS4 was used for developing the poverty projections models.

Ethiopia conducted twelve rounds of HFPS between April 2020 and June 2021. Round seven, which includes the SWIFT question modules, was conducted between October 19 and November 10, 2020 with a total of 2,534 households (715 rural and 1,819 urban).

The reweighting procedure for the Ethiopia HFPS consists of three steps: (i) propensity score weighting, (ii) subnational maxentropy, and (iii) post-stratification. The reference survey is the ESS4.

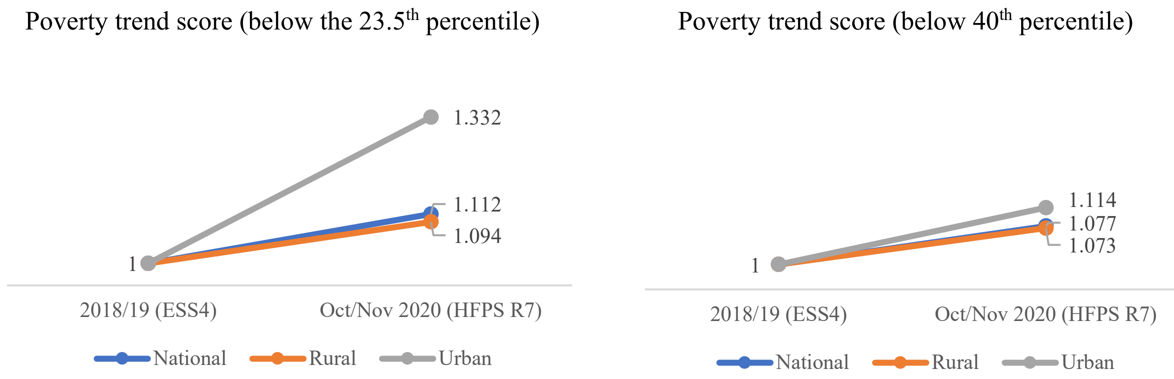
Results: Poverty projections and profiles

A. <u>Poverty</u>

In Ethiopia, ESS4 is not the household survey used for estimating official poverty statistics and does not contain poverty lines. Because the the reference survey (ESS4) does not contain poverty lines, two poverty lines – the 23.5th percentile and 40th percentile of ESS4 data – are set to estimate poverty headcount rates. The first poverty line (23.5th percentile) is selected because 23.5 percent is the most recent official poverty rate for Ethiopia. The second poverty line (40th percentile) is added to see whether the poverty trend based on the first poverty line is robust against a change in the poverty line. The 40th percentile, specifically, is chosen because it aligns with one of the World Bank's twin goals of shared prosperity, which tracks the income growth of the poorest 40 percent of a country's population.

Figure 3.2.1 shows the poverty trend score based on the 23.5th and 40th percentiles. According to these measures, at the national level, the share of people below the first poverty line increased by 11.2 percent and the share of people below the 40th percentile line increased by 7.7 percent between 2018/19 (ESS4) and October/November 2020 (HFPS round seven). This implies that at the national level, the number of people below the 23.5th percentile line and the 40th percentile line grew 11.2 percent and 7.7 percent, respectively, if the population growth between ESS4 and HFPS round seven is negligible.

Figure 3.2.1 Trends in Poverty from 2018/19 ESS4 to HFPS Round 7 (ESS4 as reference)



Source: Authors' estimation using data from ESS4 and HFPS Round 7

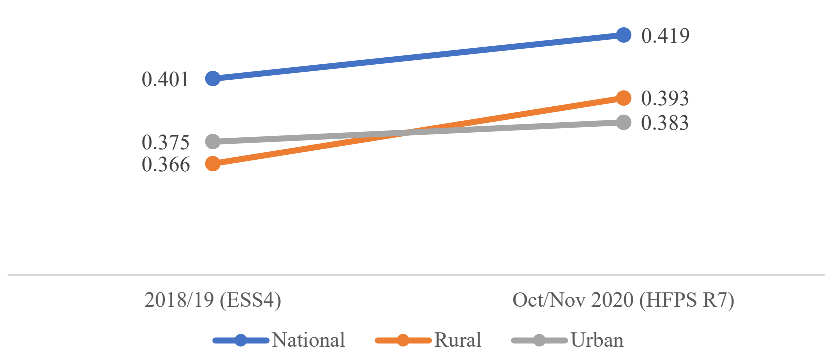
The COVID-19 pandemic has had much larger adverse effects on employment and income in urban areas. This is reflected in a much larger relative increase in poverty in urban areas. The poverty trend score shows that the share of people below the first poverty line in urban areas increased by 33.2 percent since ESS4 data was collected. The rate of growth in the poverty rate in urban areas is much faster than in rural areas, where the poverty headcount rate increased 9.4 percent. However, the contrast between urban and rural areas is much lower when using the 40th percentile poverty line, showing a growth in the poverty headcount rate of 11.4 percent in urban areas and 7.3 percent in rural areas. Despite the much smaller pace of increase in poverty in rural areas, the sheer size of the rural population, combined with higher poverty rates (26 percent in rural areas and 15 percent in urban areas), means that the increase in the absolute number of poor people was much higher in rural areas.

The probability that poverty did, in fact, increase from 2018/19 ESS4 to HFPS round seven (October/November 2020) at the national, urban, and rural levels are 78.1 percent, 81.7 percent and 73.0 percent, respectively. Based on the 40th percentile line, the probability that poverty increased is 79.6 percent nationally and 71.4 and 71.4 percent for rural and urban areas, respectively.

B. <u>Inequality</u>

Figure 3.2.2 shows that the Gini coefficients at the national level are above 0.4, indicating a sizeable income gap in Ethiopia between the rich and the poor. Inequality in Ethiopia has increased since the outbreak of the COVID-19 pandemic, with a Gini coefficient of 0.42 in October/November 2020. In 2018/19, inequality was higher in urban areas compared to rural areas, with Gini coefficients of 0.375 and 0.366, respectively. However, the ranking is reversed in the COVID-era.

Figure 3.2.2 Trends in Inequality from ESS4 to HFPS Round 7 (Gini Coefficient)

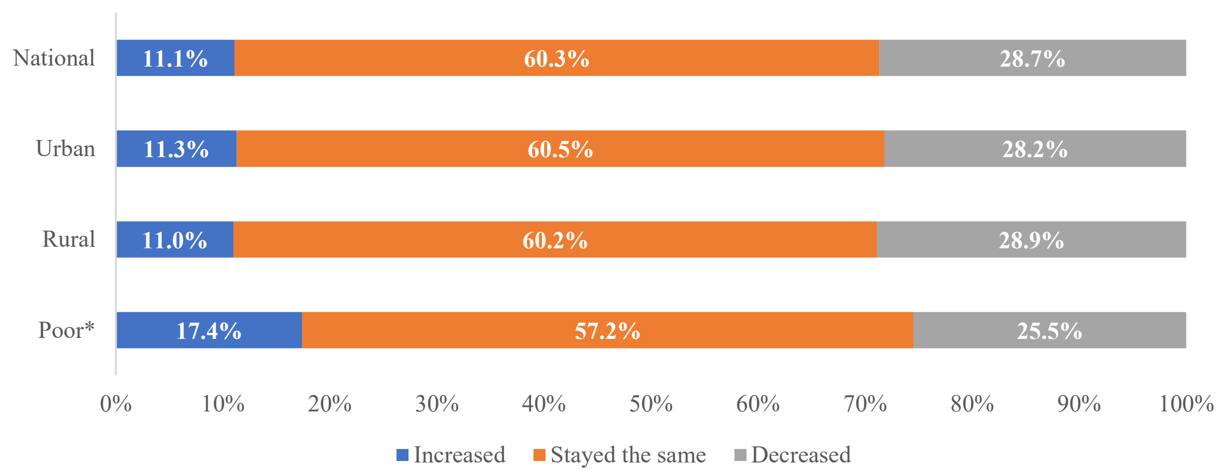


Source: Authors' estimation using data from ESS4 and HFPS Round 7

C. Total income changes from the previous round

Since HFPS round seven does not include data on income changes, data from HFPS round six (September/October 2020) is used to compare income changes after using the household ID to match the poverty status estimated from HFPS round seven. According to round six data, 11.1 percent of households experienced an increase in total income since ESS4, with similar increases in rural and urban areas. However, 28.7 percent of the national population experienced a decrease in total income, again with similar rates in rural and urban areas. The poor (as of round seven) experienced a faster recovery than the overall population, with 17.4 percent of the poor experiencing a total income increase and 25.5 percent facing a decrease.

Figure 3.2.3. Comparison of total income loss for different groups as of September/October 2020 (HFPS R6)

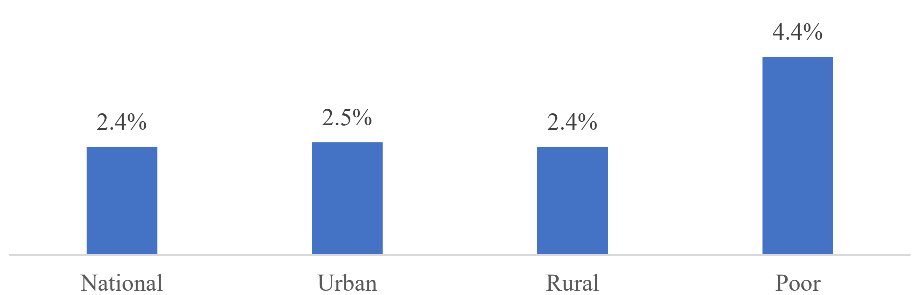


Source: Authors' estimation using data from HFPS round 6 and round 7.
Note: * refers to the fact that the poverty status was defined by SWIFT projections using HFPS round 7.

D. Assistance for food and cash transfer

HFPS round seven data is used to analyze the comparative distribution of three categories of assistance: food assistance only, food assistance and/or cash transfer, and cash transfer only. However, since the coverage of cash transfers was very low, this subsection shows the results of food assistance only. Figure 3.2.4 shows that the coverage of food assistance in Ethiopia was also limited. Only 2.5 percent of households reported to have received assistance. The coverage was very similar for both urban and rural areas. Among the poor, the coverage of food assistance was 4.4 percent, which is low but significantly larger than the national average.

Figure 3.2.4. Comparison of food assistance for different groups during October/November 2020 (HFPS R7)

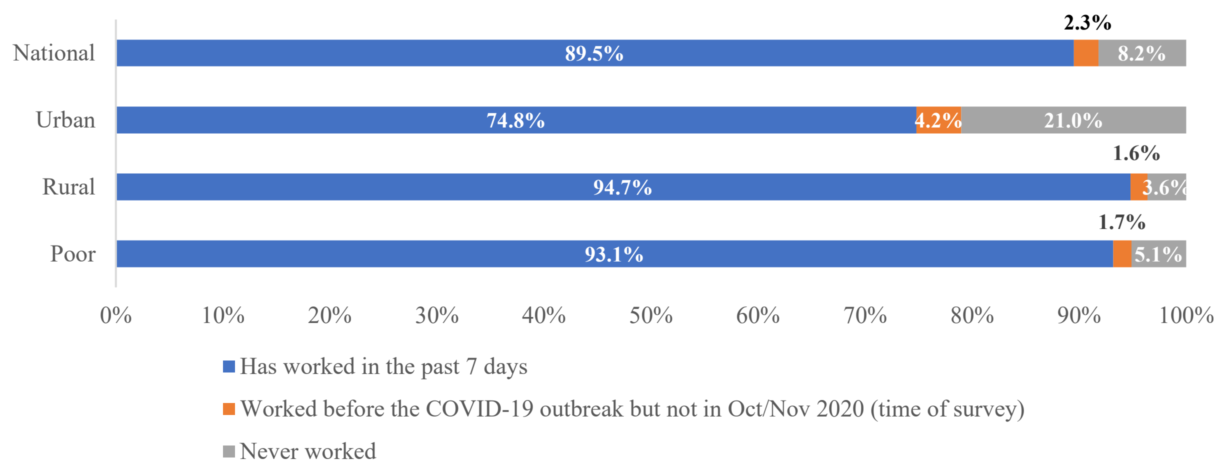


Source: Authors' estimation using data from HFPS round 7

E. Employment Status

For the HFPS round seven survey, all respondents were asked whether they were working last week, and if not, whether they were working before the start of the pandemic. According to the HFPS round seven data, the share of respondents who were working was 89.5 percent at the national level, with a much lower percentage of respondents working in urban areas (74.8 percent) compared to rural areas (94.7 percent). In urban areas, 21 percent of respondents were not employed before the pandemic or during the past week, in contrast to only 3.6 percent in rural areas. The share of the poor who were working last week was 93.1 percent, higher than the national and urban averages but slightly lower than the rural average. The percentage of job stoppage (those who were working before the start of the pandemic but not during the time of the survey) was low for all groups, with the largest percentage in urban areas (4.2 percent).

Figure 3.2.5. Comparison of employment status across groups during October/November 2020 (HFPS R7)



Source: Authors' estimation using data from HFPS round 7

Summary

Since the outbreak of the pandemic, Ethiopia has collected multiple rounds of COVID-19 High-Frequency Phone Surveys (COVID-19 HFPS). The seventh round, which was used for analysis in this note, took place between October and November 2020.

Estimates show that poverty rates increased in October/November 2020 compared to the pre-pandemic period of 2018/19. The poverty headcount rates increased at the national level and for both rural and urban areas, but the pace of growth in urban areas was much faster than in rural areas. This is particularly true when observing the lower poverty line. Inequality, as measured by the Gini coefficient, increased at all levels; however, the ranking of inequality between urban and rural areas was reversed — inequality in urban areas was higher than in rural areas in 2018/19 but lower than in rural areas during the COVID-era.

Profiling of the poor on the selected topics provides some interesting results. First, the recovery in income for the poor appears slightly faster than that for other groups. Second, although overall coverage was limited, the coverage of food assistance was pro-poor, in that the poor have received food assistance at higher rates than that of other groups. Lastly, the employment rate of the poor was high (93.1 percent), only slightly lower than the rural average but significantly higher than the urban average. These observations show that the situation among the poor can be very different from the national, urban and rural averages and highlight the benefits of poverty profiling derived by with the SWIFT methodology.

III. Southern Rural Malawi

This section shows country specific information for Malawi (rural south) SWIFT poverty projections and profiling. Further details on the following subsections (data, reweighting, and results), as well as descriptions of the SWIFT models and estimates for southern rural Malawi, can be found in the companion paper, Yoshimura et al. (2021). The companion paper also includes an analysis on poverty and vulnerability.

Data and Reweighting

Since August 2020, Malawi has implemented monthly surveys, including a baseline survey, with the Rapid and Frequent Monitoring System (RFMS) for 4,200 households in six districts (Balaka, Chiradzulu, Chikwawa, Mangochi, Phalombe, Zomba) in the southern region of the country.

The RFMS sampling frame is based on listing information and cartography from the 2018 Population and Housing Census, across the six districts in Malawi (Balaka, Chiradzulu, Chikwawa, Mangochi, Phalombe and Zomba). First, 400-450 households were chosen from randomly selected EAs in each traditional authority in each district. An additional 1,600 households were oversampled from Balaka, Chikwawa, Mangochi and Phalombe, where USAID and FCDO operate projects, in order to make the sample representative in their project areas. Thus, a total of 4,245 households were selected for the survey.

Relevant to the analysis in this report, SWIFT questions were asked in August 2020 (to be referred to as RFMS round one) and December 2020 (to be referred to as RFMS round two). All respondents from the August survey (4,245) were surveyed again in December.

The fourth Integrated Household Survey (IHS4) was used to develop the poverty projection models.

Unlike other countries in this report, Malawi collected data for this analysis through in-person enumerators who live in the villages they survey. However, even though the data is not coming from phone surveys, reweighting on key summary statistics is still conducted to ensure that the survey data is fully representative of Malawi's rural south. The reweighting procedure for the Malawi RFMS includes (i) maxentropy at the district level and (ii) post-stratification. The reference survey is IHS4.

Results: Poverty projections and profiles

The following section shows the trends in poverty and inequality between the pre-COVID period, August 2020 (RFMS round one), and December 2020 (RFMS round two).

A. Poverty

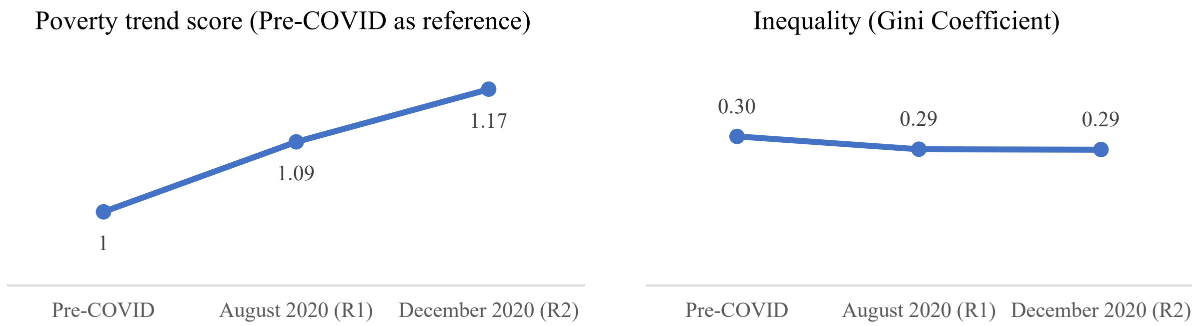
Figure 3.3.1 shows the poverty trend score. According to this measure, poverty incidence increased 9 percent between the pre-COVID era and August 2020 (RFMS round one). The poverty rate in December 2020 (RFMS round two) increased 17 percent compared to the pre-COVID era.

The probability that the poverty rate increased (more than zero percentage points) is more than 99 percent for both time periods — between the pre-COVID period and August 2020 as well as between the pre-COVID period and December 2020. The probability of a more than 3 percentage point increase in the poverty rate is also more than 99 percent in both periods.

B. Inequality

Based on the imputed consumption expenditures, the Gini coefficient was estimated for the pre-COVID period, round one, and round two data. Estimates show that inequality did not change in Malawi from the pre-COVID period to December 2020.

Figure 3.3.1. Trends in Poverty and Inequality from Pre-COVID Era to RFMS Round 2

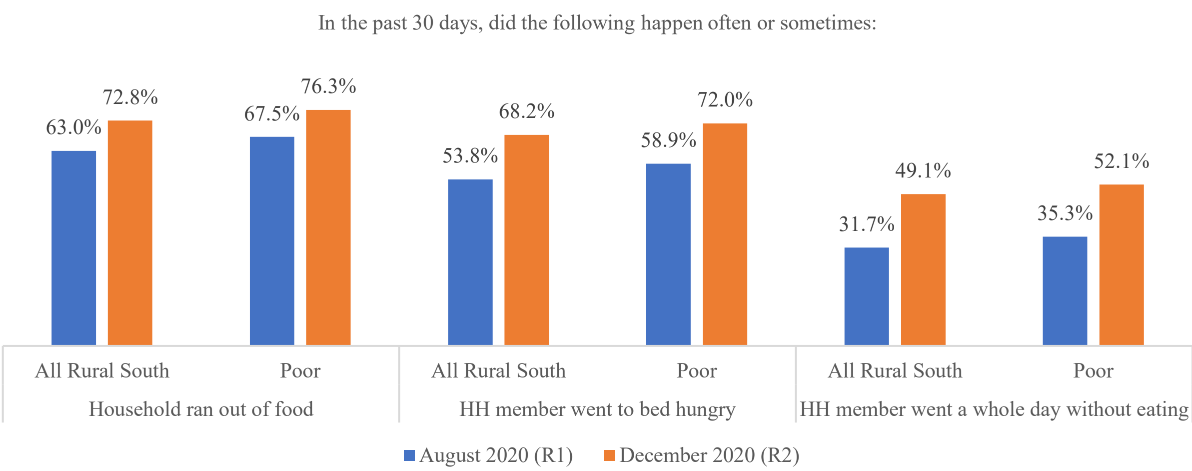


Source: Authors' estimation using data from RFMS rounds 1 and 2

C. Food security

Food security is measured by three different questions. Households are asked if in the past 30 days they have experienced any of the following due to a lack of money or other resources: running out of food, a member going to bed hungry, and a member not eating for a whole day. Figure 3.3.2 shows the results of these food security questions for the total population in southern rural Malawi as well as for just the poor in the region. Food security worsened throughout this time period for all groups on all measures. The food security of the poor was worse than the southern rural Malawi average on all measures and in each survey round.

Figure 3.3.2. Food security indicators for Southern Rural Malawi and the poor



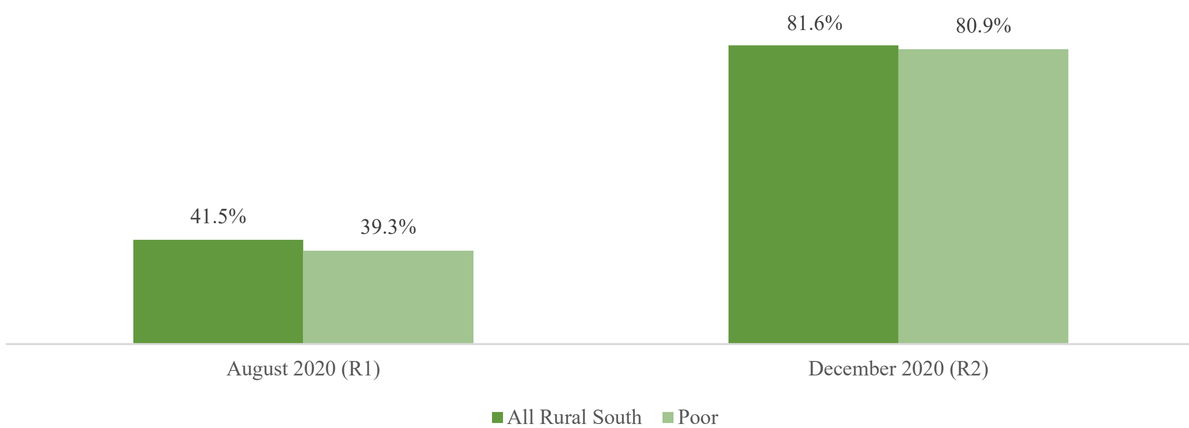
Source for figures 2-4: Authors' estimation using data from RFMS round 1 and round 2

D. Employment status

To measure employment, respondents were asked if they had worked for payment in the past 6 months. Employment was low overall in August 2020, with only 42 percent of the population in southern rural Malawi reporting to have worked in the past 6 months. By December 2020, employment recovered

significantly, with 82 percent of the rural south population reporting to have worked in the past 6 months. The poor fared slightly worse than the rural south average in both August and December 2020.

Figure 3.3.3. Worked for payment in the past 6 months, by group

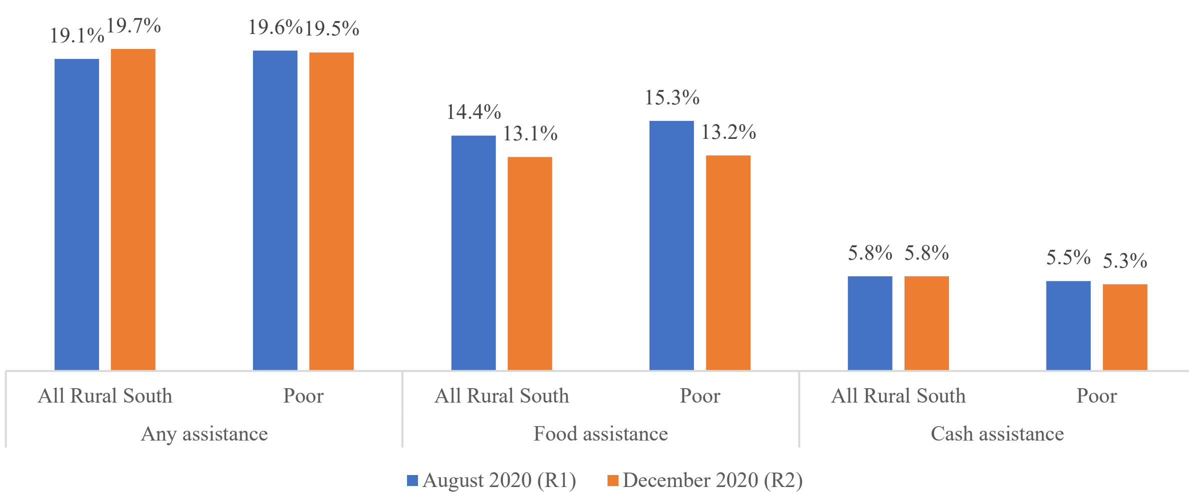


Source: Authors' estimation using data from RFMS round 1 and round 2

E. <u>Coverage of assistance</u>

The coverage of cash transfers was low, with less than 6 percent coverage in the overall rural south and among the poor in both August and December 2020. The coverage of food assistance was slightly better; Around 14 percent of households received food assistance in August 2020, but the coverage declined slightly in December 2020. The coverage of food assistance among the poor was only slightly better than the rural south average.

Figure 3.3.4. Cash Transfer by group



Source: Authors' estimation using data from RFMS round 1 and round 2

Summary

Malawi integrated SWIFT COVID-19 questions into two rounds of the RFMS, in August 2020 (round one) and in December 2020 (round two).

Estimates show a steady increase in poverty incidence in August and December 2020 compared to before the COVID-19 outbreak — the relative poverty score increased from 1 to 1.09 and 1.17 in August and December, respectively. The probability that poverty increased by more than 3 percentage points compared to pre-COVID rates is more than 99 percent in both rounds. Inequality did not change much since the pre-COVID era.

On most indicators, the poor did not fare substantially worse than the rural south average. The total population experienced high levels of food insecurity, but these levels have been only slightly higher for the poor on all food security indicators. Employment improved significantly between August and December 2020 (41.5 to 81.6 percent in rural southern Malawi), with the poor faring only slightly worse than the rural south average. Government assistance was distributed at mostly equal rates between the rural south population and the poor, but the coverage of any type of assistance was around 20 percent or lower in both survey rounds.

IV. Somalia

This section shows country specific information for Somalia SWIFT poverty projections and profiling. Further details on the following subsections (data, reweighting, and results), as well as descriptions of the SWIFT models and estimates for Somalia, can be found in the companion paper, Kotikula et al. (2021).

Data and Reweighting

The COVID-19 Somalia High Frequency Phone Survey (COVID-19 SHFPS) interviewed households from seven states (Banadir, Jubaland, South West, HirShabelle, Galmudug, Puntland and Somaliland).[4] The sampling frame came from the 2014 UNFPA Population Estimation Survey of Somalia (UNFPA PESS 2014). Surveys were conducted between June 18 and July 23, 2020. The sample includes 2,811 households: 1,727 urban, 619 rural, 435 nomads, and 30 IDPs. Due to the small sample size for IDPs, the poverty estimates for IDPs in the following section should be interpreted with care. The second round of the Somalia High Frequency Survey (SHFS2) was used to develop the poverty projection models.

The reweighting procedure for the Somalia HFPS includes (i) PSW and (ii) post-stratification. The reference survey is SHFS2.

Results: Poverty projections and profiles

The following section shows the trends in poverty and inequality from 2017 to July 2020, including estimates for the periods of time directly before and after the COVID-19 outbreak. This section also compares profiles on food security, employment status, and the coverage of social protection for several key groups: the poor, those in rural areas, those in urban areas, nomads, and IDPs.

A. Poverty

Figure 3.4.1 shows the poverty trend score. The poverty rate for SHFPS round one is estimated using the SWIFT Plus methodology. According to this measure, poverty incidence increased 12 percent (not 12 percentage points) between the pre-COVID era and July 2020 (round one COVID-19 SHFPS).

The probability that the poverty rate increased by 3 or more percentage points between the pre-COVID era and July 2020 is 87 percent.

B. Inequality

Based on the imputed consumption expenditures, the pre-COVID and round one Gini coefficients were estimated. Both Gini coefficients are above 0.4, indicating a sizeable income gap in Somalia. Since the start of the pandemic, inequality has decreased, with the Gini coefficient falling from 0.46 to 0.42.

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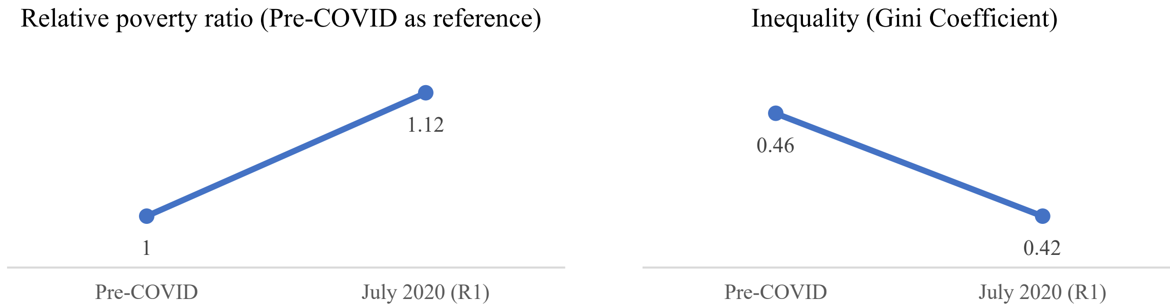
[4] Technically, Banadir is not itself a Federal Member State, but an administrative region (Banadir Regional Administration - BRA). The Federal Republic of Somalia is composed by five member states (HirShabelle, South West State, Jubaland, Galmuduug and Puntland), BRA and the claimed State of Somaliland.

Figure 3.4.1. Trends between Pre-COVID period and July 2020 (COVID-19 SHFPS R1)



Source: Authors' estimation using data from HFS 2017 and COVID-19 SHFPS round 1

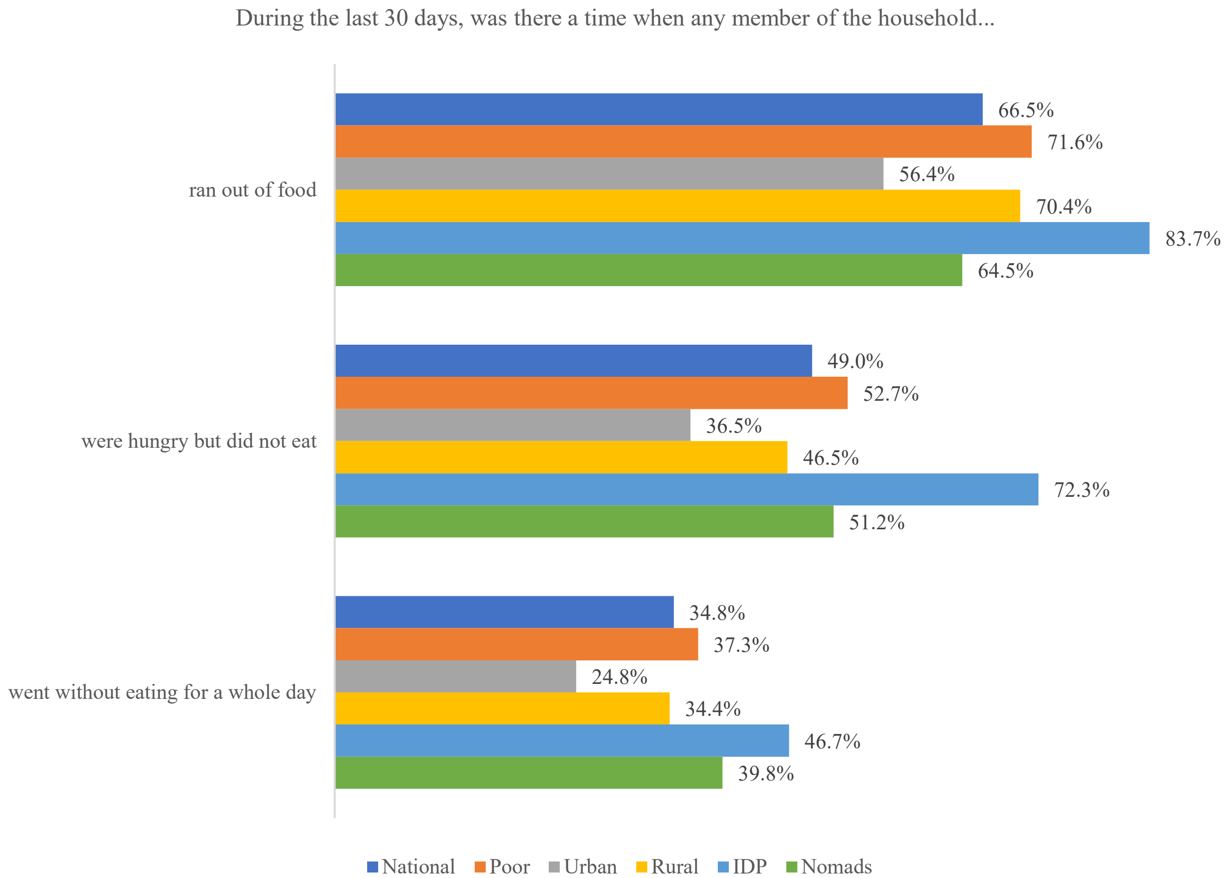
Table 3.4.1. Probability of poverty increase in July 2020 (R1) compared to pre-COVID time

Probability poverty increased more than 0 percentage points	96%
Probability poverty increased more than 3 percentage points	87%

C. Food Security

Food security is measured by three questions: whether or not the household ran out of food, if an adult in the household was hungry but did not eat, and if an adult in the household went without eating for a whole day (all three questions asked about the past 30 days and if this was due to a lack of money or other resources). On all three questions, the poor showed higher rates of food insecurity compared to the national average. Running out of food was the most pervasive form of food insecurity, with the national average above 66 percent and the highest rate among IDPs at 84 percent. Answers to whether or not an adult in the household went without eating for a day showed the lowest rates, with under 35 percent of the total population.

Figure 3.4.2. Comparison of food security indicators across different groups during July 2020 (SHFPS R1)

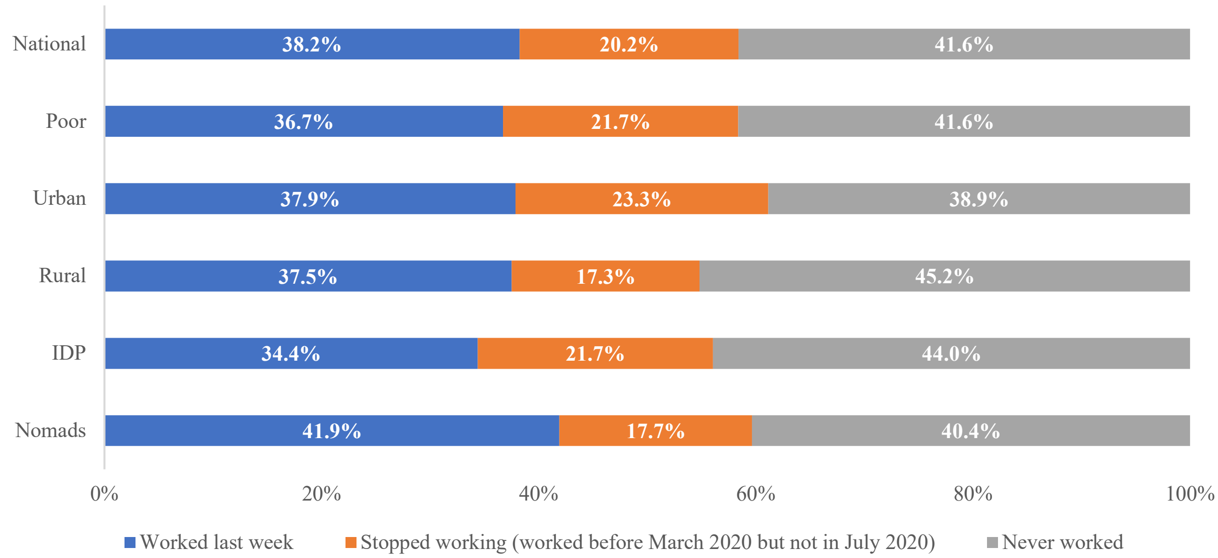


Source: Authors' estimation using data from COVID-19 SHFPS round 1

D. Employment status

In the first round of the HFPS, all respondents were asked whether they were working last week and, if not, whether they were working before the COVID-19 outbreak (i.e., before March 20, 2020). According to the round one data, only 38 percent of the population was working in July 2020 (during the round one COVID-19 SHFPS) and 20 percent reported to have stopped working (worked prior to the COVID-19 outbreak but not in July 2020). The poor had the same percentage of those who had never worked and only slightly lower rates of employment compared to the national average. The percentage of job stoppage among the different groups was relatively even, with slightly higher rates among the urban population and slightly lower rates among the rural population and nomads. The share of those currently employed among the poor was slightly worse than the national average and other groups except for IDPs.

Figure 3.4.3. Comparison of employment across different groups during July 2020 (SHFPS R1)

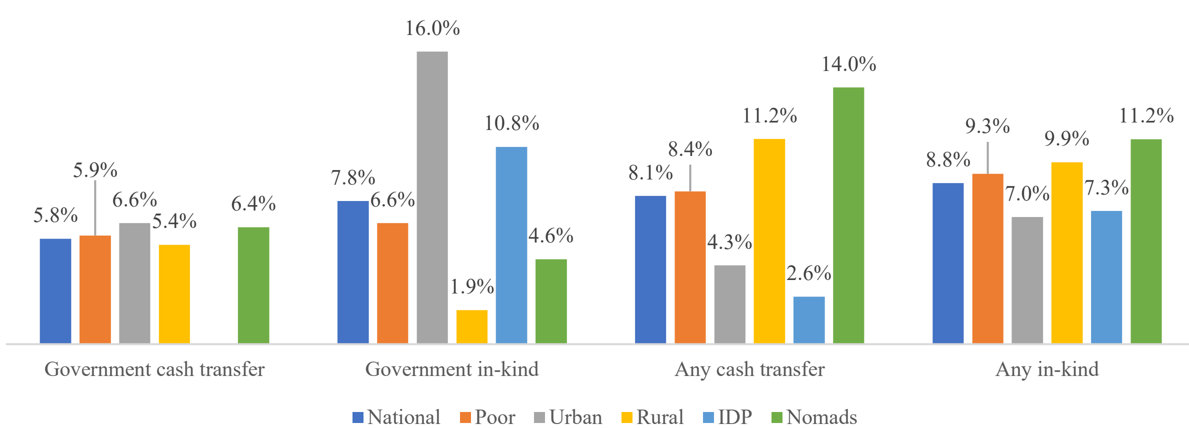


Source: Authors' estimation using data from COVID-19 SHFPS round 1

E. Coverage of assistance

In Somalia, the coverage of government assistance varied between groups and by types of assistance (cash transfers or in-kind assistance). The coverage of assistance for the poor did not differ much from the national average. Government assistance was not pro-poor, with the poor receiving roughly equal levels of cash assistance and lower levels of in-kind assistance compared to the national average. However, overall assistance was slightly pro-poor, with the poor receiving marginally higher rates of assistance from all sources. The urban population was the most likely to receive both types of assistance from the government, being marginally more likely to receive cash assistance, but over 8 percentage points more likely to receive in-kind assistance compared to the national average. With regards to cash transfers in general (not specifically government provided), nomads were much more likely to have received assistance, with 14 percent of nomads receiving a cash transfers compared to 8 percent nationally. For general in-kind assistance (not specifically government provided), all groups received roughly the same assistance, around the national average of 8.8 percent, with the except of nomads who again had higher rates of assistance.

Figure 3.4.4. Comparison of government assistance across different groups as of July 2020 (SHFPS R1)



Source: Authors' estimation using data from COVID-19 SHFPS round 1

Summary

Since the beginning of the pandemic, Somalia has collected two rounds of COVID-19 High-Frequency Phone Surveys (COVID-19 SHFPS), the first in July and detailed in this report.

Estimates show an increase in poverty in July 2020 compared to before the COVID-19 outbreak – the relative poverty score increased from 1 to 1.12 and the probability that poverty increased more than 3 percentage points is 87 percent. Inequality estimates have decreased slightly from the start of the pandemic to July 2020 but remain quite high.

On most indicators, different population groups fared equally poorly overall, with some groups doing worse in some indicators. IDPs experienced the most severe food insecurity and those in urban areas had the highest rates of job stoppage. Government assistance (cash and in-kind) was low overall, but more successful at giving in-kind assistance to the urban population.

V. Rwanda

This section shows country specific information for Rwanda SWIFT poverty projections and profiling. Further details on the following subsections (data, reweighting, and results), as well as descriptions of the SWIFT models and estimates for Rwanda, can be found in the companion paper, Asai et al. (2021).

Data and Reweighting

Round one of the Rwanda COVID-19 HFPS drew its sample from a database of telephone numbers from 192 Enumeration Areas (EAs) spread across the 30 districts in Rwanda, originally collected in the Labor Force Survey (LFS) in 2019. 1,522 households were successfully reached; however, the survey's final sample declined to 1,428 households because some households did not agree to participate in the second round of HFPS.

The first round of HFPS was collected between November 24 and December 4, 2020 and the second round between January 18 and February 15, 2021. All respondents from the first round were contacted for interviews in the second round, but due to nonresponses, the second round's final sample is 1,415.

The reweighting procedure for the Rwanda HFPS includes (i) PSW, (ii) maxentropy for urban and rural areas, and (ii) post-stratification. The reference survey is the Integrated Household Living Conditions Survey round 5 (EICV5).

Results: Poverty projections and profiles

The following section shows the trends in poverty and inequality from the pre-COVID period (March 2020) to January 2021 (HFPS round two), including estimates for the periods of time directly before and after the COVID-19 outbreak. Following the results on poverty and inequality are profiles of employment and government assistance for the poor and other groups.

A. Poverty

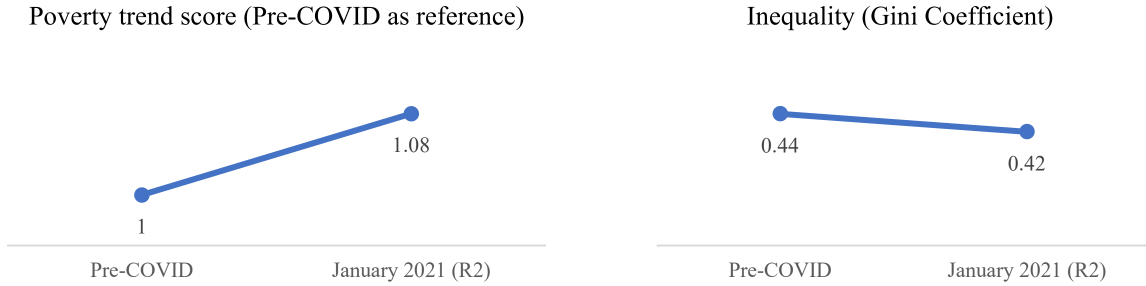
Figure 3.6.1 shows the poverty trend score. According to this measure, poverty incidence increased 8 percent (not 8 percentage points) between the pre-COVID era and January 2021 (HFPS round two).

The probability that the poverty rate increased by any amount between the pre-COVID period and January 2021 is 68 percent.

B. Inequality

Based on the imputed consumption expenditures, the pre-COVID and round two Gini coefficients were estimated. Both Gini coefficients are above 0.4, indicating a sizeable income gap in Rwanda, even before the COVID-19 outbreak. After the COVID-19 outbreak, the Gini coefficient declined slightly to 0.42 in January 2021 (HFPS round two), indicating a small reduction in inequality.

Figure 3.6.1. Trends in Poverty and Inequality from Pre-COVID Era to HFPS Round 2

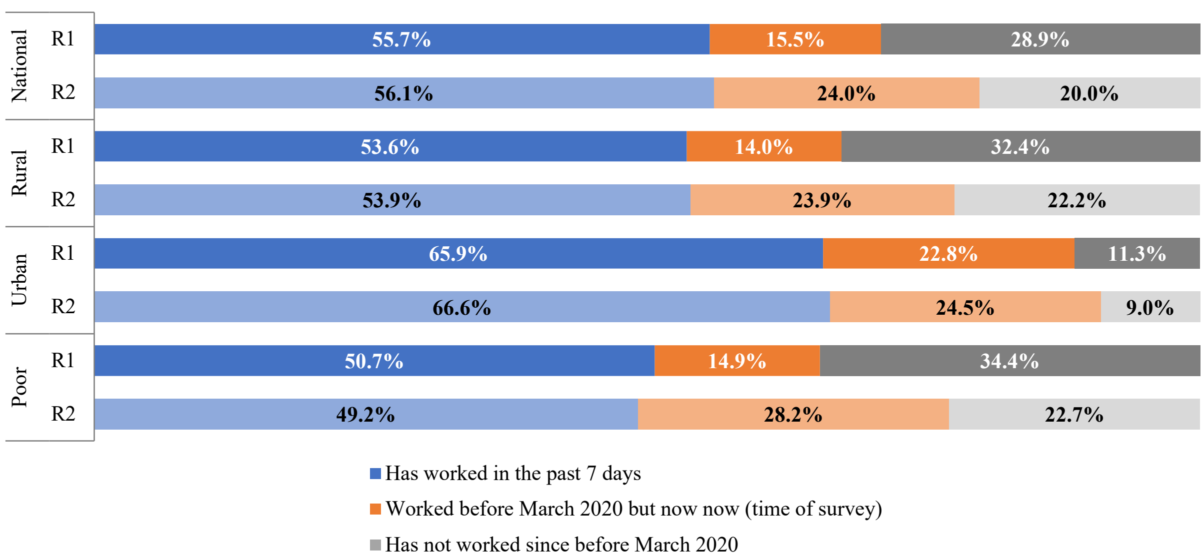


Source: Authors' estimation using data from HFPS round 2

C. Employment Status

In each survey round, respondents were asked if they had worked in the past week, and, if not, whether they had worked before the COVID-19 outbreak (i.e. before March 2020). According to the data, the rate of job stoppage — those who were working before the start of the pandemic but not at the time of the survey — increased for all groups from November 2020 (HFPS round one) to January 2021 (HFPS round two). For both survey rounds, job stoppage was higher in urban areas. Job stoppage among the poor was slightly lower than the national average for HFPS round one, but higher than the national average for HFPS round two. However, in both rounds, the percentage of the poor who were employed was still lower than the national average. Furthermore, the employed share among the poor declined between November 2020 and January 20201.

Figure 3.6.3. Comparison of employment status across different groups



Source: Authors' estimation using data from HFPS round 1 and round 2
Note: sample size R1 & R2: National (1396), Rural (988), Urban (408), Poor (453)

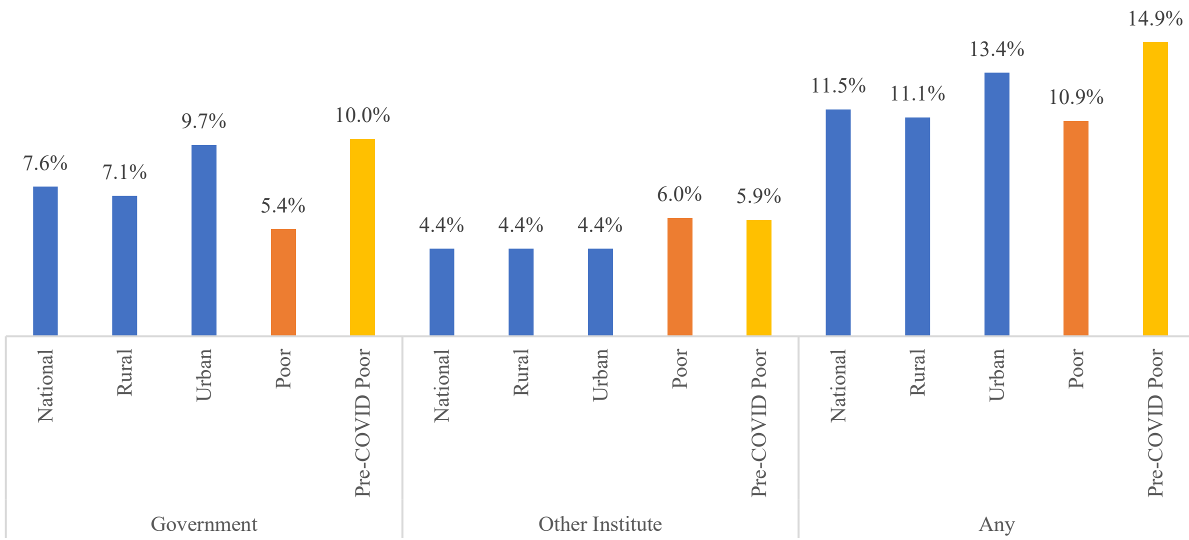
D. Government Assistance

Figure 3.6.4 compares the coverage of cash transfers across different groups. In the discussion and figure below, the "pre-COVID poor" refers to the group of individuals who would have been considered poor prior to the COVID-19 outbreak. At the national level, 7.6 percent of households received a cash transfer from the government between March 2020 and January 2021. The coverage was slightly higher in urban areas than in rural areas. The coverage among the poor was 5.4 percent, which is lower than the national

average and for those in urban and rural areas. On the other hand, the coverage among the pre-COVID poor was higher than any other group. This may be because updating aid beneficiaries takes time — those who became poor later were not immediately included in government assistance, while those who were considered poor before March 2020 were included.

The coverage of cash transfers from other agencies was lower than that of the government but highest among the poor. Combining both sources, the coverage of cash transfers was 11.5 percent at the national level. The coverage in urban areas was 13.4 percent, slightly higher than that of rural areas. Again, the coverage among the pre-COVID poor was the highest at 14.9 percent, which is significantly bigger than that of the poor in January 2021.

Figure 3.6.4. Comparison of the coverage of cash transfers across different groups as of January 2021 (R2)



Source: Authors' estimation using data from HFPS round 2
Note: sample size R1 & R2: National (1396), Rural (988), Urban (408), Poor (453)

Summary

Since the beginning of the pandemic, Rwanda has collected two rounds of COVID-19 High-Frequency Phone Surveys (COVID-19 HFPS), the first in November 2020 and the second in January/February 2021.

Estimates show an increase in poverty in January/February 2021 compared to before the COVID-19 outbreak – the poverty trend score increased from 1 to 1.08 and the probability that poverty increased by any amount is 68 percent. Inequality decreased slightly (but still remains high with a Gini coefficient above 0.4) from the start of the pandemic to January/February 2021.

Overall, the poor did not fare completely worse than the national population. The poor experienced less job stoppage in HFPS round one; However, the poor experienced the lowest share of employment in both rounds one and two and the highest share of job stoppage in round two. The data also suggests signs of slow adjustments in the government's beneficiary list for cash transfers — the coverage of cash transfers among the current poor (those considered poor in January 2021) was lower than the national average, but the coverage among the pre-COVID poor (those who were considered poor before the COVID-19 outbreak) was higher than the national average.

VI. Zimbabwe

This section shows country specific information for Zimbabwe SWIFT poverty projections and profiling. Further details on the following subsections (data, reweighting, and results), as well as descriptions of the SWIFT models and estimates for Zimbabwe, can be found in Swinkle et al. (2021).

Data and Reweighting

The Zimbabwe National Statistics Agency (ZIMSTAT), together with the World Bank and UNICEF, launched a High-Frequency Phone Survey in July 2020. The COVID-19 HFPS[5] drew its sample from the Poverty, Income, Consumption, and Expenditure Survey (PICES) of 2017 and 2019 and includes a total of 1,747 households in round one and 1,639 households in round two, from all ten provinces in the country.

The first round was conducted between July 6 and 24, 2020 and the second round between August 24 and September 23, 2020. Round two included the SWIFT modules and is used for COVID era poverty analysis in this report.

The reweighting procedure for the Rwanda HFPS includes (i) PSW, (ii) maxentropy for urban and rural areas, and (ii) post-stratification. The reference survey is the Poverty, Income, Consumption, and Expenditure Survey in 2019 (PICES 2019).

Results: Poverty projections and profiles

The following section shows the trends in poverty and inequality between PICES 2017, PICES 2019, and HFPS round two (August/September 2020).

The following analysis on food security, employment, and government assistance compares the profiles of the poor with those of other groups. The analysis includes two groups for the poor – those who were considered poor in 2019 ("Poor (2019)") and those who were considered poor when HFPS round two (August/September 2020) was collected ("Poor (HFPS2)"). The former group can include those who were no longer poor when HFPS round two was collected, while the latter group can include those who were not poor in 2019 but were poor in HFPS round two.

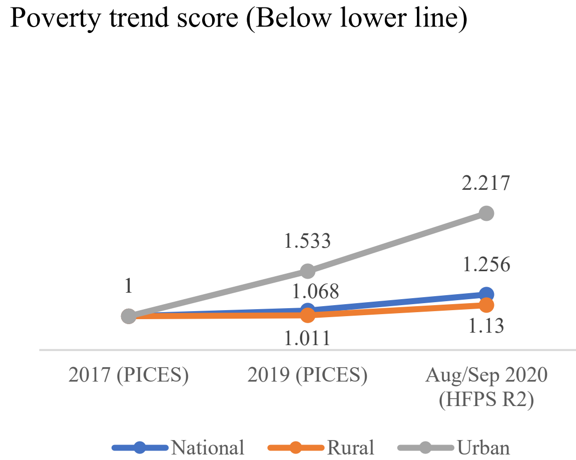
A. <u>Poverty</u>

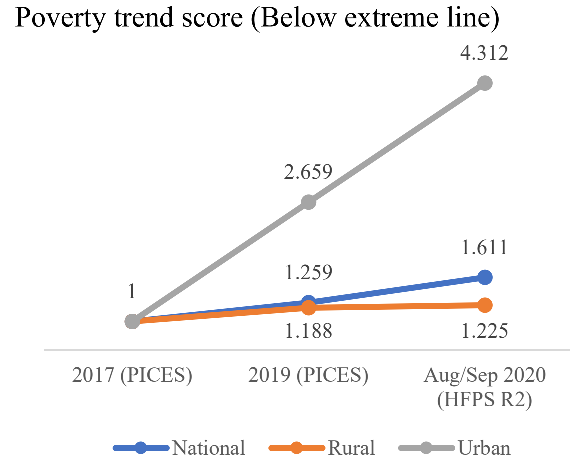
Figure 3.7.1 shows the poverty trend score based on the lower poverty line and the extreme poverty line, using PICES 2017 as the reference period. According to these measures, the national poverty incidence below the lower line increased 6.8 percent (not 6.8 percentage points) between 2017 (PICES) and 2019 (PICES) and increased by 25.6 percent between 2017 (PICES) and September 2020 (HFPS round two). This trend is also calculated for rural and urban areas. Poverty increased 221.7 percent in urban areas from 2017 (PICES) to September 2020 (HFPS round two), which is significantly higher than the national average. Similar trends are found for the share of the population below the extreme poverty line.

With respect to the lower poverty line, the probability that the poverty rate increased by 5 or more percentage points from 2017 to September 2020 (HFPS round two) is 83.9 percent at the national level and 67.5 and 62.9 percent for rural and urban areas, respectively. With respect to the extreme poverty line, the same probability is 94.8 percent at the national level and 91.7 and 52.3 percent for rural and urban areas, respectively.

[5] In Zimbabwe, this survey is named the Rapid PICES Monitoring Telephone Survey, but this paper will refer to this survey as a High Frequency Phone Survey (HFPS) for consistency and clarity.

Figure 3.7.1. Trends in Poverty from 2017 (PICES) to August/September 2020 (HFPS round 2)



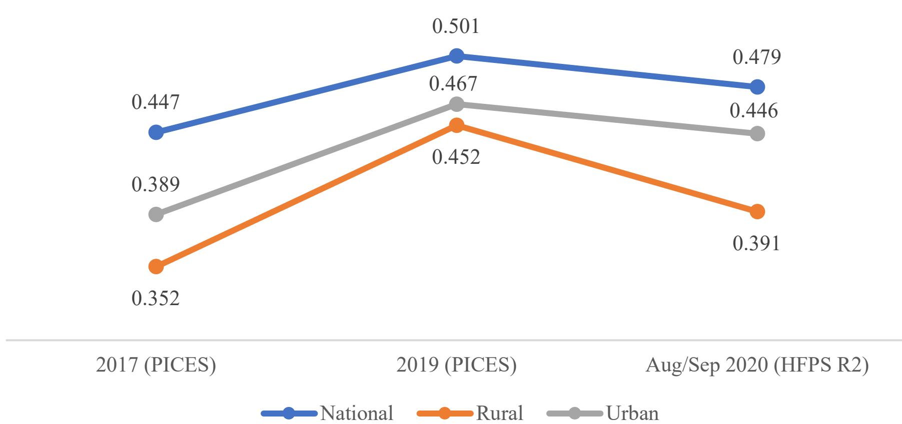


Source: Authors' estimation using data from PICES17, PICES19, and HFPS round 2

B. Inequality

Based on the imputed consumption expenditures, the Gini coefficient was estimated for 2017 (PICES), 2019 (PICES), and August/September 2020 (HFPS round two). At the national level, the Gini coefficients are above 0.4 for all three time periods, indicating a sizeable income gap in Zimbabwe. The level of inequality increased significantly between 2017 and April/May 2019, with the Gini coefficient moving from 0.45 to 0.50, due to the financial crisis in 2019. Inequality slightly decreased, with the Gini coefficient dropping down to 0.48, after the COVID-19 outbreak. The same trend occurred in rural and urban areas. However, rural areas saw the sharpest increase and subsequent decrease in inequality, despite always being lower than inequality in urban areas and at the national level.

Figure 3.7.2. Trends in Inequality from Pre-COVID Era to HFPS round 2 (Gini Coefficient)



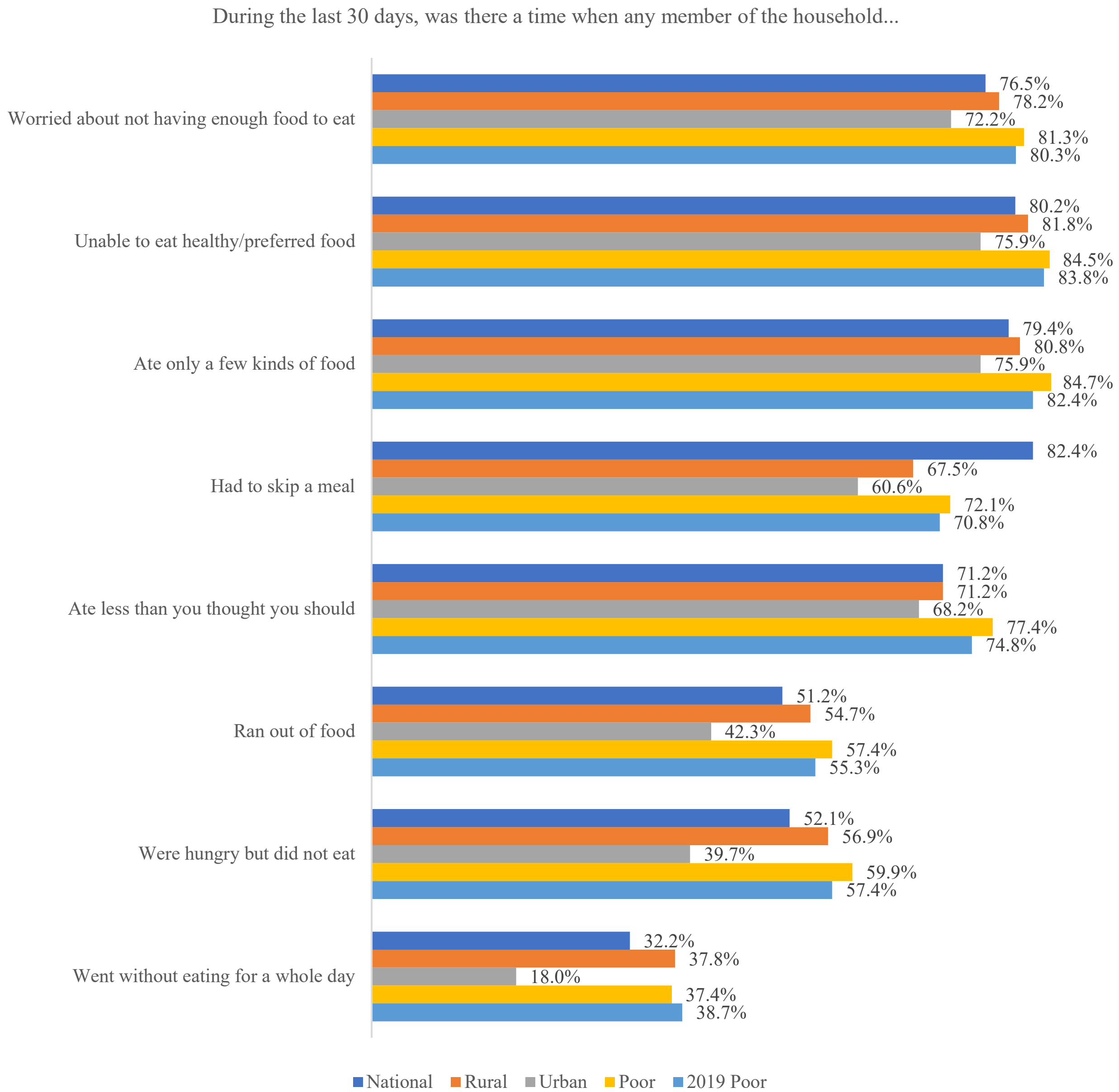
Source: Authors' estimation using data from PICES17, PICES19, and HFPS round 2

C. Food security

Food security is measured by eight questions included in the Food and Agriculture Organization (FAO)'s food security measurement. The survey yielded several major findings. First, the poor's (both 2019 Poor and HFPS2 Poor) food security conditions were worse than the national average for all indicators except for skipping a meal. However, the poor's food security worsened since the COVID-19 outbreak. Compared to the 2019 poor, the poor in August/September 2020 suffered more from food insecurity except for the last indicator – going without eating for a whole day. Lastly, those in rural areas experienced greater food

insecurity than those in urban areas, especially with regards to not eating when hungry and going an entire day without eating.

Figure 3.7.3. Comparison of food security across groups in HFPS round 2



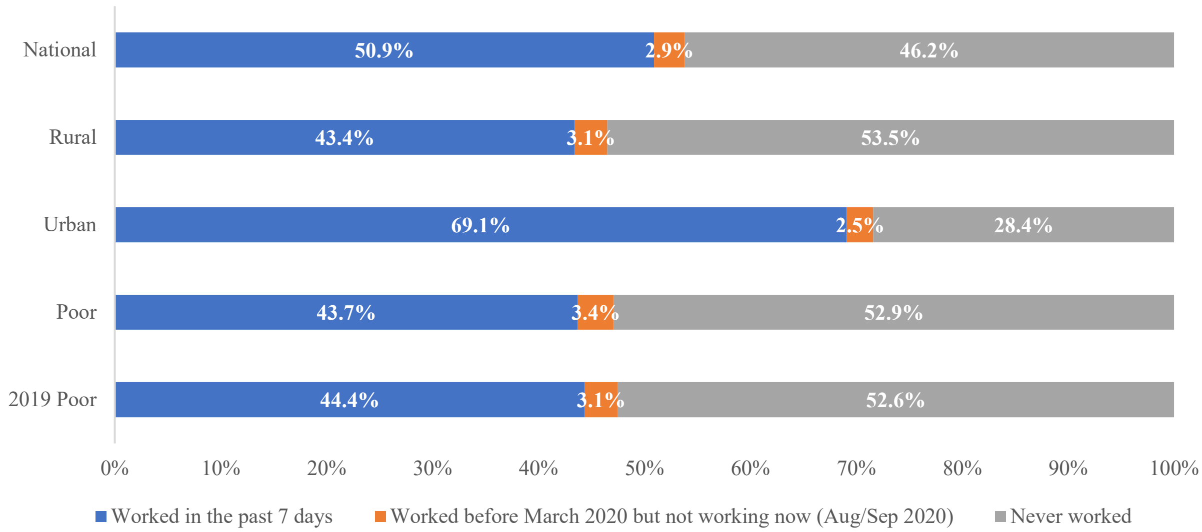
Source: Authors' estimation using data from PICES 2019 and HFPS round 2

D. <u>Employment Status</u>

For the HFPS round two survey, all respondents were asked whether they were working last week, and if not, whether they were working before the start of the pandemic (March 2020) or not. According to the HFPS round two data, the share of respondents who were working last week was 50.9 percent at the national level and 69.1 and 43.4 percent for urban and rural areas, respectively. In rural areas, 53.5 percent were unemployed both before the outbreak and when the HFPS round two data was collected in August/September 2020, compared to 28.4 percent in urban areas. The share of people who were working last week was 44.4 percent among those who were poor in 2019 and 43.7 percent among those who were

poor when HFPS round two was conducted. Results suggest that the employment status of the poor, irrespective of *when* they were poor, is similar to the rural average but notably worse than the urban average. Lastly, that rates of job stoppage — those who had work before the pandemic but not at the time of the HFPS survey — were low for all groups, ranging from 2.5 to 3.4 percent, suggesting that the COVID-19 pandemic did not have huge impacts on labor force participation during August/September 2020.

Figure 3.7.4. Comparison of employment status across groups in HFPS round 2



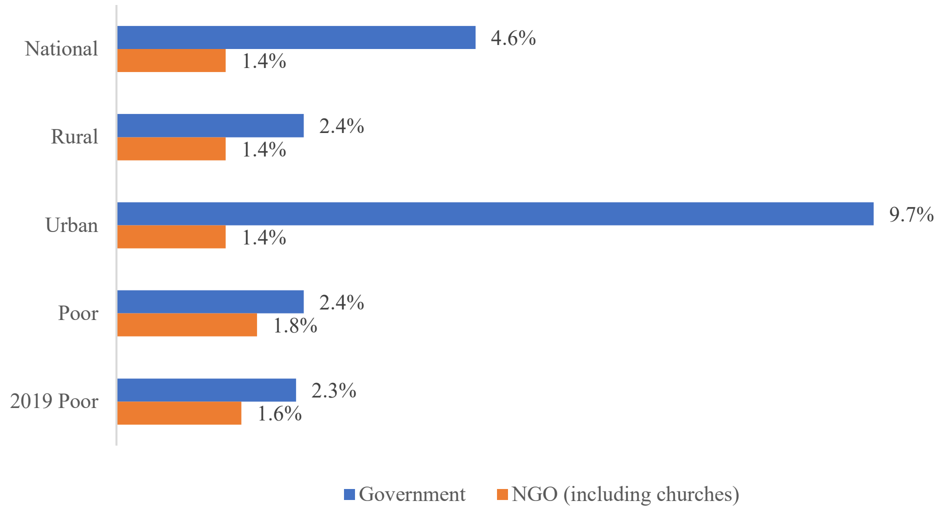
Source: Authors' estimation using data from HFPS round 2

E. Coverage of Governmental and NGO Assistance

Coverage of assistance is divided into two main categories – assistance from the government and assistance from NGOs (including churches). Figure 3.7.5 shows the comparison between government and NGO assistance and Figure 3.7.6 shows the coverage of different types of government assistance (cash transfers, free food, and other assistance). Based on Figure 3.7.5, the coverage of government assistance was higher than that from NGOs for all groups, with the highest assistance coverage in urban areas at 9.7 percent. NGO assistance ranged from 1.4 to 1.8 percent for all groups, with the 2019 poor receiving the highest coverage.

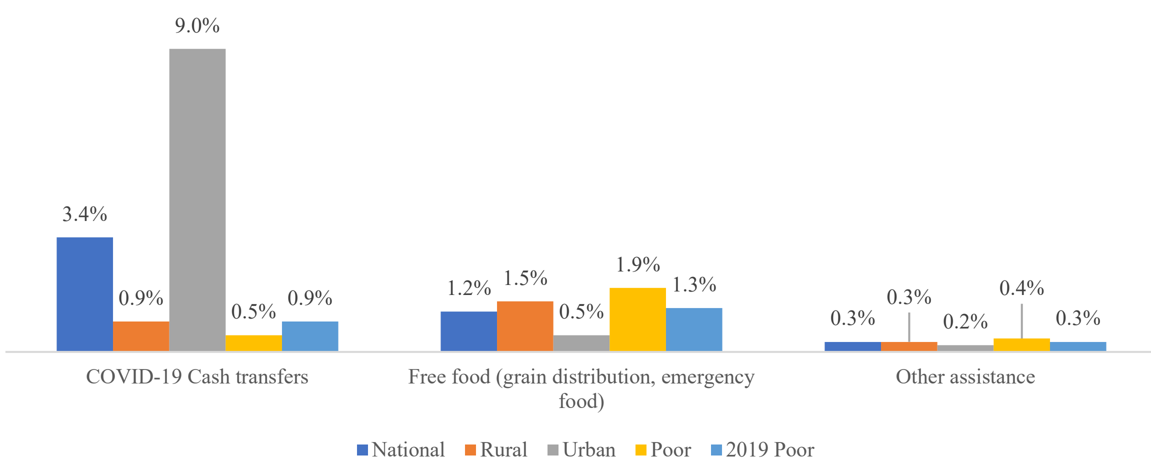
Within government assistance, national coverage was highest for COVID-19 cash transfers, with those in urban areas having the highest rates (9.0 percent) and the 2019 poor having the lowest rates (0.5 percent). Food assistance reached 1.2 percent of the national population with little difference between groups, though the 2019 poor were most likely to receive food assistance at a rate of 1.9 percent. Differences in government assistance between the 2019 poor and the HFPS2 poor were small and inconsistent, suggesting that there was not a major lag in identifying and reaching the newly poor.

Figure 3.7.5. Comparison of overall assistance for different groups as of Aug/Sept 2020 (HFPS R2)



Source: Authors' estimation using data from HFPS round 2

Figure 3.7.6. Comparison of government assistance for different groups as of Aug/Sept 2020 (HFPS R2)



Source: Authors' estimation using data from HFPS round 2

Summary

Since the outbreak of the pandemic, Zimbabwe collected several rounds of COVID-19 High-Frequency Phone Surveys (COVID-19 HFPS), the second taking place in August/September 2020.

Estimates show that the poverty rate increased in August/September 2020 compared to 2017 and 2019. Urban areas experienced a significantly larger increase in poverty measured by both the lower and extreme poverty lines. Inequality, measured by the Gini coefficient, declined between 2019 and August/September 2020 (during the COVID-19 pandemic), but still remains higher than it was in 2017.

The profiling analysis of the poor is based on HFPS round two data. On most indicators, the poor have fared worse than the national average during the pandemic, though with regards to food insecurity and job stoppage, the discrepancy is not large. The coverage of government assistance was greater than assistance from NGOs for all groups, but was not pro-poor – overall, urban households received the highest coverage of assistance from the government. Though much less overall, NGO assistance was slightly more pro-poor.

Concluding remarks

This report shows the results of a pilot of using the SWIFT-COVID19 package to estimate poverty and inequality trends and the profiles of the poor during the COVID-19 pandemic. Data from a Rapid and Frequent Monitoring System (RFMS) is used for southern rural Malawi and data from the COVID-19 High Frequency Phone Surveys (HFPS) is used for Saint Lucia, Ethiopia, Rwanda, Somalia, and Zimbabwe.

Results confirm that all countries experienced substantial poverty increases during the pandemic. For Saint Lucia, where data was collected multiple times since the COVID-19 outbreak, we see a spike of poverty incidence in the beginning of the pandemic followed by gradual recovery. The impact on inequality is varied — rising in some countries and declining in others. Comparisons of poverty profiles between the poor and the national population show both that the poor suffered from food insecurity and employment losses and that they did not always fare far worse than the national average, which suggests the impact of COVID-19 has been wide-spread. Social assistance was generally pro-poor, but with some signs of slow adjustments to reach those who fell into poverty after the start of the pandemic. Further research is required to obtain more precise interpretation of these results.

This pilot reveals the possibility of monitoring poverty and inequality more frequently and more cost-effectively than ever before. The cost of collecting one round of a phone survey with a sample of around 2,000 households is less than 50,000 USD in most countries and the additional cost of adding questions for poverty and inequality projections is less than 5,000 USD. Traditionally, poverty estimates have been based on data that costs over one million USD and requires three or more years to complete. As a result, tracking poverty and inequality on an annual basis has been near impossible. This pilot shows promise in the ability to track poverty quarterly or even monthly.

This report also shows various challenges for such frequent poverty monitoring. First, phone surveys may be cheap and fast, but the data acquired is not necessarily of the highest quality. The primary issue is sampling bias due to a lack of phone ownership among everyone in developing countries. The SWIFT-COVID19 package uses a reweighting technique to remove this bias and make data nationally representative, but the reweighting is not flawless. Additionally, reporting bias in phone interviews has been observed, particularly when collecting consumption related information. As such, all variable candidates for poverty projections must be carefully examined for consistency with other variables and reviewed with consulting country poverty economists in the World Bank who are familiar with country-specific conditions.

Second, poverty projections during a pandemic are not simple. As discussed in the report, the SWIFT methodology develops poverty projection models from the latest household survey, but a large shock like the COVID-19 pandemic can change the relationship between household expenditure/income and poverty correlates. As a result, models developed from the most recent household survey might be unable to produce precise poverty estimates for periods of time after the COVID-19 outbreak. To overcome this, the SWIFT Plus approach is used for all the countries in this pilot. SWIFT Plus addresses the model instability issue by including variables that more quickly respond to changes in socio-economic conditions.

This report is the first in a series. There are plans for updates to include more countries and more results. The pilot took place in around 20 countries and the results of the pilot are still under preparation in some countries at the time this report was prepared. Additionally, since some countries started to collect full consumption data in the traditional approach, the reliability of the SWIFT-COVID19 package can be tested in future work.

This report includes profiling of the poor and estimation of inequality but the empirical evidence on the reliability of these estimations is limited in the literature. To fill the knowledge gap, this report conducts empirical assessments on the reliability of the estimation of inequality and poverty profiling based on the SWIFT methodology following Christiaensen et al. (2012), and includes the results in annex 2 and 3. The results of the empirical assessment are encouraging because the SWIFT based estimations of inequality and poverty profiling are close to those based on actual household expenditures. Such findings give credence to the theory that the SWIFT-COVID19 package can be used with HFPS or RFMS to continuously monitor poverty and inequality in even the poorest countries at a low cost.

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Annex 1. Asset ownership before and after COVID-19 outbreak

Table A.1. Asset ownership before and after COVID-19 outbreak

	pre-COVID	COVID-era	Total in 2019/20
Mobile phone	73.0	74.3	73.7
Television	16.8	21.0	19.0
Radio	32.8	30.4	31.6
Car	2.7	3.0	2.9
Motorcycle	9.7	7.4	8.5
Generator	0.2	0.1	0.2
Solar	33.1	32.0	32.6
Computer	2.0	1.9	2.0
Agricultural land	65.4	62.4	63.9
Cattle	43.9	40.0	41.9

Source: Uganda National Household Survey 2019-20.

Annex 2. Estimation of inequality measures using the SWIFT

This annex evaluates how well we can predict inequality measures, like the Gini coefficient, from household expenditures imputed by SWIFT models. To see this, we adopted an empirical out-of-sample and model stability test proposed by Christiaensen et al. (2012). This test uses two consecutive rounds of household budget surveys from eight countries to evaluate the performance. We train the SWIFT models with the first round of data, impute household expenditures using the models in the second round of the survey, and compare Gini coefficients estimated from the imputed household expenditures with those of actual consumption data in the second round of data. Following Yoshida et. al. (2022), if the distribution of household expenditure in the training data (or the first round data) is different from a normal distribution, we apply the MI-PMM method (StataCorp, 2021) or the small area estimation method (Elbers, Lanjouw and Lanjouw, 2003, and Nguyen et al., 2018).[6]

Unlike poverty estimations, the estimation of inequality is vulnerable to outliers drawn from multiple imputations. Therefore, it is often recommended to include outlier corrections. This evaluation, therefore, adds two types of outlier corrections: (i) Dropping imputed household expenditures greater or smaller than the median of imputed expenditures plus three standard deviations (method 1), and (ii) Replacing the outliers detected above with the thresholds (method 2).

Table A.2 shows the results of this evaluation. The first two rows show the Gini coefficients directly calculated from actual consumption data in both rounds of data. The third to fifth rows show the Gini coefficients predicted by the SWIFT models. The third row shows the estimates of the Gini coefficient without any outlier corrections. The fourth row shows the estimates of the Gini coefficient with method 1 of the outlier correction, and the fifth row shows the results of method 2.

The predictions without outlier corrections perform well in general. The average absolute difference between the true Gini coefficients and those predicted by the SWIFT models is two percentage points. The largest difference is 4.2 percentage points for Malawi (2005 – 2010) data, while the smallest difference is 0.1 percentage points for Rwanda (2006 – 2011) data.

Outlier corrections do not always reduce the bias in the estimation of inequality. We see a significant reduction in bias for West Bank and Gaza (2006 – 11), 1.6 percentage points, and minor reductions in estimating the Gini coefficient for Afghanistan (2011 – 2016) and Albania (2005 – 2008) data. For other countries, outlier corrections increase the bias. This observation suggests that outlier corrections should be done when we see clear and large outliers. The use of outlier corrections for the above three countries reduces the average bias to 1.66 percentage points.

In conclusion, the SWIFT methodology can estimate inequality well. However, it requires careful selection of imputation methods and outlier corrections.

[6] Details of models are upon request.

Table A.2. Estimation of Gini coefficient (Second year) using SWIFT

Country	Sri Lanka (2009-12)	West Bank and Gaza (2016-11)	Mongolia (2018-16)	Afghanistan (2011-16)	Malawi (2005-11)	Rwanda (2006-11)	Albania (2005-2008)	Uganda (2009-2012)
Actual Gini (first year)	36.1%	34.4%	32.7%	29.2%	40.0%	52.4%	29.7%	41.6%
Actual Gini (second year)	38.5%	33.7%	32.4%	26.6%	45.5%	49.6%	26.8%	40.0%
Prediction of Gini (second year)								
Prediction wo. outlier corrections	37.0%	35.3%	32.2%	30.6%	41.3%	49.5%	30.4%	40.7%
Absolute difference with prediction wo outlier corrections	1.50%	1.60%	0.20%	4.00%	4.20%	0.10%	3.60%	0.70%
Prediction w. outlier correction method 1	33.6%	33.7%	31.3%	30.3%	37.9%	44.6%	29.5%	39.9%
Prediction w. outlier correction method 2	35.0%	33.9%	31.6%	30.5%	39.7%	47.2%	30.1%	40.5%
Best estimates	37.0%	33.7%	32.2%	30.3%	41.3%	49.5%	29.5%	39.9%
Absolute difference with best estimates	1.50%	0.00%	0.20%	3.70%	4.20%	0.10%	2.70%	0.10%

Source: Authors' estimations using the household surveys of the countries included.
Note: Detailed models are available upon request.

Annex 3. Performance of profiling of the poor by SWIFT

This annex evaluates how well we can predict profiles of poverty using household expenditures imputed by SWIFT models, using an empirical out-of-sample and model stability test proposed by Christiaensen et al. (2012). More specificatlly, this test uses two consecutive rounds of household budget surveys from four countries (Mongolia 2016–18, West Bank and Gaza 2011–16, Rwanda 2006-11, and Sri Lanka 2009-12). We train the SWIFT models with the first round of data, impute household expenditures using the models in the second round of the survey, identify the poor and nonpoor using the imputed expenditures, and estimate means of variables for the poor and the nonpoor identified by the imputed expenditures.[7] We then compare them with the means for the poor and the nonpoor identified by actual household expenditures in the second round of household budget survey.

We first evaluate how accurately SWIFT can predict poverty rates in the second round of the household budget survey (Table A.3). The absolute difference between imputed and actual poverty rates for these four countries is less than 1.6 percentage points. Note that for Sri Lanka, we select the 40th percentile as a poverty line since the official poverty line is too low to estimate summary statistics for the poor.

Table A.3. SWIFT poverty prediction results

	Actual	**Imputed**
Mongolia 2016 - 2018	**0.296** (0.005) [0.287, 0.306]	**0.286** (0.008) [0.270, 0.302]
West Bank and Gaza 2011 - 2016	**0.258** (0.014) [0.230, 0.286]	**0.267** (0.013) [0.240, 0.293]
Rwanda 2006 - 2011	**0.449** (0.008) [0.434, 0.464]	**0.433** (0.010) [0.413, 0.453]
Sri Lanka 2009 - 2012	**0.400** (0.007) [0.386, 0.414]	**0.400** (0.006) [0.387, 0.413]

Note: Except for Monogolia, the first year in each country's date range is the year of the survey used as the training data. The second year in each country's date range is the year of the survey used to impute poverty rates; the actual poverty rate and imputed poverty rate are for the second year in the date range. For Mongolia, the 2018 survey is used as the training data while the 2016 data are used to impute poverty rates.

Table A.4 shows the means of variables included in SWIFT models. For each country, we select two variables. Whether the poor and the nonpoor are identified by household expenditures imputed by SWIFT models or actual household expenditures does not make much difference with regards to the variable means. Except for Mongolia 2016's ownership of refrigerator among the poor, the means for the poor and the nonpoor identified by imputed household expenditures are not statistically significantly different from those identified by actual household expenditures.

[7] Note that in the case of Mongolia, we train the models using the 2018 data and estimate the profiles of the poor and the nonpoor using the 2016 data.

Table A.4. Variables in the prediction model

Mongolia, 2016 - 2016

Household size	Actual	Imputed
Poor	**4.65** (0.030) [4.597, 4.713]	**4.66** (0.036) [4.586, 4.728]
Not Poor	**3.14** (0.016) [3.108, 3.169]	**3.15** (0.018) [3.119, 3.189]

Household owns a refrigerator	Actual	Imputed
Poor	**0.70** (0.008) [0.684, 0.715]	**0.74** (0.010) [0.725, 0.764]
Not Poor	**0.84** (0.003) [0.3834, 0.847]	**0.83** (0.004) [0.819, 0.834]

West Bank and Gaza, 2011 - 2016

HH head is a refugee	Actual	Imputed
Poor	**0.39** (0.021) [0.346, 0.427]	**0.35** (0.027) [0.296, 0.403]
Not Poor	**0.22** (0.017) [0.188, 0.257]	**0.24** (0.021) [0.194, 0.277]

Number of rooms in dwelling	Actual	Imputed
Poor	**3.69** (0.057) [3.58 3.80]	**3.65** (0.070) [3.51 3.79]
Not Poor	**4.10** (0.042) [4.02 4.18]	**4.11** (0.042) [4.03 4.19]

Rwanda, 2006 - 2011

HH head did wage work last 12 months	Actual	Imputed
Poor	**0.30** (0.008) [0.285, 0.316]	**0.33** (0.009) [0.307, 0.344]
Not Poor	**0.37** (0.007) [0.351, 0.379]	**0.34** (0.008) [0.328, 0.360]

HH head is employed in private sector	Actual	Imputed
Poor	**0.06** (0.004) [0.048, 0.066]	**0.07** (0.005) [0.056, 0.076]
Not Poor	**0.12** (0.004) [0.110, 0.128]	**0.11** (0.005) [0.101, 0.119]

Sri Lanka, 2009 - 2012

Dwelling floor is permanent/semi-permanent	Actual	Imputed
Bottom 40%	**0.88** (0.006) [0.866, 0.890]	**0.88** (0.007) [0.867, 0.893]
Not Bottom 40%	**0.97** (0.002) [0.967, 0.976]	**0.97** (0.003) [0.964, 0.975]

Household owns a sewing machine	Actual	Imputed
Bottom 40%	**0.31** (0.008) [0.289, 0.321]	**0.29** (0.009) [0.272, 0.308]
Not Bottom 40%	**0.56** (0.006) [0.546, 0.571]	**0.57** (0.007) [0.554, 0.582]

Note: Except for Mongolia data, the first year in each country's date range is the year of the survey used as the training data. The second year in each country's date range is the year of the survey used to impute poverty rates; the actual mean and imputed mean of each variable are for the second year in the date range. For Mongolia, the 2018 survey is used as the training data while the 2016 data are used to impute poverty rates.

Table A.5 shows the means of variables that are not included in SWIFT models. Like before, each country shows the means of two variables. All the means for the poor and the nonpoor identified by imputed expenditures are not statistically significantly different from those based on actual household expenditrues.

In conclusion, irrespective of whether variables are included in SWIFT models, the means of the variables for the poor and the nonpoor identified by imputed expenditures are similar to those of actual expenditures.

Table A.5. Variables not in the prediction model

Mongolia 2016	**Job in last 7 days is a wage worker**	
	Actual	**Imputed**
Poor	**0.30** (0.058) [0.285 0.321]	**0.30** (0.012) [0.280 0.328]
Not Poor	**0.44** (0.009) [0.424 0.447]	**0.43** (0.008) [0.418 0.448]

Mongolia 2016	**Received state pension during last 12 months**	
	Actual	**Imputed**
Poor	**0.20** (0.008) [0.185, 0.214]	**0.22** (0.011) [0.196, 0.238]
Not Poor	**0.32** (0.005) [0308, 0.327]	**0.31** (0.005) [0.302, 0.322]

West Bank and Gaza 2016	**Household owns a computer**	
	Actual	**Imputed**
Poor	**0.15** (0.016) [0.120, 0.183]	**0.16** (0.022) [0.117, 0.204]
Not Poor	**0.38** (0.018) [0.342, 0.412]	**0.36** (0.021) [0.315, 0.401]

West Bank and Gaza 2016	**HH head is employed in government**	
	Actual	**Imputed**
Poor	**0.24** (0.029) [0.183, 0.297]	**0.23** (0.037) [0.154, 0.305]
Not Poor	**0.30** (0.015) [0.274, 0.332]	**0.30** (0.017) [0.262, 0.328]

Rwanda 2011	**Share of household that attended school**	
	Actual	**Imputed**
Poor	**0.64** (0.003) [0.632, 0.645]	**0.64** (0.004) [0.634, 0.649]
Not Poor	**0.71** (0.004) [0.706, 0.721]	**0.71** (0.004) [0.702, 0.717]

Rwanda 2011	**Received public income support cash last 12 months**	
	Actual	**Imputed**
Poor	**0.14** (0.009) [0.124, 0.159]	**0.16** (0.010) [0.140, 0.181]
Not Poor	**0.18** (0.009) [0.165, 0.200]	**0.17** (0.008) [0.150, 0.184]

Sri Lanka 2012	**Number of employed in household**	
	Actual	**Imputed**
Bottom 40%	**1.58** (0.016) [1.545, 1.609]	**1.58** (0.017) [1.543, 1.610]
Not Bottom 40%	**1.50** (0.012) [1.475, 1.521]	**1.50** (0.013) [1.474, 1.525]

Sri Lanka 2012	**Received Samurdhi (transfer) last 12 months**	
	Actual	**Imputed**
Bottom 40%	**0.32** (0.008) [0.308, 0.337]	**0.30** (0.009) [0.282, 0.316]
Not Bottom 40%	**0.11** (0.004) [0.098, 0.115]	**0.12** (0.005) [0.113, 0.133]

Note: Except for Mongolia data, the first year in each country's date range is the year of the survey used as the training data. The second year in each country's date range is the year of the survey used to impute poverty rates; the actual mean and imputed mean of each variable are for the second year in the date range. For Mongolia, the 2018 survey is used as the training data while the 2016 data are used to impute poverty rates.