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Rapid Feedback Monitoring System (RFMS) – real-time, cost-effective, shock-resilient monitoring of living conditions and food security

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Abstract

This paper shows the results of poverty and inequality estimations using a SWIFT-COVID19 package with the data from the Malawi Rapid and Frequent Monitoring System (August 2020 and December 2020). The SWIFT-COVID19 package includes the imputation of household expenditures using SWIFT-Plus, a new poverty projection method for times of sharp economic downturn, and adjustments for sampling weights to address a phone 'survey's sampling bias. The package shows Malawi likely experienced a sizeable increase in poverty between the pre-COIVID era and August 2020 and again between August and December 2020. However, inequality as measured by the Gini coefficient appears to have been unaffected over these time periods. The poor have experienced high levels of food security, though not at substantially higher rates than the rural south overall. Employment has seen recovery among all groups. However, our vulnerability analysis shows that the poor are at higher risk of deeper poverty and the trends may indicate that the situation is getting worse.

I. Introduction

Malawi is a landlocked country with high population density and a high percentage of people dependent on agriculture, making the majority of the population vulnerable to weather-related shocks. The country is often affected by floods and dry spells, which are becoming more frequent and severe due to climate change. The poor are most vulnerable to weather shocks since they have limited coping mechanisms. In the 2020-21 period, in addition to relatively mild but persistent weather-related shocks, Malawi's economy has been hit hard by COVID-19 and associated policy responses. Although Malawi's infection rates appear low compared to the U.S. and Europe, the poor and vulnerable have experienced severe changes to their socioeconomic condition, likely caused by the government implemented containment measures, including restrictions on movement and border crossings and closures of schools and places of worship.

Due to the vulnerability of the poor, designing and implementing pro-poor policies is especially important in times of negative economic shocks. However, in order to design effective resilience programming, rapid, frequent, and continuous data collection must take place to observe how communities are affected by and cope with shocks. Like many other countries, Malawi conducts a large national survey every three years (Integrated Household Survey (IHS)), collecting data on a wide variety of socio-economic conditions. The IHS data is rich in content and has many uses, but does not allow for monthly or quarterly monitoring of living conditions and livelihoods during economic downturns, even in a year when IHS data is collected.

To address this data gap, the World Bank, together with USAID, FCDO, Catholic Relief Services (CRS) and Cornell University, and in collaboration with the Malawi National Statistics Office, co-designed the Rapid and Frequent Monitoring System (RFMS). RFMS collects household level data on a monthly basis to provide real-time tracking of food security, coping strategies, and shocks experienced over time, linked to household characteristics that may make them more or less resilient. The goal is to enable the government, development partners, and local communities to easily measure and better understand resilience and wellbeing of households, and in turn improve and refine resilience programming.

RFMS is able to produce frequent insights into poverty and resilience in a cost-effective and timely manner due to a few key features. First, to reduce the survey implementation cost (in particular, transportation and lodging), RFMS hires and trains local enumerators. Second, RFMS integrates CRS-Cornell University's Measurement Indicators for Resilience Analysis (MIRA) survey protocol,[1] to monitor resilience, with the World Bank's Survey of Well-Being through Instant and Frequent Tracking (SWIFT), to monitor poverty.

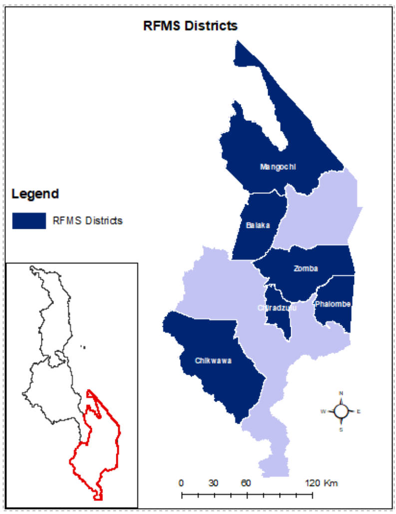
SWIFT is a rapid poverty monitoring tool that uses machine learning and multiple imputation techniques to create a model to estimate household expenditure/income. The models are constructed using data from 10 to 15 simple questions, which can be collected using Computer Assisted Personal Interview (CAPI) software in 3-5 minutes (per household). By adding SWIFT questions into the RFMS questionnaire, household expenditure/income and related poverty statistics can be estimated for each household in the sample without largely increasing interview time. Since most questions are simple yes-no questions, they are easily integrated into the existing questionnaire without a substantive training burden. Estimating household expenditure and producing poverty statistics enables us to profile the poor and the non-poor separately and see how resilience and poverty are interrelated. A new SWIFT approach called SWIFT Plus has also been adopted to better

[1] MIRA focuses on food key food security indicators and subjective shock reports and has been implemented in Malawi since 2017 and Madagascar since 2018 (see Knippenberg et al. 2018 and Upton et al. 2019).

capture sudden changes in poverty due to economic shocks, allowing for more accurate estimations during the COVID-19 pandemic.

The objectives of this paper are to demonstrate how SWIFT works in the context of the RFMS in Malawi; to introduce key findings on poverty and inequality; and to describe the relationship between poverty and resilience in this context. The paper is organized as follows: Section II describes the RFMS data collection and dissemination platform, Section III explains how poverty is estimated using SWIFT and how the sampling weights are adjusted, and Section IV reviews the SWIFT models for Malawi. Section V presents the trends of poverty and inequality and poverty profiles, Section VI presents findings on the relationship between poverty and various resilience indicators of MIRA, and Section VII concludes.

II. Background: Malawi RFMS surveys



Since August 2020, RFMS has implemented a baseline survey and follow-up monthly surveys for 4,200 households in six districts (Balaka, Chiradzulu, Chikwawa, Mangochi, Phalombe, Zomba) in Southern Malawi. RFMS uses innovative survey instruments to track indicators that are likely to change quickly in response to changing climatic and economic conditions. This includes short-term food security outcomes, shocks experienced, and potential "resilience capacities," such as significant expenditures, changes in assets, migration, or assistance received. The system allows questions to be added or removed as needed for maximum adaptability; for example, a COVID-19 module was developed to track how the pandemic is affecting household resilience. The survey application has case management functionality to prompt respondents about previous shocks, allowing for seamless tracking of subjects and analysis of changes over time. As enumerators capture data via smartphone, the data is automatically uploaded to the cloud, enabling near-real time data visualization and analysis. This data collection is made possible by engaging locally embedded enumerators who are residents of the area where they collect data, which fosters trust in communities, enhances cost efficiency, and offers employment opportunities to local youth.

The RFMS sampling frame is based on listing information and cartography from the 2018 Population and Housing Census. It first rolled out in six districts (Balaka, Chiradzulu, Chikwawa, Mangochi, Phalombe and Zomba), expanding in July 2021 to include four more (Nsanje, Mulanje, Machinga, and Thyolo). First, 400-450 households were chosen from randomly selected Enumeration Areas (EAs) in each district. An additional 1,600 households were oversampled in Balaka, Chikwawa, Mangochi and Phalombe, where USAID and FCDO are implementing projects aimed to build resilience of vulnerable households, in order to make the sample representative in their respective project areas. Thus, a total of 4,200 households were selected for the initial survey, and a total of 6,000 including the expanded districts.

Since the questionnaire is comprehensive, some modules are asked bimonthly or quarterly to keep overall length at any given time to a minimum. The questions which are asked every month are referred to as the "Core Modules" and include questions on shocks experienced in the past month, coping strategies, food consumption, health, and COVID-19 impacts. Other questions on livelihoods, WASH & nutrition, project-specific questions (e.g. related to the adoption of targeted technologies), and for SWIFT estimations are asked quarterly. The frequency and sequencing of the different modules through August 2021 is shown in Box 1.

Box 1. RFMS questionnaire module schedule

Module	Content	Aug 2020	Sept	Oct	Nov	Dec	Jan 2021	Feb	Mar	Apr	May	June	July	……
Baseline	Fixed infrastructure, complete household roster													
Monthly "Main"	Food Security, Shocks, EW Indicators, Migration													
Monthly Individual Health	Health, shock follow-up													
Covid-19	Knowledge, experience, impacts of shutdown													
SWIFT +	Poverty ranking, assets													
Livelihoods	Livelihoods, agriculture													
WASH & Nutrition	Water sources, sanitation													
Project-Specific	Exposure to technologies, program participation													

Relevant to the rest of the paper, SWIFT questions were asked in August 2020 (to be referred to as RFMS round one (R1)) and December 2020 (to be referred to as RFMS round two (R2)). All respondents from the August survey (4,245) were surveyed again in December.

III. Methods: Poverty Projections using SWIFT

Survey of Well-being via Instant and Frequent Tracking (SWIFT) combines machine learning techniques and the latest ICT technology to estimate household consumption expenditure and produce poverty statistics, making it possible for users to obtain reliable poverty data and profile the poor within budget. A key advantage is that it requires only 10 to 15 questions on poverty correlates, such as ownership of assets, housing conditions, and household demographics. The model then projects household income or expenditure using those correlates in a statistical model, and estimates statistics on poverty and inequality from the projected income or expenditure data. SWIFT has proven to be highly accurate and useful for tracking poverty during the implementation of more than 100 projects in over 50 countries.

The following section gives an overview of the whole SWIFT approach, including how SWIFT has been modified for the current COVID-19 climate, how SWIFT produces poverty estimates, and how the data used is reweighted for improved accuracy.

Reliability of SWIFT in the COVID-19 pandemic

Supported by years of quality control efforts, SWIFT has produced reliable estimates on poverty, inequality, and income growth. SWIFT models are tested by using two rounds of comparable household expenditure data for a given country. The models are developed from the first round of data and applied to the second round to estimate poverty statistics. The poverty estimates are then compared with the official poverty rates to see how well the SWIFT estimates match up. As shown in Table 1, the differences between SWIFT estimates and the official poverty rates are small; all estimates are less than 1.5 percentage points away from official poverty rates, and in 5 out of 6 cases, the differences are statistically insignificant at the 5 percent level. The only exception is the estimation for 'Romania's rural area, where the estimate is still close in magnitude but statistically different at slightly outside the 95 percent confidence interval. More evidence on the reliability of SWIFT estimates is available in Yoshida et al. (2020).

Table 1. SWIFT model prediction power over time

Country	year gap	Region	Absolute Difference
Uganda	**3**	Urban	**1.09%**
		Rural	**0.16%**
Romania	**1**	Urban	**0.03%**
		Rural	1.46%
Sri Lanka	**3**	Urban	**0.15%**
		Rural	**0.85%**

Note: Predictions are in bold lie within 95% confidence interval of original poverty rates.

However, Yoshida et al. (2020) found that SWIFT does not perform well during a large negative economic shock, like the COVID-19 pandemic. Afghanistan (2011 – 2016) and the West Bank and Gaza (2011 – 2016) both experienced severe economic downturns where the percentage of poor people 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 the West Bank and Gaza, respectively.

Yoshida et al. (2020) show 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 (which we will refer to also as *time-invariant* indicators). 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 higher expenditure than their current lived poverty. This leads to the standard SWIFT model producing underestimates of poverty during economic downturns.

SWIFT Plus: Refining poverty estimation in the face of shocks

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 indicators highly correlated with household expenditure/income, SWIFT Plus selects indicators that quickly reflect current economic conditions, even though they are only moderately correlated with household expenditure/income. Specifically, SWIFT Plus includes dummies for purchase of specific items, such as meat or clothing. 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 can change quickly depending on the economic conditions. SWIFT Plus replaces time-invariant (or slowly changing) poverty correlates from the standard SWIFT model with the above-mentioned time-variant (quickly changing) poverty correlates. The different set of indicators makes SWIFT Plus more sensitive to short-term changes. Yoshida et al. (2020) provide evidence for the accuracy of SWIFT Plus; for both the Afghanistan and the West Bank and Gaza cases, SWIFT Plus accurately estimated the substantial increases in poverty levels due to fast-moving economic downturns.

We adopt the SWIFT Plus approach to estimate poverty rates using the fit-for-purpose RFMS data, which tracks the necessary time-variant indicators like consumption of specific items, food security, employment conditions, and economic sentiment are added into the RFMS questionnaire.

Pre-COVID and COVID-era poverty projections

Estimating the impact of the COVID-19 pandemic on poverty requires both the *pre-COVID* (just before the pandemic) and *COVID-era* (during the pandemic) poverty estimates. If the latest household survey was conducted just before the COVID-19 outbreak, that 'survey's poverty rates can be treated as the pre-COVID poverty rates. However, if the latest household budget survey was conducted even one year prior to the start of the pandemic, the true pre-COVID poverty rate could be different from the poverty rate estimated from that survey. If there was no survey collected just prior to the COVID-19 outbreak, , pre-COVID poverty rates need to be estimated as accurately as is possible using data collected during the pandemic. The standard SWIFT model's utilization of time-invariant (slowly changing) indicators serves well to estimate poverty rates just prior to the start of the crisis. For example, housing conditions would not have changed unless households moved or made significant renovations, both of which would be unusual at the beginning of a pandemic. Ownership of assets also would not change rapidly in this period, as sales of assets are limited by a lack of efficient second-hand markets for consumer durables. Therefore, the current status of many indicators used in a standard SWIFT model 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 above), replacing some time-invariant indicators with time-variant indicators collected via RFMS surveys.

Table 2 illustrates the estimation process for pre-COVID and COVID-era poverty rates, showing an example of data from two rounds of COVID-19 RFMS. First, a standard SWIFT model (f_s) is estimated using a full set of time-invariant indicators (X) and a SWIFT Plus model (f_{sp}) is estimated using a subset of time-invariant indicators (X') and time-variant indicators (Z) from the latest household budget survey.

Ideally, the pre-COVID poverty rates should be estimated using data collected just before the COVID-19 outbreak, but this is not possible in many countries, including Malawi. Therefore, we use time-invariant or slowly changing indicators collected during round one of the RFMS (X_1), since they are not changing much from the period of time just prior to the COVID-19 outbreak. We insert a full set of time-invariant indicators from round one RFMS into the standard SWIFT model (f_s) to estimate pre-COVID household expenditure ($\boldsymbol{Y_0}$) and poverty rate ($\boldsymbol{P_0}$).

To estimate poverty rates of round one, we insert a subset of round one RFMS time-invariant variables(X'_1) and time-variant variables (Z_1) into the SWIFT Plus model (f_{sp}) to estimate household expenditures ($\boldsymbol{Y_1}$) and poverty rate ($\boldsymbol{P_1}$) for the round one time period. For round two estimations (RFMS December 2020), we integrate the time-variant variables (Z_2). While it is not necessary to integrate updated time-invariant variables for round two (X'_2), as they are very slow to change (in other words, $X'_1 \approx X'_2$), it can improve the accuracy to include them if they are available. We estimate round two household expenditure and poverty rates by inserting both round two time-invariant and variant variables (X'_2 and Z_2) into the SWIFT Plus model (f_{sp}).

Table 2. Illustration of SWIFT COVID-19 projections

	Pre-COVID (Round 0)	**Round 1**	**Round 2**
Time-invariant (slowly 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
Time-variant (quickly changing) variables strongly correlated with real-time welfare level:	Z_0 (unavailable)	Z_1	Z_2
Household expenditures	$\boldsymbol{Y_0} = f_s(\mathrm{X}_1)$	$\boldsymbol{Y_1} = f_{sp}(\mathrm{X'}_1, \mathrm{Z}_1)$	$\boldsymbol{Y_2} = f_{sp}(\mathrm{X'}_2, \mathrm{Z}_2)$
Poverty rates	$\boldsymbol{P_0}$	$\boldsymbol{P_1}$	$\boldsymbol{P_2}$

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

Reweighting to obtain poverty estimates representative of southern rural Malawi

To make the sample representative of Malawi's rural south and to accurately compare the basic statistics of the IHS4 and World Bank phone surveys both at the district level and at the national level, sampling weights are adjusted so that the weighted averages of key statistics become representative of southern rural Malawi. This ensures that weighted averages of key statistics from RFMS are close to the representative reference survey. The reweighting process typically consists of three major steps: (i) Propensity Score Weighting, (ii) Subnational-level Maxentropy, and (iii) Post-stratification.

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

To refine the weights further, we execute maxentropy at the district level. Even after PSW, summary statistics in the target survey could differ largely from those in the reference survey. Such differences can reflect real changes, particularly when a long time has elapsed between the reference and target surveys. Still, it is unlikely that summary statistics of time-invariant (or slow-changing) indicators like household size, dependency ratios, household head's education attainment, or population shares of districts would change significantly. Maxentropy adjusts weights to match the summary statistics of these time-invariant variables between the reference and target surveys in an exact manner. Box 2 briefly explains how maxentropy works.

Box 2. Maxentropy

Maxentropy is a STATA command that selects weights that maximize entropy while matching averages of pre-selected indicators between the reference and target surveys. The selection of indicators is important. The indicators need to be time-invariant or slow-changing. Otherwise, since some time would have elapsed between the reference and target surveys, the averages of indicators can change. Ignoring the real changes and forcing the averages between the two surveys to be equal can bias all statistics estimated from the target survey. Therefore, it is important to select indicators that are time-invariant or slow-changing.[2] 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 the multiple rounds of comparable household surveys in the past before selecting the indicators for matching.

We modify the above procedure in this case because the implementation of PSW hinges upon the availability of the microdata for both the reference and target surveys, which we do not have access to for Malawi. However, we do have district-level summary statistics of target variables. To address this issue, we skip PSW and conduct only the last two steps of reweighting (district-level maxentropy and post-stratification), which matched all target variable means between the target survey and the reference survey. More details on all of the above-mentioned reweighting, PSW, and maxentropy can be found in Zhang et al. (2021); further details on reweighting for Malawi can be found in Annex 3.

IV. Malawi Pre-COVID and COVID-era Models

A SWIFT model was created using time-invariant (slowly changing) poverty correlates from RFMS round one to estimate the pre-COVID poverty rates. Table 1 in Annex 2 shows the full model. Weights from IHS4 are used to ensure the data from RFMS round one is representative for rural southern Malawi, shown in the comparison of means of the independent variables for the weighted RFMS round one data and the data from IHS4. The pre-COVID SWIFT model takes the standard approach, primarily using dwelling conditions and asset ownership as poverty correlates.

A SWIFT Plus model was created using time-variant (quickly changing) poverty correlates to estimate the poverty rate using RFMS data from August 2020 (round one) and December 2020 (round two), as shown in Table 2 in Annex 2. Again, weights from IHS4 are used to reweight the RFMS data. In order to capture short-term changes in consumption and poverty, the SWIFT Plus model excludes dwelling conditions and asset ownership and instead includes indicators for food security and consumption.

V. Poverty projections and profiles for Malawi

The following section shows the trends in poverty and inequality from the pre-COVID period,[3] August 2020 (round one), and December 2020 (round two). Analysis focuses on a few selected dimensions to give a wholistic picture of the poor's experiences over the course of the pandemic. In addition to poverty and inequality statistics, brief profiles on food security, employment status, and the coverage of assistance are covered here.

[3] The "pre-COVID period" refers to the time directly preceding the COVID-19 outbreak. Since pre-COVID figures are estimates, there is no definitive corresponding date.

Poverty

Poverty is tracked by a poverty trend score, which is the ratio of the poverty rate in August and December 2020 (rounds one and two) to that of the pre-COVID era; in other words, 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 increased 10 percent. If the population size between the pre-COVID era and the RFMS survey time remained the same, the score of 1.1 implies a 10 percent increase in the poor population.[4] This poverty trend score has been used widely in the Latin America region to show the fluctuation of income poverty since the start of the COVID-19 pandemic.

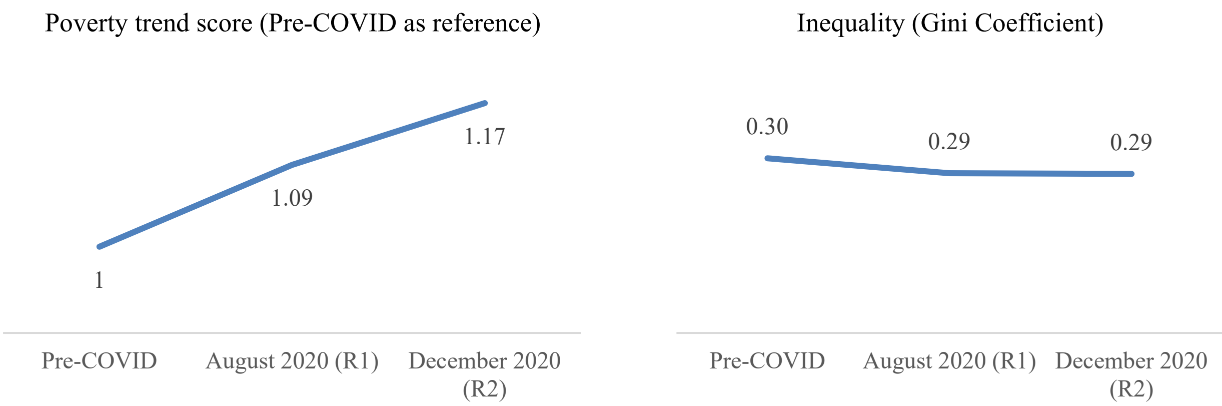
Figure 1 shows the poverty trend score. According to the SWIFT estimations, poverty incidence increased 9 percent (not 9 percentage points) between the pre-COVID era and August 2020 (RFMS round one). The poverty rate in December 2020 (RFMS round two) was 17 percent higher than the pre-COVID era.

Thus far, we have assessed poverty trends using point estimates. However, all estimates involve noise or standard errors, meaning even if we see an increase in the poverty rate, the probability of the increase might not be so high. To see the certainty in the increases in poverty, we estimate the probability that poverty increased by any amount from the pre-COVID era to August 2020 and from the pre-COVID ear to December 2020. This probability was more than 99 percent for both time periods. Similarly, the probability that poverty increased by three or more percentage points in both this time periods is also 99 percent.

Inequality

Based on the imputed consumption expenditures, the Gini coefficient is estimated for the pre-COVID period, August 2020 (round one), and December 2020 (round two). Estimates show that inequality has not changed in Malawi during the pandemic.

Figure 1. Trends in poverty and inequality from the pre-COVID era to December 2020



Source: Authors' estimation using RFMS data

Food security

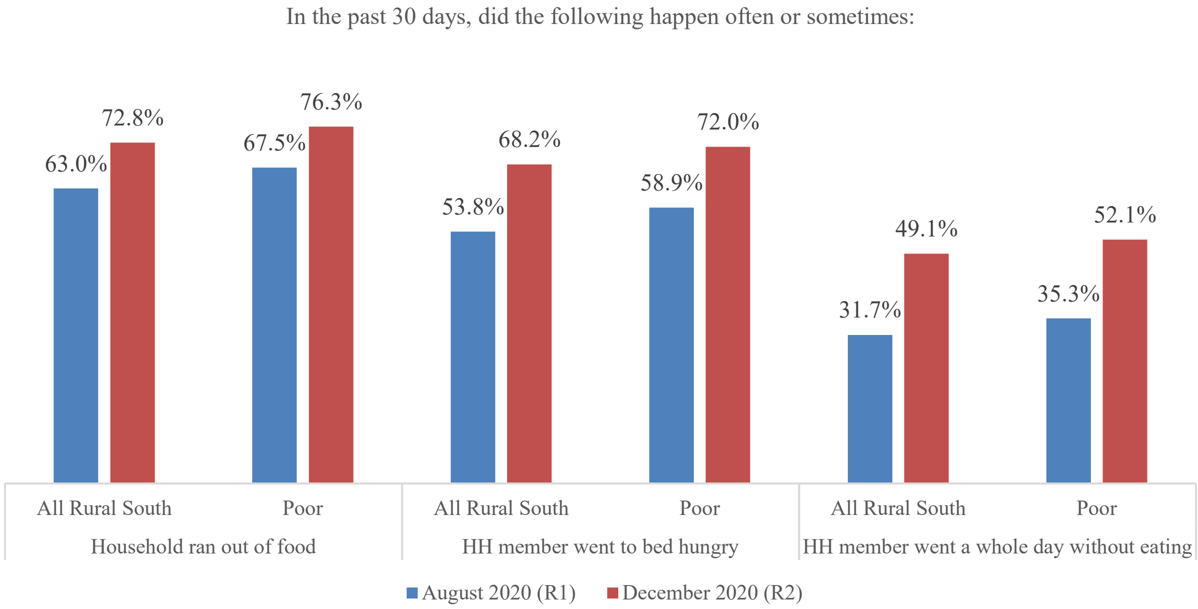
The poverty profiling analysis here focuses on three different questions related to food security to provide an idea of how the poor fared compared to the national average. Households are asked if whether in the past 30 days, they have experienced any of the following as a result of a lack of money or other resources: running out of food, a member going to bed hungry, and a member not eating for a whole day.[5] Figure 2 show the results of

[4] 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.

[5] These three coping strategy questions are components of the weighted Household Hunger Scale (HHS), a food security indicator described and shown in aggregate in Section VI, Figures 9 and 10.

these food security questions for all of southern rural Malawi as well as for just the poor. Food security has worsened throughout the pandemic for both groups on all measures. The food security of the poor, as measured by these three questions, was worse than the southern rural Malawi average on all measures and in each survey round.

Figure 2. Food security indicators by group



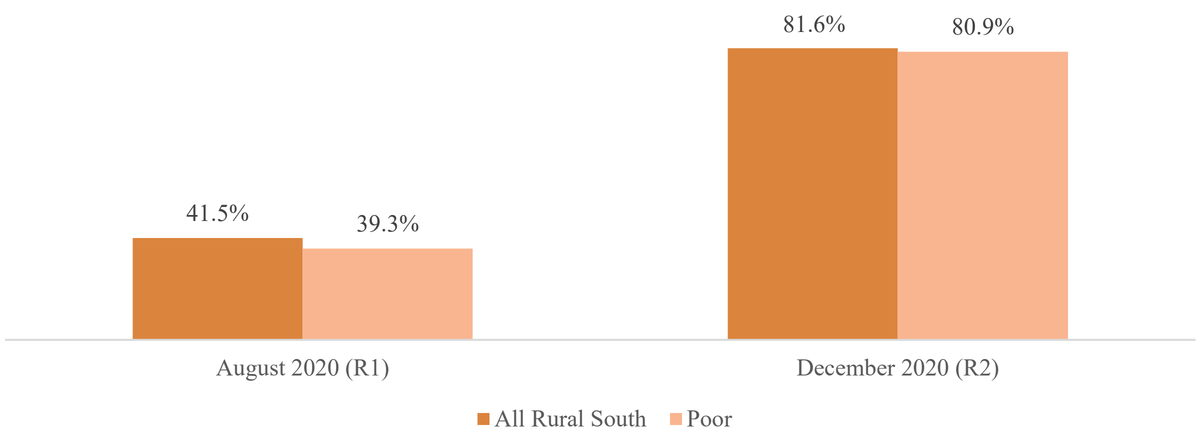
Source: Authors' estimation using RFMS data

The above analysis highlights one aspect of how the poor have experienced food insecurity compared to the general population. In the next section, Section VI, a more comprehensive set of food insecurity indicators are presented to identify the correlation between poverty and vulnerability/resilience.

Employment status

To measure employment, respondents were asked if they had worked for payment in the past six months (Figure 3). Employment was low overall in August 2020, with only 42 percent of the rural south population reporting to have worked in the past six months. By December 2020, employment recovered significantly, with 82 percent of the rural south population reporting to have worked in the past six months. The poor fared slightly worse than the rural south average in both August and December 2020.

Figure 3. Worked for payment in the past 6 months, by group

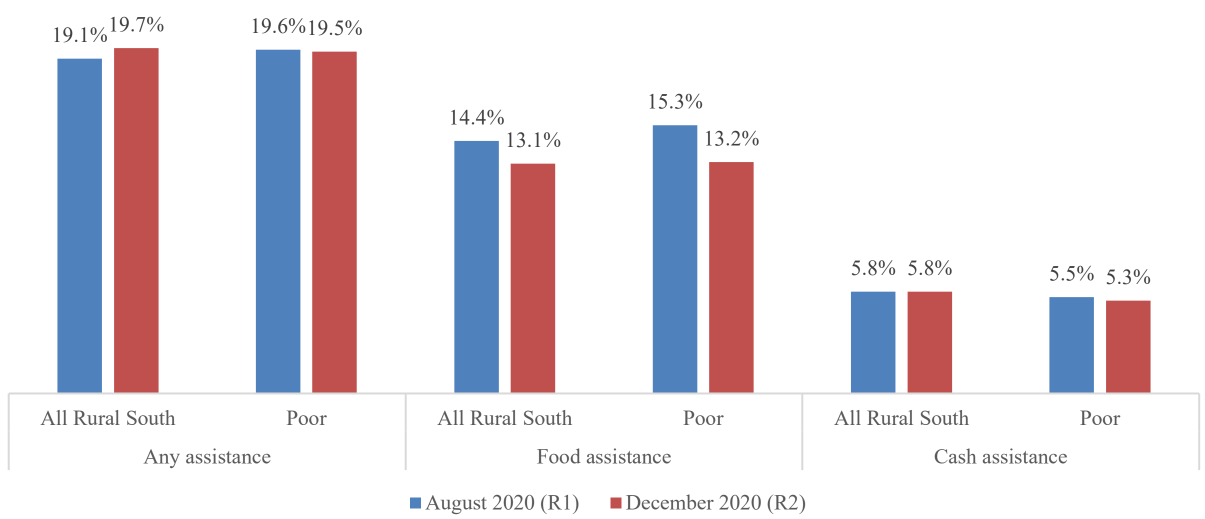


Source: Authors' estimation using RFMS data

Coverage of assistance

The coverage of cash transfer was low, with a less than 6 percent coverage rate for the overall rural south and the poor in both August and December 2020 (Figure 4). This is because according to consultations with community members, cash transfers were not targeted at the poorest households, but rather towards those in business or in a better position to stimulate the economy.[6] The coverage of food assistance was better overall. Around 14 percent of households received food assistance in August 2020, but the coverage declined slightly to 13 percent in December 2020. The coverage of food assistance among the poor has been only slightly better than the rural south average.

Figure 4. Assistance by group



Source: Authors' estimation using RFMS data

[6] Conversations with community members also revealed that to participate in the cash transfer program, recipients must have a cell phone.

VI. Relationship between poverty and Vulnerability/Resilience

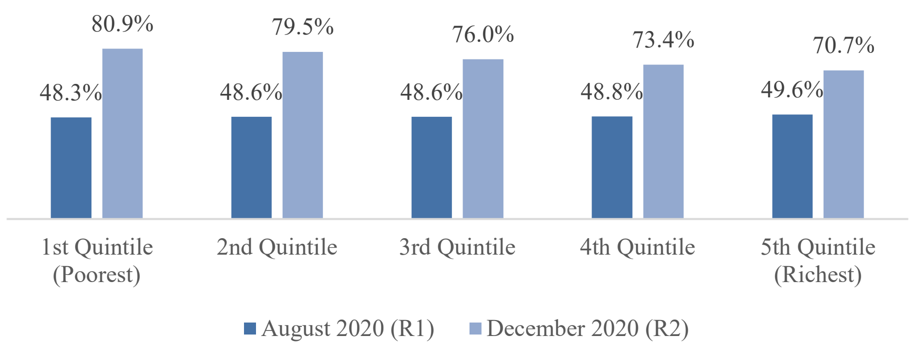
The relationship between poverty and vulnerability to shocks has been widely discussed, but there has been a lack of any supporting empirical evidence. The following section uses data from RFMS to shed light on this relationship in rural southern Malawi.

Vulnerability: Shocks including dry spell and COVID-19

Malawi has frequently been exposed to various weather-related shocks, including dry spells and flooding. Because the majority of the population is still heavily dependent on maize farming and only cultivates it for one cycle each year, they are particularly vulnerable to these natural disasters. Furthermore, in 2020, COVID-19 hit the country hard, just as in other countries. In the RFMS, every month, households are asked whether they have experienced any natural and/or socioeconomic shocks[7]. After the start of the pandemic, questions to measure the impact of COVID-19 were also added. The following section shows how these shocks affected the household consumption/expenditure of different welfare groups and how vulnerability, resilience, and poverty are intertwined.

Figure 5 shows the percentage of households who experienced any type of shocks, grouped by five different consumption quintiles based on SWIFT estimations. Although there seems to be no noteworthy difference in August, when about half the population encountered some sort of shock, a significant difference is observed in December 2020, when more than 80 percent of the poorest households experienced some kind of shock. Poorer households tend to appear more vulnerable to shocks compared to richer households.

Figure 5. Percent of households that experienced any type of shock



Source: Authors' estimation using RFMS data

Dry spells are some of the most impactful natural shocks in Malawi. Figure 6 shows the percentage of households in each consumption quintile who answered that they experienced a dry spell in the past month. In both August and December, but more notably in December, it is clear that poorer households suffered more from drought. This result may be counterintuitive, as drought is a typical covariant shock, and unlike other idiosyncratic shocks, it is generally thought to affect entire communities, regions, or even entire countries, regardless of the welfare levels of each household. In reality, better off households are often better situated to weather dry spells. They may own more assets, like livestock, which make them more resilient and are also more likely to practice crop diversification and purchase improved or drought resistance seeds. Furthermore, better off households may rely less on farming activities and are instead involved in small business enterprises or have other off-farm livelihoods.

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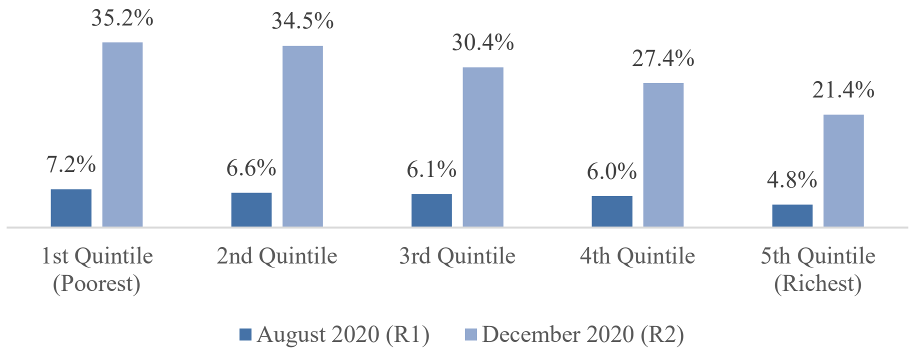
[7] The shocks include 1) Dry spell, 2) Flood/water logging, 3) Crop pest or disease, 4) Livestock disease, 5) Household busines failure, 6) Loss of job/non-payment of salary, 7) Loss of assistance/aid, 8) Loss of remittances from outside HH, 9) Fall in sale price of crops, 10) A rise in prices of food, 11) Death in the household, 12) Break-up of the household, 13) Illness or injury of someone in household, 14) Outbreak of illness in broader community (epidemic), 15) Theft, 16) Strong wind, 17) House damaged due to fire

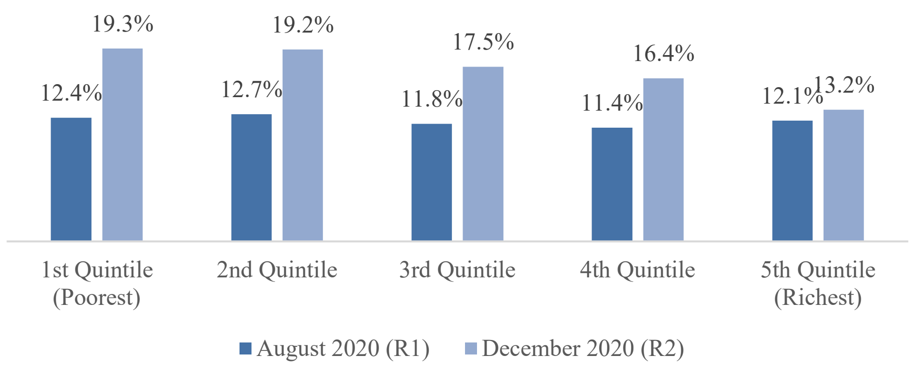
Figure 6. Percent of households that experienced dry spells



Source: Authors' estimation using RFMS data

Figure 7 shows the percentage of households who answered that their farming has been affected by COVID-19. There seems to be no real difference between the quintiles in August, but in December, 19 percent of the poorest households reported that COVID-19 had affected their farming activities, compared to 13 percent in the richest quintile. The cause for this discrepancy is still unclear. It is possible that poorer households were unable to sell their products in the market, get farming inputs on time, or access the hired labor. To shed more light on the nature of these impacts, questions were added to subsequent survey rounds to determine how farming activities were impacted (results forthcoming).

Figure 7. COVID-19 impacts on farming

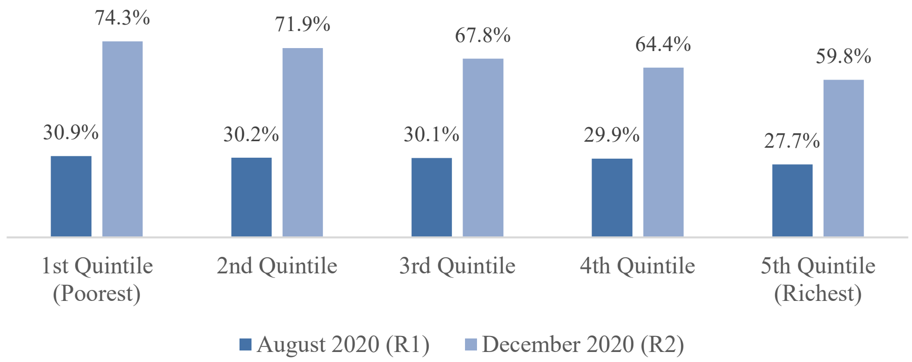


Source: Authors' estimation using RFMS data

Resilience and Food Security

While vulnerability can be defined as the degree to which an individual or household is adversely affected during the occurrence of a hazardous event, the concept of resilience integrates the ability to absorb and recover from disruptive shocks. One simple measure that points toward a household's resilience is whether they were able to recover from the experience of a shock. Figure 8 shows the percentage of households in each quintile who answered that they have not recovered from the shocks that they have experienced in the past month. While these are self-reported measures and as such may suffer from non-classical measurement error, the survey data clearly suggests that poorer households are less resilient than the rich and tend to recover more slowly.

Figure 8. Shock non-recovery



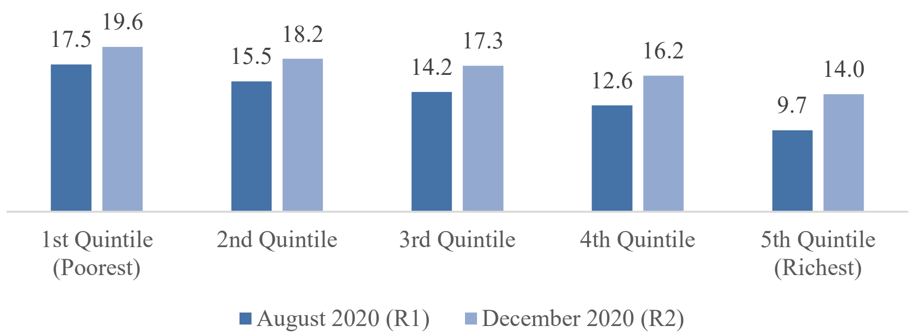
Source: Authors' estimation using RFMS data

Regardless of whether a shock is drought or disease, households must find ways to cope, and often the easiest solution is to reduce food consumption. To see the degree to which households rely on these coping strategies, we use the Reduced Coping Strategy Index (rCSI). Households are asked about the five following behaviors to determine how they are coping with negative shocks:

1. Relying on less preferred and less expensive foods
2. Borrowing food or relying on help from friends or relatives
3. Limiting portion size at mealtime
4. Restricting consumption by adults in order for small children to eat
5. Reducing the number of meals eaten in a day

rCSI is then calculated by multiplying the frequency and weight assigned to each question. Higher numbers indicate that households tend to rely more on these unfavorable coping strategies. Figure 9 shows that poorer households are more likely to utilize measures which deteriorate their food security in order to cope with the shocks.

Figure 9. Reduced Coping Strategy Index (rCSI)

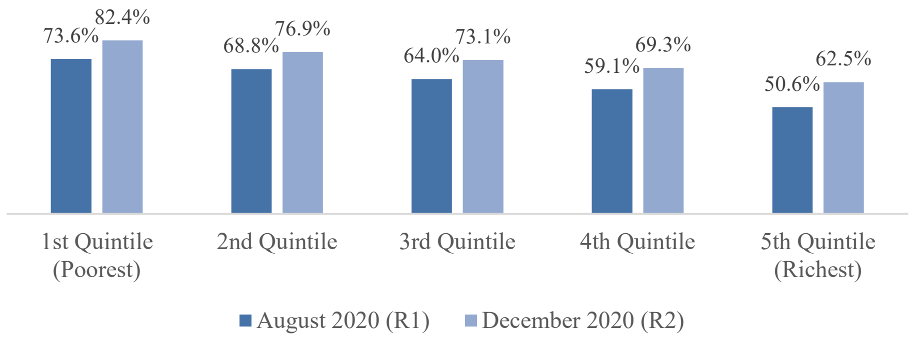


Source: Authors' estimation using RFMS data

While rCSI shows how shocks hamper food security, the household hunger scale (HHS) provides a more direct indicator to measure food security while addressing more severe coping strategies (Ballard et al. 2011). The HHS is measured by three different questions. Households are asked if due to a lack of money or other resources they have experienced having no food of any kind in the household, a household member going to bed hungry, and a household member not eating for a whole day, all over the past 30 days. The answers to these

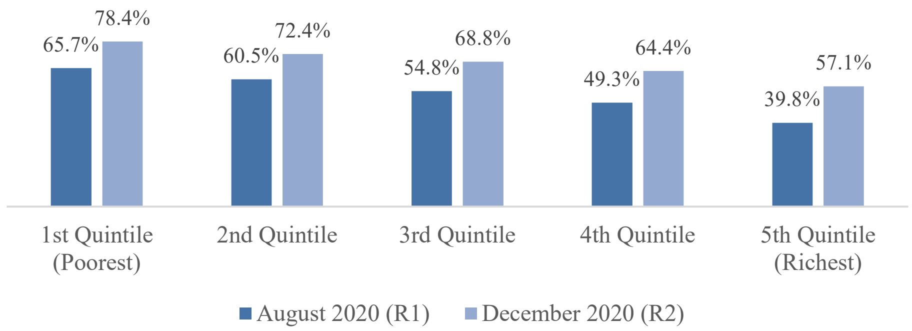
questions are then aggregated into one HHS indicator. Figures 10, 11, and 12 show the results of these three food security questions for each quantile. While food security has worsened throughout the pandemic for all groups on all measures, the poorer households have suffered the most.

Figure 10. Household ran out of food



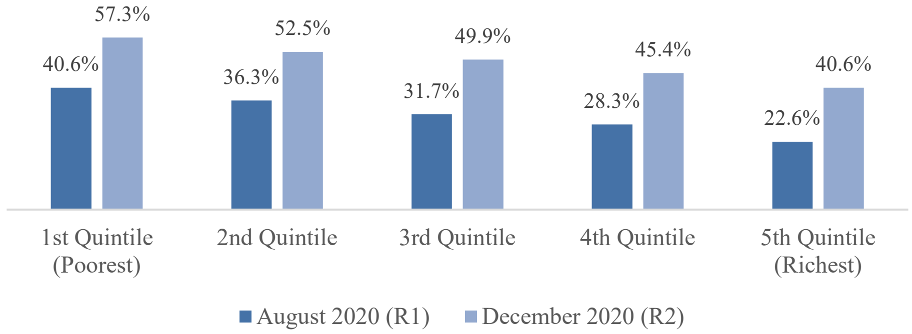
Source: Authors' estimation using RFMS data

Figure 11. Household member went to bed hungry



Source: Authors' estimation using RFMS data

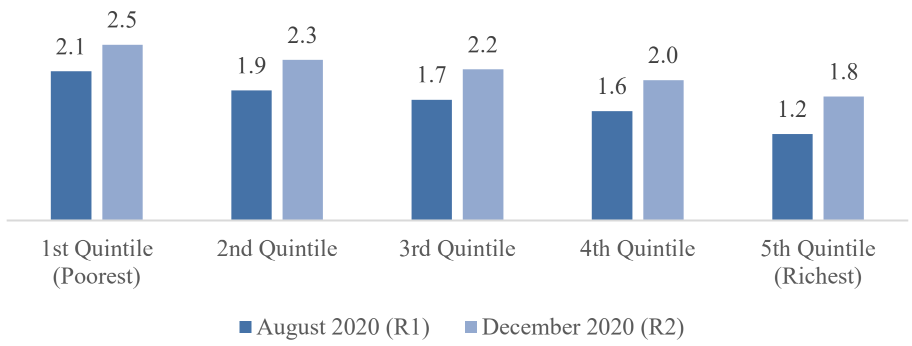
Figure 12. Household member went a whole day without eating



Source: Authors' estimation using RFMS data

Figure 13 shows the aggregated HHS, summarizing the previous finding that poorer households suffer more from food insecurity. HHS scores in the range of 0-1 indicate little to no hunger in the household, 2-3 indicate moderate hunger, and 4-6 indicate severe hunger in the household. In August (round one), only the poorest quintile had an average score more than 2, implying the prevalence of moderate hunger among the households in this group. However, by December (round two), all groups except for the richest quintile have scores above 2. The situation in December was much worse than in August, which may be expected since December falls in the midst of Malawi's lean season.

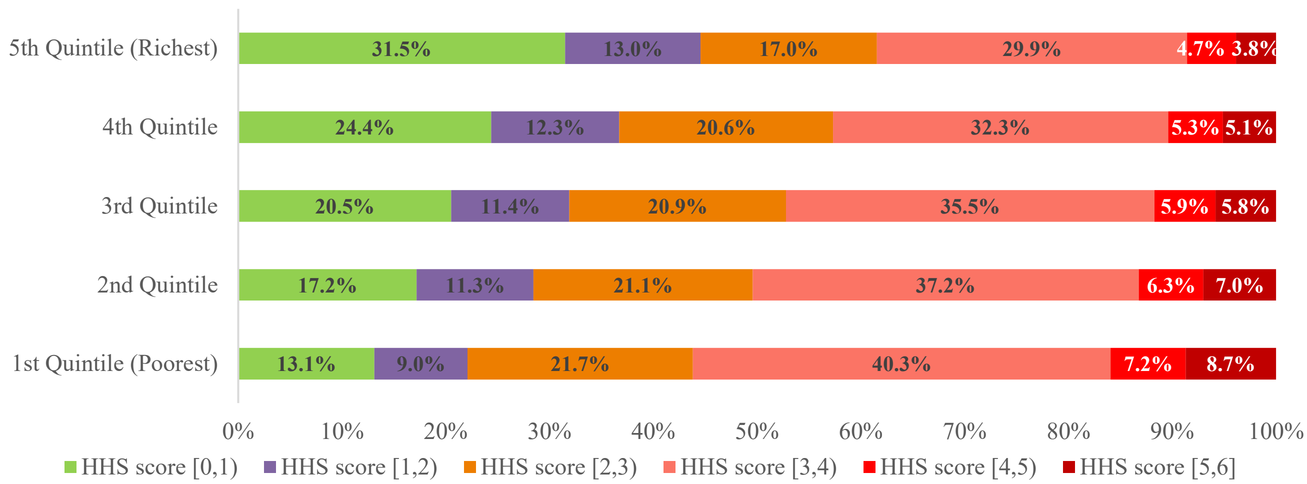
Figure 13. Household Hunger Scale (HHS)



Source: Authors' estimation using RFMS data

Figure 14 shows the HHS distribution in each quintile and reveals that 78 percent of the poorest households suffer from moderate hunger and as high as 16 percent suffer from severe hunger. However, it should also be noted that even among the richest households, more than half (56 percent) suffer from moderate hunger, which shows the severity of the prevalence of food insecurity in rural Malawi.

Figure 14. HHS Score Distribution in December 2020 (R2)

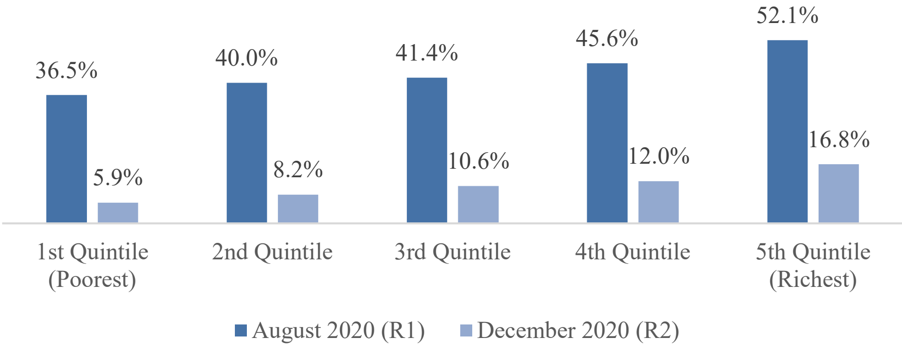


Source: Authors' estimation using RFMS data

The dire situation of the poor's food security is best highlighted by observing household's maize stocks. In rural Malawi, harvest season for maize is normally only once per year in March/April — after that, households will consume bags of harvested maize until their stock is depleted. Once a household has run out of their own harvested maize stocks, they must either purchase maize from the market or rely on less expensive food, such as sorghum. Figure 14 shows the percentage of households within each quintile that reported still having a stock of maize at home during the time of the survey. It is striking that in August, only four to five months after the harvest season, only 37 percent of the poorest household reporting having maize stocks at home, and only 6 percent of households did in December. This suggests that approximately 94 percent of the poorest households

must purchase maize or rely on other food for most of the year, despite their main livelihood being cultivating maize.[8]

Figure 15. Household stock of maize



Source: Authors' estimation using RFMS data

VII. Conclusion

The COVID-19 pandemic has affected how to collect data and how to estimate poverty and inequality. Malawi has integrated SWIFT COVID-19 questions into two rounds of the RFMS, once in August 2020 (round one) and once in December 2020 (round two). We estimate poverty incidence and inequality from this data using the SWIFT-COVID-19 package, which adjusts the original SWIFT methodology to be more responsive to sudden economic downturns and corrects any potential sampling bias. This note includes poverty and inequality estimates, as well as vulnerability analysis, for the periods before the COVID-19 outbreak and the two rounds of RFMS (August and December 2020).

Estimates show a steady increase in poverty incidence in August and December 2020 compared to poverty rates 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 in both rounds compared to pre-COVID period is more than 99 percent. Inequality, as measured by the Gini index, has not changed much since the pre-COVID era, although the poorest were the most affected by high rates of food security over this time period.

On most indicators, the poor did fared substantially worse than the rural south average. The total population experienced high levels of food insecurity, but these levels were 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 south 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.

The analysis on vulnerability and poverty shows that poorer households are more likely to experience the impacts of the COVID-19 pandemic and droughts, be less resilient against these shocks, face very severe food insecurity, and have a very limited stock of maize compared to richer households. However, even the richest 20 percent of households also appeared to face a high rick of food insecurity and limited recovery from shocks. The trends in poverty and vulnerability between August and December 2020 feed concerns that the food security situation is worsening in rural southern Malawi.

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[8] These findings are consistent with other estimates from the RFMS data. In Malawi, the average land holding in the RFMS districts is approximately 0.25 hectares and may be slightly more in Chikwawa and Nsanje, however the land in these two districts is less productive largely due to overgrazing. The average yield per hectare ranges from 2 – 2.5 metric tons of grain (maize) depending on practices employed and variety used. It estimated that each person consumes 270 Kg of maize per year. If the average household size is 4.5, that implies that households require at least 1215 Kg of grain per year. Therefore, households on average produce enough food to last on average from 3 – 6 months which tallies with the estimates produced by using the data from the RFMS.

References

Ballard, T., Coates, J., Swindale, A., and Deitchler, M. (2011). Household Hunger Scale: Indicator Definition and Measuurement Guide. USAID / FANTA III Report.

Maxwell, D. and Caldwell, R. (2008). The Coping Strategies Index: Field Methods Manual. USAID, WFP, 2008.

Rosenbaum, P. R., and D. B. Rubin. (1983). "The Central Role of the Propensity Score in Observational Studies for Casual Effects." *Biometrika* 70 (1): 41-55.

Rosenbaum, P.R., and D.B. Rubin. (1984). "Reducing Bias in Observational Studies using Subclassification on the Propensity Score." *Journal of the American Statistical Association*. 79: 516-524.

Yoshida, N., X. Chen, S. Takamatsu, K. Yoshimura, S. Malgioglio, and S. Shivakumaran. (2020) "The Concept and Empirical Evidence of SWIFT Methodology." Mimeo.

Zhang, K., Chen, X., and Yoshida, N. (2021). "Phone Survey Reweighting: Case Studies from the Philippines, St. Lucia, Zimbabwe, and Uganda." *World Bank Group*. 1-34.

Annex 1

Table 1. Estimation of poverty

Model	Timing	Mean	Std. Err.	95% Confidence Interval	
Pre-COVID (SWIFT, time-invariant)	IHS 4 2016	0.65	0.009	0.64	0.67
	Pre-COVID	0.66	0.014	0.64	0.69
COVID-era (SWIFT Plus, time-variant)	August 2020 (RFMS R1)	0.73	0.014	0.70	0.76
	December 2020 (RFMS R2)	0.78	0.013	0.75	0.80

Table 2. Probability of poverty increase since pre-COVID

	Prob(>0)	Prob(>3%)
August 2020 (RFMS R1)	100%	98%
December 2020 (RFMS R2)	100%	100%

Annex 2. Pre-COVID and COVID-era SWIFT Models

Table 1. Pre-COVID Model (SWIFT using RFMS Round 1)

ln(Consumption)	Coef.	Robust Std. Err.	RFMS R1 Mean	IHS4 Mean	SD	Min	Max
Demographics							
HH size	-0.234	0.013	4.42	4.18	1.94	1	16
HH size (squared)	0.966	0.114	0.23	0.21	0.19	0.01	2.56
Dependency ratio	-0.179	0.034	0.54	0.49	0.25	0	1
Male HH head	0.041	0.018	0.60	0.63	0.48	0	1
Highest education is plse	0.106	0.021	0.18	0.15	0.36	0	1
Highest education is jce	0.094	0.024	0.11	0.11	0.31	0	1
Highest education is msce	0.153	0.033	0.13	0.08	0.27	0	1
HH head can read/write Chichewa	0.058	0.017	0.65	0.63	0.48	0	1
Dwelling							
Walls made of mud brick (unfired)	0.048	0.016	0.62	0.60	0.49	0	1
Floors made of smoothed mud	-0.101	0.022	0.82	0.79	0.41	0	1
No toilet	-0.409	0.075	0.03	0.09	0.29	0	1
Toilet without roof	-0.368	0.072	0.37	0.24	0.43	0	1
Toilet with roof	-0.323	0.070	0.57	0.65	0.48	0	1
Water source is open public well	0.062	0.027	0.04	0.07	0.26	0	1
Waste disposal is rubbish pit	0.081	0.016	0.62	0.44	0.50	0	1
Waste disposal is burning	0.099	0.035	0.09	0.06	0.24	0	1
Waste disposal is public rubbish heap	0.095	0.030	0.05	0.08	0.27	0	1
Cooking fuel is collected firewood	0.223	0.039	0.86	0.83	0.37	0	1
Cooking fuel is purchased firewood	0.397	0.050	0.06	0.06	0.25	0	1
Cooking fuel is charcoal	0.537	0.050	0.05	0.06	0.25	0	1
Assets							
iron	0.181	0.026	0.08	0.09	0.28	0	1
mortar	0.065	0.016	0.37	0.45	0.50	0	1
radio	0.087	0.017	0.29	0.35	0.48	0	1
bed	0.221	0.020	0.25	0.25	0.43	0	1
bicycle	0.108	0.017	0.35	0.40	0.49	0	1
Constant	12.429	0.091					

Table 2. COVID-era Model (SWIFT Plus using RFMS Round 1 and 2)

ln(Consumption)	Coef.	Robust Std. Err.	RFMS R1 Mean	RFMS R2 Mean	IHS4 Mean	Std. Dev.	Min	Max
Demographics								
HH size	-0.233	0.013	4.42	4.42	4.18	1.94	1	16
HH size (squared)	1.029	0.112	0.23	0.23	0.21	0.19	0.01	2.56
Dependency ratio	-0.158	0.040	0.54	0.54	0.49	0.25	0	1
Male HH head	0.049	0.020	0.60	0.60	0.63	0.48	0	1
HH head age	0.013	0.003	43.56	43.56	43.78	17.08	15	97
HH head age (squared)	-0.010	0.003	22.31	22.34	22.09	17.21	2.25	94.09
Highest education is plse	0.128	0.021	0.18	0.18	0.15	0.36	0	1
Highest education is jce	0.158	0.024	0.11	0.11	0.11	0.31	0	1
Highest education is msce	0.286	0.032	0.13	0.14	0.08	0.27	0	1
HH head can read/write Chichewa	0.089	0.017	0.65	0.66	0.63	0.48	0	1
HH head is divorced/separated	-0.033	0.023	0.18	0.18	0.17	0.38	0	1
Food Security								
Someone in the HH reduced number of meals eaten in a day (past 7 days)	-0.082	0.017	0.67	0.83	0.52	0.50	0	1
HH preferred less expensive food (past 7 days)	-0.118	0.018	0.80	0.92	0.71	0.45	0	1
Consumption								
Purchased clothing (past month)	0.275	0.015	0.46	0.33	0.48	0.50	0	1
HH member consumed meat/fish/animal product (past 7 days)	0.162	0.019	0.54	0.40	0.82	0.38	0	1
HH member consumed milk/milk product (past 7 days)	0.444	0.026	0.02	0.04	0.09	0.28	0	1
Other								
Housing is more than adequate (past month)	0.162	0.033	0.03	0.01	0.05	0.22	0	1
Constant	11.898	0.070						

Annex 3. Inputs for Reweighting

To make all estimates comparable to rural South Malawi, we apply a weight (reweighting) calculated by using a reference survey (IHS4) and the 2020 RFMS survey in Malawi. Since micro data for the reference survey is not accessible, we are not able to perform propensity score weighting. Hence, we skip the step of PSW and directly conduct subnational level maxentropy using the district-level summary statistics. This procedure matches the included variables (household size, dependency ratio, age of household head, gender of household head, cooking fuel being collected firewood, floor material being sand/smoothed mud, and district dummies) in an exact manner for each of the six districts in rural South Malawi, namely, Mangochi, Zomba, Chiradzulu, Phalombe, Chikwawa, and Balaka. Following the subnational maxentropy procedure, lastly, we match the district-level population shares between the phone survey and the reference survey for all six districts, using a procedure named "post-stratification". Post-stratification makes additional weight adjustments so that the population shares of each district become identical between the reweighted COVID-19 RFMS and the reference survey.

Table 1shows the comparison of the four aforementioned indicators after the post stratification, which match satisfactorily in the 2 surveys. It suggests the validity of the weights we applied to the data.

Table 1. Summary Statistics with Final Weights

	household size		dependency ratio		head age	
	Weighted	Reference	Weighted	Reference	Weighted	Reference
R1	4.5	4.50	0.58	0.58	43.63	43.63
R1	4.49	4.49	0.53	0.53	41.64	41.64
R3	4.17	4.17	0.48	0.48	44.07	44.07
R4	4.48	4.48	0.55	0.55	44.52	44.52
R5	4.37	4.37	0.51	0.51	43.82	43.82
R6	4.32	4.32	0.53	0.53	45.01	45.01
National	4.42	4.40	0.54	0.52	43.56	43.14

	head sex		floor		cooking	
	Weighted	Reference	Weighted	Reference	Weighted	Reference
R1	0.53	0.53	0.85	0.85	0.93	0.93
R1	0.61	0.61	0.74	0.74	0.79	0.79
R3	0.56	0.56	0.73	0.73	0.72	0.72
R4	0.68	0.68	0.88	0.88	0.9	0.9
R5	0.69	0.69	0.86	0.86	0.88	0.88
R6	0.60	0.60	0.86	0.86	0.88	0.88
National	0.60	0.69	0.82	0.71	0.86	0.73

Annex 4. Household Hunger Scale questions

No.	Question	Response Option	Code
Q1	In the past [4 weeks/30 days], was there ever no food to eat of any kind in your house because of lack of resources to get food?	0 = No (Skip to Q2) 1 = Yes	|___|
Q1a	How often did this happen in the past [4 weeks/30 days]?	1 = Rarely (1–2 times) 2 = Sometimes (3–10 times) 3 = Often (more than 10 times)	|___|
Q2	In the past [4 weeks/30 days], did you or any household member go to sleep at night hungry because there was not enough food?	0 = No (Skip to Q3) 1 = Yes	|___|
Q2a	How often did this happen in the past [4 weeks/30 days]?	1 = Rarely (1–2 times) 2 = Sometimes (3–10 times) 3 = Often (more than10 times)	|___|
Q3	In the past [4 weeks/30 days], did you or any household member go a whole day and night without eating anything at all because there was not enough food?	0 = No (Skip to the next section) 1 = Yes	|___|
Q3a	How often did this happen in the past [4 weeks/30 days]?	1 = Rarely (1–2 times) 2 = Sometimes (3–10 times) 3 = Often (more than 10 times)	|___|