IARIW 2022

11 Friday - 13 Sunday November

Poverty projections and profiling based on Ethiopia's High-Frequency Phone Surveys of households using a SWIFT-COVID-19 package

Christina Wieser
(World Bank)
cwieser@worldbank.org

Nobuo Yoshida
(World Bank)
nyoshida@worldbank.org

Shinya Takamatsu
(World Bank)

Kexin Zhang
(World Bank)

Danielle Aron
(World Bank)

Paper prepared for the IARIW-TNBS Conference on "Measuring Income, Wealth and Well-being in Africa", Arusha, Tanzania November 11-13, 2022

Session 9: The Impact of COVID-19 in Africa II

Time: Saturday, November 12, 2022 [3:30 PM - 5:00 PM]

Poverty projections and profiling based on Ethiopia's High Frequency Phone Surveys of households using a SWIFT-COVID-19 package

Christina Wieser, Shinya Takamatsu, Nobuo Yoshida, Kexin Zhang, and Danielle Aron

This paper shows the results of poverty and inequality estimations using a SWIFT-COVID19 package with the Ethiopia High-Frequency Phone Surveys (round 7). The SWIFT-COVID19 package includes the imputation of household expenditures using a SWIFT-Plus approach, a rapid poverty monitoring tool, with adjustments for sampling weights to address a phone survey's sampling bias. The package shows Ethiopia likely experienced a sizeable increase in poverty between the pre-COVID era and October/November 2020. Inequality also appears to have increased slightly over this time period. Despite low levels of government assistance, income and job losses were lower among the poor compared to the national averages.

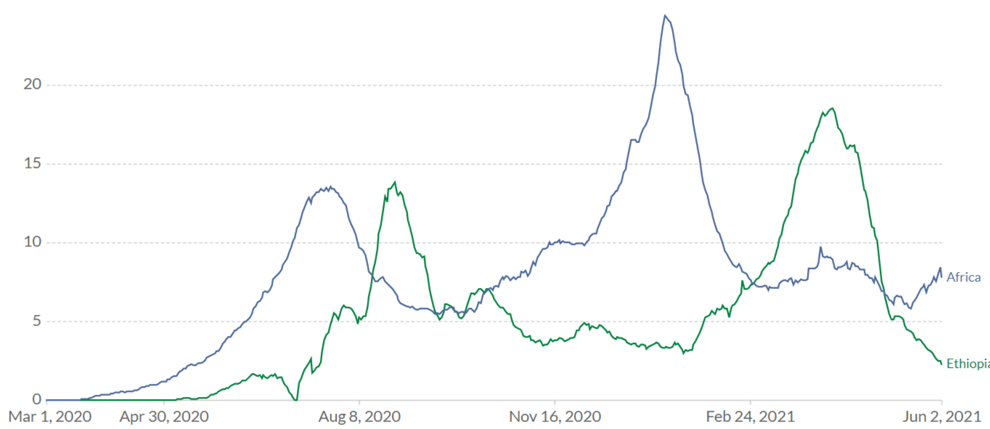
I. Introduction

The COVID-19 pandemic has spread fast in the world, and many countries in Sub-Saharan Africa have implemented social distancing policies and lockdowns to contain the spread of the virus. However, these policies can have high social costs, especially for the poor and vulnerable. Those who are already poor are less likely to have existing buffers for times of crisis — they have little savings or food stocks, are heavily dependent on casual daily labor, and the majority cannot work from home. Given the significant impact that social distancing policies have had on in-person and casual daily labor, having reliable data to monitor the effects of these policies, especially on the poor and the vulnerable, is of utmost importance.

The COVID-19 pandemic has reshaped the global economy and daily lives of people across the world. Economic projections predict large declines in growth across countries and the World Bank's most recent Poverty and Shared Prosperity Report shows the pandemic could push some 100 million people into extreme poverty in 2020 alone, leading to an increase in global poverty for the first time since 1998. Increases in poverty associated with firm closures and job losses, together with rising debts and failing tax revenues, put at risk decades of development strides made in many low-income economies.

With a recent surge in infection and fatality rates, the COVID-19 pandemic continues to pose serious risk for Ethiopians' health and economic wellbeing. Early-on, Ethiopia took several steps to halt the spread of COVID-19 infections and to stave off its negative impacts on the economy, including declaring a State of Emergency (SOE) in April 2020. The swift government response partly explains the smaller number of COVID-19 cases between November 2020 and February 2021 compared to other countries in Africa (Figure 1). As restrictions loosened with the lifting of the SOE in September 2020, confirmed cases have been on the rise (Figure 1). At the time of writing, Ethiopia showed a positivity rate between 15 to 20 percent and a total of 272,036 confirmed cases as of June 2, 2021.

Figure 1: Daily new confirmed COVID-19 cases per million people in Ethiopia and Africa



Source: Johns Hopkins University CSSE COVID-19 Data

The World Bank Group launched the COVID-19 High-Frequency Phone Surveys (HFPS) in April 2020 to monitor the socio-economic conditions of the COVID-19 pandemic. Phone surveys enable data collection even when enumerators cannot visit sample households due to social distancing policies and lockdowns, allowing for continued monitoring of socio-economic outcomes. However, phone surveys must be short and cannot include the full-length modules traditionally used to estimate household welfare through income or consumption aggregates. Instead, phone surveys in some countries, including the Ethiopia HFPS, adopted the Survey of Well-being via Instant and Frequent Tracking (SWIFT) methodology. SWIFT, developed by Yoshida et al. (2015), applies machine learning and multiple imputations techniques to estimate household expenditures/incomes by collecting a small set of simple questions. This methodology lends itself for inclusion into HFPS, as households can easily answer the simple yes-no questions via phone and the questions can be easily integrated into phone interviews without heavily training enumerators. Subsequently, household expenditure can be estimated, from which we can produce poverty statistics and profiles of the poor and non-poor.

However, because these surveys are conducted over the phone, households without access to a phone, that are usually poorer, are not included in our estimations. To overcome this "non-poor" sampling bias, a new SWIFT-COVID-19 package is applied, which incorporates sampling weight adjustments, including propensity score weighting (originally proposed by Rosenbaum and Rubin (1983 and 1984)) and post-stratification weighting (such as raking or Stata's *maxentropy* command). The SWIFT-COVID-19 package also uses a new SWIFT methodology, called SWIFT Plus, which produces poverty rates that are more accurate in times of rapidly changing economic conditions.

The objective of this note is twofold. First, it presents how poverty and inequality are estimated using the SWIFT-COVID-19 package. Second it illustrates how the poverty data derived by the SWIFT-COVID-19 package can be used to estimate poverty and inequality trends and profile the poor in Ethiopia during the COVID-19 pandemic.

This note is structured as follows: Section II describes data used to derive the findings for Ethiopia. Section III describes how COVID-era poverty projections are produced using SWIFT Plus and section IV describes the weight adjustments applied. Section V describes the poverty trends and profiles in Ethiopia based on HFPS data and Section VI concludes.

II. Data in Ethiopia

The Ethiopia HFPS monitors the economic and social impacts of and responses to the COVID-19 pandemic on households, by calling a sample of households over a 15 months period for a total of twelve survey rounds. The HFPS is representative for households with access to a mobile phone at the national level and for urban and rural areas.

The sample for the HFPS is a subsample of the 2018/19 Ethiopia Socioeconomic Survey (ESS). The ESS collects panel data on household and community characteristics in both rural and urban areas. Four waves have been conducted since 2011, the most recent in 2018/19 (ESS4). ESS4 included a total of 6,770 households. In the ESS interview, households were asked to provide phone numbers, either their own or that of a reference household (i.e. friends or neighbors), so that they can be contacted in the follow-up ESS surveys, should they move from their sampled location. At least one valid phone number was obtained for 5,374 households (4,626 owning a phone and 995 with a reference phone number). These households established the sampling frame for the HFPS. The Ethiopia COVID-19 HFPS drew its sample from the database of telephone numbers from ESS4; however, the final sample size decreased due to respondent and enumeration fatigue.

The sample size was low at the outset of the survey, as the phone penetration rate in rural Ethiopia is low at around 40 percent compared to urban Ethiopia where over 90 percent have access to a phone. The ESS data was used not only as a sampling frame, but also served as a reference survey for reweighting and offered a sampling frame for the Ethiopia COVID-19 HFPS. The ESS data is also used to develop SWIFT poverty projection models and the poverty estimates from the ESS data are used as pre-COVID poverty estimates.

Ethiopia conducted twelve rounds of HFPS between April 2020 and June 2021. The timeline and number of completed interviews of the HFPS are outlined in Table 1. Round-on-round attrition was high due to (i) enumerator and respondent fatigue, (ii) challenges with network connectivity, particularly in rural Ethiopia; and (iii) a conflict which erupted in the North of Ethiopia and prevented calls among households in the Tigray regions after round 7. Round 7, which includes the SWIFT modules, was conducted between October 19th and November 10th, 2020 with a total of 2,534 households (715 rural and 1,819 urban). HFPS round 7 data is mainly used for the poverty, inequality analysis, and profiling of the poor.

Table 1: Number of Completed Interviews by Round

	Round 1 (Apr 22-May 13, 2020)	Round 2 (May 14-June 3, 2020)	Round 3 (June 4- 26, 2020)	Round 4 (July 27-Aug14, 2020)	Round 5 (Aug 24-Sep 17, 2020)	Round 6 (Sep 21- Oct 13, 2020)	Round 7 (Oct 19-Nov 10, 2020)	Round 8 (Dec1-21, 2020)	Round 9 (Dec 28, 2020-Jan 22, 2021)	Round 10 (Feb 1-23, 2021)	Round 11 (Apr 12 – May 8, 2021)	Round 12 (Jun 1 -18, 2021)
Rural	978	940	934	838	775	760	716	576	553	537	442	Tbd
Urban	2,271	2,167	2,124	2,040	1,995	1,944	1,821	1,646	1,524	1,641	1,540	Tbd
National	3,249	3,107	3,058	2,878	2,770	2,704	2,537	2,222	2,074	2,178	1,982	Tbd

For all rounds, due to the limited and biased phone ownership and the significant attrition, the sampling weights needed to be adjusted. The reweighting process was conducted to regain the national representativeness for key demographic statistics. The reweighting process will be described in section IV.

III. Poverty Projections using the SWIFT-COVID-19 package

SWIFT is used to estimate poverty rates from the Ethiopia COVID-19 HFPS round 7 data. SWIFT 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 cost-effectively. Roughly 10 to 15 questions on poverty correlates are collected, such as ownership of assets, housing conditions, and household demographics; projects household income or expenditure using those correlates in a statistical model; and statistics on poverty and inequality are estimated from the projected income/expenditure data. SWIFT has demonstrated its usefulness in over 50 countries on more than 100 projects.

Reliability of SWIFT in the COVID-19 pandemic

Supported by years of quality assurance 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 accurate the SWIFT estimates are compared to the original estimates. Table 2 shows the results of such tests conducted in Yoshida et al. (2020), highlighting that differences between SWIFT estimates and the official poverty rates are small.[1] All estimates are less than 1.5 percentage points

[1] Such tests cannot be done easily because data from many developing countries are not directly comparable over time. In Yoshida et al. (2020), after confirming the datasets used in Table 2 are comparable over time, the accuracy of SWIFT estimations were examined.

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 slightly outside the 95 percent confidence interval. More evidence on the reliability of SWIFT estimates is available in Yoshida et al. (2020).

Table 2. 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, as experienced during 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 percentage points in Afghanistan and 14 percentage points in the West Bank and Gaza. 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, such as 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.

Creation of SWIFT Plus

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 consumption of specific items such as 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. SWIFT Plus replaces time-invariant (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 SWIFT Plus. For both Afghanistan and the West Bank and Gaza cases, SWIFT Plus estimated substantial poverty increases which were very close to the actual increases.

In Ethiopia, the SWIFT Plus approach is adopted to estimate poverty rates using the seventh round of the COVID-19 HFPS data. To run SWIFT Plus, time-variant (quickly changing) indicators like consumption of specific items, food security, employment conditions, and economic sentiment are added into the COVID-19 HFPS questionnaire. The final urban and rural models are available in the annex (see Annex 2, table A3 and A4). These models include food insecurity, employment status, and dwelling characteristics as poverty correlates. The dwelling characteristics and household demographics are time-invariant or slow changing over time, but they are good predictors for cross-sectional variations, which are also important to estimate poverty and inequality.

IV. Reweighting to obtain nationally representative poverty estimates

One shortcoming of the COVID-19 HFPS is its lack of national representativeness, as only those who have access to a phone can answer the survey. People who respond to phone interviews may have systematically different characteristics than people who do not respond to phone interviews. For example, in rural Ethiopia, many poor households do not own phones, while better off households do. Phone ownership also differs substantially between urban and rural areas in Ethiopia. Since phone ownership is essential for phone interviews, an unbalanced distribution of phone ownership across the country makes it challenging to obtain nationally representative statistics, since the collected data represents phone owners rather than the entire population. In addition to the unbalanced phone ownership, responses to phone interviews are often not uniform. Similar to face-to-face interviews, better off households, which tend to be located in urban areas, are less likely to respond to phone interviews compared to poor households. As a result, statistics from phone surveys are unlikely to represent a country uniformly and are not nationally representative.

To address these limitations associated with phone surveys, we adjust sampling weights. This ensures that weighted averages of key statistics from the phone survey are close to the representative reference survey. The reweighting procedure for the Ethiopia HFPS consists of three steps: (i) propensity score weighting, (ii) subnational maxentropy, and (iii) post-stratification.

Propensity Score Weighting (PSW) is a method designed to adjust a phone survey's sampling weights by comparing the phone survey with a nationally representative household survey (or a reference survey), in this case the ESS4. PSW appends the reference survey and the phone survey and estimates each household's probability in the merged data of being included in the phone survey. PSW then ranks all households in the merged data by the predicted probability and creates quintiles based on that probability. The weights assigned to each household 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 in the phone survey are adjusted so that the sum of their weights in each quintile becomes identical to their counterpart in the reference survey.

To refine the weights further, subnational maxentropy is executed at the rural and urban level, respectively. Even after PSW, summary statistics in the phone survey could differ largely from those in the reference survey. Such differences can be real, particularly when time has passed between the reference and phone surveys. Nevertheless, it is unlikely that summary statistics of time-invariant (slowly changing) indicators like household size, dependency ratios, household head’s educational attainment, or population shares of districts would change significantly in a relatively short period of time. Maxentropy adjusts weights to match the summary statistics of these time-invariant variables between the reference and phone survey in an exact manner. The following box briefly explains how maxentropy works.[2]

[2] Inputs for reweighting process are available in Annex 1.

Box 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. The indicators need to be time-invariant or slow-changing. Otherwise, due to the relatively long time span between the reference and phone surveys, the averages of indicators can change; ignoring the real changes and forcing the means to be equal can bias all estimates from the phone survey. Therefore, it is important to select indicators that are time-invariant or slow-changing to be matched using maxentropy. 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 comparable household surveys in the past before selecting the indicators for matching.

Lastly, the sampling weights are adjusted to match the urban and rural population shares of the phone survey to those of the reference survey. The second stage of adjustment matches summary statistics of key time-invariant variables for urban and rural areas, but unless the urban and rural population shares of the phone survey are matched to those of the reference survey, all summary statistics of the phone survey do not match those of the reference survey at the national level. This adjustment is called a "post-stratification" adjustment. This post-stratification does not affect urban and rural summary statistics while making the national average statistics of the phone survey match those of the reference survey. The results of this reweighting are available in the annex.[3]

V. Results – Poverty projections and profiles

The following section shows the trends in poverty and inequality from ESS4 and HFPS round 7 data and provides a brief overview of the profile of the poor. We report changes in poverty during COVID-19 as relative changes[4] compared to 2018/19 using ESS4.[5]

The COVID-19 pandemic has affected economic activity in Ethiopia with significant adverse effects on employment, particularly at the onset of the pandemic. However, Ethiopia has stark differences in the structure of the labor market in urban and rural areas, resulting in vastly diverging outcomes on employment and income dynamics during the COVID-19 pandemic. In rural areas, where 80 percent of the Ethiopian population resides, COVID-19 had a much smaller impact on people's livelihoods compared to urban areas (Wieser et al. 2021 and Ambel et al. 2021). Employment rates plunged in the early days of the pandemic, with 8 percent of respondents losing their job at the beginning of the outbreak, with much higher job losses in urban areas (20 percent) than in rural areas (3 percent). Moreover, the COVID-19 pandemic has had severe impacts on household incomes, resulting from reduced employment and wages. About 55 percent of respondents reported that household incomes were either reduced or had completely disappeared, affecting urban and rural households alike in the early weeks of the pandemic (HFPS round 1). Using poverty estimates derived from HFPS round 7, we observe that these adverse effects on employment and income are also reflected in welfare outcomes, with increased poverty and inequality.

[3] More details on all of the above-mentioned reweighting techniques, including PSW and maxentropy can be found in Zhang et al. (2021).

[4] Relative changes in poverty are calculated as follows: (R7 poverty rate)/(ESS4 poverty rate) = percent change where ESS4 poverty rate = 100

[5] We cannot report on actual poverty rates using ESS4 as ESS4 is not recognized as a survey from which official poverty rates can be derived. In Ethiopia, official poverty estimates are derived by the Central Statistics Agency from the Household Consumption and Expenditure Survey (HCES), the latest of which was collected in 2016. To avoid comparisons of poverty rates across surveys that are not comparable (i.e. the ESS4 and HCES), there are no poverty rates derived from ESS4. Rather, we look at trends across time using relative changes in poverty, rather than absolute change in poverty rates.

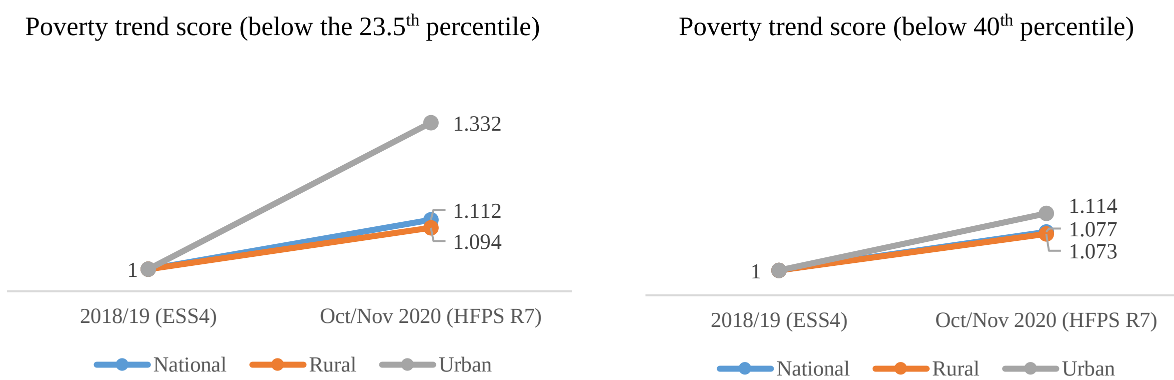
Poverty

In Ethiopia, ESS4 is not the household survey used for estimating official poverty statistics and ESS4 does not contain poverty lines. Instead, the following 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 the most recent official poverty rate for Ethiopia is 23.5 percent. The second poverty line (40th percentile) is added to see whether or not 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 the World Bank's twin goals of shared prosperity, which tracks the income growth of the poorest 40 percent of a country's population.

Poverty based on the HFPS is tracked by a poverty trend score, which is the ratio of the poverty rate in HFPS round 7 (October/November 2020) to that of ESS4 (2018/19). The poverty trend score indicates the rate of change in the poverty rate since ESS4. For example, if the score is 1.1, the poverty headcount rate increases 10 percent compared to the baseline (ESS4 – 2018/19). If the population size between ESS4 and the HFPS round 7 remains the same, the score of 1.1 implies a 10 percent increase in the poor population.[6]

Figure 2 shows the poverty trend score based on the 23.5th percentile and 40th percentile. According to this measure, at the national level, the share of people below the 23.5th percentile 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 7). This implies that, at the national level, the population 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 7 is negligible.

Figure 2. 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 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. Poverty rates in urban areas increased substantially in terms of percent changes. 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 in 2018/19. 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 less 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 – the poverty rate in rural

[6] If the population growth between ESS4 and HFPS round 7 is x and the poverty trend score is y, then the growth of the poor population is xy.

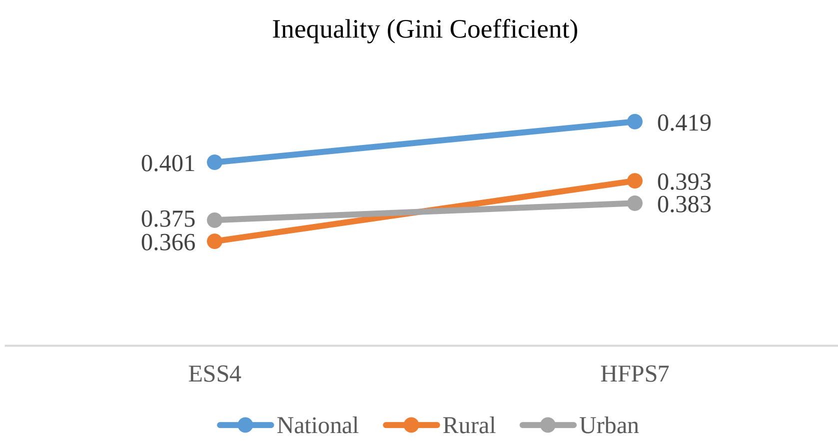
Ethiopia stood at 26 percent compared to 15 percent in urban Ethiopia – means that the increase in the absolute number of poor was much higher in rural areas.

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 of the poverty increase from 2018/19 ESS4 to HFPS round 7 (October/November 2020) at the national, urban, and rural levels. We find that the probability of an increase in poverty is 78.1 percent at the national level, 81.7 percent for urban areas, and 73.0 percent for rural areas. If we use the 40th percentile line, the probability of increasing poverty is 79.6 percent nationally, 71.4 percent in rural, and 71.4 percent in urban areas.

Inequality

Based on the imputed consumption expenditures using the SWIFT-COVID-19 package, the Gini coefficient can be estimated for the HFPS round 7 data. Figure 3 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.[7] Inequality in Ethiopia has increased since the outbreak of the COVID-19 pandemic, with a Gini coefficient in October/November 2020 of 0.42. In 2018/19, inequality was higher in urban areas, with a Gini coefficient of 0.375 compared to rural areas with a Gini of 0.366. However, the ranking is reversed in the COVID-era.

Figure 3. Trends in Inequality from ESS4 to HFPS Round 7



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

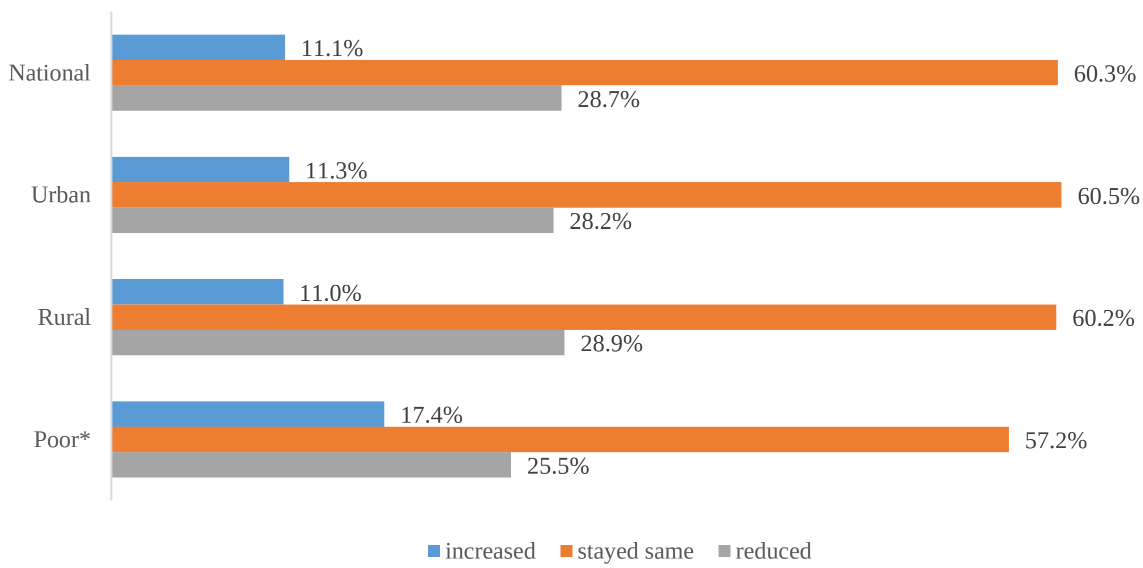
[7] A higher Gini coefficient indicates greater inequality, with high-income individuals receiving a much larger percentage of the total income of the population.

Profiling of the poor

(i) Total income changes from the previous round

Since HFPS round 7 does not include data on income changes, data from HFPS round 6 (September/October 2020) is used after matching the poverty status estimated from the HFPS round 7 using the household ID. According to round 6 data, 11.1 percent of households experienced an increase in total income since the ESS4, with similar increases in rural and urban areas. However, 28.7 percent of the national population faced an income loss and again the effect is similar for rural and urban areas. The poor (as of round 7) experienced a faster recovery than the average of the overall population, with 17.4 percent of the poor experiencing a total income increase and 25.5 percent facing a decrease.

Figure 4. Comparison of total income loss across different groups as of HFPS round 6

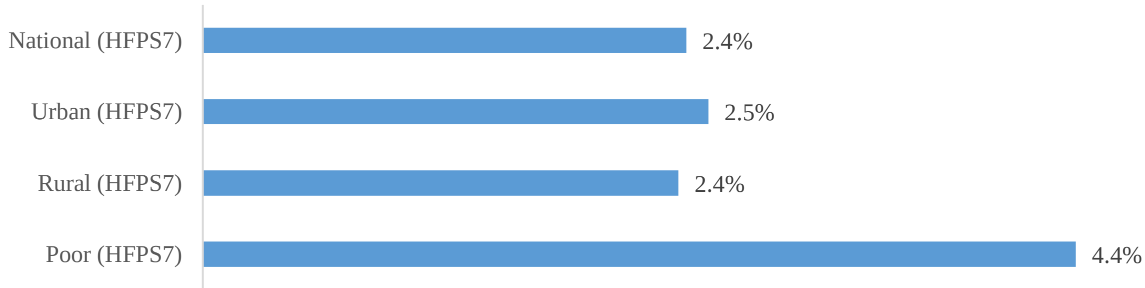


Source: Authors' estimation using data from HFPS round 6 and round 7.
Note: * refers to the fact that the poverty status was defined by SWIFT projections using HFPS round 7.

(ii) Assistance for food and cash transfer

Using HFPS round 7 data, we analyzed impacts on assistance using three categories: food assistance only, food assistance and/or cash transfer, and cash transfer only. However, since the coverage of cash transfers are very low, this subsection shows the results of food assistance only (Figure 5). Figure 4 shows that the coverage of food assistance in Ethiopia was also limited. Only 2.5 percent of households reported they received assistance. The coverage is very similar for both urban and rural areas. Among the poor, the coverage of food assistance (as of HFPS round 7) was 4.4 percent, which is low but significantly larger than the national average.

Figure 5. Comparison of food assistance across different groups

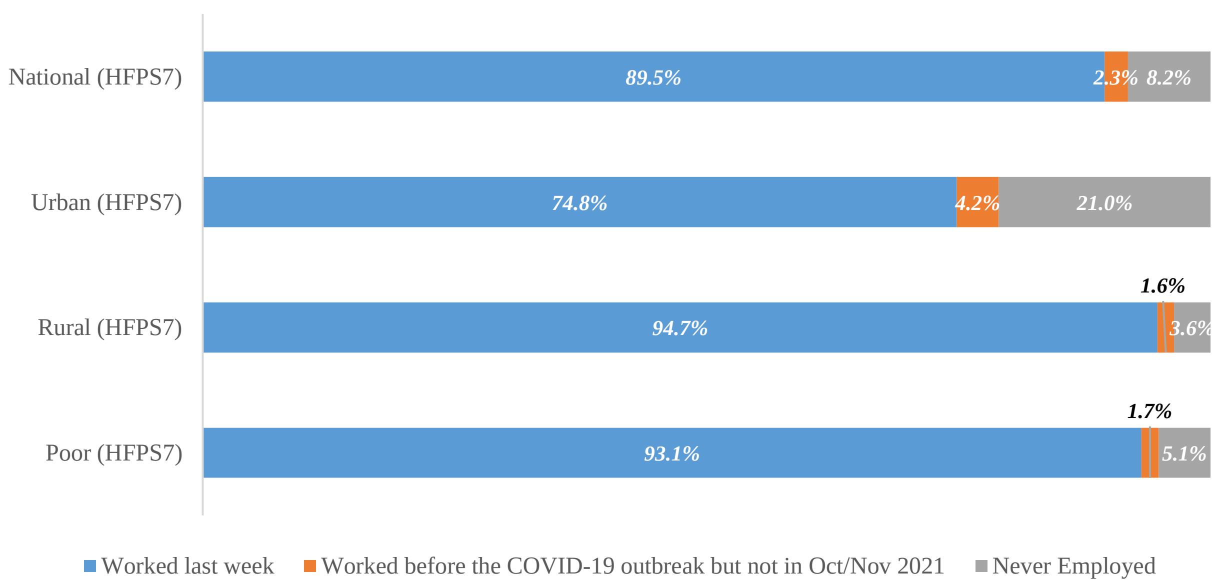


Source: Authors' estimation using data from HFPS round 7

(iii) Employment Status

For the HFPS round 7 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 7 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 of job stoppage in urban areas (4.2 percent).

Figure 6. Comparison of employment status across groups



Source: Authors' estimation using data from HFPS round 7

VI. Conclusions

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. Poverty incidence and inequality were estimated using the SWIFT-COVID-19 package, which adjusts the original SWIFT methodology to be more responsive to sudden economic downturns and applies reweighting techniques to addresses sampling bias due to phone interviews. This technical note includes poverty and inequality estimates for the Ethiopia HFPS round 7 data.

Estimates show that the 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 a lower poverty line is selected. Inequality, as measured by the Gini coefficient, increased at all levels; however, the income gap experienced a reversed trend — inequality in urban areas was higher than in rural areas in 2018/19 but lower than 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 other groups. Second, although the coverage was limited, the coverage of food assistance has been pro-poor, in that the coverage of the poor has been higher than that of other groups during the COVID-era. 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 the situation among the poor can be very different from the national, urban and rural averages and highlight the benefit of having poverty profiling derived by the SWIFT COVID-19 package.

References

Ambel, A.A., Cardona Sosa, L.M., Kassa, W.Y., Tsegay, Haile, A.T., and Wieser, C. (2021). “Monitoring COVID-19 Impacts on Households in Ethiopia: How COVID-19 is Affecting households: Results from the High-Frequency Phone Surveys of Households from April 2020 through January 2021”. *World Bank Group*.

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.

Wieser, C., Cardona Sosa, L.M., Ambel, A.A., Tsegay, A.H., and Pimhidzai, O. (2021). “Monitoring COVID-19 Impacts on Households in Ethiopia: COVID-19 and the Rural Economy: Evidence from High Frequency Phone Surveys”. *World Bank Group*.

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. Inputs for Reweighting

To make all estimates nationally comparable, we apply a weight (reweighting) calculated by combining the Ethiopian Socioeconomic Survey (ESS) together with round 7 of the 2020 phone survey in Ethiopia. The main assumption is that the probability of a household being selected to take the high-frequency phone survey (COVID-19 HFPS) and to be reached is solely determined by the selected households' characteristics. We use the reference survey as a benchmark and compare the respondents' probability of being "selected" into the phone survey with the reference probability. To plausibly estimate this probability for both surveys, we include all variables that are available from both the reference and phone surveys as below: 1) household size and household size squared, 2) dependency ratio, 3) literacy of household head, 4) regions the household is residing in, 6) floor material being mud/dung, 7) floor material being cement, and 8) floor material being tiles. Then we divide all observations into 5 quintiles based on this predicted probability. We then made adjustments in weights – reweighting – by assigning a higher weight to the quintile of respondents that was underrepresented in terms of their "predicted probability" to participate in the phone survey compared to the reference survey and underweighting those households that were overrepresented in the phone survey compared to reference survey.

Table A1. Summary Statistics with propensity score matching weights

	Reference	Phone Survey - original	Phone/Web -PSM
Household size	4.48	5.14	5.05
Urban/Rural locality	0.32	0.33	0.3
Dependency ratio	0.43	0.43	0.45
Age of household head	42.91	42.82	43.7
Gender of household head	0.74	0.76	0.72

However, even with propensity score weighting, variables such as household size and age of household head, still exhibit a large difference between the adjusted phone survey and the reference survey, suggesting non-comparability (Table A1). To eliminate the gap, we conduct subnational level maxentropy, which exactly matches the included variables (household size, household size squared, dependency ratio, age of household head, gender of household head, ratio of male members, literacy of household head, floor materials, and region dummies of the household) at the urban and rural regions, respectively. After the maxentropy procedure at the subnational level, lastly, we match the urban/rural household shares with the reference survey, using a procedure named "post-stratification". Post-stratification makes additional weight adjustments so that the household shares of urban and rural regions become identical between the reweighted COVID-19 HFPS and the reference survey.

Table A2 shows the comparison of the four aforementioned indicators after the post-stratification, which match satisfactorily in the two surveys. It suggests the validity of the weights we applied to the data.

Table A2. Summary Statistics with Final Weights

Household size			Urban			Dependency ratio		
	Weighted	Reference		Weighted	Reference		Weighted	Reference
urban	3.65	3.65	urban	1	1	urban	0.32	0.32
rural	4.88	4.88	rural	0	0	rural	0.49	0.49
national	4.56	4.48	national	0.26	0.32	national	0.44	0.43

Household head's age			Household head's sex		
	Weighted	Reference		Weighted	Reference
urban	38.73	38.73	urban	0.65	0.65
rural	44.92	44.92	rural	0.78	0.78
national	43.29	42.91	national	0.74	0.74

Annex 2. COVID-era Models

Table A3. COVID-era Rural Model (SWIFT using HFPS Round 7)

ln(Consumption)	**Coef.**	**Robust Std. Err.**	**ESS4 Mean**	**HFPS 7 Mean**
Region				
Tigray	-0.333	0.047	0.066	0.066
Amhara	-0.355	0.027	0.266	0.266
SNNP	-0.242	0.028	0.213	0.213
Demographics				
HH size	-0.211	0.020	4.885	4.885
HH size (squared)	0.081	0.015	2.863	2.863
Food insecurity				
Reduced consumption of preferred foods in the past 7 days	-0.171	0.030	0.238	0.408
Reduced number of meals eaten in a day	-0.024	0.035	0.170	0.379
Employment				
Anyone in HH is in agriculture last week	0.116	0.039	0.852	0.865
Anyone in HHs is in non-farm business last week	0.247	0.040	0.078	0.120
Dwelling				
Number of rooms (excluding kitchen, toilet and bath)	0.074	0.011	1.852	1.837
Floors made of cement	0.290	0.083	0.023	0.023
Floors made of tiles	0.310	0.161	0.005	0.005
Floors made of other materials	0.227	0.073	0.019	0.019
Constant	10.022	0.067		

Table A4. **COVID-era Urban Model (SWIFT using HFPS Round 7)**

ln(Consumption)	**Coef.**	**Robust Std. Err.**	**ESS4 Mean**	**HFPS 7 Mean**
Region				
SNNP	-0.119	0.025	0.150	0.150
Demographics				
HH size	-0.241	0.014	3.647	3.647
HH size (squared)	0.101	0.011	1.751	1.751
HH literate	0.233	0.021	0.753	0.753
Food insecurity				
Reduced consumption of preferred foods in the past 7 days	-0.038	0.030	0.214	0.345
Reduced number of meals eaten in a day	-0.263	0.033	0.164	0.269
Employment				
Anyone in HH is in agriculture last week	-0.119	0.025	0.147	0.186
Anyone in HHs is in non-farm business last week	0.087	0.020	0.264	0.261
Dwelling				
Number of rooms (excluding kitchen, toilet and bath)	0.099	0.008	1.973	1.938
Floors made of cement	0.277	0.021	0.418	0.418
Floors made of tiles	0.461	0.038	0.063	0.063
Floors made of other materials	0.228	0.094	0.009	0.009
Constant	10.185	0.043		