# ZIMBABWE POVERTY UPDATE

## 2017–19

**JOINT REPORT**

**ZIMSTAT and World Bank**

ZimStat Zimbabwe National Statistics Agency

zimref ZIMBABWE RECONSTRUCTION FUND

WORLD BANK GROUP

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# ABBREVIATIONS

| | |
|---|---|
| AMTO | Assisted Medical Treatment Order |
| APM | Agricultural Productivity Module |
| BEAM | Basic Education Assistance Module |
| CPI | Consumer Price Index |
| CPS | Consumer Price Survey |
| CRRP | Community Recovery and Rehabilitation Program |
| CS | Consumer Surplus |
| CV | Compensating Variation |
| DRB | Daily Record Book |
| EA | Enumeration Area |
| EV | Equivalent Variation |
| GDP | Gross Domestic Product |
| HSCT | Harmonized Social Cash Transfer |
| LV | Laspeyres Variation |
| MI | Multiple-Imputation Method |
| MPSLSW | Ministry of Public Service, Labour and Social Welfare |
| MSE | Mean Square Error |
| NGO | Nongovernmental Organization |
| OLS | Ordinary Least Squares |
| PDL | Poverty Datum Line |
| PICES | Poverty, Income, Consumption and Expenditure Survey |
| PPP | Purchasing Power Parity |
| PV | Paarsche Variation |
| RTGS | Real Time Gross Settlement |
| STEM | Science, Technology, Engineering, and Mathematics |
| SWIFT | Survey of Well-being via Instant and Frequent Tracking |
| WFP | World Food Programme |
| ZIMREF | Zimbabwe Reconstruction Fund |
| ZIMSTAT | Zimbabwe National Statistics Agency |


Photo: Arne Hoel/World Bank

# FOREWORD

In 2017 the Zimbabwe National Statistics Agency (ZIMSTAT) completed a Poverty, Income, Consumption and Expenditure Survey (PICES) that generated a welfare and poverty estimate for that year. However, the economic and social events in late 2018 and early 2019 may have led to changes in the poverty levels of the population, suggesting the need for an update. Notably, rapid food price inflation, coupled with poor rainfall during the 2018/19 agricultural season, may have significantly affected poverty levels. These events also increased the proportion of food-insecure Zimbabweans, especially during the lean season when household stocks are exhausted. The decline in the exchange rate of the Zimbabwean dollar led to rising costs of imports. This, combined with increasing transport costs, has also negatively impacted households since 2017. Therefore, the Government and its development partners indicated the desire to obtain an updated picture of poverty levels and living conditions in the country. This triggered the need for the Mini-PICES 2019.

## *Objectives of the survey*

The two major objectives of the Mini-PICES 2019 are to:

- update the poverty estimates for the country; and
- obtain a quick understanding of living conditions post 2017.

This report presents the survey findings. It also presents the changes that resulted from an exercise to rebase the poverty measurement methodology. The survey was guided by the PICES Technical Committee, chaired by ZIMSTAT, and comprised members from the World Bank, United Nations Children’s Fund, the United Nations Development Programme, the Ministry of Finance and Economic Development, and the Ministry of Public Service, Labour and Social Welfare.

ZIMSTAT is grateful for the financial support from the Zimbabwe Reconstruction Fund and the technical support provided by the World Bank. The Government of Zimbabwe facilitated the funding process and provided the human resources for the survey. As Director General, I personally wish to express my profound gratitude to the Government and development partners for their support throughout the survey. My sincere gratitude also goes to the members of the PICES Technical Committee and ZIMSTAT staff for successfully and proficiently implementing the Mini-PICES 2019 project. Furthermore, I wish to thank the ZIMSTAT field staff, supervisors, and data capture operators for a job well done. Finally, I also thank the survey respondents who provided the information.

**Taguma Mahonde**
**Director General**
**Zimbabwe National Statistics Agency**
**Harare**
**November 2020**

# ACKNOWLEDGMENTS

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Photo: Arne Hoel/World Bank

# EXECUTIVE SUMMARY

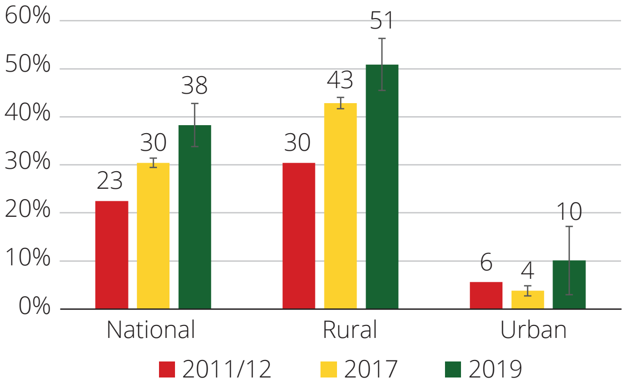
**This report presents updated poverty estimates for Zimbabwe for April–May 2019.** The Zimbabwe National Statistics Agency (ZIMSTAT) conducted the Poverty, Income, Consumption and Expenditure Survey (PICES) in 2017, and poverty estimates for that year were published in the *Zimbabwe Poverty Report 2017*. However, due to the rapid economic changes that occurred in the Zimbabwean economy from 2017 to 2019, a poverty update was needed. ZIMSTAT achieved this by conducting a household survey, the Mini-PICES 2019, from April 15 to May 23, 2019. The survey was supported by funding from the Zimbabwe Reconstruction Fund (ZIMREF) and technical support from the World Bank. Sampled households were a subsample of the PICES 2017 households covered in February–June 2017.

**The Mini-PICES 2019 uses an innovative and cost-effective approach for measuring per capita consumption.** It is a "hybrid survey" that collects detailed consumption data from a small subsample of households while also collecting poverty-related indicators from all surveyed households. Data were collected from 2,201 households, with complete consumption data collected from a subsample of 478 households (Table 3.2). An estimation model of the relationship between the poverty-related indicators and consumption expenditure was then used to impute consumption expenditure for households for whom no consumption data was collected. Consumption expenditure was then used as a measure of welfare for households and individuals.

## *Key findings*

**The analysis presented in this report uses the "rebased" poverty measurement approach that was adopted by ZIMSTAT with technical assistance from the World Bank.** The rebased poverty headcount rates for 2017 are slightly higher than those calculated with the method used in the past and published in ZIMSTAT's

**FIGURE ES-1**
**Extreme Poverty Based on the Food Poverty Line of US$29.80 per Person per Month**




Source: Based on the PICES 2011/12, PICES 2017, and Mini-PICES 2019.
Note: The 2011/12 estimates are based on the earlier measurement method (pre-rebasing); therefore, comparison with the rebased estimates for 2017 and 2019 should be made with caution. The 2019 estimates are for the April–May 2019 period and not for the entire year. The error bars on the graph indicate the 95 percent confidence intervals.

*Zimbabwe Poverty Report 2017*. However, the differences between the two methods are minimal.

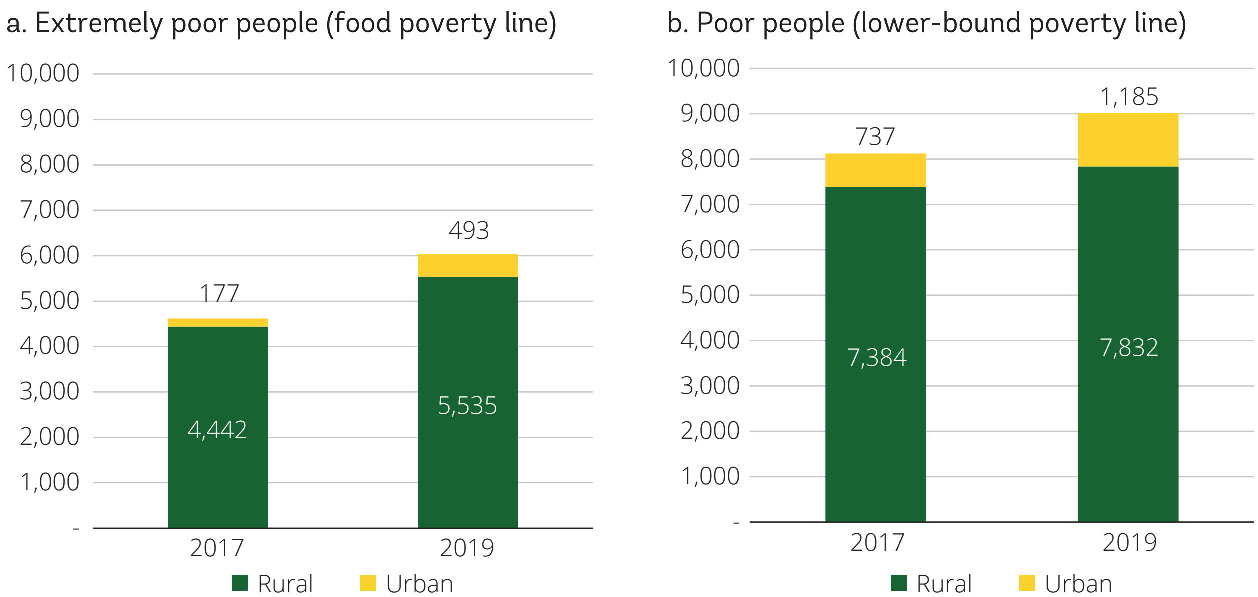
**Extreme poverty rose from 30 percent in 2017 to 38 percent in April–May 2019, and general poverty (measured by the lower-bound poverty line) rose from 43 percent to 51 percent during the same period.** Although extreme poverty increased in both urban and rural areas, in *relative* terms, extreme poverty rose more in urban areas. In *absolute* terms, rural extreme poverty remained much higher than urban extreme poverty (see Figure ES-1). The general poverty rate based on the *lower-bound* poverty line remained high. It changed marginally for the rural population, but in urban areas it rose sharply, from 16 percent to 24 percent during the same period.

**The number of extremely poor people rose from 4.5 million in 2017 to 6 million during April–May 2019, but the number of poor people measured by the lower-bound poverty line rose from 8.0 million to 8.9 million during the same period (see Figure ES-2).** Furthermore, whereas the number of extremely poor people in urban areas increased by about 327,000, it rose by 1.1 million in rural areas. The increase in poverty rates and the number of extremely poor and poor people during the period under review can be attributed to high inflation coupled with the contraction of the economy and a poor 2018/19 rainfall season. These negative changes in the economy are likely to have stressed the livelihoods of many Zimbabweans, thereby affecting households in urban areas more in relative terms compared to households in rural areas.

**Consumption expenditure fell for all welfare groups except the richest 10 percent, or decile.** The welfare groups in the lower end of the income distribution (lower deciles) had the largest proportional declines in consumption expenditure. Consequently, inequality rose as the Gini index increased from 44.7 in 2017 to 50.4 in 2019. The increase in inequality was driven by a rise in inequality *within* urban and *within* rural areas rather than *between* urban and rural areas.

**The profile of the extreme poor changed slightly as their proportion that is engaged in income-generating activities other than working on their own**

**FIGURE ES-2**
**Number of Poor People in Urban and Rural Areas (in '000)**



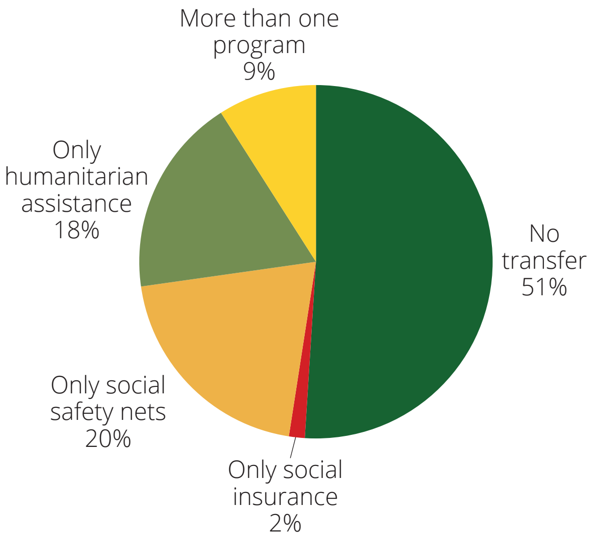

Source: Based on the PICES 2017 and Mini-PICES 2019; numbers are for the whole country, extrapolated from the survey estimates.
Note: The 2019 period is for April–May.

**farms rose by 10 percentage points.** It increased from 21 percent of the extreme poor in 2017 to 31 percent in 2019. Some characteristics of the extreme poor did not change. They still live mostly in large households and tend to have low educational attainment. About one-third live in a female-headed household, similar to the population as a whole. Furthermore, children younger than 15 years old formed almost half of the poor and the extremely poor, but they only made up four-tenths of the population.

**Household heads with secondary education were a little more affected by the economic downturn than other groups.** However, the relationship between educational achievement and per capita consumption is relatively weak in Zimbabwe, suggesting that many factors other than education determine welfare differences.

**The proportion of the extreme poor covered by social assistance programs increased between 2017 and 2019, but such programs still reached only half of the extreme poor** (Figure ES-3). All programs were shown to be progressive, benefiting the poor more than the rich, but there is scope to improve the targeting of the poor because only 40 percent of all social assistance program beneficiaries are extremely poor. The cash-for-work program was the most effective in terms of having an impact on poverty reduction.

**FIGURE ES-3**
**Social Protection and Humanitarian Assistance Coverage of the Extremely Poor in April–May 2019**




Source: Based on the Mini-PICES 2019.
Note: The term *extremely poor* refers to those living below the food poverty line. *Social insurance* includes pensions, social security benefits, and employment services. *Social safety* nets include the Basic Education Assistance Module; the Science, Technology, Engineering, and Mathematics Scholarship Program; the Community Recovery and Rehabilitation Program; health benefits; and other public disaster relief benefits, which are all mostly government funded. *Humanitarian assistance* includes food and cash for work and food relief; these are mostly donor funded.

**Simulations show that the rapid price increases that affected Zimbabwe between April–May 2019 and December 2019 may have increased extreme poverty from 38 percent to 52 percent.** The study shows that the price increases of maize, bread, and cereals had the largest impact on poverty. According to the PICES 2017 data, the share of maize *meal* in total household consumption is three times higher in urban areas (1.8 percent) than in rural areas (0.3 percent). Maize meal subsidies thus benefit urban households more than rural ones. It was also noted that within urban areas, maize meal subsidies were more likely to benefit the middle groups than the poorest groups. Rural households were unlikely to benefit from maize meal subsidies because they rely on their own-produced maize *grain,* which forms 11 percent of their total consumption expenditure. However, this is unlikely to be the case in a poor rainfall year such as 2018/19, when rural households have to purchase maize grain and maize meal.

**The urban population spends much more on transport fuels than the rural population, even when measured as a proportion of their total consumption.** Efforts to moderate fuel prices thus benefit the richest segment of the population more than the poorest segment. For transport fares, differences in *relative* spending among welfare quintiles in urban areas are small, with households in the poorest quintile spending only a little less than the richest urban quintile.

**In 2017, households in the poorest urban quintile spent, on average, 1.5 percent of their consumption expenditure on electricity, compared to 4.5 percent for the richest quintile.** This implies that the richer urban households benefit most from any effort to keep electricity prices low.

**The proportion of the urban working-age population that worked informally[1] rose from 34 percent in 2017 to 43 percent in 2019.** The percentage of the

[1] For example, without a labour contract and/or working in an informal business.

working-age population with a formal job dropped from 29 percent to 26 percent, and those not working for pay or for an income fell from 37 percent to 31 percent during the same period. This implies that as the availability of formal jobs dropped and economic hardship worsened, household members were forced to take jobs in the informal sector to earn some income. It was also shown that between 2017 and April–May 2019, the proportion of children between the ages of 14 and 17 working for pay rose from 4 percent to 7 percent in urban areas and from 3 percent to 7 percent in rural areas.

**Access to health care worsened.** During April–May 2019, a quarter of rural households and a little more than a quarter of urban households were unable to obtain medicine prescribed for an illness. In rural areas, the main reason for failing to obtain medication when ill was due to a lack of availability; in urban areas, households were unable to afford the medication due to high cost.

**During the 12 months preceding the Mini-PICES 2019 conducted in April–May 2019, the proportion of children out of school was lower than in 2017.** This was possibly because in 2019 schools were no longer sending children away when school fees were unpaid.[2] Although this is positive, it is likely to have had a negative impact on the availability of school funds for purchasing teaching materials.

**Ninety percent of urban households stated that their transport costs to work went up during the first four months of 2019.** Twenty percent of urban households stated that higher transport prices had affected their children's ability to access education services, and 10 percent of the households asked their children to walk at least part of the trip to school. In rural areas, this seems to have been less of a problem, probably because children were already walking to school.

**During April–May of the Mini-PICES 2019, 50 percent of rural households were either *moderately or severely* food insecure, whereas close to 52 percent were so during March–June 2017 according to data gathered through the PICES Agricultural Productivity Module, which was applied to a subsample of the PICES 2017 during that period.** Despite this slight drop in rural food insecurity, extreme poverty in April–May 2019 was much higher than the average for 2017. The high increase in extreme poverty, compared to a relatively stable (albeit high) level of food insecurity, reflects the deterioration of the nonagricultural economy between 2017 and April–May 2019. This affected household consumption expenditure more broadly, but the food security situation in April–May 2019 was at a similar level as March–June 2017. Also, the

[2] Almost half (46 percent) of rural households indicated that their children were sent away from school temporarily at least once because of nonpayment of fees.

preharvest period of March–May 2017 was affected by two consecutive years of poor harvests (the 2014–15 and 2015–16 growing seasons had low and poorly distributed rainfall) and the food security situation was precarious. However, poverty was measured over the whole of 2017 and is likely to have dropped after the good harvest in May of that year, giving a lower poverty rate for the whole of 2017 when compared to April–May 2019.

**The data show that richer households are more likely to have a household member living abroad compared to poorer ones.** Among households with a member abroad, poorer households received fewer remittances. The monthly amount of remittances received per capita dropped from US$29 in 2017 to US$21 in April–May 2019 for those households that received remittances.

**The continued economic instability, coupled with the COVID-19 pandemic, is likely to have further worsened the poverty situation in 2020 and demonstrates the need for even more rapid data collection on poverty changes.** Although the Mini-PICES 2019 managed to deliver a quick update of poverty indicators and living conditions in the country, Zimbabwe's current volatile economic and social state of affairs calls for even faster data collection to track poverty developments and monitor the effectiveness of mitigation policies. Available household survey data can be used to conduct ex-ante assessments of the welfare impact of price increases or mobility restrictions on different population groups.

## The rapid PICES telephone survey 2020/21

To meet the demand for rapid updates of poverty indicators and the effectiveness of mitigation policies, ZIMSTAT—with ZIMREF funding and technical support from the World Bank—embarked on a high-frequency phone survey in July 2020. It will be conducted in nine rounds. At the same time, available household survey data from the PICES 2017 and the Mini-PICES 2019 can be used to conduct ex-ante assessments of the welfare impact of price increases or mobility restrictions on different population groups. Both activities can inform pricing and subsidy policies as well as mitigation programs, making sure they meet the needs of the people that most require support, particularly the poorest and the most vulnerable.

# 1

# INTRODUCTION

*This report presents an update of the poverty situation in Zimbabwe in 2019. It uses data from the Mini Poverty, Income, Consumption and Expenditure Survey (Mini-PICES 2019) that was implemented from April 15 to May 23, 2019, by the Zimbabwe National Statistics Agency (ZIMSTAT) with funding from the Zimbabwe Reconstruction Fund (ZIMREF) and technical assistance from the World Bank.*

**ZIMSTAT conducts a PICES every five years, with the PICES 2017 being the most recent one.** However, given the rapid changes in the Zimbabwean economic environment in 2018 and early 2019, it became clear that the poverty estimates based on the PICES 2017 could be outdated and in need of updating. Consequently, a shortened version of the PICES, called the Mini-PICES 2019, was carried out. The objective of the Mini-PICES 2019 survey was to update the 2017 poverty indicators to assess the impact of the economic difficulties on the welfare and living conditions of urban and rural Zimbabweans. The key findings from the Mini-PICES show that extreme poverty rose substantially between 2017 and April–May 2019, with urban areas affected most in relative terms. It was observed that half of all extremely poor people were covered by at least one social assistance program.

**In 2018, ZIMSTAT, with technical assistance from the World Bank, completed a rebasing of the poverty measurement in Zimbabwe.** In comparison to earlier surveys, the PICES 2017 collected more detailed information on household assets and captured details on food consumption from own production, making it possible to refine the poverty measurement. This rebasing essentially implied starting a new series of poverty measurements from 2017. The analysis presented in this report uses this methodology to compare poverty indicators in 2017 with those in April–May 2019.

**This report consists of five chapters.** Chapter 1 provides an introduction to the report. Chapter 2 then presents a brief discussion of the macroeconomic context during the period from 2017 to April–May 2019. A summary of the key methodological changes involved in rebasing the poverty measurement is presented in Chapter 3. This same chapter also explains the "within-survey imputation" methodology applied in the Mini-PICES 2019 to measure consumption. Chapter 4 then presents the survey findings, including the updated poverty lines, poverty trends, and the changes in expenditure and inequality. Chapter 4 also discusses a brief poverty profile and the results of a simulation exercise on the impact of the price increases that took place during the remaining months of 2019 after the survey was completed in May. The changes in a few selected important nonmonetary poverty indicators, including food security, are also discussed in this chapter. Finally, Chapter 5 presents the conclusions.

2

# MACROECONOMIC DEVELOPMENTS DURING THE PERIOD 2017–19

*This section briefly presents the macroeconomic developments in Zimbabwe during the period between the completion of the PICES 2017 and the start of the Mini-PICES 2019.*

**Zimbabwe reported an economic growth rate of 4.7 percent in 2017 and 4.8 percent in 2018, then the economic environment sharply worsened.** It is estimated that gross domestic product (GDP) contracted in 2019 due to multiple factors, including below-normal rainfall during the 2018/19 agricultural season. The macroeconomic environment became unstable due to a rapid depreciation of the Zimbabwean dollar, foreign exchange and fuel shortages, and high inflation, which contracted domestic demand for goods and services. The agricultural sector is estimated to have declined due to a severe drought, the effects of Cyclone Idai, and the high cost of inputs. The negative impact on agriculture resulted in increased food insecurity during that period. The manufacturing and mining sectors were adversely affected by shortages of foreign currency and power outages. The high inflation also negatively impacted the budget deficit, leading to suppressed domestic demand.

**Inflation increased sharply after October 2018 (Figure 2.1), driven by rising fiscal deficits, price distortions, and the depreciation of the Zimbabwean dollar.** Year-on-year inflation reached 98 percent in May 2019, the second month of data collection for the Mini-PICES survey, compared to 5.4 percent in September 2018. Moreover, prices of food items rose by

## TABLE 2.1
## Macroeconomic Indicators, 2017–19

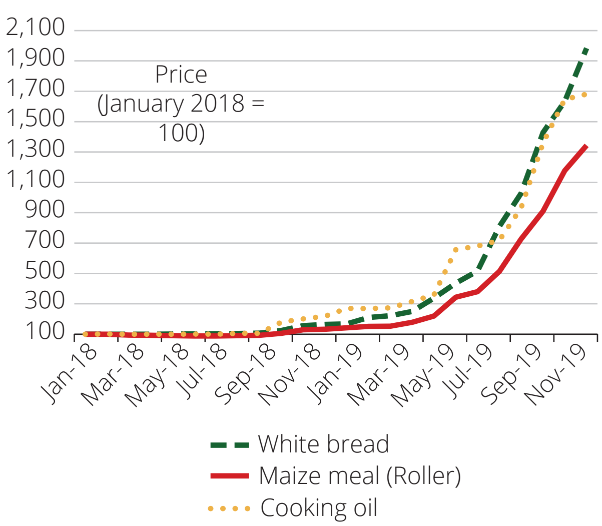
| | 2017 | 2018 | 2019 |
|---|---|---|---|
| Real GDP growth, at constant market prices (%) | 4.7 | 4.8 | — |
| Agriculture (%) | 10.0 | 18.3 | — |
| Industry (%) | 2.5 | 3.2 | — |
| Services (%) | 5.0 | 1.5 | — |
| Inflation (annual average) (%) | 0.9 | 10.6 | 255 |
| Inflation (end of period) (%) | 3.5 | 42.1 | 521 |
| Population growth (%) | 1.5 | 1.4 | 1.4 |
| Real GDP growth per capita (%) | 2.4 | 2.3 | — |

Source: Based on data from ZIMSTAT and MOFED.
Note: GDP = gross domestic product; official estimates for GDP and sectoral growth for 2019 are not yet available.

126 percent and nonfood inflation was 68 percent. The year-on-year inflation surged to 521 percent in December 2019, with food prices increasing by 719 percent; nonfood inflation was about 429 percent. Consequently, disposable incomes were eroded, resulting in a severe loss of purchasing power. Inflation was further fueled by poor harvests and reduced fuel and electricity subsidies. The introduction of a local currency in February 2019 ended the multicurrency regime that had been in place for over a decade. Following rapid depreciation of the Zimbabwean dollar, the Government announced the reintroduction of the U.S. dollar alongside the Zimbabwean dollar in March 2020, allowing consumers to conduct purchases in foreign currency to alleviate the hardship caused by the COVID-19 pandemic.

**In summary, the macroeconomic environment between the two survey periods was characterized by high inflation and a severe contraction of the economy.** This has negatively affected the livelihoods of many Zimbabweans, particularly the poor.

## FIGURE 2.1
## Price Trend of Maize Meal, Bread, and Cooking Oil




Source: Based on the ZIMSTAT consumer price index in local currency.
Note: The graph shows data from January 2018 through December 2019.

# 3

# METHODOLOGY

*This chapter discusses the methodology applied to estimate the 2017–19 poverty update. It explains the approach for rebasing the poverty measurement in Zimbabwe starting with the PICES 2017, including the computation of the consumption aggregate and the calculation of the poverty lines for 2017. The chapter then presents the within-survey imputation methodology applied in the Mini-PICES 2019 to estimate consumption, followed by the approach used to update the poverty lines for April–May 2019. Finally, it elucidates the methodology used to simulate the impact of the price increases on poverty between April–May 2019 and December 2019.*

## 3.1 Rebasing the poverty measurement

**Poverty-measurement methodologies require periodic updating in response to improved data and analytical techniques, changing country conditions and consumption habits, and new consensus on which expenditures should be included in the welfare aggregate.** Therefore, it was necessary to update the approach used to measure poverty in Zimbabwe. This update included methods for measuring per capita household consumption (known as the welfare aggregate) and establishing the poverty lines. It led to a "rebasing" of the poverty measurement in Zimbabwe, which was first applied to the PICES 2017 data and then to the Mini-PICES 2019 data.

**The PICES 2017 questionnaire improved upon the one used for the PICES 2011/12.** The data collected in 2017 enabled a further refinement of the poverty measurement methodology. For the PICES 2017, the detailed data from the monthlong food consumption diary, also called daily record books (DRBs), were entered in the computer. A DRB is a written record of the daily consumption expenditures kept by the household during the PICES interview month. The DRB data were available for the computation of the food consumption aggregate. Previously, only the total value of large food product groups was available for analysis. With the detailed information from the DRBs now accessible, a more accurate measurement of expenditure shares for individual food items (for example, maize) could be calculated. The availability of more information made it possible to refine the construction of the minimum-needs food basket and update it from 1995, when it was last constructed. This refined minimum-needs food basket accurately reflects the consumption patterns of low-welfare Zimbabwean households in 2017. Second, the PICES 2017 questionnaire includes more detailed questions on assets owned—including their ages, purchase price, and current value—allowing more precise estimates of the use values of the assets. Third, the PICES 2017 questionnaire used a longer recall period for infrequently bought consumption items, such as clothes and purchases of other durable and semi-durable goods. The PICES 2011/12 questionnaire only had a one-month recall period for all consumption items.

**Zimbabwe's poverty measurement methodology was modified for five components.** These components are as follows: (i) the use value of owned assets, (ii) a longer recall period for infrequently purchased consumption items, (iii) the composition of the food basket that forms the basis of the food poverty line, (iv) the use value of owner-occupied housing, and (v) the treatment of lumpy expenditures such as hospitalizations and weddings. The use values of owned durables were calculated using depreciation measures based on their ages, purchase prices, and estimated current values. The rental value of owner-occupied housing was calculated using regression methods rather than self-assessment by survey respondents. By revising the five components, a new consumption aggregate was constructed. Appendix A discusses the technical details of these modifications to the consumption aggregate measurement.

### 3.1.1 Rebasing the poverty lines: Food component

**The food consumption basket that has been used to construct the food poverty line in Zimbabwe was updated to better reflect current consumption patterns.** The food component of the poverty line is based on a basket of food items consumed by low-income Zimbabwean households that provides 2,100 calories per person per day. Information from the DRBs was used to measure the consumption of each individual food item that is not only obtained through purchase but also from transfers in kind, consumption of own produce, gifts, and other transfers. In past PICES dataset constructions, the last four categories of consumption expenditures were aggregated by the large product group when entered in the computer. For example, data about own consumption of maize, sorghum, and other grains were aggregated into a single consumption value: own consumption of cereals. As a result, the individual quantities of maize from own consumption could not be identified.

**In rural parts of Zimbabwe, own consumption and transfers represent a significant share of food consumption, particularly for foods such as maize.** Even in urban areas, lower-welfare households typically have access to own-produced maize either as transfers from rural areas or from urban agriculture. Without the information from the DRBs, basic information like expenditure shares of typically consumed goods could not be accurately measured. Including the information from the DRBs in the main data files allowed for an update of the food basket and a rebasing of the poverty measurement with confidence that consumption shares accurately reflect consumption from all sources of each good.

**In line with international standards, one single food basket was computed for the country as a whole.** Only food items for which calorie values were available, and for which monthly Consumer Price Survey (CPS) prices are obtained from all provinces were considered for the food basket. Households in the 10th–50th percentiles of the per capita consumption distribution were used as the reference group for calculating the food consumption basket that provides 2,100 calories per person per day. The share of each food item in the food basket was used to create weights for each item. Each food item in the basket was valued using the average national CPS price to calculate the national food poverty line. The average monthly provincial prices of items in the basket were used to calculate spatial and temporal price deflators. These were used to correct for price differences between provinces and between the months of the survey. The new minimum-needs food basket calculated from the PICES 2017 is presented in Appendix B.

### 3.1.2 Rebasing the poverty lines: Nonfood component

**In addition to the food poverty line, two other poverty lines were calculated.** These poverty lines account for the basic needs for nonfood items such as housing and clothing. These two additional poverty lines are called the lower-bound poverty line and the upper-bound poverty line. The lower-bound poverty line is calculated by assessing the nonfood consumption expenditures for all households whose *total consumption expenditure* is “close” to the food poverty line. The upper-bound poverty line is calculated by assessing the nonfood consumption of households whose *total food consumption* is “close” to the

### TABLE 3.1
### Rebased 2017 Poverty Lines in Zimbabwe Compared to the International Poverty Lines in PPP

| Food poverty line/extreme poverty line | | | Lower-bound poverty line | | | Upper-bound poverty line | | |
|---|---|---|---|---|---|---|---|---|
| National | | International (low-income countries) | National | | International (lower-middle-income countries) | National | | International (upper-middle-income countries) |
| US$/month | US$ PPP/day | US$ PPP/day | US$/month | US$ PPP/day | US$ PPP/day | US$/month | US$ PPP/day | US$ PPP/day |
| 29.80 | 1.83 | 1.90 | 45.60 | 2.80 | 3.20 | 66.10 | 4.10 | 5.50 |
| $31.30 per person/month was the earlier national food poverty line | | | | | | $70.40 per person/month was the earlier national poverty line | | |

Note: PPP = purchasing power parity. All values are per person. In 2017 the U.S. dollar was the de facto local currency.

food poverty line. In the past, ZIMSTAT opted to use all three poverty lines, but the PICES 2011/12 and 2017 poverty reports[3] focused on the upper-bound poverty line, which tends to give high poverty rates. It should be noted that most lower-middle-income countries like Zimbabwe use the lower-bound poverty line for policy information and planning, although both are valid. For low-income countries[4] the extreme poverty line is most applicable.

**Although this report presents results for all three poverty lines, it proposes the adoption of the lower-bound poverty line as the main poverty line for Zimbabwe, in addition to the extreme poverty line.** It was observed that the extreme poverty line (in purchasing power parity, or PPP, terms) is very close to the international extreme poverty line for low-income countries of US$1.90 per person per day—corrected for PPP (see Table 3.1)—and is thus useful. As the main poverty line for Zimbabwe, the lower-bound poverty line is arguably more relevant than the upper-bound poverty line. The justification for this is as follows:

- The method to compute the lower-bound poverty line is commonly used by other countries. Moreover, the value of the lower-bound poverty line in Zimbabwe is US$45.60 per person per month, which equals US$1.50 per person per day, or $2.80 per person per day in PPP.[5] This is much closer to the international poverty line for lower-middle-income countries of PPP US$3.20 than the upper-bound poverty line in Zimbabwe, which is equivalent to PPP US$4.10 (Table 3.1).

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[3] ZIMSTAT 2013, 2019.

[4] Those with a gross national income per capita below US$1,036 per year.

[5] For Zimbabwe, the 2011 PPP is 0.535. That means that the purchasing power of US$1.00 in Zimbabwe is equal to US$0.535 in the United States. Vice versa, when compared to the United States, US$1.00 in Zimbabwe has a purchasing power of US$1.87.

- Second, for policy analysis purposes, it is helpful if the poverty line does not lead to poverty rates that are so high that nearly everyone in the country is regarded as poor. It makes it hard to distinguish the population groups that are most in need and that should be targeted by poverty-reduction policies. The upper-bound poverty line for Zimbabwe currently shows a poverty rate of 70 percent (and 87 percent for the rural population), and the lower-bound line shows a rate of 53 percent.

In line with international best practices, poverty lines and poverty rates are presented at the individual level, not at the household level.

In Zimbabwe, the upper-bound poverty line is also referred to as the total consumption poverty line or the poverty datum line (PDL) and is used for wage negotiations. There has been a demand for updating this monthly PDL. However, the poverty line includes imputed rent and use values of assets that are not directly related to actual household income or consumption.

Moving forward, the food prices as collected for the Consumer Price Index (CPI) should be used to update the value of each of the food items that constitute the food poverty line. The CPI collects price data for both food and non-food components. The nonfood component of the poverty line should be updated using the aggregate nonfood CPI.

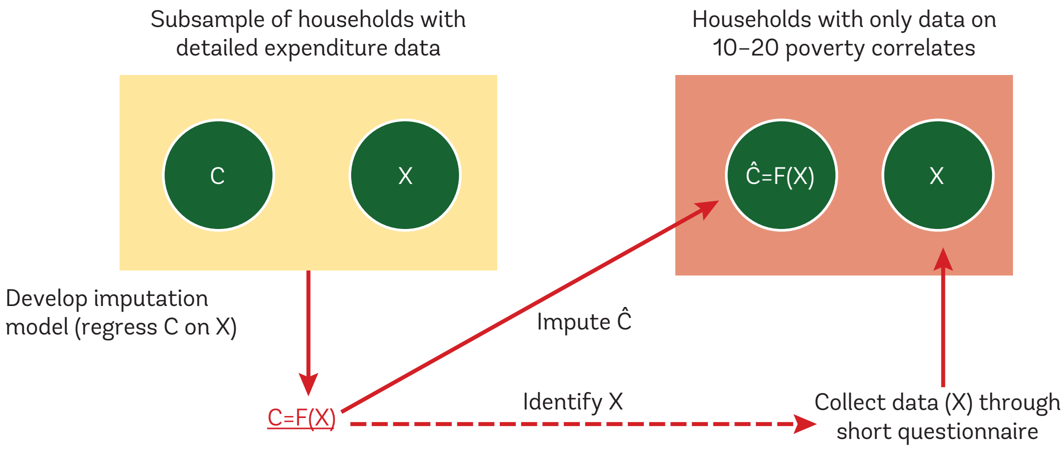
## *3.2 Measuring consumption using "hybrid surveys" and SWIFT*

**To meet the urgent need for updated monetary poverty estimates for 2019, an innovative approach was used that is quicker and more cost-effective than traditional household expenditure surveys.** This approach involves conducting a "hybrid survey" that collects detailed consumption data from only a small subsample of households and nonconsumption data from all surveyed households.[6] The collection of nonconsumption data involves variables that tend to be strongly correlated with poverty, such as household characteristics, household ownership of durable consumption goods, housing quality, and education level and employment status of the head of the household. An estimation model of the relationship between the poverty correlates and consumption is then used to impute consumption for households for whom no consumption data were collected (Figure 3.1). The imputation approach uses the technique developed in the Survey of Well-being via Instant and Frequent Tracking (SWIFT) approach.[7]

6 Ahmed et al. 2014.

7 This innovative approach is called the SWIFT 2.0 approach as opposed to the traditional SWIFT (1.0) approach, where no consumption data are collected (Yoshida et al. 2020).

**FIGURE 3.1**
**The Within-Survey Imputation Approach Using the SWIFT Approach**




C: Consumption
X: Household variables (e.g., education, employment)
Ĉ=F(X): Projected consumption data

Source: World Bank 2018.

The SWIFT modeling process involves multiple steps to improve the formula's ability to project household expenditures. This includes estimating the distributions of both the coefficients and the projection errors. To detect "overfitting" of the model—that is, the model performing well within the sample used for the model but performing poorly outside the dataset—cross-validation analysis is conducted. It separates data used for developing the model from those used for evaluating the model's fitness. More specifically, a household survey dataset is split randomly into 10 subsamples. Each of these subsamples is called a "fold." Consumption models are estimated using the data in each of these nine folds by running stepwise ordinary least squares (OLS) regressions. After a model is estimated, the household expenditure is imputed in the remaining folds using the multiple-imputation method (MI).[8] This analysis is repeated 10 times; each round uses a different fold as testing data to test the performance in terms of mean squared errors (MSEs) and the absolute value of the difference between the projected and actual poverty rates. See Appendix C for further detail on the SWIFT calculation method.

**The Mini-PICES 2019 aimed to revisit 3,000 households out of the 31,189 that were interviewed for the PICES 2017.** The 3,000 households were a subsample of the households interviewed in February–June 2017 for the PICES 2017. The design involved collecting detailed consumption data from 600 households: 300 in rural

[8] The MI can be implemented easily using Stata (StataCorp 2019).

## TABLE 3.2
**Sample Design and Realized Sample of the Mini-PICES 2019**

| | Full data collection, including consumption data | | | Collection of only 10–20 poverty correlates | | | Total |
|---|---|---|---|---|---|---|---|
| | Total | Rural | Urban | Total | Rural | Urban | |
| Design | 600 | 300 | 300 | 2,400 | 1,700 | 700 | 3,000 |
| Realized | 478 | 248 | 230 | 1,723 | 1,376 | 347 | 2,201 |

areas, and 300 in urban areas. Poverty correlates (the *X* variables in Figure 3.1) were collected from all households. Data collection was successful for 2,201 households, and complete consumption was collected from a sample of 478 households among these (Table 3.2, see Appendix I for details of the sample design). The 2,201 household sample without consumption data is considered to be statistically representative for urban and rural areas of Zimbabwe, but the 478 household sample with consumption data alone is statistically representative only at the national level due to the small sample size. The consumption aggregate was constructed following the rebased method adopted for the PICES 2017. The poverty line was adjusted using the CPI prices, as described earlier.

**Separate consumption estimation models were developed for urban and rural areas.** In the final estimation, the imputation method described in Elbers et al. (2003) was applied using Povmap 2.0 software to impute consumption for the 1,723 households for which no consumption data was collected. One hundred imputations per household were conducted, and the poverty estimate was calculated with the simple mean of the 100 poverty estimates from each imputation. Combining the household data on actual consumption with households with imputed consumption made the poverty estimates in urban and rural areas more accurate; the standard errors declined from 5.1 percent to 4.4 percent in urban areas and from 4.7 percent to 2.5 percent in rural areas.

**Several caveats exist.** Unlike the earlier surveys, the Mini-PICES 2019 is not a year-round survey; it was conducted only during April and May. The Mini-PICES is therefore not representative for the whole year and may be subject to seasonal bias. Likewise, because detailed consumption data was collected from only 478 households, consumption data were measured with less precision than usual. In addition, the Mini-PICES was conducted during a period of rapid price increases,[9] making it difficult to precisely measure the value of consumption. It is also worth noting that the country had dropped the U.S. dollar as its de facto national currency and had adopted the Zimbabwean dollar at a value of one U.S. dollar equals one

9 The price of maize meal, for example, rose twofold between May and June 2019.

Zimbabwean dollar during the months preceding the Mini-PICES. As the new currency declined in value over time, it may have been difficult for some households to express consumption values in the right currency. The Mini-PICES used the Zimbabwean dollar as its unit of measurement.

## 3.3 Updating the poverty lines for 2019

**To update the food poverty line to April–May 2019, the newly calculated PICES 2017 food basket was taken and valued at May 2019 prices using the mean of the regional prices for all items in the food basket.** The prices of the food basket items were obtained from ZIMSTAT's regular price monitoring done through the CPS. The value of the nonfood part that needs to be added to the food poverty line to obtain the lower- and upper-bound poverty lines was updated using the nonfood CPI from June 2017 to June 2019.[10] The ratio of the 2019 and 2017 food poverty lines was 2.66.

## 3.4 Simulating the impact of further price rises on poverty in 2019

**The removal of fuel and electricity subsidies in 2019, coupled with other factors, led to further price increases in Zimbabwe between April–May 2019 and December 2019.** These price increases are likely to have negatively impacted on poverty. After the subsidy was removed, the price of electricity[11] soared by more than 700 percent during the following seven months. The price of maize[12] and other cereals increased by more than 550 percent, and the price of cooking oil[13] increased by almost 400 percent. Furthermore, the price of diesel and petrol[14] increased

[10] The price data collected in June are thought to better reflect the fast price rises that took place during May.

[11] The Zimbabwe Electricity Supply Authority has been selling electricity to consumers at 9.83 cents per kilowatt-hour, which is well below the breakeven price of 12.8 cents per kilowatt-hour. The authority adopted a cost-recovering tariff structure in August 2019. In November 2019, an indexation formula was introduced to protect the electricity company from inflation and exchange rate changes.

[12] The Government—through the Grain Marketing Board—had been selling maize to millers below the price it paid to local farmers (which was above the international market price). This was discontinued in November 2019. The grain subsidies were replaced by targeted subsidies of roller meal and the standard loaf of bread for vulnerable communities.

[13] Imported cooking oil had benefited from the preferential allocation of foreign currency at below-market exchange rates. This was discontinued in November 2019.

[14] Fuel was sold to consumers at about RTGS$1.30 (Real Time Gross Settlement dollars). At a prevailing parallel market rate of US$1 equals RTGS$3, this corresponded to less than US$0.50 per liter, far below the world market price. The fuel price was then partly liberalized in January 2019, but suppliers still had preferential access to a favorable exchange rate and the price increase was therefore still relatively low.

## TABLE 3.3
### Price increase from May to December 2019 for Selected Goods

| | (1) *Nominal* price increase from May to December 2019 (%) | (2) Estimated *real*[a] price increase from May to December 2019 (%) | (3) Average household budget share in the Mini-PICES 2019 (%) |
|---|---|---|---|
| Maize | 576 | 342 | 5 |
| Bread and cereal (excluding maize) | 566 | 332 | 8 |
| Cooking oil | 399 | 165 | 4 |
| Fuel for personal transportation (diesel and petrol) | 270 | 36 | 1 |
| Other transportation service | 349 | 115 | 0 |
| Electricity | 719 | 485 | 2 |

Source: Based on ZIMSTAT Consumer Price Index and the Mini-PICES 2019.
Note: a. Based on public sector wage trends.

by 270 percent while transportation[15] services increased by almost 350 percent (Column 1 in Table 3.3).

***Real* price increases are hard to calculate because data on income trends for the period under study are difficult to obtain.** However, it was noted that overall inflation levels were higher than wage increases in the public and private sectors. Based on public sector wage increases, which rose by more than twofold between May and December 2019, the drop in real incomes (Column 2 in Table 3.3) resulted in the erosion of real and disposable household incomes. These developments are likely to have had negative implications on poverty levels, with the effect for each household depending on the share of these items in household budgets (Column 3 in Table 3.3) and how these shares differ among households along different parts of the income distribution.

**To further assess the poverty impact of the rapid price rises and the removal of subsidies from May to December 2019, a microsimulation modeling approach was employed.** The simulation involves an estimation of household consumption adjustments following the price increases. Using data from the Mini-PICES 2019, each household's welfare changes in the survey were simulated, following the price shocks. This was done by calculating the welfare loss of these

[15] Transport prices rose rapidly due to the fuel price increases that started in January 2019.

price rises and then using that to adjust their consumption levels. When price increases of goods are large, it is likely that households reduce the consumption of these items. If the original quantities of consumption are used with the new price, consumption loss will be overestimated. Therefore, to assess the poverty impact, the behavioral response of households to the price increases was modeled. Considering the large magnitude of price increases, consumer surplus was used to measure welfare loss. An approach described in Araar and Verme (2016) was used. See Appendix D for details.

**To assess the impact of maize prices on farm households, there was a need to assess whether surveyed households were net buyers or net sellers of maize.** In otherwords, it needed to be determined whether farm households bought more maize than they sold, or the reverse. However, the data from the Mini-PICES 2019 did not distinguish between net maize buyers and net sellers. It was decided, therefore, to use the data from the PICES 2017 Agricultural Productivity Module (APM) to determine the average household maize production per quintile of per capita consumption. To simulate the impact of the low rainfall of the 2018/19 growing season compared to the 2016/17 season, a 50 percent reduction in maize production was then imputed and used to estimate the proportion of net sellers and net buyers per welfare quintile. Subsequently, the information was merged into the Mini-PICES dataset, making households net buyers or net sellers based on a set of farm household characteristics linked to the likelihood of them being a net buyer or a net seller. It was assumed the welfare of net sellers will not increase when the price of maize rises because the Mini-PICES did not have information on the quantity of maize sold by farm households. That was likely to overestimate the poverty impact as farmers could benefit from the maize price price increase.

**In summary, the adoption of refinements to the poverty measurement methodology in Zimbabwe provides a solid basis for future analysis of poverty and inequality, starting with the 2017–19 poverty update presented in this report.** The hybrid approach for estimating household consumption that was applied in the Mini-PICES 2019 provides a rapid and low-cost approach for updating poverty estimates in between large surveys. The simulation of the distributional impact of the rapid price increases of various consumption goods that took place in 2019 after the completion of the Mini-PICES in May, in turn, made it possible to determine what population groups were most affected by these price rises and estimate the impact of price increases on poverty.

# 4

# FINDINGS

*This chapter presents the 2017–19 poverty update. First, the rebased 2017 poverty estimates are discussed, followed by those for April–May 2019, when the Mini-PICES 2019 survey was conducted. Consumption expenditure trends for different welfare groups are then presented, and the changes in welfare inequality are discussed. Subsequently, a brief profile of the poor is presented that shows their characteristics and discusses how they differ from the nonpoor. Furthermore, selected nonmonetary poverty indicators, including food security, migration, and remittances, are discussed. Where possible, the PICES 2011/12 values are used for comparison purposes.*

## 4.1 Monetary poverty trends

### 4.1.1 Rebased poverty rates for 2017

**The rebased poverty headcount rates for 2017 are slightly higher than those published in ZIMSTAT's PICES 2017 poverty report, which used the old method.** This is true for poverty measured using the *food poverty line* and the *lower-bound poverty line*, but not for the *upper-bound poverty line*. However, the differences are small. The food poverty rate was 1.1 percentage points higher (30.4 percent instead of 29.3 percent) despite a drop in the poverty line, and the poverty rates for the *upper-bound poverty line* were unchanged even if the poverty line dropped. The poverty rate based on the *lower-bound poverty line* was 54 percent with rural poverty at 72 percent and urban poverty at 16 percent (Table 4.1).

## TABLE 4.1
### Poverty Rates for 2017 Using ZIMSTAT's Earlier Measurement Methodology and the New Rebased Approach

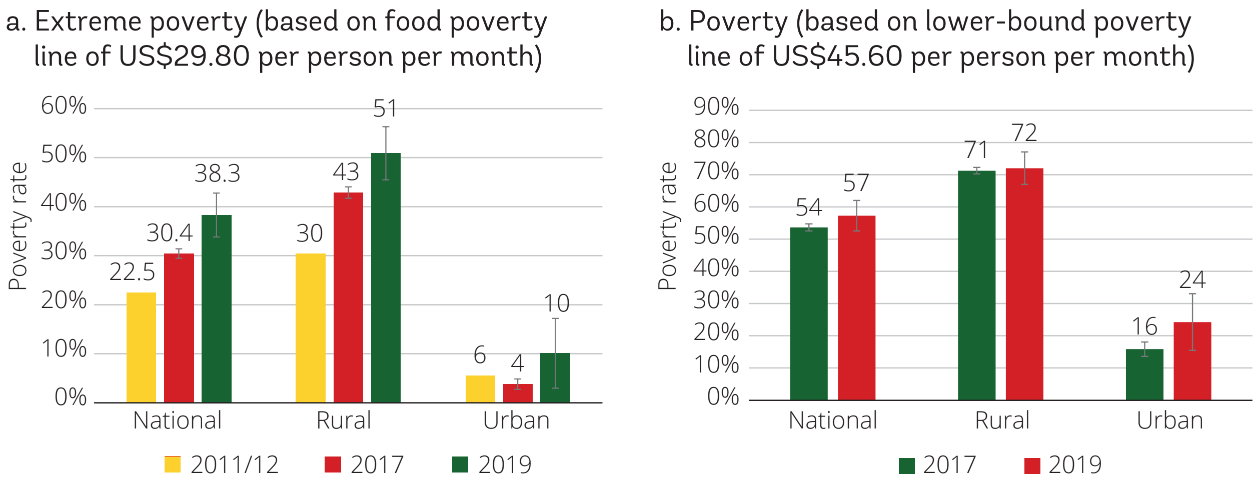
| | Old method, 2017 | | | Rebased, 2017 | | |
|---|---|---|---|---|---|---|
| | Food poverty line | Lower-bound line | Upper-bound line | Food poverty line | Lower-bound line | Upper-bound line |
| Whole country (%) | **29.3** | **N.A.** | **70.5** | **30.4** | **54.2** | **70.4** |
| Rural (%) | 40.9 | N.A. | 86.0 | 43.4 | 71.6 | 86.8 |
| Urban (%) | 4.4 | N.A. | 37.0 | 3.9 | 15.9 | 34.5 |
| Poverty line (US$/person/ month) | 31.30 | N.A. | 70.40 | 29.80 | 45.60 | 66.10 |

Source: Based on the PICES 2017.
Note: The food poverty line is very close to the international extreme poverty line; the lower-bound poverty line is close to the international poverty line for lower-middle-income countries (see Table 3.1).

### 4.1.2 Poverty update for 2017 to April–May 2019

**Extreme poverty rose from 30 percent in 2017 to 38 percent in April–May 2019.** Extreme poverty increased in both urban and rural areas. However, in relative terms, extreme poverty increased more in urban areas. It was 2.5 times higher in April–May 2019 than in 2017. In absolute terms, rural extreme poverty remains higher than urban poverty (see Figure 4.1, Panel A). Poverty based on the

## FIGURE 4.1
### Poverty Update for 2017–19




Source: Based on the PICES 2011/12, PICES 2017, and Mini-PICES 2019.
Note: The 2011/12 estimates are based on the earlier measurement method (pre-rebasing) and comparison with the rebased estimates for 2017 and 2019 should be made with caution. The 2019 estimates are for April–May 2019. Error bars are 95 percent confidence intervals.

*lower-bound* poverty line was high but remained unchanged for the rural population, but it rose in urban areas from 16 percent to 24 percent (Figure 4.1, Panel B). A similar pattern was observed in the proportion of people below the *upper-bound* poverty line (Appendix E).

**The confidence intervals for the poverty estimates in the Mini-PICES 2019 are large, especially for urban areas.** The confidence intervals are much larger than those in the PICES 2017 due to a much smaller sample size, leading to relatively elevated sampling errors (Table 4.2). This implies that the Mini-PICES 2019 poverty estimates need to be treated with caution, particularly those for urban areas.

### TABLE 4.2
### Extreme Poverty in 2017–19: Confidence Intervals

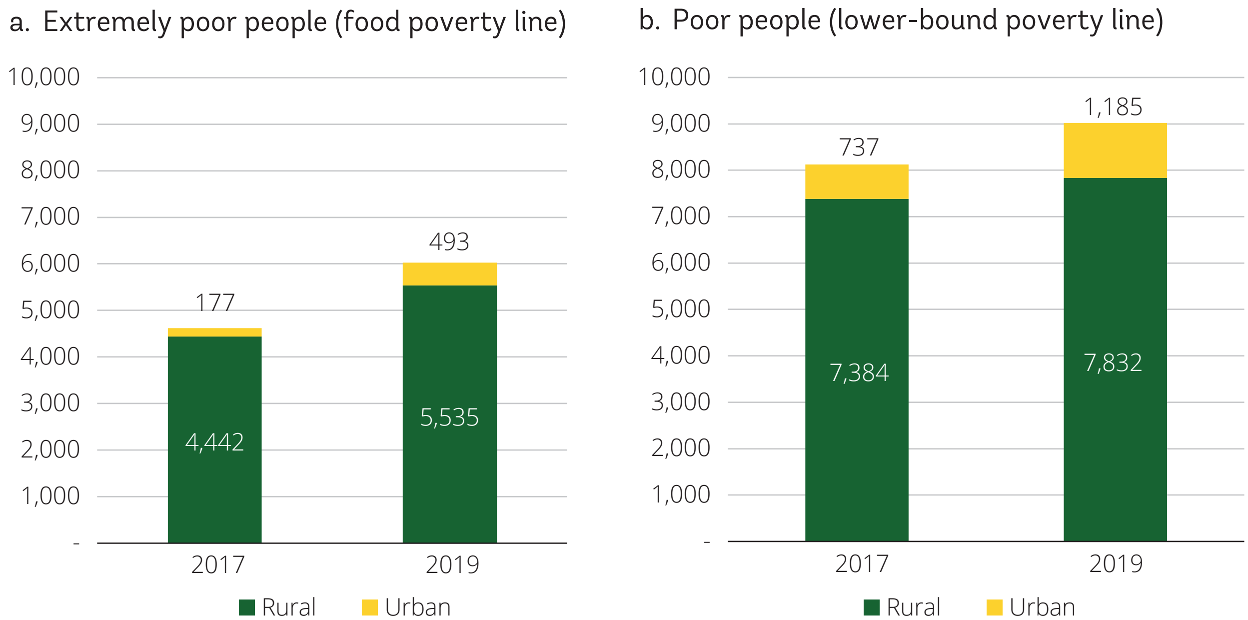
| | 2017 | | April–May 2019 | |
|---|---|---|---|---|
| | 95% confidence interval | | 95% confidence interval | |
| National (%) | 29.3 | 31.6 | 30.1 | 40.4 |
| Rural (%) | 41.6 | 44.2 | 39.9 | 53.2 |
| Urban (%) | 2.7 | 4.9 | 2.4 | 14.9 |
| Number of households in the survey | 30,158 | | 2,201 | |

Source: Based on the PICES 2017 and Mini-PICES 2019.

**The number of extremely poor people increased from 4.5 million in 2017 to 6 million in 2019 (April–May), and the number of poor (lower-bound poverty line) rose from 8.0 million to 8.9 million during the same period.** The number of extremely poor people increased by about 327,000 in urban areas and rose by 1.1 million in rural areas (Figure 4.2). In April–May 2019, 8 percent of the extremely poor lived in urban areas, up from 4 percent in 2017. Using the lower-bound poverty line, 13 percent of the poor people lived in urban areas in April–May 2019, up from 9 percent in 2017. Median urban consumption was about three times higher than median rural consumption.

**The extreme poverty gap also increased from 8 percent in 2017 to 12 percent in April–May 2019 (Table 4.3).** The poverty gap estimates the "depth" of poverty by considering how far, on average, the poor are from the poverty line. The poverty gap is an important indicator used to estimate the total amount of money needed to take the extreme poor in the population out of extreme poverty under perfect targeting. In 2019, this amount was substantial and constituted US$672 million per year (or US$56 million per month), a significant increase compared to US$426 million in 2017 (Table 4.3).

**FIGURE 4.2**
**Number of Poor People in Urban and Rural Areas (in '000)**




Source: Based on the PICES 2017 and Mini-PICES 2019; numbers are for the whole country, extrapolated from the survey estimates.

**TABLE 4.3**
**Extreme Poverty Gap and Extreme Poverty Deficit in 2017 and 2019, by Location**

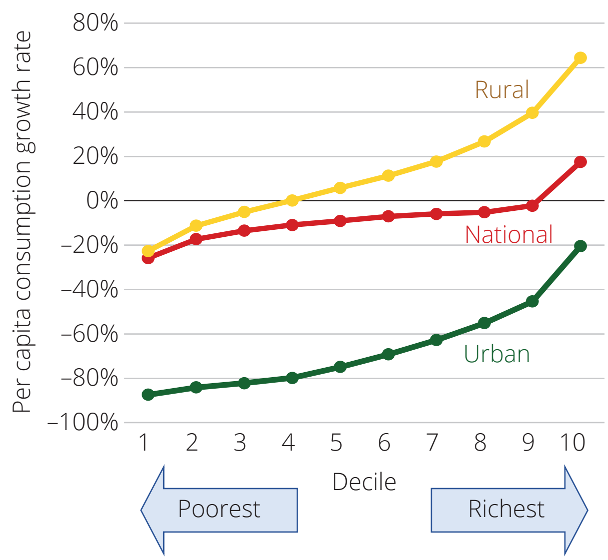
| Extreme poverty gap | 2017 | 2019 |
|---|---|---|
| Rural (%) | 11.3 | 17.4 |
| Urban (%) | 0.6 | 2.4 |
| **Whole country (%)** | **7.8** | **12.8** |
| Poverty line (US$/month) | 29.80 | 29.80 |
| Number of people (millions) | 15.3 | 15.8 |
| Deficit (US$, millions/month)[a] | 36 | 60 |
| **Deficit (US$, millions/year)** | **426** | **672** |

Source: Based on the PICES 2017 and Mini-PICES 2019.
Note: The 2019 figures are for April–May.
a. This figure is obtained by multiplying the poverty gap by the extreme poverty line and the total number of people in the country. In 2019 this gives 12% × US$29.80 × 15.8 million people = US$60 million per month. In 2017 this was 8% x US$29.80 x 15.3 million people = US$36 million per month. It assumes perfect targeting of transfers.

## *4.2 Changes in consumption expenditure and inequality*

**Between 2017 and April–May 2019, consumption expenditure fell for all welfare groups except for the richest 10 percent (decile).** The largest proportional declines occurred in the lower end of the income distribution. Whereas consumption expenditure dropped by about 25 percent for the poorest 10 percent of the population and by 17 percent for the second poorest, it rose for the richest decile by 17 percent (red line in Figure 4.3). In urban areas, consumption expenditure levels dropped by 60 percent or more for the poorest seven deciles (green line). The rural population experienced much lower consumption losses, possibly because it was less affected by the economic downturn. The poorest three deciles had their consumption drop by 5–22 percent, but the richest three deciles had an increase ranging from 26 percent to 64 percent (orange line).

**FIGURE 4.3**
**Per Capita Consumption Growth Rate Between 2017 and April–May 2019 (Growth Incidence Curve)**

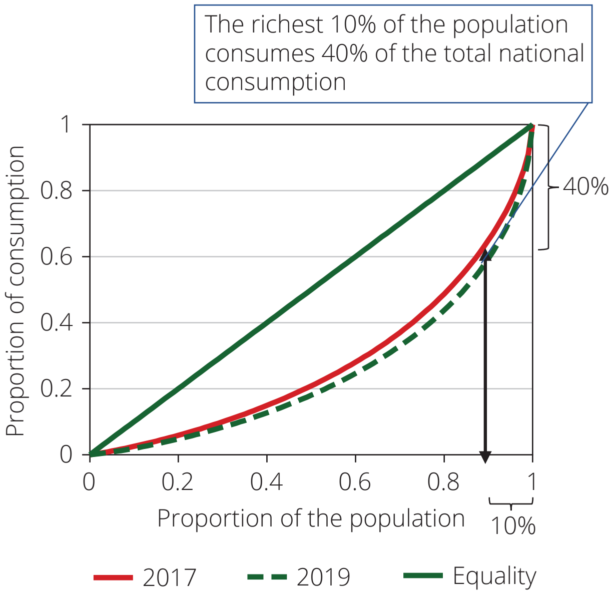



Source: Based on the PICES 2017 and Mini-PICES 2019.

**Inequality, as measured by the Gini index, rose from 44.7 in 2017 to 50.4 in 2019 (Table 4.3).** Only 12 other countries have a larger Gini index; of these, 7 are African countries.[16] The Gini index is a measure of the distribution of income across a population. It is often used as a gauge of economic inequality, measuring income distribution or wealth distribution among a population. A higher Gini index indicates greater inequality, with high-income individuals receiving a much larger percentage of the total income of the population than low-income groups. The Lorenz curve depicts inequality in graphical form (Figure 4.4) and shows that in 2019 the richest 10 percent of people had 41 percent of national consumption, up from 37 percent in 2017. The poorest 10 percent only consumed 2.0 percent of total national consumption, up from 1.9 percent. The richest 10 percent of the population thus consumes 20 times as much as the poorest 10 percent.

[16] This includes Honduras (50.5), St. Lucia (51.2), Suriname (51.2), Angola (51.3), Brazil (53.9), Mozambique (54), Eswatini (54.6), Sao Tome and Principe (56.3), Oman (56.3), Namibia (59.1), South Sudan (63), and South Africa (63).

**FIGURE 4.4**
**Lorenz Curve Showing the Distribution of Welfare Across the Population in 2017 and in April–May 2019**




Source: Based on the PICES 2017 and Mini-PICES 2019.

Furthermore, it can be seen that the richest 20 percent consumes 11 times more than the poorest 20 percent (Figure 4.4).

**The increase in inequality between 2017 and April–May 2019 was driven by a rise in inequality *within* urban and *within* rural areas rather than *across* urban and rural areas.** In April–May 2019, the median real consumption expenditure in urban areas was 2.4 times larger than in rural areas (corrected for price differences), down from 2.6 times in 2017. The urban Gini index rose from 39 to 47, and the rural Gini index increased from 35 to 43. When the Gini index is broken down into within-group and between-group inequality, it shows that within-group inequality increased and between-group inequality dropped. However, inequality *between* rural and urban areas remains larger than *within* rural and *within* urban areas (Table 4.4).

**TABLE 4.4**
**Breakdown of Gini Coefficient by Rural and Urban Areas**

| | 2017 | 2019 |
|---|---|---|
| **Total** | **44.7** | **50.4** |
| Urban/rural | | |
| within-group inequality | 17.4 | 21.4 |
| Between-group inequality | 23.6 | 22.9 |
| Overlap | 3.6 | 6.0 |

Source: Based on the PICES 2017 and Mini-PICES 2019.

## *4.3 Poverty profile*

**The profile of the extreme poor changed a little between 2017 and April–May 2019.** The profile became slightly more urban, and the proportion of the extreme poor whose main livelihood was obtained from their own farm fell by 10 percentage points. The proportion of the extreme poor who have completed secondary education increased.

**Overall, the extreme poor continue to live mostly in rural areas, in large households, work on their own farms, and tend to have low educational attainment.** About one-third live in a female-headed household, which is about the same as the population as a whole. Half of the extreme poor received no benefits from any of the social assistance programs during the survey period of April–May 2019. About 40 percent of all social assistance program beneficiaries are extremely poor.

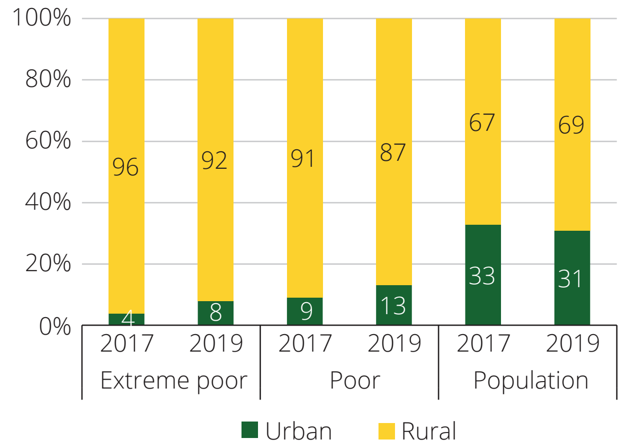
### 4.3.1 Location of the poor

**Although poverty remains overwhelmingly rural, the proportion of the extreme poor who live in urban areas increased from 4 percent in 2017 to 8 percent in April–May 2019.** When using the lower-bound poverty line, the proportion of the poor who live in urban areas went up from 9 percent to 13 percent during the same period. Furthermore, the percentage of the poor who live in rural areas dropped from 91 percent to 87 percent. That percentage is still higher than the proportion among the general population of 69 percent in 2019 (see Figure 4.5). As noted in Figure 4.1, Panel B, the urban poverty rate—using the lower-bound poverty line—rose from 15 percent to 24 percent between 2017 and April–May 2019.

### 4.3.2 Household size of the poor

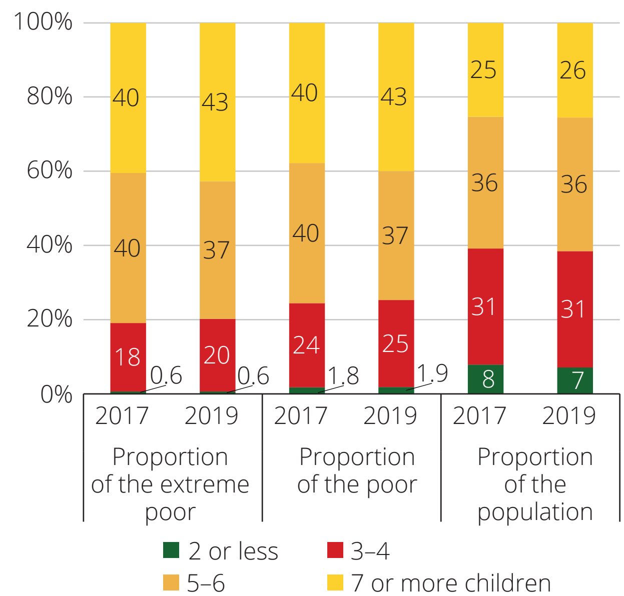
**The extreme poor typically have large households, and this proportion increased between 2017 and April–May 2019.** Those living in households of seven members or more formed 43 percent of the *extreme* poor in 2019—up from 40 percent in 2017—but they only formed 26 percent of the population as a whole. Small households remained underrepresented among the extreme poor (Figure 4.6).

**FIGURE 4.5**
**Distribution Across Rural and Urban Areas of the Extreme Poor, Poor, and General Population in 2017 and April–May 2019**



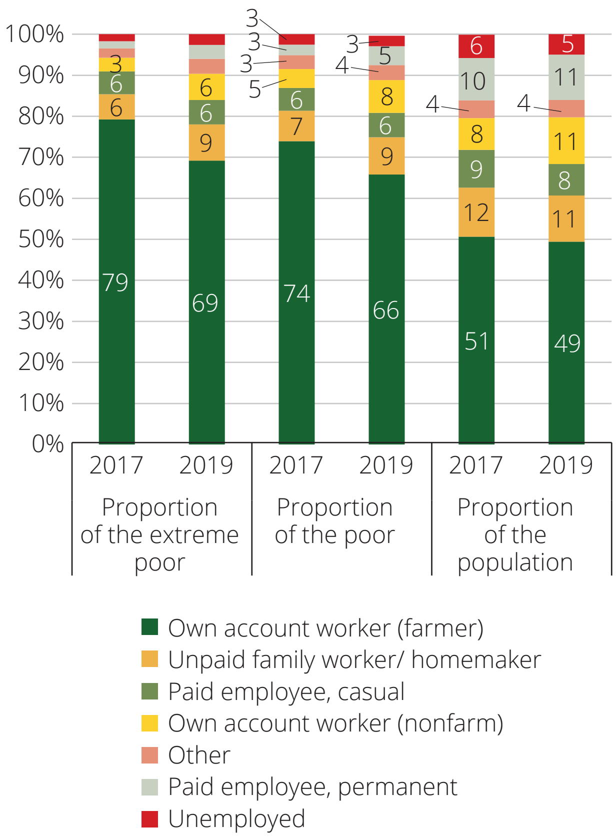

Source: Based on the PICES 2017 and the Mini-PICES 2019.
Note: The classification of *poor* is based on the lower-bound poverty line.

**FIGURE 4.6**
**Distribution of Household Size Groups Among the Extreme Poor, Poor, and the General Population**




Source: Based on the PICES 2017 and Mini-PICES 2019.
Note: The classification of *poor* is based on the lower bound poverty line.

**FIGURE 4.7**
**Occupation of the Extreme Poor, Poor, and General Population**




Source: Based on the PICES 2017 and Mini-PICES 2019.
Note: The classification of *poor* is based on the lower-bound poverty line. *General population* refers to the population that is 10 years old and older, excluding students.

**Children younger than 15 formed almost half of the poor and the extreme poor, but they made up only four-tenths of the population.** Children clearly were overrepresented among the poor, even if this decreased slightly from 2017 to 2019. In contrast, those aged 55 and older were somewhat underrepresented among the poor. They formed only 10 percent of the poor and 11 percent of the population as a whole.

### 4.3.3 Occupation of the poor

**Those working on their own farm remained by far the largest occupational group of the poor.** However, the proportion of the extreme poor whose main livelihood was obtained from their own farm fell from 79 percent in 2017 to 69 percent in 2019. The proportion of the general poor (using the lower-bound poverty line) mainly relying on their own farm also fell: from 74 percent to 66 percent during the same period. In contrast, the proportion of the extreme poor who are own account *nonfarm* workers went up from 3 percent to 6 percent, and permanent paid employees went up from 2 percent to 3 percent (Figure 4.7) during the same period. The economic downturn appears to have hit those working in the nonfarm sector in particular, thereby increasing their representation among the poor.

### 4.3.4 Education levels of the poor

**People who have completed secondary education appear to have been affected more by the economic downturn than other educational groups.** The extreme poverty rate among individuals with secondary education increased from 21 percent in 2017 to 30 percent in April–May 2019, which is a relative increase of 37 percent. Among those with just primary education, the poverty rate increased from 37 percent to 44 percent during the same period, which is a relative increase of only 18 percent (Table 4.5).

[17] This classification is based on the lower-bound poverty line.

## TABLE 4.5
### Extreme Poverty Rate by Educational Achievement of Individuals

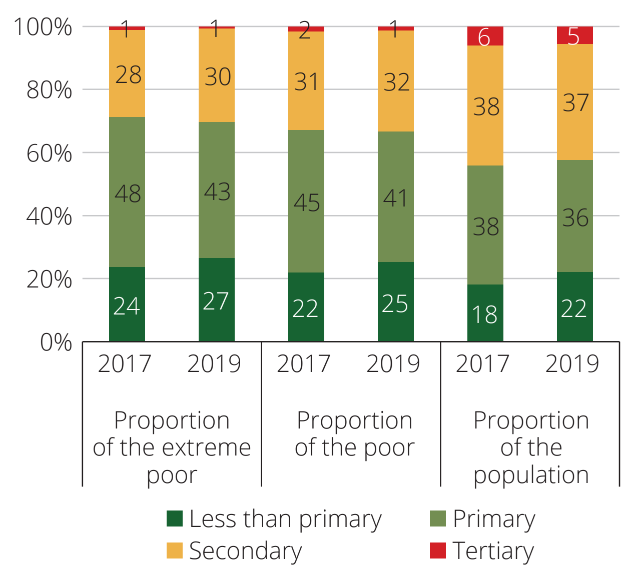
| | Extreme poverty rate (%) | | |
|---|---|---|---|
| **Education level completed** | **2017** | **2019** | ***Relative* increase** |
| None | 41 | 47 | 14 |
| Primary | 37 | 44 | 18 |
| Secondary | 21 | 30 | 37 |
| Tertiary | 5 | 4 | –24 |

Source: Based on the PICES 2017 and Mini-PICES 2019.

**When the education of household heads is considered, the picture is similar: the extreme poverty rate among those living in a household whose head has secondary education showed a relative increase of 29 percent.** Both figures were higher than the relative increase in extreme poverty for the population as a whole of 26 percent.

**The *proportion* of the extreme poor who have completed secondary education rose from 28 percent in 2017 to 30 percent in April–May 2019, whereas the proportion of the poor[17] who completed secondary education rose from 31 percent to 32 percent during the same period** (see Figure 4.8). Zimbabwe has a relatively well-educated population. Its literacy and net secondary enrollment rates are in the top six of sub-Saharan African countries. However, those with secondary education formed 30 percent of the extreme poor and 32 percent of the poor (Figure 4.8), which is a higher proportion than in other African countries.

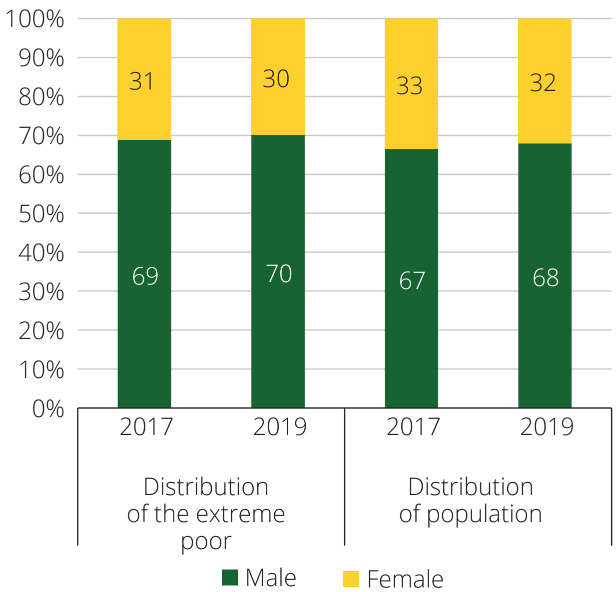
## FIGURE 4.8
### Distribution of the Extreme Poor, Poor, and General Population According to Household Head Education Level




Source: Based on the PICES 2017 and Mini-PICES 2019.
Note: The classification of *poor* is based on the lower-bound poverty line.

**In April–May 2019, the median per capita consumption among households whose head had primary education was only 5 percent higher than those whose head had not completed any education.** During that same period, household heads who had completed secondary education had a per capita consumption that was 46 percent higher than a household head with no education, down from 52 percent in 2017. These are relatively small differences given the

**FIGURE 4.9**
**Distribution of the Extreme Poor and the Population According to Household Head Gender**




Source: Based on the PICES 2017 and Mini-PICES 2019.

income distribution: for example, those at the 80th percentile of the income distribution had a consumption level that was 2.9 times larger than those at the 20th percentile. This confirms that in Zimbabwe many factors other than education determine welfare differences.

### 4.3.5 Gender of the poor

**The proportion of the extreme poor who live in female-headed households was 30 percent in April–May 2019, which is slightly lower than the proportion among the population as a whole (32 percent).** The proportion of the extreme poor who lived in a female-headed household dropped slightly from 31 percent in 2017 to 30 percent in April–May 2019. The percentage of the extreme poor who lived in a male-headed household rose from 69 percent to 70 percent during the same period (see Figure 4.9). A more sophisticated analysis of different household types is needed to investigate the change in relationship between gender and poverty.

## *4.4 Social protection programs*

**The PICES 2017 and Mini-PICES 2019 offer an important insight into which population groups received social protection benefits, the value of transfers received, and the role of social protection programs in reducing poverty.**[18] The analysis presented here grouped programs by different types—namely, education benefits, food transfers, public works (food and cash for work), and other social safety net programs. The analysis looked at coverage,

[18] The sample size of the Mini-PICES 2019 was too small for sufficient coverage of all individual programs because questions on transfers were only asked from a subset of 478 households. Some programs were not captured because they were not active during the period covered in the survey. For this reason, the analysis may underestimate the performance of the social protection system in Zimbabwe, and results need to be interpreted with caution.

incidence, and the relative benefit level or adequacy. *Coverage* refers to the portion of the population that receives the transfer, and *incidence* examines how well the programs target the poor. *Relative benefit level or adequacy* refers to the mean transfer amount received by a group as a share of its total consumption. The focus of the analysis was on social assistance programs, which consist of government-supported social safety nets and donor-funded humanitarian assistance.

The main social safety net programs delivered through the MPSLSW include

- the Harmonized Social Cash Transfer (HSCT) program, targeting labour-constrained and food-poor households;
- Public Assistance, a discretionary grant provided by District Social Welfare Officers to vulnerable households;
- Food Deficit Mitigation, providing food assistance to vulnerable households during the peak lean season to address food insecurity;
- the Basic Education Assistance Module (BEAM), aiming to improve access to primary and secondary schools for vulnerable children, prioritizing orphans; and
- the Assisted Medical Treatment Order (AMTO), enabling free access to health care for vulnerable households.

The main humanitarian assistance programs implemented by the United Nations and nongovernmental organizations (NGOs) include

- Lean Season Assistance, implemented by the World Food Programme (WFP), providing food assistance to food insecure households in rural areas during the peak lean season;
- Food for Assets, implemented by the WFP, providing cash and food for work and supporting resilience-building public works in rural areas; and
- other cash and food assistance provided by multiple NGOs.

### 4.4.1 Social assistance coverage

**The proportion of the *total population* covered[19] by social assistance programs increased twofold from 2017 to April–May 2019, mostly driven by social**

[19] *Program coverage* is the portion of the population in each group that receives the transfer. Coverage includes direct and indirect beneficiaries: all members of a household where at least one member receives a social protection program.

**safety net programs and humanitarian assistance.**[20] The proportion of the total population receiving at least one social protection program increased from 16 percent in 2017 to 37 percent in 2019. This was driven by an increase of coverage by both social safety net and humanitarian programs from 12 percent in 2017 to 31 percent in April–May 2019. This increase is likely due to the increase in food relief by international donors coupled with government payment of arrears in several social safety net programs.

**None of the Mini-PICES 2019 respondents mentioned having received cash transfers from the HSCT, the Public Assistance program, the Food Deficit Mitigation program, or AMTO.** For the HSCT, this may be because the recall period in the survey was one month but the transfers are received bimonthly. In the PICES 2017, which covers the whole year, the coverage of the HSCT was 0.6 percent and for the Public Assistance program it was 0.3 percent. The Food Deficit Mitigation Program is only active from September to March, which may explain its low coverage in the Mini-PICES 2019. In the PICES 2017, 2 percent of households reported having benefited from the program. Around 3 percent of the Mini-PICES 2019 respondents reported having received assistance from the BEAM program in paying school fees during the current academic year, whereas this was 4 percent in 2017. No households reported receiving AMTO assistance, which could be partly related to the one-month recall period applied. However, in the PICES 2017, coverage was also very low: only 0.04 percent of households reported having received this assistance. Appendix F provides more detail on the coverage of social protection programs.

**The increase in the proportion of the *extreme poor* covered by social assistance programs was higher than for the population as a whole.** This implies the program expansion was relatively well targeted to those most in need. The proportion of the extreme poor covered by at least one form of social assistance increased from 17 percent in 2017 to 48 percent in 2019. Coverage rose for all program types. This included education payments as part of the BEAM and the Science, Technology, Engineering, and Mathematics (STEM)[21] programs (reaching 20 percent of the

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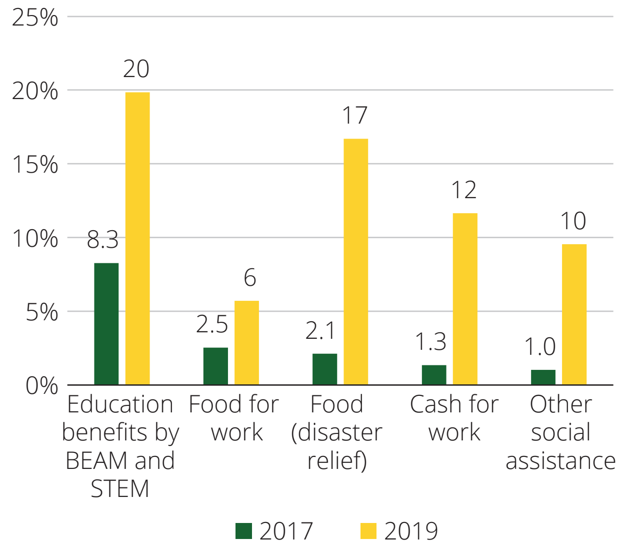
[20] The Mini-PICES 2019 did not ask for the source of program finance. Therefore, for the programs captured in the survey, it was assumed that cash- and food-for-work programs and food (disaster relief) were humanitarian assistance given that a large proportion of these programs were implemented by the WFP at the time of data collection. *Food (disaster relief)* refers mostly to the WFP program Lean Season Assistance because the Government's Food Deficit Mitigation program is active only from September to March. The Government does not have a cash- or food-for-work program at the central level, so we assumed that these programs were mostly funded by donors (such as the Food for Assets program). Some local governmental entities may implement cash-for-work programs, but these are not covered in the survey.

[21] The STEM Scholarship Program ran from 2016 to 2018.

extreme poor); food aid provided as disaster relief (17 percent); cash-for-work programs (12 percent); food-for-work programs (6 percent); and other social safety nets (10 percent) (Figure 4.10). Food relief coverage for the extreme poor had the greatest increase: it went up from 2 percent of the extreme poor in 2017 to 17 percent in April–May 2019. This increase possibly could be because the period covered in the Mini-PICES 2019 was a single month in the lean season of a poor rainfall year, when food aid had reached its peak; in contrast, the PICES 2017 covered all 12 months, and food aid needs were lower as the 2016/17 season benefited from adequate rainfall.

**FIGURE 4.10**
**Percentage of the Extreme Poor Covered by Social Assistance Programs and Humanitarian Assistance Programs**




Source: Based on the PICES 2017 and Mini-PICES 2019.
Note: BEAM = Basic Education Assistance Module; STEM = Science, Technology, Engineering, and Mathematics Scholarship Program. Other social assistance includes the Community Recovery and Rehabilitation Program and other public programs for disaster relief.

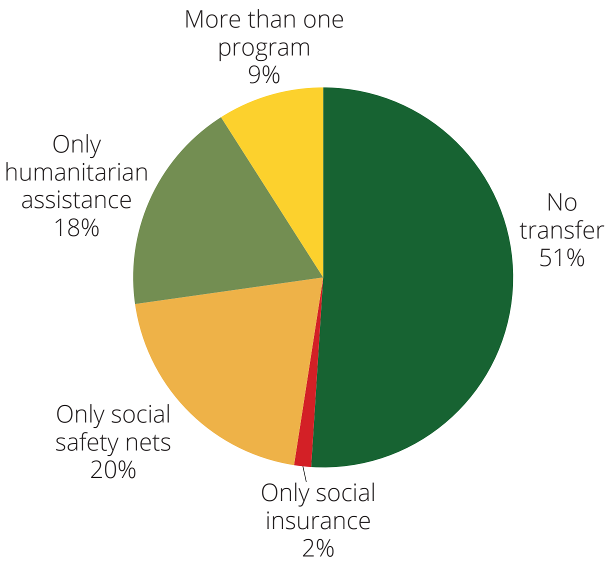
**Despite this increase in coverage, still half of the extreme poor received no benefits from any of the social assistance programs.** About 20 percent of the extreme poor received benefits from one single social safety net program, and 18 percent received humanitarian assistance only. Two percent received only social insurance programs, which consist of contributory pensions and early retirement packages. About 9 percent of the extreme poor received benefits from more than one program in any of the social protection categories. About 51 percent of the extreme poor did not receive benefits from any program (see Figure 4.11).

### 4.4.2 Incidence of social protection beneficiaries

**About 40 percent of all social assistance program beneficiaries[22] are extremely poor.** The highest proportion of the extremely poor among beneficiaries[23] is found in the food-for-work program, where 70 percent of beneficiaries were extremely poor[24] (Figure 4.12). Public works programs, in general, tend to be progressive, meaning that a high proportion of the beneficiaries

[22] Beneficiaries' incidence shows the proportion of program beneficiaries who are poor or extremely poor.
[23] A high proportion of the poor among program beneficiaries is referred to as a *progressive incidence*.
[24] In the food-for-work program, 62 percent of beneficiaries are in the poorest quintile and 11 percent are in the second-poorest quintile, so 73 percent of beneficiaries are in the poorest two quintiles.

**FIGURE 4.11**
**Social Protection and Humanitarian Assistance Coverage of the Extreme Poor**




Source: Based on the Mini-PICES 2019.
Note: The term *extreme poor* refers to those below the food poverty line, also called *extremely poor. Social insurance* includes pensions, social security benefits, and employment services. *Social safety nets* include the Basic Education Assistance Module (BEAM); the Science, Technology, Engineering, and Mathematics (STEM) Scholarship Program; the Community Recovery and Rehabilitation Program; health benefits; and other public disaster relief benefits; these are all mostly government funded. *Humanitarian assistance* includes food and cash for work and food relief; these are mostly donor funded.

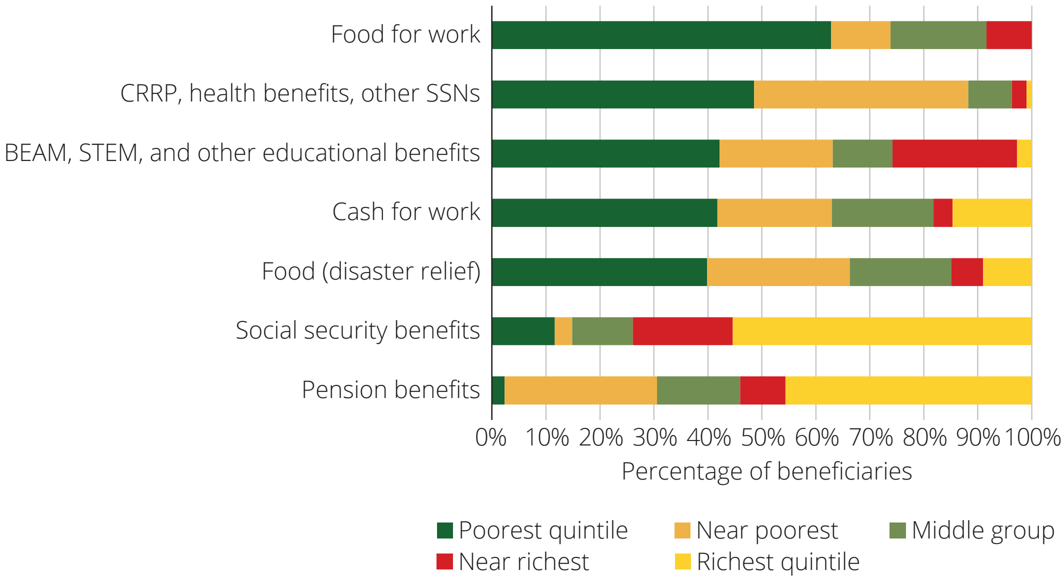
are low income, as only the most deprived are interested in participating in them. The incidence of the extreme poor is smaller for other programs. For example, 42 percent of all beneficiaries of the BEAM and other education programs were in the poorest 20 percent (quintile) of the population. Of the beneficiaries who received food relief, 40 percent were in the poorest quintile and 34 percent were in the richest three quintiles (Figure 4.12). As can be expected, only 2 percent of pension beneficiaries and 12 percent of social security beneficiaries belong to the poorest quintile. In contrast, 46 percent of pensions and 55 percent of social security benefits, respectively, belong to the richest quintile. See Appendix G for social protection incidence curves.

### 4.4.3 Level of benefits

**The extreme poor received cash-for-work program benefits totaling 70 percent of their consumption,[25] the highest share of household welfare of all social assistance programs.** Cash-for-work programs are mainly implemented by humanitarian agencies, such as the WFP, and are generally designed to provide income support of last resort. Therefore, the benefits relative to total household consumption tend to be higher than other social assistance programs. Food relief transfers and food for work both constitutes about 14 percent of the consumption of the extreme poor, whereas education benefits only presented 9 percent. Social assistance benefits as a share of beneficiary consumption is higher for the extreme poor than for the nonpoor, as can be expected (Figure 4.13). The findings also demonstrate that humanitarian assistance programs are much larger than the social safety net programs. The humanitarian programs that were implemented during April–May 2019 included donor-funded cash- and food-for-work programs, which were relatively large during the survey period and were larger than the government-funded social safety net programs.

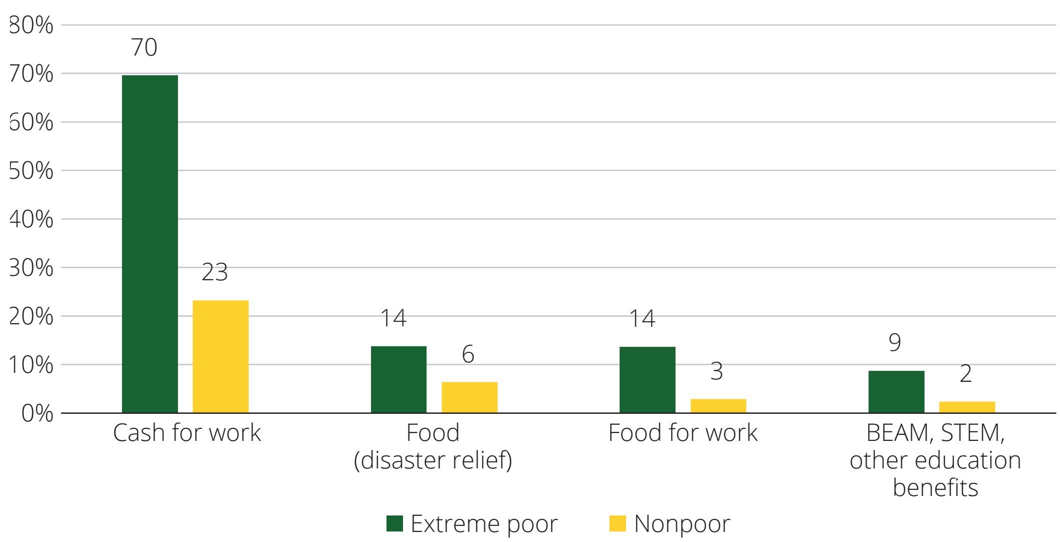
[25] The relative benefit level or "adequacy" is the mean transfer amount received by a group as a share of the total consumption (welfare) of the beneficiaries in that group.

## FIGURE 4.12
### Distribution of Social Protection Beneficiaries by Quintile of Pretransfer Consumption in April–May 2019




Source: Based on Mini-PICES 2019.
Note: BEAM = Basic Education Assistance Module; CRRP = Community Recovery and Rehabilitation Program; SSNs = social safety nets; STEM = Science, Technology, Engineering, and Mathematics Scholarship Program.

## FIGURE 4.13
### Benefits Received as a Proportion of Beneficiary Post-Transfer Consumption for Those Who Receive Them




Source: Based on the Mini-PICES 2019.
Note: BEAM = Basic Education Assistance Module; STEM = Science, Technology, Engineering, and Mathematics Scholarship Program. *Benefits received* refers to those captured in the survey.

### 4.4.4 Reduction in poverty due to social assistance programs

**On average, transfers received through all social assistance programs reduced extreme poverty by 10 percent (about six percentage points) and the poverty gap by 25 percent (three percentage points) during April–May 2019.[26]** These reductions are a share of the pretransfer poverty rate and poverty gap. These results were driven by cash transfer programs because they reduced the extreme poverty rate and the extreme poverty headcount by 6 percent and 15 percent, respectively, during the same period. The impact of other programs is small. Food disaster relief, for example, did not contribute to the reduction of the extreme poverty headcount, but it reduced the poverty gap by 5 percent.

**In conclusion, the proportion of the extreme poor covered by social assistance programs has increased, but such programs still covered only half of the extreme poor.** A large number of small government programs appear to have low coverage. All of the programs were shown to be progressive, but there is much room to improve targeting to the poor. The cash-for-work program was the most promising in terms of having an impact on poverty.

## *4.5 Simulations of the impact of rapid price increases on poverty*

**The price increases that affected Zimbabwe between April–May 2019 and December 2019 are likely to have increased extreme poverty.** Simulations suggest extreme poverty may have risen from 38 percent to 52 percent during this period (Table 4.6). The price increases for maize, bread, and cereals had the largest impact on poverty. The price rises for maize grain and maize meal alone increased extreme poverty by two percentage points, from 37 percent to 39 percent, and the price rise for nonmaize cereals and bread increased extreme poverty by four percentage points, from 37 percent to 41 percent. Price increases for cooking oil and electricity[27] raised extreme poverty by one percentage point, and the price rises for fuel and transport services appeared to have had no noticeable impact on poverty (Table 4.6).[28]

[26] The estimated impact is the change in a poverty or inequality indicator due to transfer, assuming that household consumption will diminish by the full value of that transfer. The poverty impact analysis was conducted only using DRB households given that social protection transfers were asked only for those ones.

[27] Direct effects only.

[28] The impact of price increases on poverty are grounded in price elasticities of demand that were estimated using the Almost Ideal Demand System using the PICES 2017 data, except for electricity, where the source was Hope and Singh (1999). See Appendix H.

## TABLE 4.6
### Poverty Headcount Ratio in December 2019, Based on the Simulation of the Impact of Various Price Rises

| | | Poverty rate in December 2019 based on simulation of price increases of various goods since April–May 2019 | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Poverty line used** | **Poverty rate in April–May 2019** | **All price increases together** | **Maize[a]** | **Bread and cereals[b]** | **Cooking oil** | **Fuel for personal transport[c]** | **Transport services** | **Electricity** |
| Food poverty (%) | 38 | 52 | 39 | 41 | 38 | 37 | 37 | 38 |
| Lower-bound (%) | 57 | 71 | 59 | 62 | 59 | 57 | 57 | 59 |

Source: Simulations using the PICES 2017 and Mini-PICES 2019.
Note: The poverty impact estimated for each single item assumes that the prices of the other items do not change.
a. Grains and roller meal.
b. Excludes maize.
c. Diesel and petrol.

**The share of maize *meal* in total household consumption was three times higher in urban areas (1.8 percent) than in rural areas (0.6 percent), according to the PICES 2017 data.** In rural areas, consumption of maize *grain* was much more common, forming 11 percent of total consumption, whereas it formed only 2.9 percent in urban areas.

**The proportion of maize grain in total consumption was much higher for the poorest quintiles compared to the richer quintiles** (Table 4.7). The proportion of maize grain was 7.5 percent for the poorest quintile[29] in urban areas compared to 13.9 percent for the poorest quintile in rural areas. In contrast, the proportion of maize *meal* in total consumption was lower for the poorest quintiles compared to the middle quintiles (Table 4.7).

**Maize meal subsidies thus appear to benefit the urban middle groups more than the urban poorest groups.** According to the PICES 2017 data, rural households barely benefit from maize meal subsidies because they rely much more on maize grain for their consumption. However, although rural households would typically rely on their own maize production, this is less likely to be the case during a poor rainfall year such as 2018/19. In such a season, the rural poor would have to purchase more maize grains or roller meal (see also Table 4.7).

**The urban population spent much more on transport fuels, even when measured as a proportion of their total consumption (1.1 percent), than the**

29 National quintiles of per capita consumption.

### TABLE 4.7
### Consumption Share of Selected Goods and Services for Urban and Rural Households in 2017 (%)

| Welfare quintiles | Maize grain | Maize meal[a] | Energy | Transport fuels | Transport fares | Electricity |
|---|---|---|---|---|---|---|
| **Urban Zimbabwe** | | | | | | |
| Poorest | 7.5 | 2.0 | 0.5 | 0.0 | 3.4 | 1.5 |
| Near poorest | 5.6 | 2.9 | 1.2 | 0.0 | 3.0 | 3.1 |
| Middle | 4.0 | 2.5 | 1.1 | 0.1 | 4.2 | 4.4 |
| Near richest | 3.1 | 2.0 | 0.9 | 0.4 | 4.3 | 4.6 |
| Richest | 1.9 | 1.3 | 0.8 | 2.2 | 4.1 | 4.5 |
| **All** | **2.9** | **1.8** | **0.9** | **1.1** | **4.1** | **4.4** |
| **Rural Zimbabwe** | | | | | | |
| Poorest | 13.9 | 0.4 | 0.1 | 0.0 | 1.4 | 1.1 |
| Near poorest | 12.0 | 0.6 | 0.2 | 0.1 | 2.3 | 1.6 |
| Middle | 10.5 | 0.7 | 0.2 | 0.2 | 3.0 | 1.7 |
| Near richest | 8.6 | 0.8 | 0.3 | 0.7 | 3.7 | 1.8 |
| Richest | 5.6 | 0.8 | 0.4 | 1.8 | 4.4 | 2.4 |
| **All** | **11.2** | **0.6** | **0.2** | **0.3** | **2.6** | **1.6** |

Source: Based on the PICES 2017.
Note: a. Mostly roller meal.

**rural population (0.3 percent)** (Table 4.7). That implies that urban households are thus much more affected by fuel price increases than rural households. In both urban and rural areas, the richer quintiles spent a higher proportion of their consumption on both transport fuel and transport fares than the poorer quintiles.

**Efforts to moderate fuel prices thus benefit the richest segment of the population more than the poorest segment.** For transport fares, differences in *relative* spending among welfare quintiles in urban areas were small, with households in the poorest quintile spending 3.4 percent on transport fares, only a little less than the richest urban quintile (4.1 percent).

**In 2017, households in the poorest urban quintile spent, on average, 1.5 percent of their consumption expenditure on electricity, compared to 4.5 percent for the richest quintile.** This would suggest that although the better-off urban Zimbabweans benefit most from any effort to keep electricity prices low, increases in electricity prices will also have some negative impacts on the poorest urban households (Table 4.7). In 2017, all urban households spent, on average, 4.4 percent of their total consumption expenditure on electricity, compared to 1.6 percent in rural areas, where fewer people are connected. The Mini-PICES 2019 data show lower quintile estimates for the consumption of maize grain and maize meal as a proportion of total consumption (Table 4.8) than the PICES 2017 data[30] (Table 4.7).

**The simulation of the impact of the price increases on poverty suggests that the proportion of consumption that is spent on maize has more than tripled for all welfare groups.** For example, for the poorest quintile, it rose from 8.1 percent to 29 percent of total consumption (Table 4.8). For electricity it more than tripled. For the poorest quintile, for example, electricity spending rose from 1.4 percent to 7.1 percent of total consumption; for the richest quintile, it increased from 1.8 percent to 9.5 percent. The proportion of consumption spent on cooking oil dropped slightly, but for fuel, the proportion remained the same. This is likely because of much lower price elasticities of demand for fuel (-0.7) and cooking oil (-0.4) than for maize and bread (-0.2) (see Appendix H for more details on price elasticities of demand).

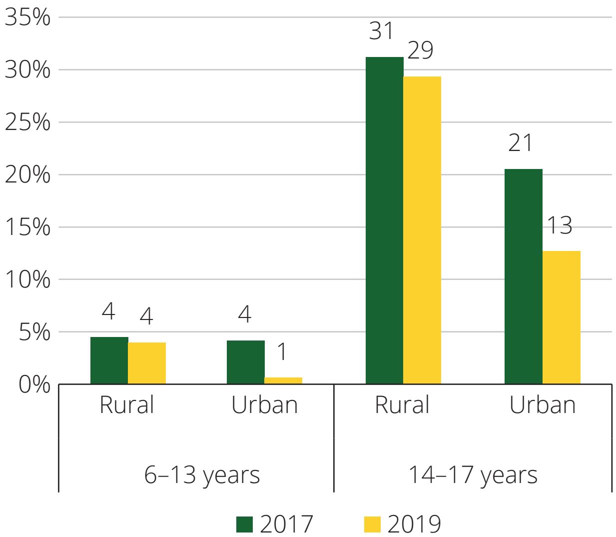
### TABLE 4.8
### Budget Share of Selected Consumption Items (%)

| Quintile | Maize[a] | Bread and cereal[b] | Cooking oil | Fuel for personal transport[c] | Other transport | Electricity |
|---|---|---|---|---|---|---|
| **Baseline: April–May 2019 (observed)** | | | | | | |
| Poorest | 8.1 | 6.4 | 5.2 | 0.0 | 0.0 | 1.4 |
| Near poorest | 6.2 | 7.8 | 3.4 | 0.1 | 0.0 | 1.5 |
| Middle | 5.5 | 9.3 | 4.4 | 0.3 | 0.0 | 1.7 |
| Near richest | 3.9 | 10.4 | 3.8 | 0.1 | 0.2 | 1.6 |
| Richest | 2.3 | 8.3 | 2.6 | 4.5 | 2.0 | 1.8 |
| **December 2019 (simulated)** | | | | | | |
| Poorest | 29.0 | 21.6 | 8.2 | 0.0 | 0.0 | 7.1 |
| Near poorest | 22.2 | 26.3 | 5.6 | 0.1 | 0.0 | 7.8 |
| Middle | 19.5 | 31.2 | 6.5 | 0.4 | 0.0 | 9.0 |
| Near richest | 13.8 | 34.9 | 6.6 | 0.1 | 0.3 | 8.2 |
| Richest | 8.2 | 27.7 | 4.7 | 4.9 | 2.9 | 9.5 |

Source: Based on the Mini-PICES 2019 and simulations using the Mini-PICES 2019 and Consumer Price Index data.
Note:
a. Grains and maize meal.
b. Excludes maize.
c. Diesel and petrol.

[30] It should be noted that in the Mini-PICES 2019, the detailed consumption measurement covered only 478 households whereas 31,189 were covered for the PICES 2017. The 2017 estimates are therefore much more robust.

**FIGURE 4.14**
**Proportion of Children Out of School by Age Group and Location**




Source: Based on the PICES 2017 and Mini-PICES 2019.

## *4.6 Nonmonetary poverty indicators*

### 4.6.1 Education

**During the 12 months preceding the April–May 2019 Mini-PICES, the proportion of children out of school was lower than in 2017.** That is possibly because in 2019 schools were no longer sending children away when school fees went unpaid.[31] Although this is positive, it is likely to have had a negative impact on the availability of funds for the purchase of teaching materials at schools. In urban areas, the proportion of children ages 6–13 who were out of school dropped from 4 percent to 1 percent, and for children ages 14–17, the proportion out of school fell from 21 percent to 13 percent between 2017 and April–May 2019. In rural areas, the percentage of children out of school in the 14–17 age group dropped slightly, from 31 percent to 29 percent, during the same period (Figure 4.14). The proportion of children who were not in school was about the same for boys and girls.

**Although the proportion of children not in school fell, in urban areas there was a sharp increase in the percentage of respondents saying that financial constraints were the main reason for not keeping children in the 14–17 age group in school.**
This proportion went up from 66 percent in 2017 to 80 percent in April–May 2019. In contrast, the proportion of respondents who faced financial constraints for keeping children in the 6–13 age group in school dropped from 84 percent to 66 percent during the same period. In rural areas, this proportion remained unchanged at 70 percent for the 14–17 age group and 80 percent for the 6–13 age group.

### 4.6.2 Employment

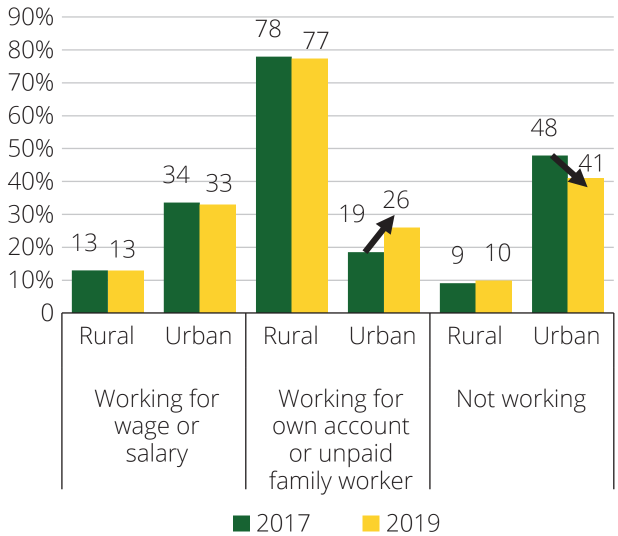
**The proportion of the urban working-age population that worked on their own account (farm and nonfarm) or as unpaid family workers rose from 19 percent**

[31] Almost half (46 percent) of rural households indicated that their children were sent away from school *temporarily* at least once because of nonpayment of fees.

**to 26 percent, and those not working (for pay or to generate income) fell from 48 percent to 41 percent between 2017 and April–May 2019.** This may suggest that fewer urban people could afford not to work and had to start informal income-generating activities to help make ends meet. The proportion with a salary or wage remained almost the same at 34 percent in 2017 and 33 percent in April–May 2019. In rural areas, changes were small. The largest proportion of the population—78 percent in 2017 and 77 percent in April–May 2019—kept working on their own account or as unpaid family workers (Figure 4.15).

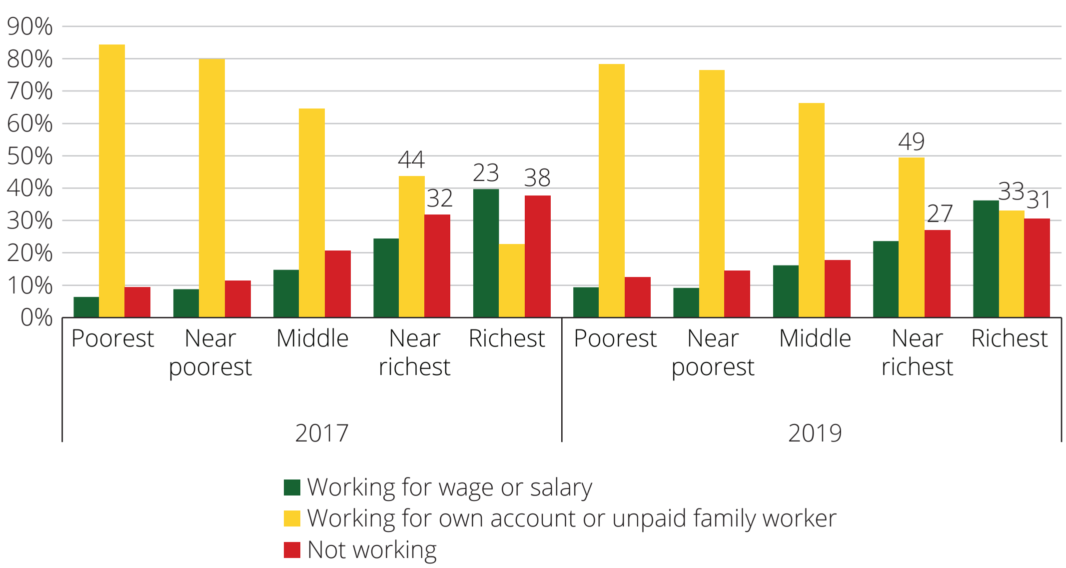
**A look at the differences among wealth groups shows that, at the national level, the largest changes were found in the richest 40 percent of the population.** This suggests that people in this particular group started to take up own account work activities rather than staying at home and not working (Figure 4.16).

### FIGURE 4.15
### Employment Status for Ages 18–64 in 2017 and April–May 2019



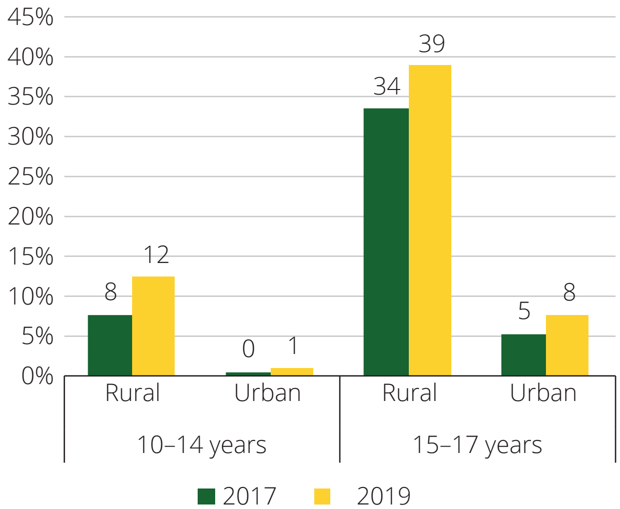

Source: Based on the PICES 2017 and Mini-PICES 2019.

### FIGURE 4.16
### Employment Status for Ages 18–64 in 2017 and April–May 2019 by Welfare Group




Source: Based on the PICES 2017 and Mini-PICES 2019.
Note: Welfare groups are per capita consumption quintiles.

**FIGURE 4.17**
**Children Working for Pay or as Unpaid Family Workers in 2017 and April–May 2019**




Source: Based on the PICES 2017 and Mini-PICES 2019.

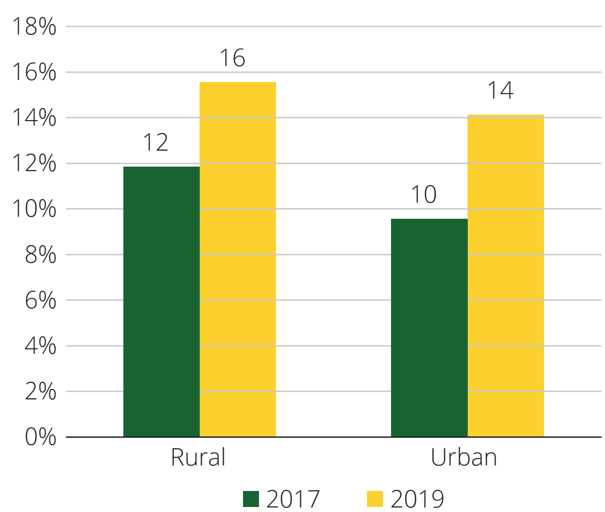
**Child labour rose between 2017 and April–May 2019.** During this period, the proportion of children in rural areas who worked rather than studied rose by four to five percentage points for ages 10–14 and 15–17. In urban areas, child labour also rose, with the increase being higher in relative terms (Figure 4.17). The economic downturn possibly led to households having to ask their children to generate income to help make ends meet. But the change could also be due to a seasonal effect given that the Mini-PICES 2019 survey was conducted in April–May 2019 only, whereas the PICES 2017 covered the whole year.

### 4.6.3 Medical services

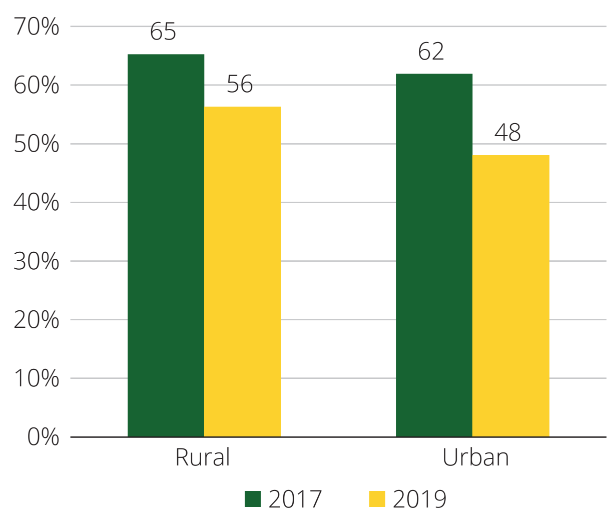
**Use of health care facilities dropped.** The proportion of survey respondents saying they were ill during the 30 days prior to the survey interview rose marginally, but the proportion of those who were sick that visited a health care facility dropped (Figure 4.18). This was mostly because of high health care costs and households preferred home treatment instead. The percentage of people

**FIGURE 4.18**
**Access to Health Care in 2017 and April–May 2019**

a. Proportion that was sick in the past 30 days (%)




b. Proportion that visited a health care provider when sick (%)




Source: Based on the PICES 2017 and Mini-PICES 2019.

who paid for medical services fell in both rural and urban areas. It dropped from 35 percent in 2017 to 30 percent in April–May 2019 for rural households and from 61 percent to 53 percent for urban households during the same period.

**During the 30 days before the interview, 25 percent of rural households and 28 percent of urban households that were prescribed medicine due to an illness were unable to obtain it.** In rural areas the main reason for being unable to obtain medicine was lack of availability, but in urban areas, the most common reason mentioned by households was that they could not afford the medicine due to high costs (Table 4.9).

**TABLE 4.9**
**Reasons for Not Being Able to Obtain Prescribed Medicine, April–May 2019 (%)**

| | Rural | Urban |
|---|---|---|
| Not affordable | 33 | **56** |
| Could not find medication | **54** | 27 |
| Did not think they were really needed | 3 | 0 |
| Used alternative/substitute medicine | 1.3 | 14 |
| Traditional healer/faith healer | 0.8 | 0 |
| Herbal medication | 0.4 | 0 |
| Other | 7 | 3 |

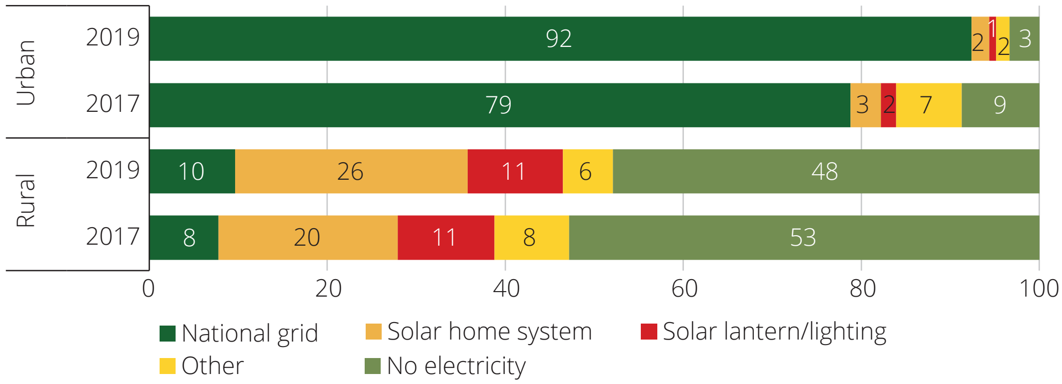
Source: Based on the Mini-PICES 2019.
Note: The question was not asked in the PICES 2017.

### 4.6.4 Drinking water and electricity

**As expected, the main sources of drinking water did not change much between 2017 and April–May 2019.** In rural areas, 60 percent of households in April–May 2019 indicated that a borehole or protected well was their main source, which was similar to the 2017 figure. This was followed by an unprotected well (23 percent in April–May 2019), which was very close to the 2017 number. The same applied to rivers, streams, or dams (8 percent) and communal taps (4 percent). For 37 percent of households, their drinking water source was more than 500 meters away. In urban areas, 39 percent of households had piped water inside their house as their main source (similar to 2017), and 33 percent had piped water outside the house. In 2019, households that relied on a borehole or a protected well formed 23 percent of the population, up from 22 percent in 2017.

**About half of the households in both urban and rural areas indicated that the adequacy of their main water source had changed.** In rural areas, this was mainly because the main source was flooded, followed by the availability of

**FIGURE 4.19**
**Access to Electricity**




Source: Based on the PICES 2017 and Mini-PICES 2019.
Note: In 2017, the question was "What is the main source of electricity?" In 2019, the question was "What is the main source of energy for lighting?"

other alternative water sources. In urban areas, the main reason was that the water source had dried up, followed by the water source being broken or not functional.

**Access to the national electricity grid rose to 92 percent in urban areas according to the Mini-PICES 2019, up from 79 percent in 2017.** In rural areas, only 10 percent of the population was connected to the national grid, and 43 percent had access to other sources of electricity, mostly home solar systems and solar lanterns for providing light, up from 39 percent in 2017 (Figure 4.19).

**In 2019, unpredictable interruptions to electricity services became a major problem for urban households.** Half of all urban households claimed this was

**TABLE 4.10**
**Main Problems with Electricity Services**

| | Rural | | Urban | |
|---|---|---|---|---|
| | 2017 | 2019 | 2017 | 2019 |
| Duration of supply (expected hours per day) (%) | 25 | 21 | 12 | 19 |
| Unpredictable interruptions (%) | 14 | 18 | 39 | 49 |
| Low/high voltage problems/fluctuations (%) | 29 | 17 | 5 | 2 |
| Too expensive (%) | 3 | 2 | 31 | 21 |
| Unexpectedly high bills (%) | 0.7 | 0.2 | 8 | 5 |
| Do not trust the supplier (%) | 0.2 | 2 | 0.2 | 0.8 |
| Cannot power large appliances (%) | 27 | 32 | 5 | 2 |
| Other (%) | 2 | 9 | 1 | 3 |

Source: Based on the PICES 2017 and Mini-PICES 2019.
Note: Percentages refer to those with access to electricity.

the main problem they experienced, up from 39 percent in 2017. Affordability and the duration of supply were mentioned as the main problems by one-fifth of urban households. Rural respondents indicated that not being able to power large appliances was their main difficulty (Table 4.10).

### 4.6.5 Transport

**Ninety percent of urban households stated that their transport costs to work went up during the first four months of 2019.** One-fifth of urban households stated that higher transport prices had affected their children's ability to access education services, and 10 percent of these households had asked their children to walk at least part of the trip to school. In rural areas, this problem was mentioned less often, probably because children were already walking to school.

## 4.7 Food security

**In April–May 2019, 50 percent of *rural* households were either *moderately or severely* food insecure,[32] which was similar to the 52 percent of rural households in March–June 2017.** Eight percent were *severely* food insecure, which was lower than the figure in March–June 2017 (15 percent). In April–May 2019, 27 percent of *urban* households were moderately or severely food insecure. A comparable number for urban areas in 2017 is not available because the PICES/APM survey that year only measured food insecurity in rural areas (Table 4.11).

**The Food Insecurity Experience Scale that was used for this analysis is a metric of severity of food insecurity at the household or individual level.** The interpretation of the indicators reveals that people experiencing moderate levels of food insecurity eat low-quality food and often must reduce the quantity

**TABLE 4.11**
**Food Insecurity in 2017 and 2019**

| | 2017 March–June | 2019 April–May | | |
|---|---|---|---|---|
| | Rural | Rural | Urban | Rural and urban |
| Moderately and severely food insecure (%) | 52 | 50 | 27 | 42 |
| Severely food insecure (%) | 15 | 8 | 5 | 7 |

Source: Based on the PICES/Agricultural Productivity Module 2017 and Mini-PICES 2019.
Note: Percentages refer to households.

[32] Using the Food Insecurity Experience Scale and data from the PICES 2017 and the Mini-PICES 2019.

of food they eat. People experiencing severe levels of food insecurity often go entire days without eating due to lack of money or other resources to obtain food. Food insecurity is expected to be highly correlated with the prevalence of undernourishment affecting lifelong learning abilities.[33]

**During the 30 days that preceded April–May 2019, more than half of all rural households (55 percent) were unable to eat nutritious food for an average of 14 days. This was a little lower than that measured around the same period in 2017, when it was 60 percent.** This figure was 36 percent and 12 days for urban households, according to the Mini-PICES 2019. According to the same survey, one-tenth of rural households spent at least one whole day without food, about double the proportion of urban households. On average, these households spent three days without food (Table 4.12).

**The small drop in rural food insecurity—despite much higher extreme poverty—reflects the deterioration of the nonfarm economy between 2017 and April–May 2019.** This affected household consumption expenditure in

**TABLE 4.12**
**Food Shortage Indicators in 2017 and 2019**

| | 2017 | | 2019 | |
|---|---|---|---|---|
| | Rural | | Rural | Urban |
| | Period covered in survey | | | |
| | March–June | Sept–Nov | April–May | |
| Proportion of households in which any adult was unable to eat healthy or nutritious food anytime during the last 30 days (%) | 60 | 46 | 55 | 36 |
| Number of days (out of the last 30 days) that adults in the household were unable to eat healthy and nutritious/preferred food because of a lack of money or other resources | N.A. | 12 | 14 | 12 |
| Proportion of households that were hungry and went without eating for a whole day anytime during the last 30 days by area (%) | 19 | 7 | 10 | 6 |
| Number of days (out of the last 30 days) that adults in the household went without eating for a whole day because of a lack of money or other resources | | 3 | 3 | 3 |

Source: Based on the PICES/APM 2017 and Mini-PICES 2019.

[33] FAO 2016.

general, and the food security situation in April–May 2019 was at a similar level as March–June 2017. Also, the preharvest period of March–May 2017 had been affected by two consecutive years of poor harvests (the 2014/15 and 2015/16 growing seasons had low and poorly distributed rainfall) and the food security situation was precarious. However, poverty was measured over the whole of 2017 and is likely to have dropped after the good harvest in May of that year, giving a lower poverty rate for the whole of 2017 when compared to April–May 2019.

**The poor food security situation in March–June 2017 was also caused by the poor macroeconomic conditions prevailing in 2016 and early 2017, including the general shortage of cash in the country.** In 2016, the importation of various goods, including peanut butter and *maheu* as well as fertilizers and other farm inputs, was banned or subjected to heavy duties. This resulted in price increases for certain food items and temporary shortages of other commodities, which negatively impacted household food security and nutrition.

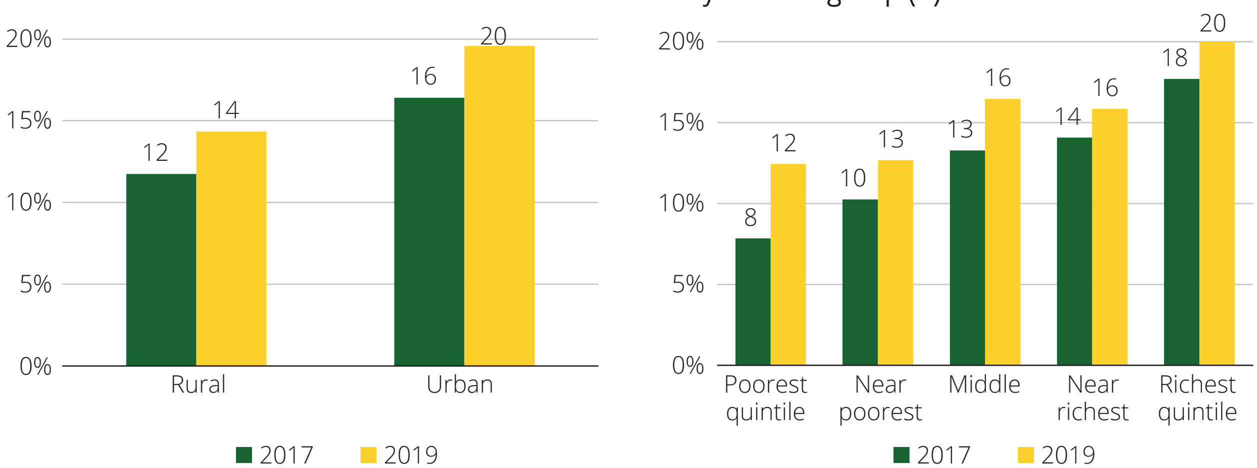
## 4.8 Migration and remittances

**The proportion of people who had at least one household member living abroad increased from 13 percent in 2017 to 16 percent in April–May 2019.** Having a migrant member was more common among urban households (20 percent) than rural ones (14 percent) (Figure 4.20, Panel A). Richer households were more

**FIGURE 4.20**
**Household Members Abroad and Proportion Receiving Remittances**

a. Proportion of households with a member living abroad (%)

b. Proportion of households with a member living abroad that received remittances, by welfare group (%)




Source: Based on the PICES 2017 and Mini-PICES 2019.

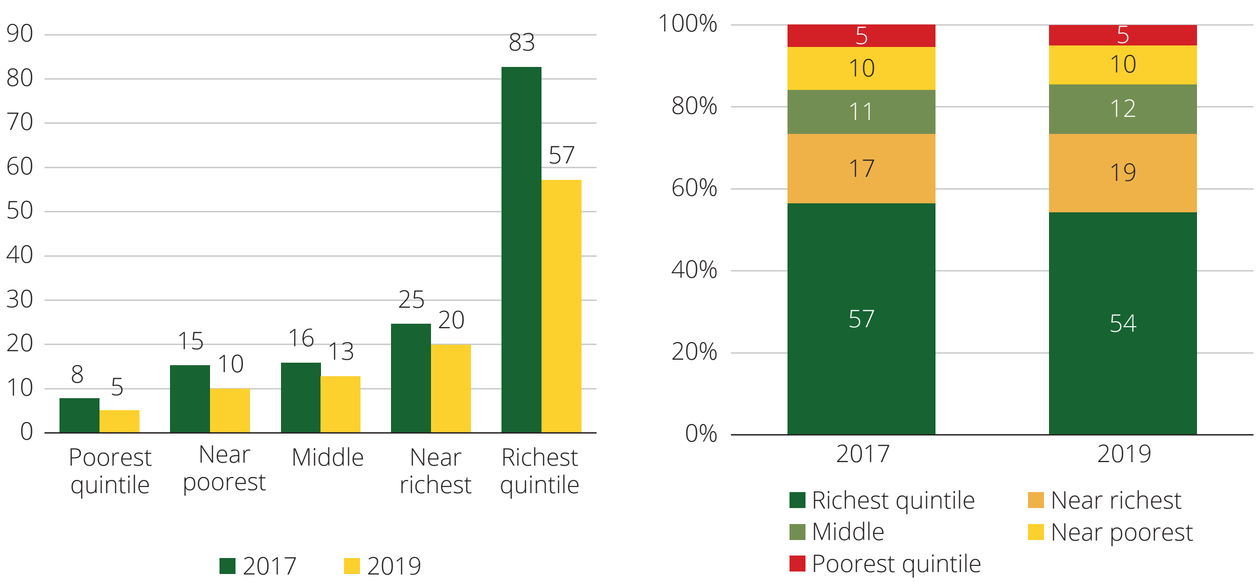
likely to have a member abroad than poorer ones. However, the increase was largest among households in the poorest quintile (Figure 4.20, Panel B).

**The proportion of households with members abroad that received remittances dropped from 58 percent in 2017 to 52 percent in 2019.** The proportion was lower in rural areas than in urban areas. It was also lower among poorer households than richer ones. Of the 20 percent of urban households with a family member abroad, in April–May 2019 two-thirds said they received remittances from them, which implies that 13 percent of all urban families received them. In rural areas, the proportion of households that received remittances was 6 percent.

**FIGURE 4.21**
**Monthly Remittance Amounts and Share by Welfare Quintiles**

a. Monthly remittance amounts received per capita for those that receive any, by welfare quintile (US$)

b. Share of each welfare group in total amount of remittances (%)




Source: Based on the PICES 2017 and Mini-PICES 2019.
Note: The amounts reported in Real Time Gross Settlement dollars were converted to U.S. dollars by dividing by 5.579, the average exchange rate during the survey period.

# 5

# CONCLUSIONS

**The Mini-PICES conducted during April–May 2019 enabled a quick updating of Zimbabwe's poverty indicators.** This confirmed that such short rapid surveys in between large household surveys can be very useful for assessing the impact of an economic shock on the welfare and living conditions of urban and rural Zimbabweans. However, standard errors for the Mini-PICES 2019 were larger than for the PICES 2017, especially for estimates for urban areas.

**The findings suggest that poverty rose sharply between 2017 and April–May 2019.** Extreme poverty increased from 30 percent in 2017 to 38 percent in April–May 2019, and general poverty (using the lower-bound poverty line) increased from 43 percent to 51 percent. In *relative* terms, extreme poverty rose most in urban areas, even though rural extreme poverty remains much higher than urban poverty. The number of extremely poor people rose from 4.5 million in 2017 to 6 million in April–May 2019. The number of extremely poor people rose by 327,000 in urban areas and increased by 1.1 million in rural areas between 2017 and April–May 2019.

**From 2017 to April–May 2019, consumption expenditure fell for all welfare groups except the richest 10 percent (decile).** The welfare groups in the lower end of the income distribution had the largest proportional declines in consumption expenditure. Inequality rose with the Gini index, increasing from 44.7 in 2017 to 50.4 in 2019. Economic instability, exacerbated by a poor rainfall season, appears to have impacted low- and middle-income households, but the poorest households were affected the most.

**The proportion of the total population receiving at least one social safety net program increased from 16 percent in 2017 to 37 percent in 2019.** The proportion of the extremely poor who benefited from at least one social safety net program rose from 17 percent in 2017 to 48 percent in 2019. This is likely due to the increase in food relief by international donors and payment of arrears in several social safety net programs by the Government.

**Half of the extreme poor received no benefits from any of the social assistance programs during the survey period of April–May 2019.** It was noted that about 60 percent of social assistance program beneficiaries do not belong to the extremely poor category. Although all the social assistance programs were shown to be progressive, there is room to improve targeting of assistance to the poor. The cash-for-work program appears to be the most effective form of assistance in its impact on poverty.

**Simulations of the impact of price increases on the welfare of different types of households provide a helpful input into policy discussions around pricing policies and subsidies.** The simulations assess the effects of price rises on poverty and compare the effectiveness of different subsidy options to protect the poorest households from price increases.

**The simulations show that price increases that affected Zimbabwe between April–May and December 2019 were likely to have further increased extreme poverty.** Extreme poverty may have risen from 38 percent in April–May to 52 percent in December 2019. The proportion of consumption that was spent on maize grains and maize meal, as well as on electricity, more than tripled for all welfare groups. It was noted that maize meal subsidies benefited the urban middle groups more than the urban poorest groups; therefore, they do not seem to be the most effective instrument to safeguard the poorest households. Efforts to moderate fuel prices benefit the richest segment of the population more than the poorest segment.

**The proportion of children out of school dropped between 2017 and April–May 2019.** This is possibly because in 2019 schools were no longer sending children away for nonpayment of their fees. However, this is likely to have had a negative impact on the availability of teaching materials at schools.

**The proportion of the urban working-age population who were farm and nonfarm own account workers or unpaid family workers rose from 19 percent in 2017 to 26 percent in 2019, and the proportion of those not working fell from 48 percent to 41 percent during the same period.** This could suggest that a growing number of urban Zimbabweans could no longer afford not to work and were forced to accept casual income-generating activities.

**The use of health care facilities for those who were sick dropped due to high costs, with households preferring home treatment instead.** The percentage of people who paid for medical services fell in both rural and urban areas. Moreover, during the 30 days before the interview, 25 percent of rural households and 28 percent of urban households who were prescribed medicine due to an illness were unable to obtain it.

**The proportion of *rural* households that were either *moderately* or *severely* food insecure in April–May 2019 was 50 percent, close to the 52 percent of rural households in March–June 2017.** However, extreme poverty was higher in April–May 2019 than it was in 2017. Poverty was measured over the whole of 2017 and is likely to have dropped after the good harvest in April 2017, giving a lower poverty rate for 2017 than for April–May 2019.

**The data suggest that richer households are more likely to have a member abroad than poorer households.** Among families with a member abroad, poorer ones received fewer remittances. For those who received remittances, the monthly amount received per capita dropped from US$29 in 2017 to US$21 in April–May 2019.

**The COVID-19 pandemic and the continued economic instability are likely to have further worsened the poverty situation in 2020 and demonstrate the need for an even more urgent response.** This also demonstrates the need for more rapid data collection. The rapid Mini-PICES 2019 has shown it can deliver rapid updates on poverty and living conditions in the country. But the COVID-19 pandemic has made it clear that even quicker data collection is needed, such as through monthly telephone surveys of households and firms that were initiated in July 2020.

**Further assessment of the impact of price increases on welfare and the economic downturn in 2020, as well as the mobility restrictions associated with the COVID-19 pandemic, should be conducted.** Data from the PICES 2017 and Mini-PICES 2019, as well as from the high frequency PICES telephone survey that was initiated in July 2020, could be useful to assess which population groups are most affected. Simulations of poverty's impact on policies such as the COVID-19 stimulus program or subsidy reform can also be done. These would inform the discussions around pricing and subsidy policies, and on mitigation programs, making sure they meet the needs of those who most require support: the poorest and the most vulnerable.

Photo: Arne Hoel/World Bank

# APPENDIX A
# REVISED METHODOLOGY FOR COMPUTING THE CONSUMPTION AGGREGATE

*This appendix briefly explains the technical details of the modifications made to the measurement of the consumption aggregate. It covers the following components: valuing own housing, durable goods, the recall period for the purchase of nonfood items, and bulky expenditures.*

## A.1 Use value of owned housing

Housing adds to utility, so its value should be included in a measure of welfare that is used to estimate poverty. Some households rent their houses and pay a rental fee. For these households, rent forms an important part of their total consumption expenditure, constituting about 25 percent on average. The provincial average varied between 21 percent and 27 percent in rural areas and between 21 percent and 35 percent in urban areas. Other households own their dwelling or have been given them free of charge by employers, friends, relatives, or others. To ensure comparability among households, a rental value needs to be imputed for those who do not rent their homes.

Traditionally, ZIMSTAT estimates the rental value by asking a household how much it would pay if it were to rent its house. If this question is not answered (which is the case for many households that do not rent), the rent per room is taken from other households who have self-reported rentals, which is then multiplied by the number of rooms. The quality of the house is not considered in this process. When the self-imputation method is used in areas where few households rent, respondents have little information on which to base their rental estimates.

The rent paid is usually related to a set of housing characteristics. This relationship can be estimated using data from households that *rent* their house through regression techniques. This relationship is then used to impute house rent for those that *own* their house. This technique is referred to as a hedonic regression. The estimates using PICES 2017 data included the following housing characteristics: number of rooms; type of roof, floor, wall, and toilet; and location variables. Of the 31,189 households in the PICES 2017, 2,850 households (9 percent) rented their homes. Of these, 2,505 were in urban areas and 345 were in rural areas. In rural areas in Zimbabwe, fewer than 2 percent of households pay rent. The validity of the hedonic regression depends on the assumption that no systematic difference exists between rented and owner-occupied housing. This is referred to as "selectivity bias." If such a bias exists, a Heckman correction needs to be applied. Using the PICES 2017, there is evidence of such a selectivity bias in the total sample, but it disappears when only using the rural sample. The quality differences between rural rented houses and rural owned houses is small,[34] but they are significant in urban areas. The hedonic model without the Heckman correction was therefore adopted for rural areas, whereas the Heckman approach was taken for urban areas. The models arrived at average rental values that were slightly lower in rural areas than the conventional method applied in Zimbabwe by ZIMSTAT (US$39 versus US$42 per month) and a little higher for urban areas (US$120 versus US$118 per month). It was agreed to use the modeled values.

## A.2 Durable goods (assets)

For owned durable goods, such as furniture, televisions, and bicycles, a "use value" should be calculated. This is an estimate of their contributions to household welfare. Durable goods provide benefits to their owners over many years, and the "flow" of benefits that households obtain from the ownership of these goods must be estimated and included in the welfare aggregate (consumption expenditures) used in the poverty analysis.

[34] Although the distance of rural renters to social facilities is significantly larger than nonrenters, the absolute differences are small.

The method traditionally used to analyze the PICES data (or those from the earlier income, consumption, and expenditure surveys) involved a "straight-line" depreciation over the expected life span. This consists of computing the use value based on the new value and the expected lifetime of the asset. The latter was estimated through interviews with experts and was standard for each good. An average market price for each asset, from ad hoc surveys in Harare, was divided by the expected life (in months) to arrive at a monthly use value. The validity of this use value depends on the correctness of the expected life and whether the estimated average market price accurately reflects the price (value) of the assets.

This approach is limited, however, because it does not take into account quality differences with each type of asset. Lacking information on the age of the asset, its purchase price, and its current value, it was assumed that all similar assets (such as cars) have the same use value. For example, a low-quality car is assumed to provide the same use value as a new Mercedes-Benz. This procedure was adopted because the ICES questionnaires used during the 1990s did not ask about the age, purchase price, or current value of owned assets. The implication was that the consumption aggregate did not adequately differentiate between the well-being associated with different quality assets.

The PICES 2017 questionnaire, however, contained new questions about asset ages and values, allowing for a more precise estimation of use values. The improved method involves calculating a specific depreciation rate for each household asset using this information on purchase price, asset age, and current value. For the PICES 2017, only observations on items that are nine years old or newer are used for the calculation of depreciation. This is to avoid using prices of goods purchased during or before the period of hyperinflation (2007–08). The median depreciation rate for each asset type is then taken and applied to the estimated current sales price of that asset provided by the household, including for those purchased before 2008. (About 15 percent of assets were bought before 2008).

Three estimation methods were used, each of which handles depreciation slightly differently, following Deaton and Zaidi (2002). The method that uses the depreciation rates computed based on information from owned assets was ultimately adopted. The estimated values of each method showed no correlation to the value using the conventional method applied in Zimbabwe by ZIMSTAT, indicating that the additional information on purchase price, purchase year, and current value improves the valuation of these assets.

## A.3 The recall period for nonfood item purchases

Using a 3-, 6-, or 12-month recall period for the purchase of nonfood items, rather than the 1-month recall as traditionally used in the surveys, likely more accurately estimates household welfare. It was noted that the 1-month recall period may not accurately represent the welfare of the household because many nonfood items are not purchased every month. The PICES 2017 used a recall period of 1 month, but the questionnaire also included recall periods of 3, 6, or 12 months, depending on the good. Unfortunately, about half of the household observations show a lower value for the 3- or 6-month recall compared to the value from the 1-month recall. Thus, the decision was made to use only the 1-month recall. Data from a longer recall period for nonfood items will continue to be collected in the future to obtain quality data.

## A.4 Bulky expenditures

In poverty analysis, consumption expenditures measure welfare, and it is assumed that higher expenditures are associated with higher levels of well-being. However, some expenditures were excluded. These include hospital fees, costs incurred for weddings, gambling expenses, and other lumpy expenditures. For schooling costs, an estimate of the "typical" monthly household expenditure was made, which was not necessarily the actual expenditure during the survey month. This is because certain schooling expenditures act like a durable good—benefits are spread over the entire school term or school year, depending on the type of expenditure. This is important for computing the expenditure aggregate for poverty analysis.

# APPENDIX B
# UPDATED MINIMUM-NEEDS FOOD BASKET

*A new food basket that provides 2,100 calories per day, reflecting Zimbabwean consumption habits of the 10th–50th percentile of consumption per capita, was calculated. The value of these food items forms the food poverty line, also referred to as extreme poverty (Table B.1).*

## TABLE B.1
### Monthly Minimum-Needs Food Basket that Provides 2,100 Calories per Person per Day

| | Share (%) | Expenditures (US$) | Unit Price | Quantity (units) = (2)/(3) | Observed unit | Quantity (Kg) = (4) * (5) | No. of 100gs = 10*(6) | Calories per 100g | Calories per month |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Maize grain (kg) | 21.3 | 5.50 | 6.7 | 0.8 | 10.0 | 8.3 | 82.8 | 357 | 29,570 |
| Pumpkin leaves (bundle) | 12.7 | 3.30 | 1.7 | 2.0 | 1.0 | 2.0 | 19.8 | 41 | 813 |
| Chicken (kg) | 6.2 | 1.60 | 6.0 | 0.3 | 1.0 | 0.3 | 2.7 | 195 | 520 |
| White sugar (kg) | 6.0 | 1.60 | 1.9 | 0.8 | 2.0 | 1.6 | 16.2 | 344 | 5,571 |
| Cooking oil (L) | 5.8 | 1.50 | 3.5 | 0.4 | 2.0 | 0.8 | 8.5 | 875 | 7,435 |
| Rice (kg) | 4.7 | 1.20 | 2.2 | 0.5 | 2.0 | 1.1 | 11.0 | 363 | 3,981 |
| Beef (kg) | 4.2 | 1.10 | 4.6 | 0.2 | 1.0 | 0.2 | 2.4 | 283 | 679 |
| White bread (loaves) | 3.4 | 0.90 | 0.9 | 1.0 | 0.7 | 0.7 | 7.0 | 261 | 1,817 |
| Okra (kg) | 2.7 | 0.70 | 1.9 | 0.4 | 1.0 | 0.4 | 3.7 | 36 | 134 |
| Sweet potatoes (kg) | 2.6 | 0.70 | 0.9 | 0.7 | 2.0 | 1.4 | 14.5 | 113 | 1,627 |
| Beans (kg) | 2.6 | 0.70 | 1.3 | 0.5 | 0.5 | 0.3 | 2.7 | 337 | 902 |
| Flour (wheat) (kg) | 2.6 | 0.70 | 2.1 | 0.3 | 2.0 | 0.6 | 6.3 | 353 | 2,210 |
| Peas (including cow peas) (kg) | 2.5 | 0.60 | 2.2 | 0.3 | 1.0 | 0.3 | 2.9 | 331 | 961 |
| Pumpkins and squash (kg) | 2.4 | 0.60 | 0.9 | 0.7 | 1.0 | 0.7 | 7.4 | 24 | 176 |
| *Nyimo*/*indlubu*/roundnuts (shelled) (kg) | 2.4 | 0.60 | 31.4 | 0.0 | 18.0 | 0.4 | 3.6 | 591 | 2,126 |

**TABLE B.1 (Continued)**
**Monthly Minimum-Needs Food Basket that Provides 2,100 Calories per Person per Day**

| | Share (%) | Expenditures (US$) | Unit Price | Quantity (units) = (2)/(3) | Observed unit | Quantity (Kg) = (4) * (5) | No. of 100gs = 10*(6) | Calories per 100g | Calories per month |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Kapenta/matemba* (small dried fish) (kg) | 2.3 | 0.60 | 2.5 | 0.2 | 1.0 | 0.2 | 2.4 | 269 | 642 |
| Fresh milk (L) | 2.3 | 0.60 | 0.8 | 0.7 | 0.5 | 0.4 | 3.5 | 79 | 277 |
| Tomatoes (kg) | 2.0 | 0.50 | 1.3 | 0.4 | 1.0 | 0.4 | 4.0 | 21 | 84 |
| Fresh/frozen bream (kg) | 1.7 | 0.40 | 3.5 | 0.1 | 0.5 | 0.1 | 0.6 | 94 | 57 |
| Groundnuts (shelled) (kg) | 1.5 | 0.40 | 31.4 | 0.0 | 18.0 | 0.2 | 2.3 | 549 | 1,260 |
| Goat meat (kg) | 1.5 | 0.40 | 5.1 | 0.1 | 1.0 | 0.1 | 0.7 | 190 | 142 |
| Salt (kg) | 1.1 | 0.30 | 1.0 | 0.3 | 2.0 | 0.5 | 5.3 | 0 | 0 |
| Sour milk (L) | 0.8 | 0.20 | 0.8 | 0.3 | 0.5 | 0.1 | 1.4 | 122 | 165 |
| Cabbage (heads) | 0.7 | 0.20 | 1.0 | 0.2 | 1.0 | 0.2 | 1.9 | 26 | 50 |
| Sorghum/*mapfunde/amabele* grain (kg) | 0.7 | 0.20 | 0.7 | 0.3 | 1.0 | 0.3 | 2.7 | 343 | 919 |
| Eggs (units) | 0.7 | 0.20 | 2.0 | 0.1 | 0.6 | 0.1 | 0.5 | 140 | 72 |
| Fruit juices and squash (kg) | 0.6 | 0.10 | 1.3 | 0.1 | 2.0 | 0.2 | 2.4 | 50 | 118.1 |
| Potatoes (kg) | 0.5 | 0.10 | 1.9 | 0.1 | 2.0 | 0.1 | 1.5 | 81 | 117 |
| *Mhunga/inyawuthi* grain (kg) | 0.4 | 0.10 | 1.0 | 0.1 | 1.0 | 0.1 | 1.1 | 349 | 396 |
| Tea (packet) | 0.4 | 0.10 | 2.2 | 0.0 | 0.1 | 0.0 | 0.0 | 4 | 0 |
| Powdered milk (kg) | 0.4 | 0.10 | 3.2 | 0.0 | 0.4 | 0.0 | 0.1 | 376 | 48 |
| Onions (kg) | 0.3 | 0.10 | 1.3 | 0.1 | 1.0 | 0.1 | 0.7 | 41 | 29 |
| | 100.0 | | | | | | | | 62,896 |

Source: Based on the PICES 2017.


Photo: Capture World Studio

# APPENDIX C
# SWIFT CALCULATIONS

## *C.1 The within-survey imputation method of consumption*

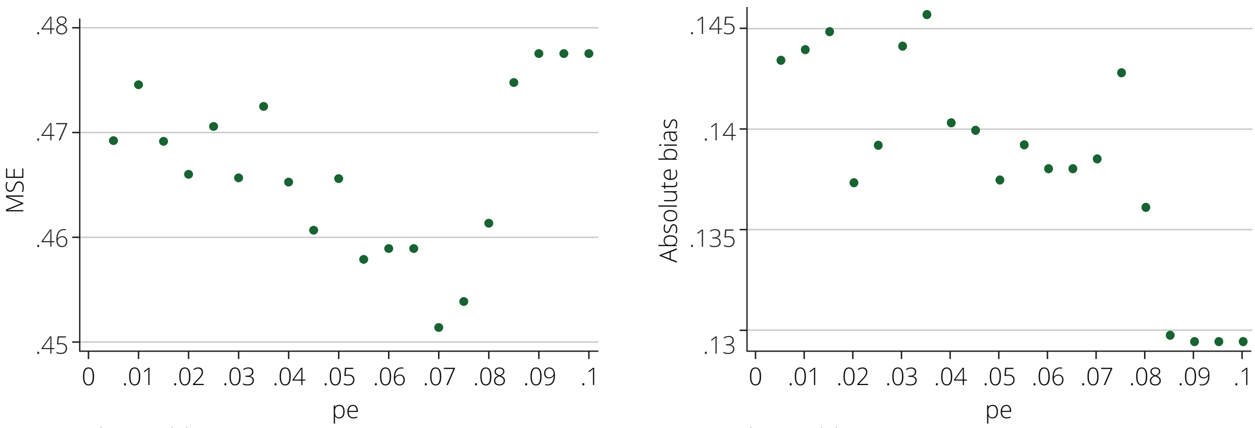
As explained in the main text, consumption data in the Mini-PICES 2019 were gathered from a subsample of 478 households, which included 230 urban households and 248 rural ones. Consumption models were estimated separately from these urban and rural households. The optimal p-values were selected using the MSEs and the absolute bias of the poverty estimate in 10 percent of the randomly selected out-of-sample data for tested p-values from 0.005 to 0.1 (Figures C.1 and C.2). In the end, the p-value 0.035 was selected for both urban and rural models.

The following relationship between household expenditure and nonmonetary indicators was assumed, as in the simplified specification used in Elbers et al. (2003),

$$Y_h = \alpha + X_n\beta + u_h$$

where the dependent variable $y_h$ is log per capita consumption of household $h$, $X_h$ is a vector of household explanatory variables, $\alpha$ is a constant and $\beta$ is a vector of coefficients, and $u_h$ is an error term. First, the parameters ã and $\tilde{\beta}$ are "parametrically" estimated using the OLS regression with the subsample with consumption data. Second, a Monte Carlo simulation is conducted 100 times and applied to the rest of the sample without consumption data. In each of the simulations, the parameters ã and $\tilde{\beta}$ are estimated with the bootstrapped samples from the subsample, and the error term $\widetilde{u_h}$ is drawn from the residuals. The bootstrapping of the error term allows us to simulate a non-normally-distributed

## FIGURE C.1
## Cross Validation Urban Result



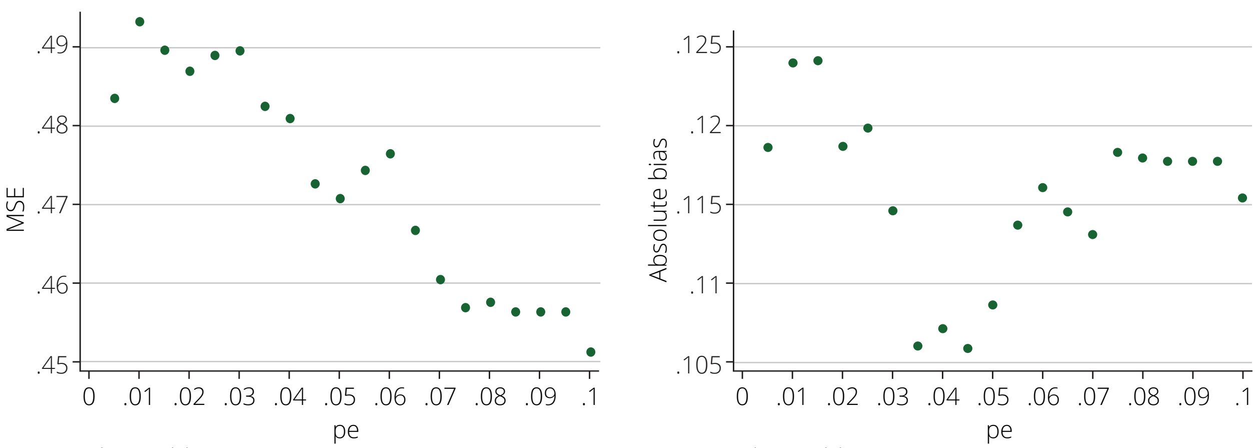

Regress Urban Model

Note: MSE = Mean Square Error

Regress Urban Model

Based on Mini-PiCES 2019

## FIGURE C.2
## Cross Validation Rural Result




Regress Urban Model

Note: MSE = Mean Square Error

Regress Urban Model

Based on Mini-PiCES 2019

error term.[35] In the end, this gives a vector of the predicted (log) consumption for the households without consumption data such that

$$\widetilde{y_h} = \tilde{\alpha} + X_h\tilde{\beta} + \widetilde{u_h}.$$

The poverty estimate or other indicators are calculated each time of the simulation, and the mean of the 100 estimates is used as the final poverty estimate. The variances of the poverty estimate or other indicators are calculated by means of Rubin's formula[36] and Stata's MI estimate command is used.[37] In this step, the actually observed consumption is used for the subsample. The estimated models are presented in Table C.1. The poverty estimates with three poverty lines and standard errors are found in Table C.2.

The cross-validation analysis showed that the normality assumption does not apply. The poverty estimates with a normality assumption using the full subsample data result in a 3.2 and a 5.3 percentage point poverty estimation bias in urban and rural areas, respectively, though it is expected that the bias will not be observed if the normality assumption is correct.[38] Therefore, the team investigated the urban and rural distributions of the collected per capita consumption and concluded that the imputation method without the distributional assumption in the error term should be used.

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[35] This is implemented using the "Bootstrapped at each replicate" in the distribution drawing method option and the "Semi parametric" option for the household effect in the Povmap 2.0 software. More detailed explanation can be found in Nguyen et al. 2018.

[36] Rubin 1987; Schafer 1999.

[37] StataCorp 2019.

[38] If the normal assumption is correct, the distribution of the unexplained consumption or an error term is normally distributed after controlling for possible predictors. The urban and rural distributions of the per capita consumption for the subsample do not look normal, though this is partially due to a small sample size.

## TABLE C.1
## SWIFT Model Results

| Ly | Coef. | Std. Err. | t | P > t | [95% Conf. | Interval] | DRB | All | Description |
|---|---|---|---|---|---|---|---|---|---|
| **Urban model result** | | | | | | | | | |
| Source | SS | | df | MS | | Number of obs | = | 248 | |
| | | | | | | F(25, 222) | = | 13.56 | |
| Model | 77.82421 | | 25 | 3.112968 | | Prob > F | = | 0 | |
| Residual | 50.95079 | | 222 | 0.229508 | | R-squared | = | 0.6043 | |
| | | | | | | Adj R-squared | = | 0.5598 | |
| Total | 128.775 | | 247 | 0.521356 | | Root MSE | = | 0.47907 | |
| elec_cook | 0.276 | 0.098 | 2.83 | 0.005 | 0.084 | 0.468 | 0.794 | 0.821 | Cooking energy= electricity or LPG gas |
| lnroom | 0.224 | 0.073 | 3.07 | 0.002 | 0.080 | 0.367 | 1.009 | 1.159 | Logarithm of number of rooms |
| hdpost | 0.302 | 0.102 | 2.97 | 0.003 | 0.101 | 0.502 | 0.219 | 0.301 | HH head completed education level = tertiary |
| room_md | –0.178 | 0.074 | –2.4 | 0.017 | –0.325 | –0.032 | 3.056 | 3.050 | Median number of rooms by zone |
| mats | –0.379 | 0.174 | –2.18 | 0.031 | –0.723 | –0.036 | 0.018 | 0.018 | Residence in Matabeleland South province |
| bsuite | 0.282 | 0.103 | 2.73 | 0.007 | 0.078 | 0.486 | 0.257 | 0.289 | Own Bedroom suite |
| Car | 0.380 | 0.111 | 3.43 | 0.001 | 0.162 | 0.599 | 0.207 | 0.286 | Own car |
| Hhsize | –0.306 | 0.054 | –5.7 | 0 | –0.412 | –0.200 | 4.594 | 4.863 | Household size |
| hhsize2 | 0.015 | 0.005 | 3 | 0.003 | 0.005 | 0.025 | 24.867 | 27.882 | (Household size)^2 |
| _cons | 6.211 | 0.259 | 23.96 | 0 | 5.700 | 6.722 | | | |
| **Rural model result** | | | | | | | | | |
| Source | SS | | df | MS | | Number of obs | = | 248 | |
| | | | | | | F(10, 237) | = | 22.62 | |
| Model | 62.89079 | | 10 | 6.289079 | | Prob > F | = | 0 | |
| Residual | 65.88421 | | 237 | 0.277992 | | R-squared | = | 0.4884 | |
| | | | | | | Adj R-squared | = | 0.4668 | |
| Total | 128.775 | | 247 | 0.521356 | | Root MSE | = | 0.52725 | |
| hdpost | 0.576 | 0.189 | 3.04 | 0.003 | 0.203 | 0.037 | 0.042 | | HH head completed education level = tertiary |
| water_bhole | 0.246 | 0.073 | 3.35 | 0.001 | 0.101 | 0.637 | 0.601 | | Main source of water for drinking and cooking = borehole/protected well |
| elec_cook | 0.536 | 0.170 | 3.16 | 0.002 | 0.202 | 0.074 | 0.039 | | Cooking energy = electricity or LPG gas |
| hdsecondary | 0.176 | 0.072 | 2.45 | 0.015 | 0.035 | 0.447 | 0.478 | | HH head completed education level = secondary |
| lsuite | 0.455 | 0.147 | 3.11 | 0.002 | 0.167 | 0.094 | 0.093 | | Own lounge suite |
| floor | 0.261 | 0.077 | 3.4 | 0.001 | 0.110 | 0.681 | 0.712 | | Material used for floor = wood/planks, parquet/polished wood, vinyl/asp |
| cattle | 0.194 | 0.076 | 2.55 | 0.012 | 0.044 | 0.531 | 0.562 | | Own cattle |
| hhsize | –0.364 | 0.048 | –7.55 | 0 | –0.460 | 5.426 | 5.545 | | Household size |
| hhsize2 | 0.018 | 0.004 | 4.52 | 0 | 0.010 | 34.666 | 36.096 | | (Household size)^2 |

Source: Based on Mini-PICES 2019.

## TABLE C.2
## Final Poverty Estimates

| Poverty by lower line | | | | | |
|---|---|---|---|---|---|
| **2,201 HHs** | **Mean** | **Std. Err.** | **[95% Conf.** | **Interval]** | **Sample size** |
| National | 0.573 | 0.024 | 0.525 | 0.621 | 2,201 |
| Rural | 0.721 | 0.025 | 0.670 | 0.771 | 1,624 |
| Urban | 0.243 | 0.044 | 0.155 | 0.331 | 577 |
| **478 HHs** | **Mean** | **Std. Err.** | **[95% Conf.** | **Interval]** | **Sample size** |
| National | 0.573 | 0.038 | 0.498 | 0.648 | 478 |
| Rural | 0.733 | 0.048 | 0.639 | 0.827 | 248 |
| Urban | 0.259 | 0.051 | 0.157 | 0.360 | 230 |
| **Poverty by upper line** | | | | | |
| **2,201 HHs** | **Mean** | **Std. Err.** | **[95% Conf.** | **Interval]** | |
| National | 0.717 | 0.021 | 0.676 | 0.758 | |
| Rural | 0.848 | 0.019 | 0.810 | 0.886 | |
| Urban | 0.422 | 0.047 | 0.329 | 0.516 | |
| **478 HHs** | **Mean** | **Std. Err.** | **[95% Conf.** | **Interval]** | |
| National | 0.716 | 0.025 | 0.667 | 0.766 | |
| Rural | 0.843 | 0.029 | 0.786 | 0.900 | |
| Urban | 0.468 | 0.049 | 0.370 | 0.565 | |
| **Poverty by food line** | | | | | |
| **2,201 HHs** | **Mean** | **Std. Err.** | **[95% Conf.** | **Interval]** | |
| National | 0.383 | 0.023 | 0.338 | 0.428 | |
| Rural | 0.509 | 0.027 | 0.455 | 0.563 | |
| Urban | 0.101 | 0.036 | 0.030 | 0.172 | |
| **478 HHs** | **Mean** | **Std. Err.** | **[95% Conf.** | **Interval]** | |
| National | 0.367 | 0.036 | 0.295 | 0.438 | |
| Rural | 0.499 | 0.047 | 0.407 | 0.592 | |
| Urban | 0.106 | 0.048 | 0.011 | 0.201 | |

Source: Based on Mini-PICES 2019
Note: HH = households. Urban/rural provinces are used as strata.

Photo: Capture World Studio

# APPENDIX D
# DETAILS OF THE MICROSIMULATION MODEL FOR ESTIMATING THE IMPACT OF PRICE RISES ON POVERTY

*The microsimulation model used to estimate the impact of the price rises between April–May 2019 and December 2019 on poverty calculated consumer surplus to measure welfare loss. The approach described in Araar and Verme (2016) was followed.*

According to this paper, these are the five most common ways to measure the welfare effects of a price shock: Laspeyres Variation (LV), Equivalent Variation (EV), Consumer Surplus (CS), Compensating Variation (CV), and Paasche Variation (PV), where LV < CV < CS < EV< PV. A rule of thumb is that it does not matter which measure to use if the price shock is small (10 percent or less), or the price shock is moderate (100 percent or less) provided the consumption share is small, because welfare measures converge to approximately the same result. However, if the price shock is large or the consumption share is large, then these measures diverge significantly, and CS and CV measures are preferred. For Zimbabwe, all five welfare measures were tried, and finally it was decided to use the CS measure because it is a median among all measures and takes into account the behavioral response. The CS is calculated using the equation

$$CS = \sum x\Delta p_{1_i}(1+0.5\eta * dp) = \sum exp_{1_i} * dp(1+0.5\eta * dp)$$

where *dp* is the real percentage change of price (such as 342 percent for maize), $\eta$ is own price elasticity of demand, and $exp_{1_i}$ is the expenditure at the old price for item *i*. The elasticity is calculated using a demand function. Following Banks and Lewbel (1997), using monthly price variation in a cross-sectional survey, the PICES 2017 is employed to estimate a quadratic Almost Ideal Demand System demand function, and the Stata codes are from Poi (2012). Here, the PICES 2017 is used instead of the Mini-PICES 2019 to estimate the demand function because PICES 2017 is a much larger survey conducted over a 12-month period, which gives us more variation in price. The budget shares of the consumption items concerned are presented in Table D.1.

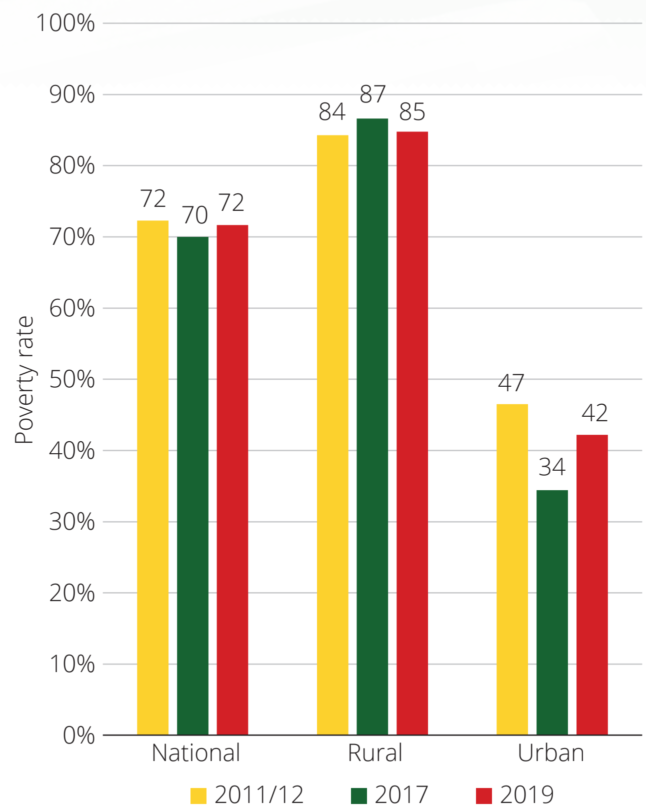
**TABLE D.1**
**Budget Share of Each Consumption Item in the Baseline and Simulation**

| Quintile | Maize (%) | Bread and cereal[a] (%) | Cooking oil (%) | Fuel for personal transport[b] (%) | Other transport (%) | Electricity (%) |
|---|---|---|---|---|---|---|
| **Baseline: April–May 2019 (observed)** | | | | | | |
| Poorest | 8.1 | 6.4 | 5.2 | 0.0 | 0.0 | 1.4 |
| Near poorest | 6.2 | 7.8 | 3.4 | 0.1 | 0.0 | 1.5 |
| Middle | 5.5 | 9.3 | 4.4 | 0.3 | 0.0 | 1.7 |
| Near richest | 3.9 | 10.4 | 3.8 | 0.1 | 0.2 | 1.6 |
| Richest | 2.3 | 8.3 | 2.6 | 4.5 | 2.0 | 1.8 |
| **December 2019 (simulated)** | | | | | | |
| Poorest | 15.1 | 9.3 | 4.7 | 0.0 | 0.0 | 4.9 |
| Near poorest | 11.5 | 11.3 | 3.1 | 0.1 | 0.0 | 5.3 |
| Middle | 10.1 | 13.5 | 3.9 | 0.3 | 0.0 | 6.2 |
| Near richest | 7.2 | 15.1 | 3.4 | 0.1 | 0.1 | 5.6 |
| Richest | 4.2 | 12.0 | 2.4 | 4.5 | 0.5 | 6.5 |

Source: Based on the Mini-PICES 2019 and microsimulations.
Note:
a. Excludes maize
b. Diesel and petrol.

# APPENDIX E
# POVERTY UPDATE BASED ON THE UPPER-BOUND POVERTY LINE

**FIGURE E.1**
**Poverty (based on upper-bound poverty line of US$66.10 per person per day)**




Source: Based on the PICES 2011/12, PICES 2017, and Mini-PICES 2019.

Photo: Arne Hoel/World Bank

# APPENDIX F
# COVERAGE OF ALL SOCIAL PROTECTION PROGRAMS

**TABLE F.1**
**Coverage of all Social Protection Programs**

| Question | Response Rate, 2017 (over no. of households) | Response Rate, 2019 (over no. of DRB households) | Issues/Suggestions |
|---|---|---|---|
| **PICES education section** | | | |
| Q. Who paid (name)'s school fees during the current academic year?<br>1. Parent<br>2. Relative<br>3. BEAM (Basic Education Assistance Module; social welfare)<br>4. STEM (the Science, Technology, Engineering, and Mathematics Scholarship Program)<br>5. Other government assistance<br>6. Nongovernmental organization (NGO)<br>7. Other (specify) | | BEAM<br>16/478 (3.25%) | According to the Ministry of Public Service, Labour and Social Welfare (MPSLSW), no other government program besides BEAM pays for school fees |

*(table continues on next page)*

## TABLE F.1 (Continued)
## Coverage of all Social Protection Programs

| Question | Response Rate, 2017 (over no. of households) | Response Rate, 2019 (over no. of DRB households) | Issues/Suggestions |
|---|---|---|---|
| Q. How much school fees assistance was received from BEAM, STEM, or from other government assistance | 1,131/30,158 (3.80%) | Not collected | What is captured in the transfer section is just a smaller subgroup of what is collected in this Education Module question (1,131 positive observations compared to 114 observations in the transfer module in 2017) |
| Q. Who granted the need-based school fee and levy waivers?<br>1. Government (BEAM, STEM, and other government assistance)<br>2. Private schools<br>3. NGO<br>4. Other (specify) | BEAM 963/30,158 (3.23%) for item 1 | BEAM 20/478 (4.18%) | Not clear what is the difference between this question and the second question above on school fees; if the same, consider consolidating into one question; the overlap between these two variables is more than 50% |
| **Transfers and other benefits received** | | | |
| BEAM Primary | 76/30,158 (0.25%) | No observations | Values for this program are asked in the Education Module; it is better to use a term or annual period rather than in the last month |
| BEAM Secondary | 38/30,158 (0.13%) | No observations | Same as above |
| Harmonized Social Cash Transfers (HSCT) | 187/30,158 (0.62%) | No observations | A last-month recall period does not work because transfers are bimonthly; arrears is also common |
| Public Assistance | 85/30,158 (0.28%) | No observations | This program is small; consider asking it together with the HSCT program |
| Assisted Medical Treatment Order | 11/30,158 (0.04%) | No observations | A last-month recall period does not work because transfers are not monthly but on a case-by-case basis (depending on the illness); transfers are made directly to hospitals |
| Food Mitigation Program | 528/30,158 (1.75%) | No observations | The exact name is "Food Deficit Mitigation Program," but people may not know this name; a last-month recall period does not work because the program is only active from September to March; this is the reason why information was not recorded in the PICES 2011 |
| Smallholder Input Support Scheme | 111/30,158 (0.36%) | No observations | This program is supposed to have large coverage, but no information was collected in 2019 and very few in 2017; consider exploring why information was not captured Maybe people do not recognize the name, so consider having a more generic name such as "Free Seeds and Fertilizer from Government"; also check the frequency of the transfers in case a last-month recall period is not adequate |

**TABLE F.1 (Continued)**
**Coverage of all Social Protection Programs**

| Question | Response Rate, 2017 (over no. of households) | Response Rate, 2019 (over no. of DRB households) | Issues/Suggestions |
|---|---|---|---|
| Support to Children in Difficult Circumstances | 20/30,158 (0.07%) | No observations | Consider a more descriptive name regarding this benefit (it is a cash transfer?); double-check what is the periodicity of this transfer |
| Maintenance of Disabled Persons | 4/30,158 (0.01%) | No observations | This program includes grants to institutions that care for old people; consider rewording to something like "Social Assistance for Disabled Persons" or "Cash Assistance for Disabled Persons" if all the assistance is in cash |
| Maintenance of Older Persons | 41/ 30,158 (0.14%) | 1/478 (0.2%) | These are grants to institutions and should be removed from the questionnaire |
| Community Recovery and Rehabilitation Program | 2/30,158 (0.01%) | 3/478 (0.6%) | Staff from the MPSLSW did not know about this program because they do not manage it; if it is public works, then it should be part of the public works subsection; consider giving a more descriptive name, in case people cannot place this program by name |
| Street Children | 4/30,158 (0.01%) | No observations | These are grants for institutions that assist street children; the program should be removed from the questionnaire |
| Public Works Programme: Food for Work | 538/30,158 (1.78%) | 12/478 (2.5%) | Consider distinguishing between government- and donor-funded programs, but only in case this is possible; would people know the difference? |
| Public Works Programme: Cash for Work | 130/30,158 (0.43%) | 46/478 (9.6%) | Same as above |
| Other social welfare benefits-Health in cash and in kind | 41/30,158 (0.14%) | 4/478 (0.8%) | Consider describing this, otherwise it is too general |
| Other social welfare benefits-Education in cash and in kind | 16/30,158 (0.05%) | 11/478 (2.3%) | Consider describing this, otherwise it is too general (is it school feeding?); if so, list school feeding separately |
| Other social welfare benefits-Food (disaster relief) estimate value of food | 554/30,158 (1.83%) | 39/478 (8.2%) | Can people distinguish between this and the Food Deficit Mitigation Program? |
| Early retirement package, public | 8/30,158 (0.03%) | 6/30,158 (1.23%) | Only a few observations are recorded; consider merging with pension benefits, e.g., "Pension benefits and early retirement" |
| Early retirement package, private | 7/30,158 (0.02%) | 1/478 (0.21%) | Same as above |
| Pension benefits, public | 373/30,158 (1.24%) | 18/478 (3.77%) | Same as above |

*(table continues on next page)*

**TABLE F.1 (Continued)**
**Coverage of all Social Protection Programs**

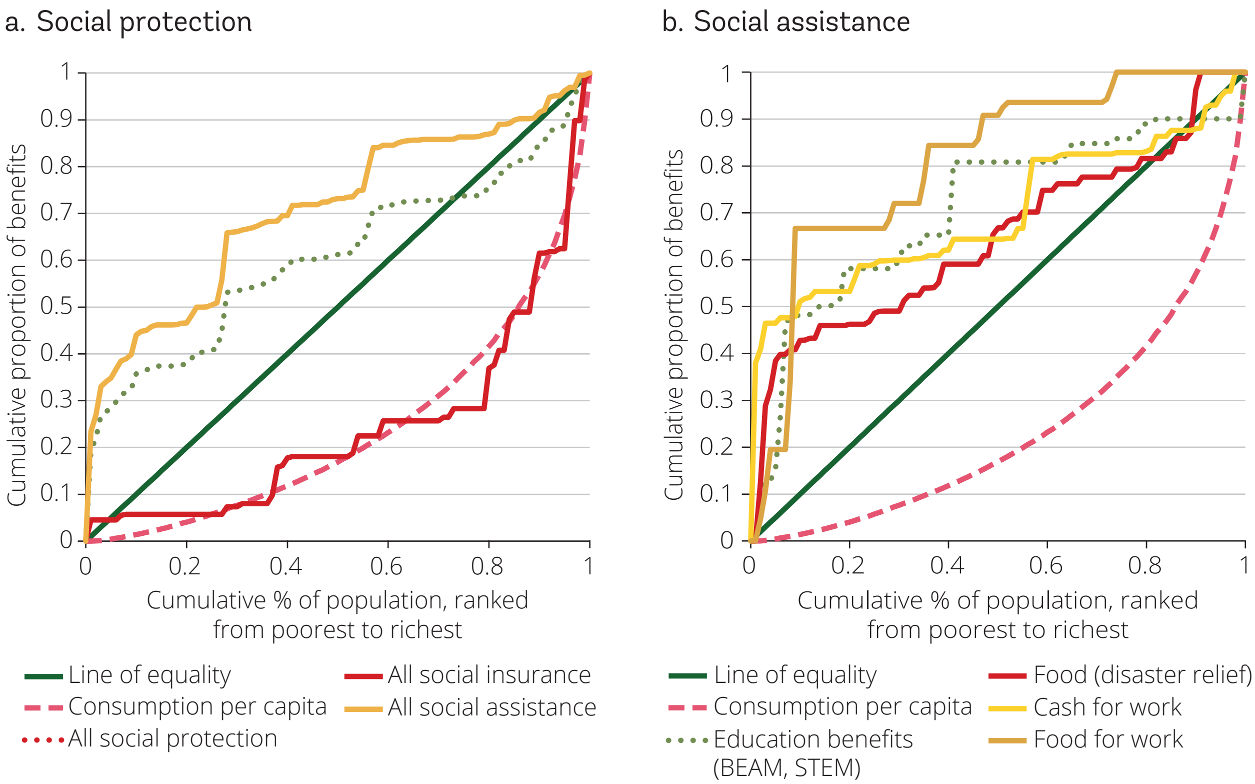
| Question | Response Rate, 2017 (over no. of households) | Response Rate, 2019 (over no. of DRB households) | Issues/Suggestions |
|---|---|---|---|
| Pension benefits, private | 138/30,158 (0.46%) | 2/478 (0.42%) | Same as above |
| Other current transfers (e.g., for disasters), public | 48/30,158 (0.16%) | 3/478 (0.6%) | Would this be cash or in-kind transfers? For example? |
| Other current transfers (e.g., for disasters), private | 37/30,158 (0.12%) | No observations | Same as above |
| Social security benefits (e.g., National Social Security Authority) | 626/30,158 (2.07%) | 18/478 (3.8%) | If these are benefits such as pensions, consider merging with the pension programs above |
| Remittances (transfers received in cash), domestic | 3,919/30,158 (13%) | 62/478 (12.97%) | |
| Remittances (transfers received in cash), abroad | 1,041/30,158 (3.45%) | 68/478 (14.2%) | This question is also asked in the International Migration Module; consider only asking once; also consider asking for the value of international transfers in kind |
| Transfers received in kind (e.g., *lobola*) | 3,946/30,158 (13.08%) | 8/478 (1.67%) | Specify if these are domestic cash transfers only or if they include transfers from abroad |

Source: Authors' compilation based on the PICES 2017 and Mini-PICES 2019.
Note: DRB = daily record book.

# APPENDIX G
# THE INCIDENCE CURVES FOR SOCIAL PROTECTION PROGRAMS

*The incidence curves of social protection programs confirm that the poorest receive a disproportionally large share of social assistance benefits. Social insurance, on the other hand, follows a similar trend as the distribution of per capita consumption, which is regressive, with richer population groups receiving a higher proportion of benefits. The incidence curves for social security programs are therefore below the line of equality (see Figure G.1).*

**FIGURE G.1**
**Incidence Curves for Social Protection Programs**




Source: Based on the Mini-PICES 2019.
Note: BEAM = Basic Education Assistance Module; STEM = Science, Technology, Engineering, and Mathematics Scholarship Program.

# APPENDIX H
# ESTIMATED PRICE ELASTICITIES OF DEMAND

*Estimated price elasticities of demand for maize as well as bread and other cereals are low, but they are relatively high for transport fuel and transport fares (Table H.1). This suggests that a steep increase in maize and bread and cereal prices will have a limited impact on the quantity bought by consumers. If the price of maize increases by 100 percent, the demand will drop by only 17 percent. In contrast, a price increase for transport fuel and transport fares leads to a relatively high drop in demand for these goods and services. If prices increase by 100 percent, the demand will drop by 70 percent (Table H.1).*

**TABLE H.1**
**Price Elasticities of Demand for Selected Goods**

| Consumption item | Price elasticity | Drop in demand if price rises by 100% |
|---|---|---|
| Maize (grain and meal) | –0.17 | –17% |
| Bread and other cereals | –0.2 | –20% |
| Cooking oil | –0.4 | –40% |
| Transport fuel | –0.7 | –70% |
| Transport fares | –0.6 | –60% |
| Electricity | –0.08 | –8% |

Source: Almost Ideal Demand System, estimated using the PICES 2017 data, except for electricity, where the source was Hope and Singh (1999).


Photo: Arne Hoel/World Bank

# APPENDIX I
# MINI-PICES 2019 SAMPLE DESIGN

## *I.1 Sample design*

The Mini-PICES 2019 sample is a subsample of the PICES 2017 for households covered in February–June 2017. The sample selection methodology for the Mini-PICES was based on a two-stage stratified sample design. The procedures used for each sampling stage are described separately here.

### I.1.1 First-stage selection of enumeration areas

At the first sampling stage, the sample enumeration areas (EAs) were selected within each stratum (administrative district) systematically with probability proportional to size from the ordered list of EAs. The measure of size for each EA was based on the total number of households identified in the 2012 population census sampling frame. The EAs for the Mini-PICES were selected using random systematic sampling.

### I.1.2 Second-stage selection of sample households within a sample EA

At the second sampling stage, a random systematic sample of 14 households were selected with equal probability from the listing for each sample EA during the PICES 2017. For the Mini-PICES 2019 a systematic subsample of 5 households was selected from the 14 households in the Bulawayo and Harare provinces, and 4 households were selected per EA in the urban strata for the other provinces. Two households were sampled per EA in Manicaland, Mashonaland East, Mashonaland West, Matabeleland North, Matebeleland South, Midlands, and Masvingo provinces from the rural strata. In Mashonaland Central province, 3 households were selected per EA in the rural strata.

## I.2 Target population

The sample is representative of all the populations in Zimbabwe living in private households for those households covered. The population living in institutions, such as military barracks, prisons, and hospitals, was excluded from the sampling frame because they constituted less than 1 percent of the population of Zimbabwe.

## I.3 Sampling frame

The sampling frame for the Mini-PICES 2019 was based on the complete frame of EAs from Zimbabwe's 2012 census and those EAs covered in the February–June 2017 PICES. The sample used for most of the national household surveys, known as the Zimbabwe master sample, was based on the 2012 census frame. A total of 210 EAs were selected from this new frame. Seventy enumeration areas were selected from the urban strata, and 140 enumeration areas were selected from the rural areas.

## I.4 Sample size and allocation for the Mini-PICES 2019

The sample size for a particular survey is determined by the accuracy required for the survey estimates for each domain as well as by the resource and operational constraints. It is therefore important that the overall sample size be manageable for quality and operational control purposes. The initial budget was estimated based on a maximum sample size of about 3,000 households. In the case of the largest administrative districts of Harare and Bulawayo, which are also individual provinces, oversampling of households was done. Table I.1 shows the final sample allocation per province by rural/urban strata.

## TABLE I.1
## Distribution of Final Sample of EAs for the PICES by Province and Rural/Urban Strata

| Province | Number of rural EAs | Number of urban EAs | Total number of EAs | Number of enumerators | Number of team leaders | Total |
|---|---|---|---|---|---|---|
| Bulawayo | 0 | 12 | 12 | 6 | 1 | 7 |
| Manicaland | 16 | 4 | 20 | 9 | 1 | 10 |
| Mashonaland Central | 20 | 1 | 21 | 11 | 1 | 12 |
| Mashonaland East | 21 | 7 | 28 | 9 | 1 | 10 |
| Mashonaland  West | 14 | 10 | 24 | 9 | 1 | 10 |
| Matabeleland North | 18 | 6 | 24 | 10 | 1 | 11 |
| Matabeleland South | 16 | 5 | 21 | 7 | 1 | 8 |
| Midlands | 17 | 10 | 27 | 10 | 1 | 11 |
| Masvingo | 17 | 4 | 21 | 10 | 1 | 11 |
| Harare | 1 | 11 | 12 | 9 | 1 | 10 |
| **TOTAL** | **140** | **70** | **210** | **90** | **10** | **100** |

N.B. Mashonaland Central had only one urban EA which was selected and 20 rural EAs.

## TABLE I.2
## Distribution of Final Sample of Households for the Mini-PICES 2019 by Province and Rural/Urban Strata

| Province | Number of DRB households selected per EA in urban areas | Total number of DRB households selected in urban areas | Number of DRB households selected per EA in rural areas | Total number of DRB households selected in rural areas | Total number of households (DRB and nonDRB) |
|---|---|---|---|---|---|
| Bulawayo | 5 | 60 | 2 | 0 | 168 |
| Manicaland | 4 | 16 | 2 | 32 | 280 |
| Mash. Central | 4 | 4 | 3 | 60 | 294 |
| Mashonaland East | 4 | 28 | 2 | 42 | 392 |
| Mash. West | 4 | 40 | 2 | 28 | 336 |
| Mat. North | 4 | 24 | 2 | 36 | 336 |
| Mat. South | 4 | 20 | 2 | 32 | 294 |
| Midlands | 4 | 40 | 2 | 34 | 378 |
| Masvingo | 4 | 16 | 2 | 34 | 294 |
| Harare | 5 | 55 | 2 | 2 | 168 |
| **TOTAL** | | **303** | | **300** | **2940** |

Note: DRB households are households from which consumption data were collected (using daily record books).
All households that responded in each EA in PICES 2017 were enumerated.


Photo: Arne Hoel/World Bank

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