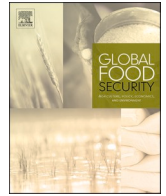




Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.



COVID-19's impacts on incomes and food consumption in urban and rural areas are surprisingly similar: Evidence from five African countries

Mywish K. Maredia^{a,*}, Adeola Adenikinju^b, Ben Belton^{a,c}, Antony Chapoto^d,
Ndèye Fatou Faye^e, Saweda Liverpool-Tasie^a, John Olwande^f, Thomas Reardon^a,
Veronique Theriault^a, David Tschirley^a

^a Michigan State University, USA

^b Centre for Petroleum, Energy Economics and Law and Dept. of Economics, University of Ibadan, Nigeria

^c The World Fish Center, Malaysia

^d Indaba Agricultural Policy Research Institute, Zambia

^e BAME/ISRA, Senegal

^f Tegemeo Institute of Agricultural Policy and Development, Egerton University, Kenya

ARTICLE INFO

JEL classification:

D12
D31
G01
O12
Q18

Keywords:

COVID-19
Income effects
Poverty
Food consumption
Food security
Africa

ABSTRACT

African governments imposed mobility restrictions to suppress the spread of COVID-19. Many observers feared these measures would dramatically decrease incomes and increase food insecurity and anticipated that urban households would be much more impacted than rural ones. We use rural and urban survey data from 4000 households across five African countries to assess the pandemic's effect on incomes and food consumption. We find that a large share of the population saw incomes drop between March and July 2020. But these decreases were 43–63% smaller than predictions and early estimates, and highly correlated with the severity of restrictions. The income and food consumption impacts of the COVID-19 shock were widespread over both rural and urban areas. Policy making during a pandemic should recognize that restrictive measures will affect rural and urban, farming and non-farming, and richer and poorer households.

1. Introduction

The COVID-19 pandemic has gripped the world's attention since March 2020. To suppress the spread of the virus, governments swiftly introduced containment measures including lockdowns and curfews (Africa CDC, 2020). These restrictions on mobility had economic costs, constraining workers from going to their jobs, consumers from visiting markets, and truckers and traders from moving food and inputs. Early in the pandemic, researchers and international organizations anticipated that these constraints would sharply reduce economic activity, and projected large increases in poverty and food insecurity in developing countries (Laborde et al., 2020a; Lakner et al., 2020; Mahler et al., 2020a; Summer et al., 2020; World Bank, 2020). Model-based simulations projected that the incidence of extreme poverty would rise 15–24%

from pre-COVID levels (Laborde et al., 2020a, 2020b; Lakner et al., 2020; Mahler et al., 2020a; World Bank, 2020). Most of these increases were predicted to take place in sub-Saharan Africa (where poverty was predicted to rise 23%) and South Asia (15%) (Laborde et al., 2020a; Mahler et al., 2020b). Country level predictions mirrored global projections—e.g., a 30–40% decline in wage income in South Africa (Arndt et al., 2020), and declines in household income of 33% in Nigeria (Andam et al., 2020).

Moreover, and of special importance to this paper, all models predicted the economic effect to be much worse in urban areas. For instance, in Sub-Saharan Africa, it was projected that numbers of poor people would increase by 15% in rural areas and 44% in urban areas (Laborde et al., 2020a). More urban workers were also expected to be put at risk of severe food deprivation compared to rural workers

* Corresponding author. Department of Agricultural, Food, and Resource Economics, Michigan State University, Justin S. Morrill Hall of Agriculture, 446 W. Circle Drive, Room 216 C, East Lansing, MI, 48824, USA.

E-mail address: maredia@msu.edu (M.K. Maredia).

<https://doi.org/10.1016/j.gfs.2022.100633>

Received 9 May 2021; Received in revised form 7 February 2022; Accepted 21 March 2022

Available online 30 March 2022

2211-9124/© 2022 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

(Teachout and Zipfel 2020). Higher urban impacts were projected because restrictions were expected to be implemented more stringently in urban areas. Rural areas were expected to be partially shielded from the restrictions because they were considered to be only partially integrated with urban areas and their markets, and because of the related notion that most rural residents were self-employed in subsistence farming and thus buffered against the income shock of COVID-19 containment policies (Teachout and Zipfel 2020).

Ex post analysis has not yet been undertaken at a nationally representative scale for multiple countries. Most studies have focused on small areas (cities, states, regions), used different sampling methods over countries, making comparison difficult, or used sampling methods that were not fully representative, such as snowballing or sub-samples drawn from past surveys (e.g., Ali et al., 2020; Ceballos et al., 2020; Gaitán-Rossi et al., 2021; Hamadani et al., 2020; Hirvonen et al., 2020; Janssens et al., 2020; Kansime et al., 2021; Middendorf et al., 2021; Rozelle et al., 2020). Some studies were based on large samples, such as Egger et al. (2021) using 16 samples of over 30,000 households from nine countries in Africa, Asia, and Latin America, but none of their samples is nationally representative. Moreover, most studies focused on the period April–May 2020, when countries were still in the first wave of stringency measures.

Our study contributes to the understanding of COVID-19 effects in three ways. First, we extend the period of analysis and assess change in income from March to July 2020 (i.e., four months into the crisis and towards the end of the first wave of curfew/lockdown measures), and indicators of food consumption during August–October 2020 (i.e., six months into the crisis when most countries had lifted lockdown measures). Second, we used consistent sampling and survey methods over five countries, allowing systematic comparison. Third, our sample is large (4000 households) and representative at national and rural/urban levels. Due to COVID-19 restrictions, we used a cell phone survey like most other surveys implemented during the pandemic. We focus on Kenya, Mali, Nigeria, Senegal, and Zambia, which are diverse in size, extent of economic transformation, agricultural season with respect to the reporting period, and policy responses to the COVID crisis.

The timing, country selection, and sample design of this study allow us to address three research questions that other studies have not been able to address. After each question we preview the main finding. (1) Was the impact of the restrictions accompanying the pandemic as severe as expected? We found that the impact, while large and meaningful for the many poor households that were affected, was well below the predicted impact in four of the five countries. (2) Were the impacts mainly in urban areas, sparing rural areas, as had been widely expected? We found that income effects in rural areas were similar to those in urban areas in three of the five countries. The two countries with deeper income effects in urban areas were Kenya and Nigeria, both of which had imposed more stringent COVID restrictions. Food consumption effects were, however, very similar in rural and urban areas across all countries. (3) Did the impacts differ a lot over African countries, perhaps expected given the heterogeneity of the countries in our sample? We found that effects on income were highly correlated with the severity of stringency measures; but effects on food consumption were surprisingly similar over the very different countries.

The remainder of this paper is organized as follows. The next section describes methods and data sources, followed by a discussion of our empirical strategy. In section 4, we give a brief overview of the COVID situation, government responses, and self-reported exposure to lockdowns to understand the level and type of shocks experienced across the five countries. In section 5, we present the results followed by a discussion of insights, implications, and concluding remarks.

2. Data and method

2.1. Survey and sampling method

We rely on data from surveys conducted in Kenya, Zambia, Mali, Nigeria, and Senegal from September 18 to November 22, 2020 with different start and end dates across the countries. The surveys were conducted by GeoPoll, a survey platform used by Mobile Accord, Inc., a company that specializes in global survey research via mobile phones.

Respondents were selected by simple random sampling (SRS) from GeoPoll's verified list of mobile subscribers in each country. This list was generated using the Random Digit Dialing (RDD) method to ensure randomization (and representativeness) of the sample. Details are in supplementary materials S1.

In each country, the survey was conducted with 800 respondents stratified equally across rural and urban areas. This sample size, based on SRS, implies a 3.5% (4.6%) margin of error and a 95% (99%) confidence level. The sample size of 400 in each of the rural and urban areas allows an estimate of effect size with 4.9% (6.5%) margin of error and a 95% (99%) confidence level.

2.2. Data representativeness

We believe our data are representative for two reasons. First, mobile penetration in the focus countries is high, especially among adults targeted by our survey. National mobile phone connection rates range from 83% in Nigeria to 109% in Senegal (DATAREPORTAL, 2020). This percentage can exceed 100% due to individual use of multiple connections. In sub-Saharan Africa, there are 0.58 unique mobile users for every mobile connection (GSMA, 2020). Applying this to the mobile connection rates in our study countries gives an estimated national percentage of unique mobile users ranging from 48% in Nigeria to 63% in Senegal. However, our sampling frame consists of adults above 18 years of age who have higher access to mobile phones than those younger than 18. Thus, the penetration rates among our sampling frame are likely to be higher than the population level statistic (likely to be more than 90%). In fact, according to DATAREPORTAL 98% of the adult population (16 years and above) in Nigeria and 96% in Kenya had access to mobile phones based on a survey conducted in 2018–2019.

Second, the SRS method in principle generates an equal probability of surveying all the adult mobile phone users from any part of the country, making the sample highly representative of the population. In practice, several factors can introduce biases. For example, although each mobile user in the country has equal probability of being selected, biases can enter if the call is unanswered, disconnected, or terminated early by respondents, and if these events are correlated with respondents' location (rural, more remote) or individual characteristics (e.g., age, gender, education, occupation, etc.) (Alvi et al., 2020) (see S1 for a report on attempted calls and outcomes for each country). Additionally, though a high percentage of the adult population has access to a cellphone, it is not 100%. Some segments of the population (e.g., women, poor, people in remote areas) are less likely to have mobile phones, which can also lead to sample bias.

We used two approaches to minimize these biases. First, within rural and urban areas, respondents were distributed across all administrative level 1 units (e.g., counties in Kenya, provinces in Zambia, states in Nigeria) and sampled by probabilities proportional to population of those units. Second, using census or prior nationally representative survey data, we applied sample weights to adjust the rural/urban split, household size, gender of household head, and education of household head—all factors that are highly correlated with the socioeconomic status of households. Throughout the paper, results are weighted based on these adjustment factors to make them representative of national population characteristics. In Supplementary Materials S4, we provide a comparison of our study sample characteristics with population level statistics to support this claim of data representativeness.

2.3. Outcome measures

Phone surveys restrict the type of data one can collect due to limited respondent patience, making it infeasible to collect detailed expenditure and consumption data. Hence, many COVID-era phone surveys have relied on perception-based assessments of degree of changes in income. Differences in subjective interpretation of such questions by respondents may give rise to misleading understandings of income shocks (Hirvonen et al., 2021). We rely on relatively coarse measures of income based on quantitative data which are less vulnerable to this criticism. Our income measure is based on direct questions about households' total monthly income in March 2020, before the COVID crisis began in Africa, and July 2020 (four months into the COVID crisis) with seven options to choose from based on income brackets that were customized for each country, and an option for 'don't know/refused.'

Based on the income category selected, total household income is calculated at three nodes of each income bracket – the upper, lower, and mid-point. These total household income estimates per month were divided by the number of household members and multiplied by (12/365) to get the corresponding per day per capita income at the three nodes. Estimated incomes were converted using the country-specific purchasing power parity dollar (PPP\$) exchange rate for 2018. All incomes reported are mid-point estimates of the income brackets. For robustness, we also present the main results based on the lower and upper end of the income brackets as noted in the Results section. To account for inflation, the reported incomes for July are adjusted using country-specific consumer price indices with March 2020 as the base month.

Three measures of food consumption are used to qualitatively assess directions of change in quantity, quality, and food insecurity. The measure of food insecurity is based on whether any member of the household "skipped meals because of lack of food." The reference period is the past month, and the direction of change is relative to the same time last year. The food insecurity vulnerability indicator is based on the period over which a household believes it can meet its food consumption needs with available income, savings, or own production.

We use a three-month recall period for questions on receipt of food or cash assistance from religious organizations, and food assistance, cash transfers, unemployment benefits, loans, subsidies, tax cuts or other types of assistance from the government.

The outcome reporting period (i.e., July) in Kenya, Mali, Nigeria, and Senegal, occurred during the lean season, but in Zambia it occurred in the post-lean period. Therefore, reported changes in income may reflect expected seasonal changes, rather than the effects of the pandemic. This concern does not apply for food consumption because we referenced the same time last year in our questions specifically to control for seasonal effects.

Since we do not have estimates of the incomes of our sampled households for July 2019, our estimates compare July 2020 with March 2020. We consider the estimated effects (if negative) to be upper bounds (in absolute terms) in Kenya, Mali, Nigeria, and Senegal, and lower bounds in Zambia. However, we expect the seasonal effects to be more pronounced in rural areas and among households that rely on farm income. We therefore examine heterogeneity of income effects by these two categories of households to mitigate this concern.

Despite the limitations of phone survey data, this study provides some of the most systematic and representative analysis of the effects of COVID-19 to date across five countries in sub-Saharan Africa, which together represent about 25% of the population in the region.

2.4. Sample characteristics

Respondent and household demographic characteristics, and level and sources of income in March 2020 (i.e., pre-COVID) are presented in Table 1. Sources of income by rural and urban households are presented in supplementary material S2. Variability in household demographics

Table 1

Respondent and household characteristics of study sample.

	Kenya	Mali	Nigeria	Senegal	Zambia
Number of households	800	800	800	800	800
1 = Resides in urban area	0.31	0.43	0.51	0.48	0.44
Respondent age	37.71	35.97	31.76	40.34	35.62
Gender of Respondent (1 = male)	0.58	0.75	0.64	0.57	0.66
Respondent education (# of years)	9.30	4.81	10.99	5.58	8.11
Household size	4.34	6.07	5.71	9.63	5.41
1 = Respondent is the household head	0.82	0.69	0.55	0.47	0.79
Age of household head	41.28	40.19	42.58	48.91	38.97
Gender of household head (1 = male)	0.64	0.87	0.81	0.70	0.73
Education of household head (# of years)	8.68	2.85	7.95	3.17	7.74
Income and sources of livelihood household had in March 2020 (pre-COVID)					
Per capita per day income (PPP\$)	4.04	3.43	3.81	4.37	3.66
1 = Per day per capita income is < PPP\$1.00	0.27	0.24	0.15	0.09	0.26
1 = Per day per capita income is < PPP\$1.90	0.52	0.41	0.40	0.34	0.51
1 = Per day per capita income is < PPP\$3.20	0.65	0.61	0.55	0.53	0.70
Number of income sources	1.97	2.96	2.14	4.02	2.70
1 = HH had income from agriculture (on-farm) sector	0.38	0.50	0.43	0.49	0.52
1 = HH had income from post farmgate sector	0.36	0.52	0.41	0.72	0.45
1 = HH had income from non-agriculture sector	0.37	0.60	0.43	0.79	0.44
1 = HH had income from professional employment	0.14	0.24	0.28	0.43	0.22
1 = HH had income from other sources (incl. remittances)	0.26	0.45	0.20	0.43	0.41

Notes: Means are sample weighted to adjust for following population level characteristics—rural/urban split, household size, household head's education and gender. Number of observations for each country is 800, except for per capita per day income variables, which are based on N = 724 (Kenya), 561 (Mali), 708 (Nigeria), 716 (Senegal), and 666 (Zambia). Less than 800 observations for the per capita income variable reflect missing data due to 'refused/don't know' responses to the income question. For all income related variables, weights are adjusted for the missing data.

Source: Phone surveys (September–November 2020)

across the countries is consistent with population characteristics of these countries. Household size is much larger, formal education of the household head is lower, and the age of the household head is higher in Mali and Senegal compared to other countries (Table 1). On average, households reported two sources of income in Kenya, two-three in Mali, Nigeria and Zambia, and four in Senegal. Relative importance of farm and non-farm sources of income varies across countries. But an important point to note is that both rural and urban households depend on income from diverse sources (supplementary material S2). Reported average per capita per day income in March 2020 in PPP\$ (henceforth referred to simply as \$) was \$3.43 in Kenya, \$3.66 in Zambia, \$3.81 in Nigeria, \$4.04 in Kenya, and \$4.37 in Senegal. We acknowledge that our income measure is different from the expenditure-based measure typically used in the development literature to assess the economic and poverty status of households, and is subject to well-known limitations (e.g., Deaton, 1997). However, our common method across all countries makes our cross-country estimates comparable.

3. COVID shocks in the study countries

Supplementary material S3 provides information on the spread of COVID-19 and government restrictions in each study country. From July to November 2020 the recall period, cases were rising rapidly in Kenya

and Zambia and growing steadily in the other countries. By the end of September 2020, the number of cases per million in Kenya had surpassed other countries in our sample and was increasing at an accelerated rate. When the survey ended in November, the cumulative cases per million ranged from around 1600 in Kenya, to 1000 in Zambia, 800 in Senegal, 330 in Nigeria, and 280 in Mali. But these may be underestimates and not comparable across countries due to low and varying testing capacities and reporting.

Although infections grew at varying rates and the numbers were still low in the early phase of the pandemic, government responses were swift. By the end of March, Kenya, Nigeria, Senegal, and Mali, and by the end of April, Zambia, had implemented lockdowns and/or curfews. These included city-wide, state-wide, or nation-wide restrictions on the operation of bars, restaurants, and informal markets, restrictions on international travel, movement of people, public gatherings, closing of schools and public transport, and stay-at-home requirements. By the end of March 2020 most countries had also imposed travel bans, instituted mandatory quarantines for travelers, and closed their borders, allowing only cargo, freight, and the expatriation of foreign nationals.

These restrictions are summarized in a ‘Stringency Index’ (Oxford, 2021). Changes in this index from January–November 2020 are depicted in S3 Panel B and show the heterogeneity in severity and duration of restrictive measures across our study countries. By the time the survey was implemented, most countries had relaxed some of the early restrictions (March to May 2020). Our recall period comes after people were exposed to at least three to four months of peak levels of government restrictions. These peak levels varied across countries, with Kenya and Nigeria imposing the most prolonged period of restrictive policies, followed by Senegal, Mali, and Zambia.

Table 2 shows self-reported exposure to lockdowns and stay-at-home restrictions. Most households reported that at least one person in the household had done stay-at-home since the start of the pandemic. This ranged from 76% in Mali to 96% in Nigeria. This micro-level shock (i.e., a shock specific to a household) was much higher than the reported meso-level shock of total or partial lockdowns (i.e., shocks that all households in a community were subject to), suggesting that either individuals were modifying their behavior voluntarily and were staying home due to health concerns or that other measures were in place that restricted their mobility. The share of households experiencing total or partial lockdown was highest in Nigeria (80%) and lowest in Zambia (40%).

4. Empirical strategy

To estimate the income effect of the COVID shock, we used panel data methods to control for potentially endogenous unobservable factors. We estimated a household fixed effects model of the outcome indicators regressed on the time variable. The following Model was estimated for each country.

$$y_{it} = \alpha + \beta T + v_i + \varepsilon_{it} \tag{1}$$

where *i* and *t* denote household and time period, *y* denotes an outcome of

Table 2
Self-reported meso- and micro-level shocks experienced by households.

	Kenya	Mali	Nigeria	Senegal	Zambia
Number of households	800	800	800	800	800
Share of households with at least one person who has done stay-at-home	0.89	0.76	0.96	0.78	0.83
Share of households who have ever experienced COVID related total or partial lockdown in the area where they live					
Yes, total lockdown	0.20	0.17	0.54	0.02	0.06
Yes, partial lockdown	0.36	0.31	0.26	0.61	0.34
No lockdown	0.44	0.53	0.20	0.37	0.60

Source: Phone surveys (September–November 2020)

interest, *T* is the dummy variable for months (0 = March; 1 = July), parameter *v_i* is the household effect, and *ε* is the idiosyncratic error. Standard errors are clustered at the unit of panel data (i.e., household level). The coefficient of interest is *β*, which estimates the effect of COVID-related macro-, meso-, and micro-level shocks that occurred between March and July. We consider pandemic shock and ensuing government responses that impacted everyone in the country (e.g., closure of border for trade and travel) as macro-level shocks, those localized in specific geographies or communities as meso-level shocks (e.g., lock-downs in certain cities or counties), and those experienced by individuals and households as micro-level shocks (e.g., job loss, COVID infection). As noted above, July falls in the lean season in Kenya, Mali, Nigeria, and Senegal, and in the post-lean season in Zambia. Thus, the month coefficient may be picking up seasonal effects in some cases, especially among households that rely on agriculture as a source of income. However, it is difficult to isolate the two effects, because we lack income data from the same time period in prior years.

Model 1 is estimated for the following measures: per capita per day income in PPP\$ (measured at the mid-point of the household income bracket) and three measures of degree of poverty: household per capita per day income less than \$1.00 (=1) or not (=0); less than \$1.90 (=1) or not (=0); and less than \$3.20 (=1) or not (=0). These thresholds were selected to closely resemble intensities of poverty often used to compare countries’ status and progress against the international poverty line. For each country, we estimated the models for these outcomes at the country- and urban and rural levels. We also note that because of refusal/don’t know option, we have missing data for income related variables. Results of the missing data bias test reported in Supplementary Materials S9 indicates no systematic correlation with any household characteristics. But to minimize any concerns of sample bias in the results of this analysis, we adjusted the sample weights (for all the countries) to account for missing data.

To understand the covariates associated with year-on-year changes in food consumption coping strategies, we estimate Equation (2) for three qualitative indicators based on responses to following questions: (1) whether the quantity of food consumed was less in the month prior to the survey compared to same time last year; (2) the same for quality of food, and (3) whether any household member skipped meals more in the past month compared to the same time last year. If the response was yes, then outcome *y* takes the value of one, zero otherwise. These Models were estimated for each country at the national level.

$$y_i = \alpha + Z_i\delta + X_i\beta + \varepsilon_i \tag{2}$$

where *i* denotes the household, *Z* is a vector of two self-reported COVID-related restrictions (specifically, whether the area where the respondent resides was ever under lockdown, whether anyone in the household had ever done stay-at-home) and an income shock (i.e., whether household income in July dropped to a lower income bracket compared to March or if this information was missing), *X* is a vector of other household-level characteristics (household’s income category in March (pre-COVID), whether household had any income from farming in March or July, rural/urban strata, age, gender and education of the household head, and the timing of the survey measured as number of days in the calendar year since December 31, 2019, and *ε* is the idiosyncratic error. Standard errors are clustered at the first administrative level (i.e., counties, states, provinces, etc.) within each country. The coefficients of interest are *δ*, which measure the correlation between COVID related restrictions or income shock and the outcome, and *β*, which estimate the correlates of household characteristics. Detailed results based on the linear probability model estimator for all outcomes by country are included in Supplementary Materials S7.

5. Results

A key result from our country-specific analysis is that the impacts of

COVID-19 shock were more widespread over urban and rural areas within a country but lower than predicted. Below we elaborate on this theme of ‘wider but lower than predicted’ impacts of COVID shock on income, poverty, and food security.

5.1. Effects on income

Three main income results stand out. First, effects are smaller than predicted by earlier model-based studies. Second, also contrary to model predictions, in three of the five countries effects on income were similar in urban and rural areas (i.e., widespread). Third, the estimated income effects are highly correlated with the stringency measures across countries.

About 14–20% of households experienced a net loss of at least one

source of income from March to July 2020 (Fig. 1, Panel A). Across countries, the loss in an income source was not statistically significantly different in rural vs. urban areas, except in Zambia where more rural households (23%) reported a net loss of an income source than urban households (15%).

The share of households experiencing a decline in income ranged from 37% in Nigeria to 11% in Zambia (Fig. 1, panel B). Contrary to the predictions discussed above, these figures are not systematically higher in urban compared to rural areas. In Nigeria and Kenya, the countries that experienced more stringent restrictions for a longer time, more urban than rural households reported a decline as expected, but rural and urban figures are comparable in Mali, Senegal, and Zambia. Also, except Zambia, more households experienced a drop in income during the crisis than an increase (Fig. 1, panel C). Unlike other countries, the

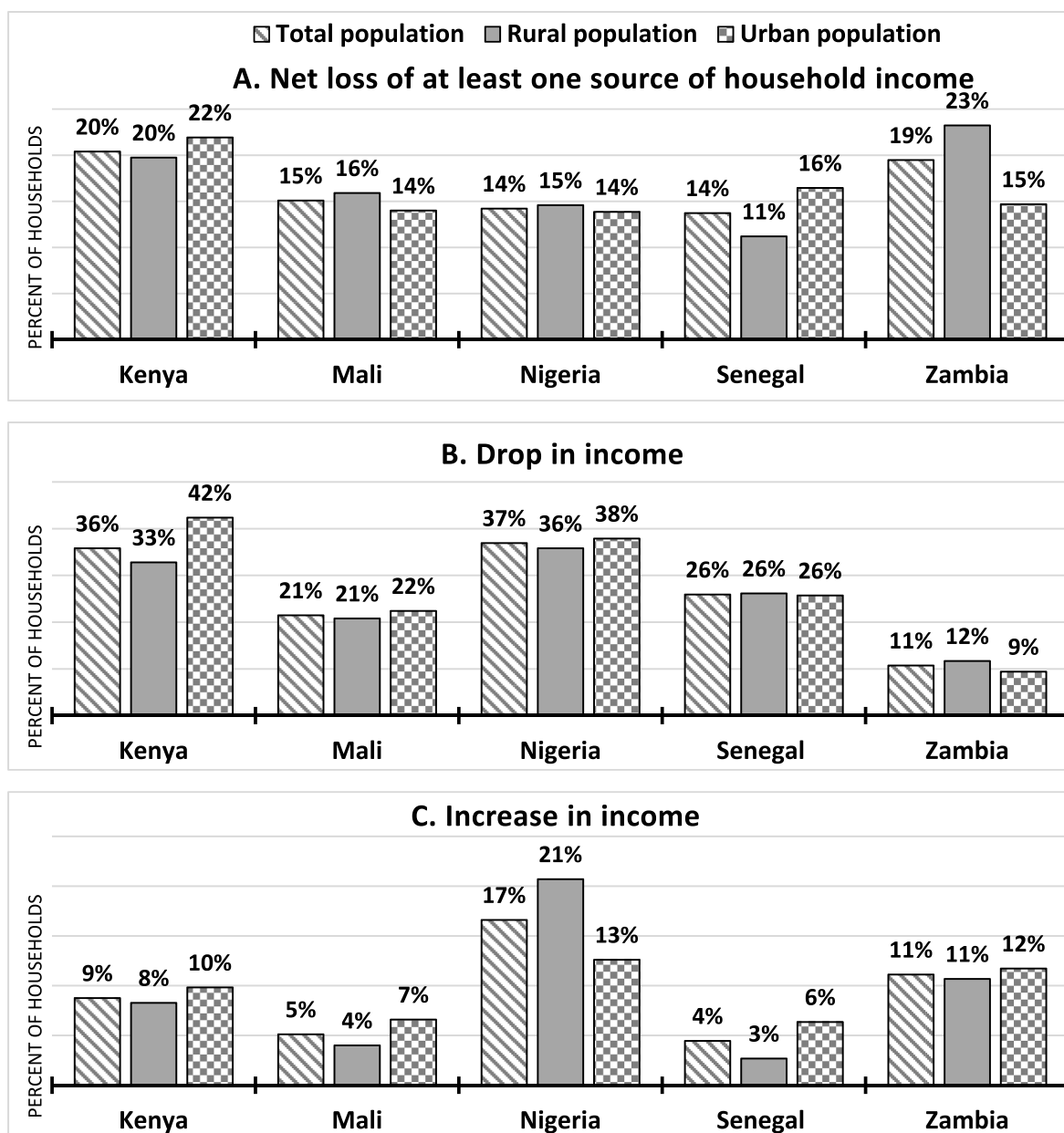


Fig. 1. Share of households experiencing net loss of at least one source of income and a drop or increase in income (in nominal terms) between March (pre-COVID) and July 2020, by total, rural and urban population of five countries. Source: Phone surveys (September–November 2020). Notes: Mean values of income drop in Kenya’s rural and urban area is statistically significantly different at $p < 0.01$ and mean values of net loss in income source in Zambia’s rural and urban area is statistically significantly different at $p < 0.02$. Other than these two cases, differences between rural and urban area in the proportion of households experiencing a decline in income or a net loss in income source are not statistically significant.

timing of the reporting period in Zambia was outside the lean period, and the stringency measures were short-lived, which could have contributed to this exception.

Between March and July 2020, we estimate a 7–19% decline in average income across all households in four countries and no change in Zambia (Table 3). Average daily per capita income dropped \$0.76 (19%) in Kenya, \$0.56 (15%) in Nigeria, \$0.41 (12%) in Mali, and \$0.32 (7%) in Senegal. The estimated drop in Zambia was \$0.10 (2.8%), which is indistinguishable from zero. Some of these estimated declines are 43%–63% lower than predictions or early estimates.¹ But they still hurt welfare, given that the average per capita income per day is less than \$4 in these countries (Table 1).

Comparing across countries, the estimated income effects are highly correlated with the stringency measures imposed by the government (Table 4). The percentage declines in income in our study countries generally follow the order of absolute increase in the stringency measures imposed between April–July 2020 and the absolute change in this index. This result generally confirms the concerns people had about increased economic costs associated with more stringent restrictions.

The decline in income was not statistically different between rural and urban samples, except in Kenya (at $p = 0.0696$) and in Nigeria ($p = 0.086$). Note that these net effects are based on fixed effects estimates, controlling for observable and unobservable household characteristics. The results are also robust to point estimates of income at upper and lower ranges of the income brackets used in the questionnaire (detailed results presented in Supplementary Material S8). The higher effects in urban Kenya and Nigeria are aligned with expectations and consistent with the stringency measures imposed for a longer duration in these two countries compared to other countries.

5.2. Poverty effects

The decline in income in Kenya, Mali, Nigeria, and Senegal pushed many households below the income thresholds often associated with poverty. We reiterate the caveat that our income measure is not equivalent to the expenditure-based measures of poverty. However, we expect the income-based thresholds we use in this paper to be highly correlated with the expenditure-based thresholds used to define international measures of extreme poverty. Results in Fig. 2 are based on the same household fixed effects model as the previous results. Full results are in supplementary materials S5. Results show the percentage points increase or decrease in the proportion of households whose per capita per day income dropped to less than \$1.00, \$1.90 and \$3.20 in July 2020 compared to March 2020 (pre-COVID) after adjusting for inflation.

Fig. 2 (and S5) supports the finding that income declines were not systematically greater in urban than rural areas. Apart from Nigeria, most of those who fell into poverty below \$1.90 or \$1 per person per day as a result of the COVID-19 situation resided in rural areas, not urban. Only at the higher poverty threshold (\$3.20/day) was the increase in the percentage of households below the poverty line statistically significantly higher in urban areas compared to rural. In the other 9 cases, this difference was not statistically significant or the decline was significantly higher in rural areas (Senegal at \$1/day). Even in Zambia, for the lowest income threshold, a greater share of rural households was driven below the income threshold of \$1/day compared to urban households,

¹ These estimates are based on three country-specific estimates or predictions of income drop we found in our review of the literature. For Kenya, we compare our estimate of 18.8% decline in income with Janssens et al. (2020)'s early estimates of income loss (based on a small rural sample) of 33% and get the figure of 43% [1-(19/33)]. For Nigeria, we compare our estimates of 14.6% decline in income with Andam et al. (2020)'s model-based predictions of 33% and get the figure of 56% [1-(14.6/33)]. For Senegal, we compare our estimates of 7.4% decline in income with Fall et al. (2020)'s model-based predictions of 20% and get the figure of 63% [1-(7.4/20)].

although the difference between the two groups is not statistically significant.

Next, for each country we take these estimated coefficients for the month variable from the regression model (Equation (1)) for rural and urban sample and multiply that with the respective population size to calculate the increase in number of people earning less than PPP\$1.00, PPP\$1.90 and PPP\$3.20 per capita per day in July 2020 compared to March (pre-COVID). The total population numbers reported in Fig. 3 are aggregates across the five countries, which show that four months into the COVID crisis, about 22 million people from households earning more than \$1/person/day in March (pre-COVID) were living below that income threshold in July 2020. The comparable figures for cutoffs of \$1.90/person/day and \$3.20/person/day are 19 million and 28 million, respectively. At the \$1.00 threshold a majority of those with declining incomes were in rural areas, but at the two higher income thresholds (i.e., \$1.90 and \$3.20), most people with income decline were urban.

In Fig. 4, we present this same statistic broken down by total, rural and urban population for each country. This shows that the urban bias in the number of people pushed below the income thresholds of \$1.90 and \$3.20 is influenced mostly by Nigeria, the most populous country in our sample. Except Nigeria (in two instances) and Senegal (in one instance), in all other countries, more rural people experienced poverty linked to COVID-19 than urban people. This larger increase in poverty in rural areas is due to two factors. First, larger shares of the population live in rural areas. Second, incomes are lower in rural areas and more people in normal times are near the poverty line, meaning that any decrease in income pushes more below that line.

5.3. Heterogenous effects and other considerations

Next, we examine if the income effects differ by household characteristics like gender and education of the household head and having income from farming. In addition to these conventional demographic characteristics, we consider two other household specific COVID-related restrictions—i.e., experienced lockdowns and practiced stay-at-home. Although the macro shock of COVID was pervasive, not everyone in the country experienced these COVID-related restrictions uniformly. We exploit this heterogeneity to understand if the income effects varied across households that self-reported experiencing (or not) these restrictions due to COVID. In Table 5, we present the estimated coefficient for the month variable comparing pre-to post-COVID (and using the same Model 1) for two groups of households that vary in these characteristics, along with the percent effect of COVID shock and the P-values of the sub-sample equality of coefficient test (for the month variable). Detailed results are in Supplementary Materials S6.

Results confirm the previous rural/urban comparison showing that income effects of COVID-shock were pervasive across both areas. With a few exceptions (noted below), the effects are not statistically significantly different by experience of lockdown or stay-at-home, gender and education of household head, or doing farming.

The exceptions are Zambia and Kenya where male-headed households suffered more losses than their counterparts. Also, in Kenya households with more than the median education lost significantly more income than other households. There was a decline in income per day \$1.29 among households with more educated heads compared to \$0.44 with less educated heads. These represent about 22% and 18% decline in income, respectively for the two groups. Farming households in Kenya suffered significantly less (10% decline in income) than those that did not have farm income (22% decline); recall from Table 3 that Kenya's rural households lost less income than did their urban counterparts. Harvesting of the main season crop in most parts of Kenya occurs between July–August, and rainfall during the 2020 growing season was generally good and so were harvests. These factors could have shielded Kenya's rural areas from the steep decline in income observed in urban areas.

Table 3

Estimated change in per capita per day income (PPP\$) between March (pre-COVID) and July 2020 in total, rural and urban population of five countries, fixed effects model estimates for total, rural, and urban sample.

	Kenya	Mali	Nigeria	Senegal	Zambia
Panel A. Total					
Month = July (base category = March)	-0.758*** (0.157)	-0.407*** (0.093)	-0.555*** (0.157)	-0.323*** (0.052)	-0.102 (0.073)
Constant	4.799*** (0.236)	3.840*** (0.140)	4.362*** (0.236)	4.693*** (0.078)	3.760*** (0.109)
Observations\	1448	1122	1416	1430	1332
R-squared	0.082	0.108	0.053	0.086	0.003
Dep var. mean (in March)	4.041	3.433	3.807	4.370	3.658
Percent effect in July	-18.8%	-11.9%	-14.6%	-7.4%	-2.8%
Panel B. Rural					
Month = July (base category = March)	-0.528*** (0.157)	-0.449*** (0.112)	-0.285* (0.154)	-0.303*** (0.051)	-0.101 (0.087)
Constant	2.977*** (0.079)	3.404*** (0.056)	2.923*** (0.077)	3.793*** (0.025)	2.584*** (0.043)
Observations\	710	548	706	718	692
R-squared	0.083	0.168	0.029	0.130	0.004
Dep var. mean (in March)	2.977	3.404	2.923	3.793	2.584
Percent effect in July	-17.7%	-13.2%	-9.8%	-8.0%	-3.9%
Panel C. Urban					
Month = July (base category = March)	-1.256*** (0.368)	-0.350** (0.160)	-0.811*** (0.265)	-0.344*** (0.093)	-0.103 (0.125)
Constant	6.341*** (0.184)	3.473*** (0.080)	4.645*** (0.132)	4.992*** (0.047)	5.094*** (0.063)
Observations\	738	574	710	712	640
R-squared	0.106	0.060	0.077	0.068	0.002
Dep var. mean (in March)	6.341	3.473	4.645	4.992	5.094
Percent effect in July	-19.8%	-10.1%	-17.5%	-6.9%	-2.0%
P-value for the test of equality of Month coefficients for rural and urban sample	0.0696	0.612	0.0860	0.700	0.989

Notes: Robust standard errors clustered at household level are in parentheses. Dependent variable is per capita per day total HH income (2018 PPP\$) (mid-point estimate of income brackets). All Models include sample weights to adjust for following population level characteristics—rural/urban split, household size, household head’s education and gender, and further adjusted for missing data. Income for July is adjusted for inflation rate using country-specific consumer price index with the base month = March 2020. ***p < 0.01, **p < 0.05, *p < 0.1.

\a Less than 1600 observations for the total, and less than 800 observations for rural and urban sample reflect missing data due to ‘refused/don’t know’ responses to the income question.

Table 4

Pre- and post-COVID stringency index and estimated income effects by country: Mean values and correlations.

	Mean Stringency Index (on a 0–100 scale)		Absolute change in stringency index (pre- to post-COVID) (c = b-a)	% Change in income per capita/day (pre- to post-COVID) (d)
	Jan–Mar 2020 (pre-COVID) (a)	Apr–Jul 2020 (post-COVID) (b)		
Kenya	22.61	86.58	64.0	-18.8
Nigeria	18.27	80.46	62.2	-14.6
Mali	9.29	59.44	50.2	-11.9
Senegal	15.20	63.29	48.1	-7.4
Zambia	12.78	50.04	37.3	-2.8
Correlation between b and d = -0.92				
Correlation between c and d = -0.96				

5.4. Effects on food consumption and food security coping strategies

Table 6 (Panel A) presents the share of households reporting reduced quantity or quality of food or skipped meals during the previous month relative to the same time last year, which was pre-COVID, but controls for seasonal effects.

A large share of households (16–60%) reported a decline in the quantity or quality of food consumed, or an increase in skipping meals (Table 6, Panel A). Kenya, Nigeria, and Zambia were most affected, with over half of respondents reporting that the quantity or quality of their diet had deteriorated last month compared to the same time last year. Zambians, who on average experienced no change in income, reported experiencing a decline in food consumption, possibly due to an increase in the cost of food (Mitimngi, 2020).

Across countries and urban and rural areas (except rural Mali and

rural Nigeria) we find a higher share of households consuming lower quality of food than lower quantities. Both in Mali and Nigeria we observe a higher share of households in rural areas who consumed lower quantities compared to last year. Also, except in Senegal and Mali, more households skipped meals due to lack of food in rural areas than in urban areas.

Supplementary material S7 presents results of the linear probability model of covariates of each of the consumption impacts (Equation (2)). In some countries these impacts are positively correlated with having done ‘stay-at-home’ and suffered income shocks and being poorer. However, we find no consistent association across countries of consumption outcomes with lockdown restrictions, whether in rural or urban areas, or by other household characteristics.

5.5. Assistance received

By April, according to the tracking report by Gentilini et al. (2020a), Kenya, Mali, Nigeria, and Senegal had initiated programs to provide cash or in-kind transfers to existing poor as well as transient poor. By July, Zambia had also launched an emergency cash transfer scheme. By the time of our surveys, all five countries had implemented some combination of cash transfers (e.g., transfer of emergency relief funds), in-kind support (e.g., food distribution, food hampers, school feeding), loans, utility waivers (such as for electricity and water bills), and public works programs (Gentilini et al., 2020b).

Our data show that some relief had reached our sampled households (Table 6, Panel B). Loans, subsidies, and tax cuts were the most cited assistance in Kenya (32%) and Mali (41%). Food assistance from the government was most cited in Senegal (47%). In Nigeria, more households reported receiving food and cash assistance from a religious organization (24%) than any kind of assistance from the government

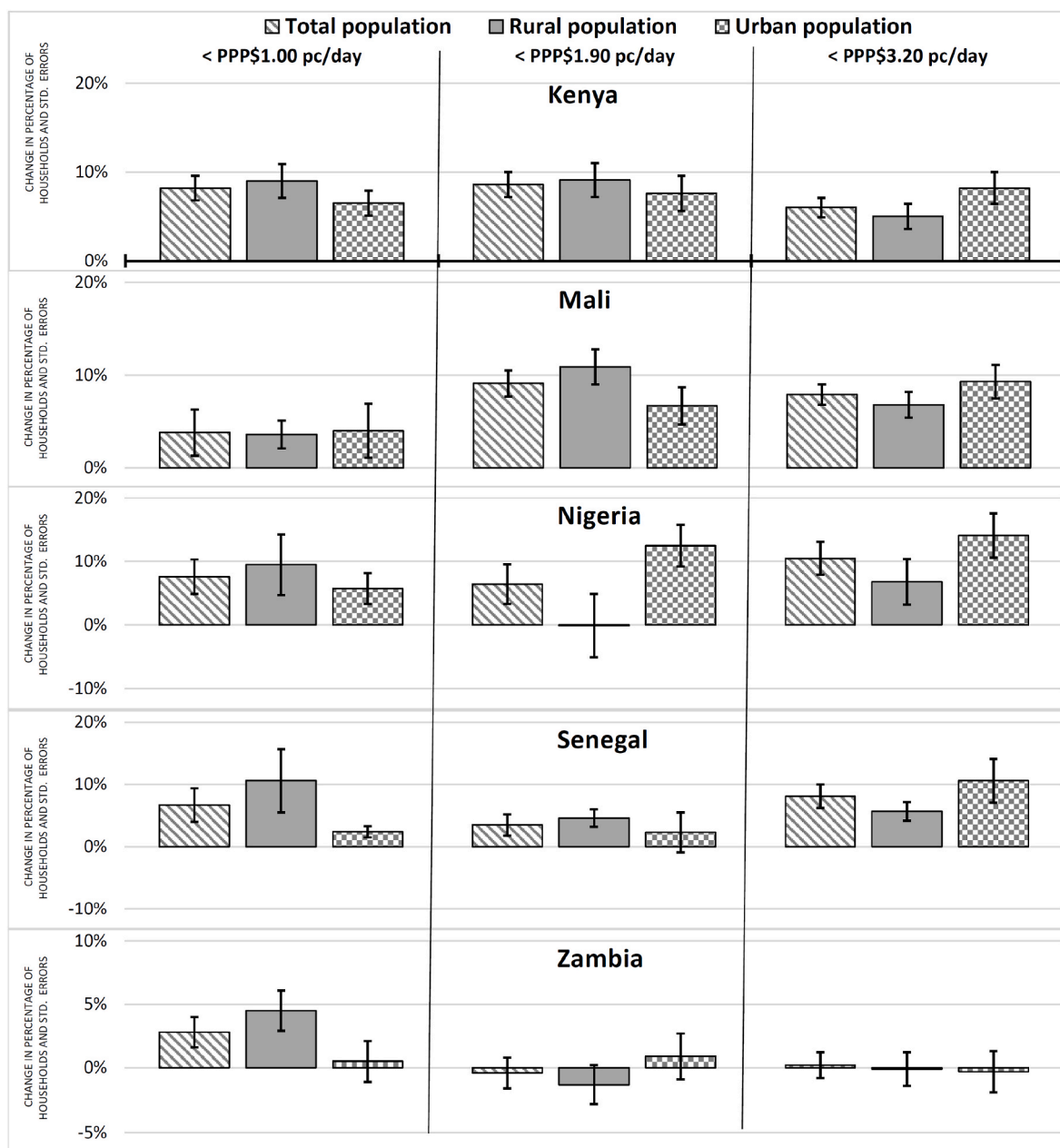


Fig. 2. Change in percentage of households earning less than PPP\$1.00, PPP\$1.90 and PPP\$3.20 per capita per day from March (pre-COVID) to July: Estimate for total, rural, and urban population. Notes on Fig. 2: This figure shows estimated coefficients and standard errors of the indicator of the month variable (1 = July 2020, 0 = March 2020) from nine separate regressions at country level—one each for total, rural and urban population by three sub-categories of households whose income dropped to less than PPP\$1.0, PPP\$1.90 and PPP\$3.20 per capita per month in July 2020 compared to March 2020 (pre-COVID). The Models are estimated using the household fixed effects where the dependent variable is per capita per day income (converted into US\$PPP and the reported income in July is adjusted for inflation using country-specific CPI with base = March 2020). Detailed results of the nine regression Models by country are presented in supplementary materials S5.

(10%). On average, the percentage of households receiving any kind of assistance from the government or a religious organization in the three months before the survey ranged from 31% in Nigeria to 60% in Senegal.

However, some of these government assistance programs, especially subsidies and loans, may have existed before COVID. Thus, we do not know how much these results put an upper limit on the share of households receiving such assistance because of COVID. Regarding food and cash assistance, these upper limits are low in most countries (ranging from 1% to 15%). This indicates that the great majority of households had to rely on private coping mechanisms and non-governmental help. The only exception was Senegal, where a large share of households (47%) reported receiving food assistance from the government, although we cannot say how much of this was because of

COVID.

In Nigeria, Senegal, and Zambia, government assistance did not vary significantly among rural and urban households (Table 6). But in Kenya and Mali, households in urban areas have benefited significantly more than their rural counterparts in terms of receiving food and cash assistance from the government (Kenya), food or cash assistance from religious organizations (Mali) and loans, subsidies, tax cuts, and other type of assistance from the government (Mali). In Senegal, more rural households reported benefiting from food or cash assistance from religious organizations than their counterparts in urban areas.

Six months into the crisis and despite the assistance programs, vulnerability of people to food insecurity remained high. When asked “How long can your household meet food consumption needs with

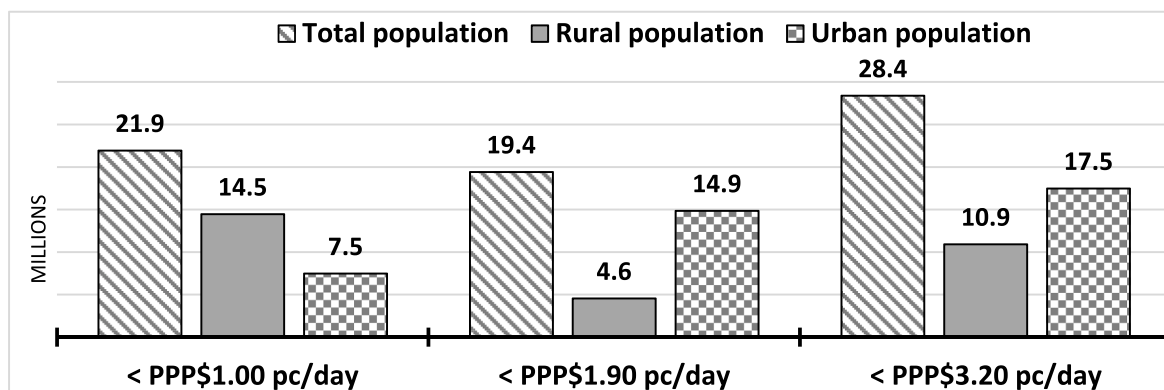


Fig. 3. Increase in number of people earning less than PPP\$1.00, PPP\$1.90 and PPP\$3.20 per capita per day in July 2020 compared to March (pre-COVID): Estimates for total, rural, and urban population across all five countries. Source: Authors' calculation. Notes: See Fig. 4 for changes in these indicators at the country level. The estimates in this figure are aggregates across the five countries. For each country the totals for rural and urban area are calculated by multiplying the estimated coefficient for the month variable from the regression Model (Equation (1)) with the respective population size. The number for total population is the sum of the estimated numbers at the rural and urban level. Reported income in July is adjusted for inflation using country-specific consumer price index (CPI) with base = March 2020.

available income or savings?" 42% of households in Kenya, 37% in Zambia, 29% in Senegal, 21% in Mali, and 19% in Nigeria responded, "less than a week" (Fig. 5). Another 15–34% had enough cash/savings to meet their food needs for an additional week. However, we do not know for what percentage of those households such a short time horizon for meeting food needs is normal or exception; many or most poor households live on daily informal sector wages or daily income from self-employment and do not generate a great deal more than their daily or weekly needs.

Across all countries, only a minority of households (from 13% in Kenya to 42% in Mali) had enough resources to meet their food needs for over a month. Again, we lack this indicator pre-COVID or in the early phase of the crisis so cannot say whether this share is normal or abnormally high because of COVID.

6. Summary of main results and discussion

Overall, the quantitative analysis of representative data across five countries in Africa confirms the concerns people had about increased economic costs associated with COVID containment policies. We find that countries with more stringent policies saw a greater decline in income and deeper urban effects few months into the pandemic. Other than this generally conforming result, the study points to several interesting findings that are contrary to expectations. First, our estimated decline in income and increase in poverty are below the predictions and early estimates based on unrepresentative samples. Despite the very real hardship that we document, these results are less pessimistic than initially expected. In Nigeria and Senegal, our estimate of the decline in income is about 56% and 63% less than the *ex-ante* predictions (Andam et al., 2020). In Zambia, contrary to predictions by UNDP (2020) we find no decline in income or increase in poverty. In Kenya, our estimate of income decline is 43% lower than earlier estimates based on a sample from low-income rural villages (Janssens et al., 2020). The estimated share of households experiencing a drop in income in urban Kenya was 42% less than the estimates based on data from low-income neighborhoods in Nairobi (Population Council, 2020). Only in Mali do we find our national estimates of decline to be higher than predicted declines (12% vs 9.4%) (Koné et al., 2020).

Note that July, the month we capture the effects, was a lean month in Kenya, Mali, Nigeria, and Senegal compared to our baseline month (March). Since incomes would be expected to drop over this period even in the absence of the COVID shock, we consider these estimates of income losses to be upper bounds in these countries. This means that in these four countries that saw income declines, these declines due to

COVID may have been less than our results show. On the other hand, in Zambia our baseline month (March) was a lean month relative to July, meaning that incomes would have normally been expected to rise over the period. This suggests that our finding of no statistically significant effect of the COVID shock in Zambia is a lower bound estimate. At the same time, the less intensity and shorter duration of restrictions in Zambia compared to other countries should have reduced the actual effect, consistent with our estimates.

Second, contrary to earlier predictions and expectations, our survey showed that the COVID shock affected rural and urban areas similarly. On our estimates of effects on income, we do find exceptions to this in the case of Kenya and Nigeria, both of which had imposed the highest levels of stringency measures, likely targeted more towards urban areas. However, in terms of net loss of at least one source of income between March and July 2020 (Fig. 1), and reduction in the quantity and quality of food consumed, the effects were quite similar in rural and urban areas in both these countries. Across countries, we also find that COVID affected a wide variety of households, including those that experienced lockdown or not, did stay-at-home or not, had farm income or not, and differed in characteristics such as gender and education of the household head, which reinforces our finding of 'wide' impacts. The few exceptions where we see the results more aligned with predictions are in Zambia (where male-headed households saw incomes drop more) and Kenya where households with heads that were male and more educated, and households with nonfarm incomes saw greater drops in income. Given the fact that the five countries in our sample are fairly heterogeneous in terms of economic development, rural transformation, and seasonality of reported results, the lack of heterogeneous effects for a range of outcomes (except the few noted) are surprising.

There are several potential explanations for our findings of wider impacts of COVID shock than were expected within and across countries. On the one hand, rapid rural transformation in these countries is expanding sources of livelihoods for rural people. Agriculture is no more the only source of income in rural areas. This is evident from our data, which show that rural households cited income from post-farmgate activities (i.e., processing, trading, transport and delivery of agricultural goods and food service) and non-farm activities just as frequently as they cited on-farm income (i.e., income from own farming or wages) (supplementary material S2).

On the other hand, the income portfolio of rural households is becoming more like that of urban households. Our data show that the share of households earning incomes from non-farm sources was surprisingly similar between rural and urban areas within a country and across countries (supplementary material S2). Together, these

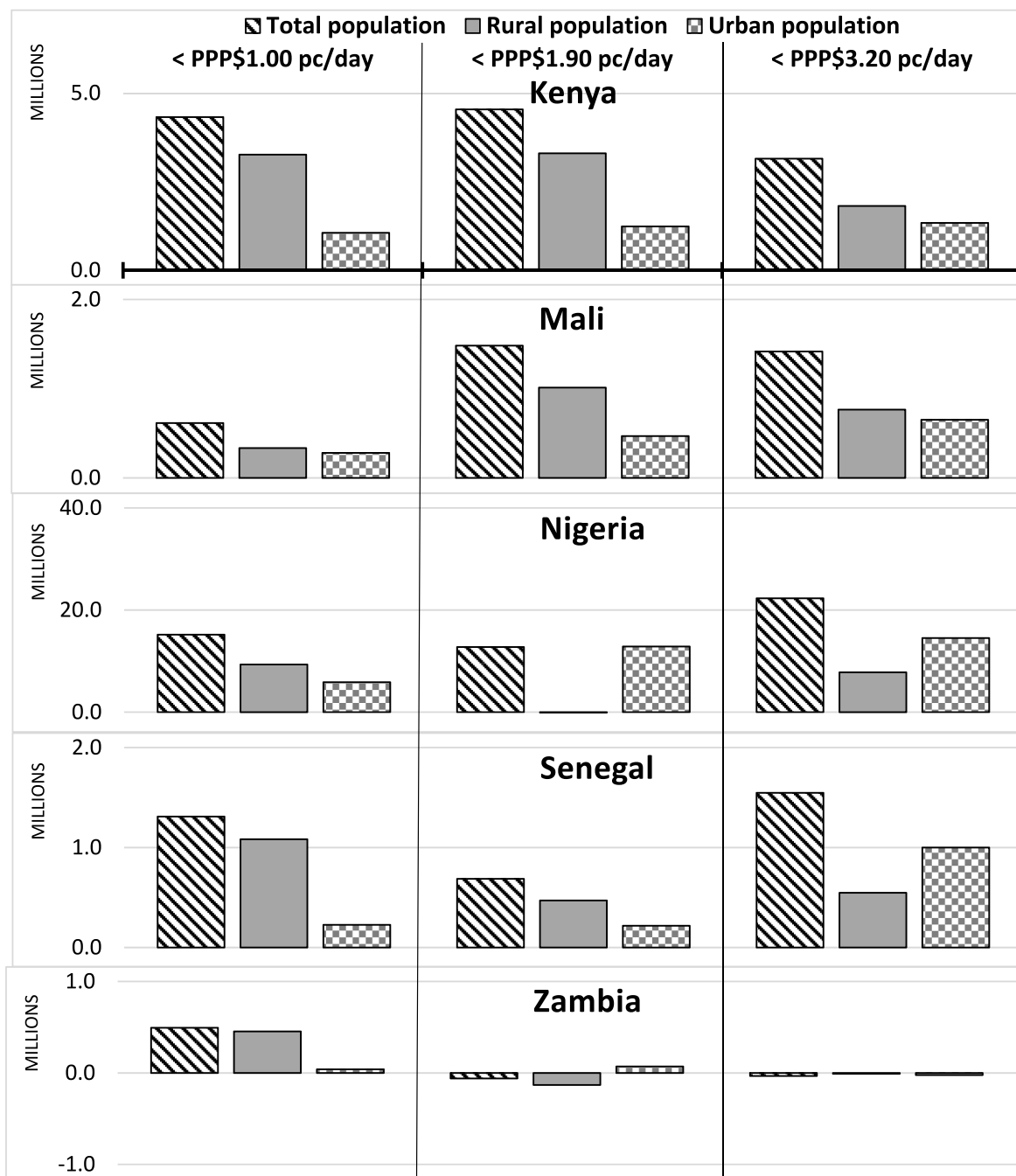


Fig. 4. Increase in number of people earning less than PPP\$1.00, PPP\$1.90 and PPP\$3.20 per capita per day in July 2020 compared to March (pre-COVID): Estimates for total, rural, and urban population, by country. Notes: For each country the totals for rural and urban area are calculated by multiplying the estimated coefficient for the month variable from the regression Model (Equation (1)) with the respective population size. The number for total population is the sum of the estimated numbers at the rural and urban level. Reported income in July is adjusted for inflation using country-specific CPI with base = March 2020.

transformations are making the rural households increasingly vulnerable to meso-level shocks such as lockdowns that directly affect nonfarm activities; these include commerce, transport, and related services that rely on commuting from rural areas to towns, moving along roads and highways, using wholesale market venues, and so on. The latter services are major shares of rural nonfarm employment in Africa (Haggblade et al., 2010). Recent study by Dolislager et al. (2020) based on LSMS data from several African countries found that own-farming constitutes only 39% of labor time allocation in terms of full-time equivalents; 61% are in wage- and self-employment in off-farm activities.

Third, and related to the previous points, these transformations are bringing rural and urban communities closer together through the

movement of people, goods, money, and information. People and communities across rural and urban areas are increasingly connected through factor markets (labor, inputs, capital; see Dolislager et al., 2020; Haggblade et al., 2010; Liverpool-Tasie et al., 2017; Tschirley et al., 2015) as well as product markets (Reardon et al., 2021; Tschirley et al., 2020). In rural areas, food is increasingly becoming purchased, implying dependence on markets for food security (Liverpool-Tasie et al., 2020). Also, lower demand for food in urban areas due to lockdowns can be transmitted back to rural areas, depressing incomes for food producers, especially for perishables produced year-round (i.e., vegetables, poultry, and fish) (Belton et al., 2021; Minten et al., 2020).

We hypothesize that these rural-urban linkages are potentially

Table 5

Change in per capita per day total household income (2018 PPP\$) from March (pre-COVID) to July: Heterogenous effects by household characteristics and other considerations.

	Kenya		Mali		Nigeria		Senegal		Zambia		
	Gender of household head										
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	
Month = July (base category = March)	-0.377** (0.187)	-0.966*** (0.218)	-0.346*** (0.086)	-0.416*** (0.105)	-0.599 (0.427)	-0.544*** (0.166)	-0.365*** (0.110)	-0.306*** (0.059)	0.086 (0.101)	-0.172* (0.092)	
Percent effect in July	-14.9%	-19.9%	-7.1%	-12.9%	-12.9%	-15.1%	-9.1%	-6.8%	3.2%	-4.3%	
Observations	434	1014	82	1040	234	1182	228	1204	330	1002	
P-values	0.040		0.606		0.904		0.633		0.060		
Education of household head is below the country's median level											
	No		Yes		No		Yes		No		Yes
Month = July (base category = March)	-1.287*** (0.247)	-0.443** (0.200)	-0.472*** (0.105)	-0.392*** (0.112)	-0.729* (0.410)	-0.520*** (0.170)	-0.465*** (0.150)	-0.290*** (0.053)	-0.184 (0.175)	-0.065 (0.071)	
Percent effect in July	-20.8%	-16.1%	-15.0%	-11.2%	-11.9%	-15.5%	-5.6%	-8.4%	-2.8%	-2.7%	
Observations	952	496	602	520	750	666	764	668	674	658	
P-values	0.008		0.601		0.638		0.270		0.528		
Household had income from farming in March 2020											
	No		Yes		No		Yes		No		Yes
Month = July (base category = March)	-0.912*** (0.202)	-0.389* (0.222)	-0.376*** (0.116)	-0.465*** (0.156)	-0.614*** (0.198)	-0.443* (0.258)	-0.348*** (0.094)	-0.299*** (0.048)	-0.128 (0.112)	-0.070 (0.089)	
Percent effect in July	-22.3%	-9.9%	-10.1%	-16.1%	-14.9%	-13.7%	-6.4%	-8.8%	-2.9%	-2.5%	
Observations	1042	406	644	478	966	450	786	644	758	574	
P-values	0.082		0.649		0.599		0.643		0.681		
Did you experience (total or partial) Lockdown in the Area?											
	No		Yes		No		Yes		No		Yes
Month = July (base category = March)	-0.983*** (0.286)	-0.587*** (0.171)	-0.447** (0.183)	-0.373*** (0.072)	-0.234 (0.357)	-0.640*** (0.171)	-0.341*** (0.089)	-0.313*** (0.064)	-0.077 (0.097)	-0.138 (0.111)	
Percent effect in July	-20.2%	-17.2%	-14.2%	-10.1%	-5.5%	-17.4%	-10.0%	-6.3%	-2.1%	-3.7%	
Observations	662	786	518	604	254	1162	544	888	812	520	
P-values	0.234		0.708		0.304		0.799		0.679		
Did anyone in the household practice stay-at-home due to COVID?											
	No		Yes		No		Yes		No		Yes
Month = July (base category = March)	-1.041** (0.429)	-0.722*** (0.170)	-0.485** (0.201)	-0.378*** (0.104)	0.672 (1.552)	-0.602*** (0.143)	-0.179* (0.098)	-0.359*** (0.059)	0.042 (0.218)	-0.134* (0.075)	
Percent effect in July	-22.5%	-21.7%	-18.2%	-12.5%	-7.8%	-19.0%	-14.3%	-11.5%	-1.0%	-0.8%	
Observations	132	1316	278	844	30	1386	190	1242	210	1122	
P-values	0.486		0.635		0.391		0.114		0.444		

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. P-values are for sub-sample equality test (for July coeff.) All Models include sample weights to adjust for following population level characteristics—rural/urban split, household head's education and gender. All regressions control for the following variables: number of income sources, indicators of sector of employment in which employed household members are engaged—agriculture, agri-food value chain (beyond farm-gate), non-agriculture, professional job, and other. See detailed results in supplementary material S6.

contributing to our findings of 'wider but smaller than predicted' impacts of the COVID shock through two complementary mechanisms. On the one hand, the linkages provide a pathway for meso-level shocks in urban areas to be transmitted to rural areas, driving widespread effects not confined to urban areas. Yet at the same time, engagement by rural households in a variety of markets serves as self-insurance against disruptions in any one market, which reduces the depth of the impact. Thus, for a macro-level shock like a pandemic, the interdependency and interconnectedness implied by these rural-urban linkages can absorb shock and also extend it, potentially explaining our findings of 'wider but smaller than predicted' impacts of the COVID shock.

7. Conclusions and implications

Using quantitative income data collected through representative surveys, we document net losses in income sources and steep – though smaller than predicted - declines in household income in our focus countries. Across countries, the drop in income is highly correlated with the severity of restrictive policies and has pushed many households below the income thresholds often associated with severe poverty. Many households said their funds will only feed them for a few weeks. Although this may be the same as the situation before COVID, this result reinforces the vulnerability of a large proportion of people to food

insecurity, which can be exacerbated with further loss of income due to public health restrictions.

Despite food and cash assistance being announced by governments as initiatives to mitigate damage from the crisis, our data show that only 1%–15% of households in four of our study countries received these types of government assistance. Our results thus highlight the need for reexamining COVID response policies to preempt the possibility of massive reversals of progress in human development in the face of current and future shocks.

To close, we reiterate the implications of three main findings of this paper. First, our estimates of decline in income and increase in poverty, while substantial, are below predictions and early *ex post* estimates. Yet because the pandemic was still unfolding when we collected the data, the results are preliminary. Two very different possibilities could have unfolded: the economies could have already bounced back after the initial shock, or they could have still been on their way down. This uncertainty suggests that continued data collection is needed to sort out the medium-to longer-term trajectory of the shock.

Second and third, our survey showed that across countries, the effects of the shock on the income were highly correlated with the stringency of COVID-19 containment policies. More prolonged and stringent policies (e.g., in Kenya and Nigeria) had higher overall economic impacts and deeper urban impacts. In countries where there were

Table 6
Self-assessed food consumption effects and receipt of assistance to cope with the COVID crises, by total population and rural/urban strata.

	Kenya			Mali			Nigeria			Senegal			Zambia		
	Total	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban
Number of observations	800	400	400	800	400	400	800	400	400	800	400	400	800	400	400
Panel A: Share of households that reported experiencing the following in the past month relative to same time last year (1 = Yes)															
Quantity of food consumed was lower	0.42	0.41	0.45	0.30	0.33	0.26	0.56	0.61	0.51	0.32	0.31	0.33	0.51	0.50	0.53
Quality of food consumed was worse	0.50	0.49	0.50	0.29	0.31	0.26	0.61	0.60	0.61	0.44	0.51	0.38	0.57	0.56	0.57
Household members skipped meals because of lack of food	0.51	0.54 ^b	0.43 ^b	0.16	0.16	0.18	0.51	0.59 ^b	0.43 ^b	0.22	0.18	0.26	0.58	0.60	0.56
Panel B: Share of households that reported having received following types of assistance in the past 3 months (1 = Yes)															
Received food or cash assistance from religious organizations	0.14	0.13	0.15	0.06	0.04	0.08	0.24	0.23	0.25	0.08	0.11 ^b	0.05 ^b	0.18	0.20	0.15
Received food assistance from the government	0.09	0.07 ^c	0.13 ^c	0.15	0.14	0.16	0.07	0.09	0.06	0.47	0.53	0.41	0.09	0.10	0.08
Received cash transfers or unemployment benefits from the government	0.07	0.05	0.10	0.03	0.03	0.03	0.01	0.01	0.02	0.02	0.02	0.01	0.07	0.06	0.07
Received loans, subsidies, tax cuts or other type of assistance from the government	0.32	0.30	0.37	0.41	0.35 ^b	0.49 ^b	0.05	0.07	0.04	0.25	0.25	0.26	0.16	0.16	0.15
Received any kind of assistance from the government	0.38	0.35 ^b	0.45 ^b	0.50	0.46	0.56	0.10	0.13	0.08	0.55	0.58	0.51	0.23	0.25	0.20
Received any kind of assistance from the government or religious organization	0.44	0.42	0.50	0.52	0.49	0.56	0.31	0.31	0.31	0.60	0.65	0.55	0.35	0.38	0.31

Notes: Superscript letters denote mean values for urban and rural strata are statistically significant at: ^a p < 0.01; ^b p < 0.05; ^c p < 0.1.
Source: Phone surveys (September–November 2020)

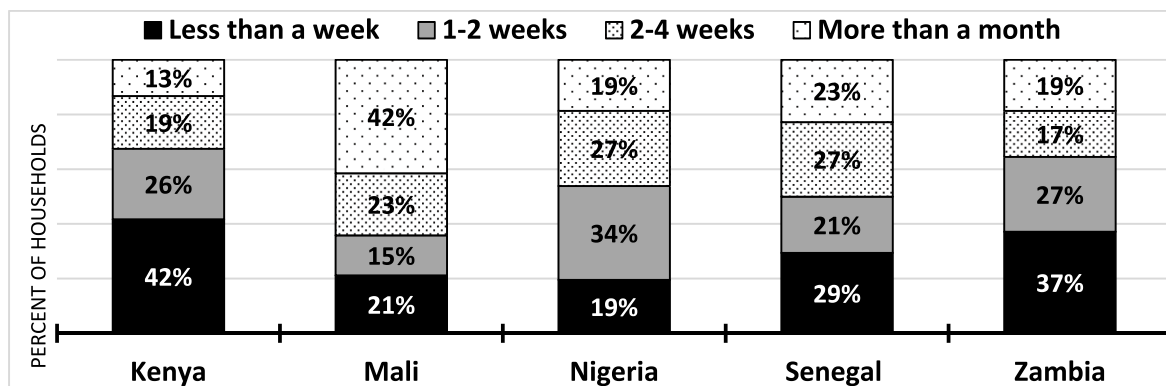


Fig. 5. Food insecurity vulnerability indicator: Share of households who can meet food consumption needs with available income/saving resources for the following projected time frame at the time of survey. Source: Phone surveys (September–November 2020).

relatively moderate to mild COVID policy responses (e.g., Mali, Senegal, and Zambia), the economic impacts were smaller and more widespread over both rural and urban areas. The food consumption effects, however, were widespread across all countries. These findings on the pervasiveness of the effects appear to support the growing evidence of interconnectedness of people and communities across rural and urban areas through factor and product markets. An implication of this finding is that for a macro-level shock like a pandemic, rural-urban linkages can be both a shock absorber and a shock extender. Thus, in designing policy responses and relief measures, decision makers should account for these broad effects of a shock that cut across locations, sector of employment, and household characteristics.

Funding

This work was supported by the U.S. Agency for International Development [grant number 7200AA19LE00001].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.gfs.2022.100633>.

References

Africa CDC, 2020. Recommendations for stepwise response to Covid-19 by African union member states. Retrieved from: <https://africacdc.org/download/recommendations-for-stepwise-response-to-covid-19/>. (Accessed 23 July 2020).
Ali, A., Ahmed, M., Hassan, N., 2020. Socioeconomic impact of COVID-19 pandemic: evidence from rural mountain community in Pakistan. *J. Publ. Aff.* 21 (4), 1–9. <https://doi.org/10.1002/pa.2355>. Article e2355.

- Alvi, Muzna, Gupta, Shweta, Meinzen-Dick, Ruth, Ringler, Claudia, 2020. Phone surveys to understand gendered impacts of Covid-19: a cautionary note. IFPRI Blog Post. July 14, 2020. <https://pim.cgiar.org/2020/07/14/phone-surveys-to-understand-gendered-impacts-of-covid-19-a-cautionary-note/>. (Accessed 5 March 2021).
- Andam, Kwaw S., Edeh, Hyacinth, Oboh, Victor, Pauw, Karl, Thurlow, James, 2020. Estimating the Economic Costs of COVID-19 in Nigeria. NSSP Working Paper 63. International Food Policy Research Institute, Washington, DC. <https://doi.org/10.2499/p15738coll2.133846> (IFPRI).
- Arndt, C., Davies, R., Gabriel, S., Harris, L., Makrelou, K., Robinson, S., Levy, S., Simbanegavi, W., van Seventer, D., Anderson, L., 2020. Covid-19 lockdowns, income distribution, and food security: an analysis for South Africa. *Glob. Food Secur.* 26, 100410. <https://doi.org/10.1016/j.gfs.2020.100410>.
- Belton, Ben, Rosen, Leah, Middleton, Lucinda, Ghazali, Saadia, et al., 2021. COVID-19 impacts and adaptations in Asia and Africa's aquatic food value chains. *Mar. Pol.* 129, 104523 <https://doi.org/10.1016/j.marpol.2021.104523>.
- Ceballos, F., Samyuktha, K., Berber, K., 2020. Impacts of a National Lockdown on Smallholder Farmers' Income and Food Security: Empirical Evidence from Two States in India, vol. 136. *World Development*, p. 105069. <https://doi.org/10.1016/j.worlddev.2020.105069>, 2020.
- Datereportal, 2020. Digital 2020: Nigeria. <https://datereportal.com/reports/digital-2020-nigeria>. Zambia. <https://datereportal.com/reports/digital-2020-zambia?rq=Zambia>. Kenya. <https://datereportal.com/reports/digital-2020-kenya?rq=Kenya>. Mali. <https://datereportal.com/reports/digital-2020-mali?rq=Mali>. Senegal. <https://datereportal.com/reports/digital-2020-senegal?rq=Senegal>. (Accessed 16 January 2021).
- Deaton, Angus, 1997. The Analysis of Household Surveys: A Microeconomic Approach to Development Policy. World Bank Group. <https://doi.org/10.1596/0-8018-5254-4>.
- Dolislager, Michael, Reardon, Thomas, Arslan, Aslihan, Fox, Louise, Liverpool-Tasie, Saweda, Sauer, Christine, Tschirley, David, 2020. Youth and adult agrifood system employment in developing regions: rural (peri-urban to hinterland) vs. urban. *J. Dev. Stud.* 57 (4) <https://doi.org/10.1080/00220388.2020.1808198>.
- Egger, Dennis, Miguel, Edward, Warren, Shana S., Shenoy, Ashish, Collins, Elliott, Dean, Karlan, Parkerson, Doug, Mushfiq, A., Mobarak, Günther Fink, Udry, Christopher, Walker, Michael, Haushofer, Johannes, Larrebourg, Magdalena, Athey, Susan, Lopez-Pena, Paula, Benhachmi, Salim, Humphreys, Macartan, Lowe, Layna, Meriggi, Niccolò F., Whirey, Andrew, Austin Davis, C., Johann Pape, Utz, Graff, Tilman, Voors, Maarten, Nekesa, Carolyn, Vernot, Corey, 2021. Falling living standards during the COVID-19 crisis: quantitative evidence from nine developing countries. *Sci. Adv.* 7 (6), eabe0997 <https://doi.org/10.1126/sciadv.abe0997>.
- Fall, Cheikh Sadibou, Pauw, Karl, Randriamamonjy, Josee, James, Thurlow, 2020. Senegal: Impacts of COVID-19 on Production, Poverty and Food Systems. IFPRI, Washington D.C. <https://www.slideshare.net/ifpri/senegal-impacts-of-covid19-on-production-poverty-and-food-systems-239925668>. (Accessed 18 February 2021).
- Gaitán-Rossi, P., Vilar-Compte, M., Teruel, G., Pérez-Escamilla, R., 2021. Food insecurity measurement and prevalence estimates during the COVID-19 pandemic in a repeated cross-sectional survey in Mexico. *Publ. Health Nutr.* 24 (3), 412–421.
- Gentilini, Ugo, Mohamed, Almenfi, Dale, Pamela, 2020a. Social Protection and jobs responses to COVID-19: a real-time review of country measures. "Living paper" version 6 (April 24, 2020). <https://openknowledge.worldbank.org/bitstream/handle/10986/33635/Social-Protection-and-Jobs-Responses-to-COVID-19-A-Real-Time-Review-of-Country-Measures-April-24-2020.pdf?sequence=5&isAllowed=y>.
- Gentilini, Ugo, Mohamed, Almenfi, Dale, Pamela, 2020b. Social Protection and jobs responses to COVID-19: a real-time review of country measures. Living paper" version 14 (December 11, 2020). <http://documents1.worldbank.org/curated/en/467521607723220511/pdf/Social-Protection-and-Jobs-Responses-to-COVID-19-A-Real-Time-Review-of-Country-Measures-December-11-2020.pdf>. (Accessed 3 March 2021).
- GSMA, 2020. The Mobile Economy 2020. The GSM Association. <https://www.gsma.com/mobileeconomy/>. (Accessed 5 March 2021).
- Haggblade, S., Hazell, P., Reardon, T., 2010. The rural non-farm economy: Prospects for growth and poverty reduction. *World Dev.* 38 (10), 1429–1441. <https://doi.org/10.1016/j.worlddev.2009.06.008>.
- Hamadani, Jena Derakhshani, Imrul Hasan, Mohammed, Baldi, Andrew J., Jamal Hossain, Sheikh, Shiraji, Shamima, Alam Bhuiyan, Mohammad Saiful, Fardina Mehrin, Syeda, Fisher, Jane, Tofail, Fahmida, Mulk Uddin Tipu, S.M., Grantham-McGregor, Sally, Biggs, Beverley-Ann, Braat, Sabine, Pasricha, Sant-Rayn, 2020. Immediate impact of stay-at-home orders to control COVID-19 transmission on socioeconomic conditions, food insecurity, mental health, and intimate partner violence in Bangladeshi women and their families: an interrupted time series. *Lancet Global Health* 8 (11), e1380–e1389. [https://doi.org/10.1016/S2214-109X\(20\)30366-1](https://doi.org/10.1016/S2214-109X(20)30366-1).
- Hirvonen, K., Abate, G.T., de Brauw, A., 2020. Food and Nutrition Security in Addis Ababa, Ethiopia during COVID-19 Pandemic: May 2020 Report. ESSP Working Paper 143. International Food Policy Research Institute, Washington, DC. <https://doi.org/10.2499/p15738coll2.133731> (IFPRI).
- Hirvonen, K., Abate, G.T., de Brauw, A., 2021. Food consumption and food security during the Covid-19 pandemic in Addis Ababa. *Am. J. Agric. Econ.* 1–18. <https://doi.org/10.1111/ajae.12206>, 00(00).
- Janssens, Wendy, Pradhan, Menno, de Groot, Richard, Sidze, Estelle, Pierre Donfouet, Hermann Pythagore, Abajobir, Amanuel, 2020. The short-term economic effects of COVID-19 on low-income households in rural Kenya: an analysis using weekly financial household data. *World Dev.* 138, 105280. <https://doi.org/10.1016/j.worlddev.2020.105280>.
- Kansime, Monica K., Tambo, Justice A., Mugambi, Idah, Bundi, Mary, Kara, Augustine, Owuor, Charles, 2021. COVID-19 Implications on Household Income and Food Security in Kenya and Uganda: Findings from a Rapid Assessment, vol. 137. *World Development*, p. 105199. <https://doi.org/10.1016/j.worlddev.2020.105199>, January 2021.
- Koné, Yenzié, Pauw, Karl, Randriamamonjy, José, James, Thurlow, 2020. Mali: Impacts of COVID-19 on Production, Poverty and Food Systems. IFPRI, Washington D.C. <https://www.slideshare.net/ifpri/mali-impacts-of-covid19-on-production-poverty-and-food-systems>. (Accessed 18 February 2021).
- Laborde, D., Martin, W., Vos, R., 2020a. Estimating the Poverty Impact of COVID-19: the MIRAGRODEP and POVANA Frameworks. IFPRI Technical Note (IFPRI, 2020). <https://tinyurl.com/y9fzbzbf>.
- Laborde, David, Martin, Will, Swinnen, Johan, Vos, Rob, 2020b. COVID-19 risks to global food security. *Science* 369 (6503), 500–502. <https://doi.org/10.1126/science.abc4765>.
- Lakner, Christoph, Yonzan, Nishant, Mahler, Daniel Gerszon, Andres Castaneda Aguilar, R., Wu, Haoyu, Fleury, Melina, 2020. Updated Estimates of the Impact of COVID-19 on Global Poverty: the Effect of New Data. *World Bank Blog*, p. 2020. | October 07. <https://blogs.worldbank.org/opendata/updated-estimates-impact-covid-19-global-poverty-effect-new-data?token=d3c7288f257b662e819adb237c06033e>.
- Liverpool-Tasie, L.S.O., Omonona, B., Sanou, A., Ogunleye, W., Padilla, S., Reardon, T., 2017. Growth and transformation of chicken and eggs value chains in Nigeria. *Nigerian J. Agric. Econ.* 7 (1), 1–15.
- Liverpool-Tasie, L.S.O., Reardon, T., Belton, B., 2020. Essential Non-essentials": COVID-19 Policy Missteps in Nigeria Rooted in Persistent Myths about African Food Value Chains. *Applied Economic Perspectives and Policy*. Published online Dec28 2020. <https://doi.org/10.1002/aep.13139>.
- Mahler, D. Gerszon, Lakner, C., Aguilar, R. Castaneda, Wu, H., 2020a. Updated Estimates of the Impact of COVID-19 on Global Poverty. *World Bank Blog*. <https://tinyurl.com/yddap4vx>, 8 June 2020.
- Mahler, Gerszon D., Lakner, C., Castaneda Aguilar, R.A., Wu, H., 2020b. The impact of COVID-19 (Coronavirus) on global poverty: Why Sub-Saharan Africa might be the region hardest hit. <https://blogs.worldbank.org/opendata/impact-covid-19-coronavirus-global-poverty-why-sub-saharan-africa-might-be-region-hardest>. (Accessed 6 March 2021).
- Middendorf, J.B.J., Faye, A., Gerad Middendorf, G., Stewart, Z.P., Prakash, K., Jha, P.K., Prasad, P.V.V., 2021. Smallholder farmer perceptions about the impact of COVID-19 on agriculture and livelihoods in Senegal. *Agric. Syst.* 190 (2021) <https://doi.org/10.1016/j.agsy.2021.103108>.
- Minten, B., Mohammed, B., Tamru, S., 2020. Emerging medium-scale tenant farming, gig economies, and the COVID-19 disruption: the case of commercial vegetable clusters in Ethiopia. *Eur. J. Dev. Res.* 32, 1402–1429. <https://doi.org/10.1057/s41287-020-00315-7>.
- Mitimingi, Taonga Clifford, 2020. Zambian inflation accelerates to four-year high in November. *Bloomberg*, November 26. <https://www.bloomberg.com/news/articles/2020-11-26/zambian-inflation-accelerates-to-four-year-high>. (Accessed 14 April 2021), 2020.
- Oxford, 2021. Oxford Covid-19 Government Response Tracker. <https://github.com/OxCGRT>. (Accessed 16 January 2021).
- Population Council, 2020. Kenya: COVID-19 Knowledge, Attitudes and Practices—Responses from Second Round of Data Collection in Five Informal Nairobi Settlements (Kibera, Huruma, Kariobangi, Dandora, Mathare) [COVID-19 Research & Evaluations Brief]. Population Council. https://www.popcouncil.org/uploads/pdfs/2020PGY_Covid_KenyaKAPStudyBriefPrelimFindings.pdf. (Accessed 16 February 2021).
- Reardon, Thomas, Tschirley, David, Lenis Saweda, O., Tasie, Liverpool, Awokuse, Titus, Fanzo, Jessica, Minten, Bart, Vos, Rob, Dolislager, Michael, Sauer, Christine, Dhar, Rahul, Vargas, Carolina, Lartey, Anna, Raza, Ahmed, Popkin, Barry M., 2021. The processed food revolution in African food systems and the double burden of malnutrition. *Glob. Food Secur.* 28, 100466. <https://doi.org/10.1016/j.gfs.2020.100466>, March 2021.
- Rozelle, S., Rahimi, H., Wang, H., Dill, E., 2020. Lockdowns are protecting China's rural families from COVID-19, but the economic burden is heavy. *Int. Food Pol. Res. Inst.* (IFPRI). Available online at: <https://www.ifpri.org/blog/lockdowns-are-protecting-g-chinas-rural-families-covid-19-economic-burden-heavy>.
- Summer, A., Hoy, C., Ortiz-Juarez, E., 2020. *Estimates of the Impact of COVID-19 on Global Poverty* (WIDER Working Paper 2020/43). UNU-WIDER, Helsinki. <https://www.wider.unu.edu/sites/default/files/Publications/Working-paper/PDF/wp2020-43.pdf>. (Accessed 15 March 2021).
- Teachout, M., Zipfel, C., 2020. The Economic Impact of COVID-19 Lockdowns in Sub-Saharan Africa. International Growth Centre. <https://www.theigc.org/wp-content/uploads/2020/05/Teachout-and-Zipfel-2020-policy-brief.pdf>. (Accessed February 2022).
- Tschirley, D., Snyder, J., Goeb, J., Dolislager, M., Reardon, T., Haggblade, S., Traub, L., Ejobi, F., Meyer, F., 2015. Africa's unfolding diet transformation: implications for agrifood system employment. *J. Agribus. Dev. Emerg. Econ.* 5 (2), 102–136. <https://doi.org/10.1108/JADEE-01-2015-0003>.
- Tschirley, David, Bricas, Nicolas, Reardon, Thomas, Sauer, Christine, 2020. Opportunities in Africa's Growing Urban Food Markets. Chapter 2 in AGRA (2020) Africa Agriculture Status Report. Feeding Africa's Cities: Opportunities, Challenges, and Policies for Linking African Farmers with Growing Urban Food Markets (Issue 8). Nairobi, Kenya: Alliance for a Green Revolution in Africa (AGRA). <https://agra.org>.

- [org/wp-content/uploads/2020/09/AASR-2020-Feeding-African-Cities.pdf](https://www.aasr.org/wp-content/uploads/2020/09/AASR-2020-Feeding-African-Cities.pdf). (Accessed 2 May 2021).
- UNDP, 2020. Mitigating the socio-economic impact of Covid-19 in Zambia: a rapid assessment. Lusaka: UNDP Zambia country Office and the consumer unity and Trust society (CUTS) Zambia Office. <https://cuts-lusaka.org/pdf/policy-brief-mitigating-the-socio-economic-impact-of-covid-19-in-zambia.pdf>. (Accessed 3 March 2021).
- World Bank, 2020. Projected poverty impacts of COVID-19 (coronavirus). June. <https://pubdocs.worldbank.org/en/461601591649316722/Projected-poverty-impacts-of-COVID-19.pdf>. (Accessed 5 March 2021), 8-2020.