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RESEARCH ARTICLE

COVID-19, climate shocks, and food security linkages: evidence and perceptions from smallholder farming communities in Tanzania

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Abstract

Insights on the indirect effects of the COVID-19 pandemic are critical for designing and implementing policies to alleviate the food security burden it may have caused, and for bolstering rural communities against similar macroeconomic shocks in the future. Yet estimating the causal effects of the pandemic is difficult due to its ubiquitous nature and entanglement with other shocks. In this descriptive study, we combine high-resolution satellite imagery to control for plot-level rainfall with household socio-economic panel data from 2014, 2016, 2019 and 2020, to differentiate the effect of the pandemic from climatic shocks on food security in Morogoro, Tanzania. We find evidence of decreased incomes, increased prices of staple foods, and increased food insecurity in 2020 relative to previous years, and link these changes to the pandemic by asking households about their perceptions of COVID-19. Respondents overwhelmingly attribute economic hardships to the pandemic, with perceived impacts differing by asset level.

Keywords: COVID-19; farmer perceptions; food security; Tanzania; rainfall

JEL Codes: O12; O13; Q18; Q54

1. Introduction

With confirmed coronavirus infections approaching 100 million worldwide by the end of 2020 (Statista, 2022),[1] official case numbers remained low in much of sub-Saharan Africa (SSA) (Adams *et al*., 2021). Many countries in the region received praise for their swift and effective handling of the pandemic, but in some cases official statistics likely underreported the true case volume due to insufficient testing and diagnostic capacity. Moreover, case numbers alone do not reflect the extent to which the pandemic has impacted livelihoods and disrupted economic activity (Mbow *et al*., 2020; Umviligihozo *et al*., 2020; Mohamed *et al*., 2021). Many of the poorest households in SSA are located

[1]This number was closer to 500 million in April 2022.

in rural agrarian communities, for which, *a priori*, the effects of an economic and health shock like the COVID-19 pandemic are unknown. Agrarian populations are uniquely affected by macroeconomic shocks like COVID-19 since they are both producers and consumers of agricultural products, and could therefore face challenges to production caused by constricted labour and input flows, as well as consumption-side issues like higher food prices and reduced access to markets (Akter and Basher, 2014). On the other hand, limited market access and subsistence agriculture might shield farmers who have little exposure to the virus and/or markets, and changes in food prices might hurt or help producing households.

This descriptive study investigates the felt-impacts of the COVID-19 pandemic among farming communities in Morogoro, Tanzania. Using panel and recall data from 2014, 2016, 2019 and 2020, we describe trends in income, prices and food security, and link economic outcomes in 2020 to the pandemic by asking households directly about their perceived experience of this shock. We also disaggregate the analysis by asset level, remoteness and gender of household head to highlight heterogeneous impacts of the pandemic as experienced by different households in our sample. We find that food insecurity is higher in 2020 relative to previous years, with the starkest increase observed among the bottom quintile of households by asset level, and no effect observed among top quintile households. Households reported lower wages in 2020 relative to 2019, with the richest households reporting the largest wage decrease in absolute terms but the *least* impact of income loss on food security. This is likely due to higher initial wage and asset levels, which enable these households to maintain sufficient food security despite significant income loss during the pandemic. Our data does not allow us to pinpoint the reason the richest households faced the highest income shock, however we speculate that these households may be more connected to labour markets which fluctuated greatly in 2020. Indeed, the poorest households were less likely to receive wages in either year, and did not see a decline in 2020. We observe significant price spikes in 2020 for maize and sugar, and 71 per cent (36 per cent) of respondents reported purchasing less sugar (maize) in 2020 relative to a typical year. Of those households who reduced their staple food purchasing in 2020, the richest were more likely to state that the change was due to increased prices rather than reduced income, while the opposite was true for the poorest households. We do not find significant heterogeneity of outcomes based on remoteness or gender of household head.

Given the econometric challenges in identifying causal impacts of COVID-19 alone, the relationships we find are suggestive, and further work is needed to tease apart the effect of the pandemic from other shocks we cannot control for. Nonetheless, we supplement our quantitative research by asking respondents about their own perceptions of COVID-19 and its impacts on household economic outcomes, and find that this qualitative data supports a narrative that the pandemic indeed contributed significantly to the worsening of food security in 2020. Studies like this one, which examine food insecurity at the household level in rural communities, are critical for providing nuanced understanding of the ways in which the pandemic is experienced by rural communities in low-income countries, and for informing appropriate policy responses to minimize its detrimental effects on livelihoods and food security. We contribute to a growing body of literature describing the global impacts of COVID-19 by providing a case study from a unique context in a country that gained attention for its lax government response (Di Caro and Beech, 2020). The Tanzanian government shut down COVID-19 testing and lifted all restrictions in June 2020, making this study an important documentation of on-the-ground events during this period, and an account of what happens to food security when restrictions are not implemented. We contribute to an understanding of which households experienced the largest effects, and of the mechanisms through which the pandemic has impacted rural livelihoods. Finally, we contribute to the methodological challenge of isolating the impacts of COVID-19 on agrarian livelihoods by merging high resolution satellite rainfall data corresponding to the GPS location of each surveyed household to control for climatic shocks such as flooding and drought, and by corroborating the findings of our quantitative analysis with farmer perceptions.

1.1 Literature review

A developing body of literature documenting the impacts of the COVID-19 pandemic on rural livelihoods and food security includes mixed evidence of its severity, highlighting the degree to which context matters. A series of studies find that the pandemic is associated with increased food insecurity (Ceballos *et al*., 2020; Amare *et al*., 2021; Mahmud and Riley, 2021; Nchanji and Lutomia, 2021). For example, Josephson *et al*. (2020) find that 77 per cent of the population across Ethiopia, Malawi, Nigeria and Uganda lost income due to the pandemic, and 25 per cent have faced difficulties in accessing food. Ragasa *et al*. (2021) find that more than half of households surveyed in rural farming communities in central Myanmar report income loss and increased food insecurity as a result of the pandemic, along with decreased prices and demand for agricultural goods, hurting net producing households. On the other hand, a few studies find limited adverse effects from the pandemic on food security (Adjognon *et al*., 2020; Kansiime *et al*., 2020; Hirvonen *et al*., 2021). Abay *et al*. (2020), for example, find that Ethiopia's Productive Safety Net Program was successful in eliminating most of the adverse effects of the pandemic on food insecurity, with greater protection for poorer households. Aggarwal *et al*. (2020) investigate price changes in Liberia and Malawi during the pandemic, finding no loss of food security among rural households despite disruptions in market activity and loss of income among vendors.

1.2 Morogoro rural context

We survey farming households across Morogoro Rural (see figure A1 in online appendix A), a district in the Morogoro region of Tanzania. Nearly 70 per cent of households in Morogoro are located in rural areas, and 73.3 per cent of rural workers in Morogoro are principally employed in own-agriculture (NBST, 2015). Forty-one per cent of rural households in Morogoro live below the basic needs poverty line of US$1.90 per day in 2011. Over 95 per cent of agricultural land in Tanzania and within Morogoro is rainfed, which makes the agricultural sector and therefore food security sensitive to climate change and deviations from normal rainfall patterns (Ojoyi *et al*., 2015; IFPRI and Datawheel, 2017). Maize is the most common crop grown in Morogoro as well as in Tanzania as a whole, accounting for 27 per cent (35 per cent) of total harvested area in Tanzania (Morogoro) (IFPRI and Datawheel, 2017).

2. Data and empirical application

2.1 Sampling strategy

Respondent households were surveyed by phone from a randomized network of 1,070 households across 47 villages in Morogoro Rural. The initial randomization process

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occurred in 2014, when farming households were selected to participate in an experimental fertilizer recommendation initiative (Harou *et al.*, 2022). Online appendix B contains more information on the initial randomization process. Data on assets, demographics, food security, and agricultural production were collected from all participating households in 2014, 2016 and 2019, although the survey changed and not every variable was collected in each year – see table A1 in online appendix C for an account of variables available by year. The fertilizer initiative succeeded in increasing input use and maize yields among treatment households in 2016, but with little to no significant remaining effect detected in 2019 (Tamim *et al.*, 2022). For the present study, all households who were reachable by phone were included with no distinction between treatment and control, and we verify that the 2014 treatment did not affect any of the outcomes we measure.

2.2 Coverage and response biases

Attrition from the initial 2014 sample pool has occurred over the years as households relocate or choose to leave the study. This has been shown to be random between 2014, 2016 and 2019 (Harou *et al.*, 2022; Tamim *et al.*, 2022). Additional attrition occurred in 2020 because some households were not reachable by phone – a limitation faced by most studies that attempt to monitor COVID-19 impacts while avoiding in-person contact during data collection (Ambel *et al.*, 2021). If households who are reachable by phone are not representative of the general population, for example if this group omits the poorest households, then phone survey data will produce biased estimates of the relationships we measure. Indeed, in our 2020 phone survey, we were able to reach only 545, or 52 per cent, of the original 1,070 households selected for the SoilDoc study in 2014 (see table A1 in online appendix C). If the households we reached do not represent a random selection of the sample pool, our estimators of interest will not be representative of the population of Morogoro Rural. We construct inverse probability weights using representative data from the most recent in-person survey conducted in 2019 to mitigate this attrition bias along observable household characteristics (see online appendix D) (Wooldridge, 2002; Baulch and Quisumbing, 2011; Gourlay *et al.*, 2021). This method has been shown to substantially reduce phone survey bias, especially when the sample is drawn from an in-person baseline survey containing a wealth of socio-demographic information on characteristics reflective of the general population, as was the case in the present study (Ambel *et al.*, 2021; Gourlay *et al.*, 2021).

Moving from in-person to phone surveys may introduce an additional source of bias in panel data comparisons if response patterns differ by interview mode, for example if respondents are more willing to report food insecurity over the phone. Some studies have found that respondents answer more accurately over the phone when asked about sensitive behaviours or private information (e.g., Langhaug *et al.*, 2010), while others find near-perfect accordance between face-to-face and phone survey responses, even about sensitive topics such as cigarette smoking and health issues (Mahfoud *et al.*, 2015) and food security (Nord and Hopwood, 2007). In the present study, each of the outcomes we measure (food security, income, and price measures) is accompanied by at least one qualitative question eliciting respondents' perceptions about the changes in 2020 relative to a typical year. Moreover, many of the key outcome variables including prices and wages are recall data, asked about over the phone in 2020 about both 2020 and 2019. In all cases these correspond with the narrative that emerges from the quantitative and panel data, and suggest that our findings are not driven by respondents' willingness to report

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more food insecurity over the phone but rather reflect a perceived decline in economic outcomes in 2020 relative to previous years. To further validate findings from the phone survey, we investigate whether responses to simple questions like age, education, and descriptions of dwelling characteristics are consistent between the phone survey in 2020 and the in-person survey in 2014, and find a high degree of consistency across these responses.

2.3 Data

The 2020 survey consisted of a 30-minute phone interview with each household, conducted beginning in late-August 2020 and ending in mid-September 2020. The survey included questions on asset ownership, housing and dwelling characteristics, patterns of food consumption, off-farm income sources, market access and prices, and respondents' perceptions and attitudes towards the ongoing COVID-19 pandemic. The module on COVID-19 was placed at the end of the survey instrument to avoid biasing responses to questions on food security, income, and other economic outcomes in 2020. To this survey data, we also add rainfall measurements for the GPS coordinates of the main maize plot for each respondent from 2014–2020 acquired from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) (Funk *et al*., 2015). CHIRPS data has been validated for accuracy in Tanzania compared to traditional rain-gauge data (Dinku *et al*., 2018). Tables A1 and A2 in online appendix C include summary statistics of key relevant variables.

3. Methods

We are interested in measuring the effect of COVID-19 on economic and food security outcomes among our respondents. Estimating the causal effect of COVID-19 is not possible due to a lack of measurable heterogeneity in the way the pandemic was felt by households in our sample. Given the panel nature of our data, however, we can explore the degree to which food insecurity and other outcome variables shifted over time while controlling for climatic shocks. To do this, we estimate the following model:

$$Y_{it} = \alpha + \sum_t \beta_t T_t + \delta \boldsymbol{X}_{it} + \gamma_i + \varepsilon_{it}, \tag{1}$$

where Y_{it} is an outcome variable of interest for respondent i in year t, including food insecurity, market prices, wages, and income, described in more detail below, and the β_t coefficients, the parameters of interest, measure the change in the outcome variable in each of t years – 2016, 2019 and 2020 – relative to the base year 2014. The years for which we have data differ depending on the outcome variable under investigation – see tables A1–A2 in the online appendix for a breakdown of available data by year, and the year dummies included in the model change accordingly to reflect this. γ_i is a household fixed effect while ε_{it} measures idiosyncratic error. Standard errors are clustered at the village level. $\boldsymbol{X}$ is a vector of exogenous time-varying controls consisting of a rainfall measure and two land use measures which are likely to be related to food security outcomes in 2020 independently of the pandemic. The rainfall variable measures total rainfall on farmers' main maize plot during anthesis, or the silking period, when maize is particularly vulnerable to drought and flooding. This measure is constructed following Lobell *et al*. (2011) using CHIRPs daily precipitation index to aggregate total rainfall at

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each GPS plot location during the anthesis period. The measure is thus a control for both drought and flooding at the plot level.

We are also interested in determining whether the shocks of a certain year differentially affect certain segments of the population, i.e., better-off households as measured by an asset index, households that are more remote, or female-headed households. To look at this heterogeneity among respondents, we incorporate interaction terms into the model as follows:

$$Y_{it} = \alpha + \sum_{t} \beta_t T_{it} + \sum_{t} \sum_{q=1,5} \delta_{tq} T_{it} Q_{iq} + \sum_{q=1,5} \lambda_q Q_{iq} + \delta \boldsymbol{X} + \gamma_i + \varepsilon_{it}, \tag{2}$$

where Q_{i1} (Q_{i5}) are dummy variables equal to one for respondents in the highest (lowest) quintile of asset ownership or proximity to nearest market, or for male- (female-) headed households. The parameters of interest are δ_{tq}. The other variables and indices are the same as those defined in equation (1). The models presented in equations (1) and (2) allow us to see the changes in outcome variables among our respondents over time while controlling for rainfall, land owned and land cultivated, and how these changes differ among households on the basis of asset ownership, remoteness and gender.

4. Results and discussion

4.1 Food security status

To assess changes in food security status among our respondents over time, we compare data on skipped meals, collected in 2014, 2016 and 2020. In each year, we asked respondents how many months out of the past 12 any adult household member skipped one or two meals per day on at least one day due to lack of resources. We construct a simple weighted index as follows:

$$I = \frac{1}{3}\delta_1 + \frac{2}{3}\delta_2, \tag{3}$$

where I is an index variable capturing the depth of food insecurity, δ_1 is the number of months during which a household member skipped one meal, and δ_2 is the number of months during which a household member skipped two meals (in one day). As a robustness check, we also estimate food security proxied by the number of months households skipped zero, one or two meals, respectively. Furthermore, to gain a better understanding of the multidimensionality of the food insecurity faced by respondents, we administered the Food Insecurity Experience Scale (FIES) survey module[2] to a subset of 96 households randomly selected from our 2020 sample. The FIES module, developed by the UN FAO Voices of the Hungry project (Nord, 2014), uses eight questions to assess respondents' level of food insecurity based on food-related behaviours such as skipping meals, eating less nutritious food, or worrying about having enough food to eat (Ballard *et al.*, 2013). The questions are intended to capture the depth of food insecurity, with positive responses indicating increasing severity of food insecurity as the scale progresses from item 1 to 8. The eight items in the FIES module can be aggregated to produce a raw score,[3] which indicates the severity of food insecurity ranging from mild food insecurity (1–3) to severe food insecurity (7–8) (Smith *et al.*, 2017). We elicited respondents' FIES

[2] The FIES is available at http://www.fao.org/3/i7835e/i7835e.pdf.

[3] The raw FIES score is valid on the assumption the data produced by the questions fits the Rasch Item Response Theory model (Rasch, 1960; Nord, 2014; Adjognon *et al.*, 2020).

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Table 1. Food insecurity regressions

Variables	(1) Food insecurity index	(2) 0 skipped meals	(3) 1 skipped meal	(4) 2 skipped meals	(5) FIES score
2016	0.244 (0.0948)	−0.606 (0.223)	0.633 (0.219)	0.0495 (0.123)	–
2020	0.497 (0.172)	−1.474 (0.432)	1.607 (0.386)	−0.0584 (0.130)	1.422 (0.365)
Rainfall	0.000574 (0.00157)	−0.00170 (0.00426)	0.00167 (0.00450)	2.59×10^{-5} (0.00120)	−0.00713 (0.0087)
Land owned (acres)	−0.0150 (0.00779)	0.0394 (0.0205)	−0.0368 (0.0209)	−0.00404 (0.00752)	0.0331 (0.0471)
Land cultivated (acres)	−0.0449 (0.0203)	0.0971 (0.0502)	−0.0609 (0.0491)	−0.0369 (0.0214)	−0.128 (0.0722)
Constant	1.651 (0.757)	7.850 (2.051)	3.220 (2.150)	0.867 (0.596)	5.784 (3.933)
Observations	1,585	1,585	1,585	1,585	189
R^2	0.041	0.051	0.059	0.005	0.370
Number of respondent ID	535	535	535	535	96

Notes: The outcome variables in each column are regressed on year dummies and include farmer fixed effects. Robust standard errors are clustered at the village level and shown in parentheses. Regressions are weighted to account for attrition. Ten respondents are missing GPS coordinates and are dropped from all regressions because we are unable to calculate the rainfall level. For columns 1–4 (5), the base year is 2014 (2019). Robust standard errors in parentheses.

score for the period March–August 2020, and for the same period the preceding year (March–August 2019) for comparison. Thus, the 2019 FIES score is recall data, asked over the phone in 2020.

Table 1 shows a significantly higher level of food insecurity in 2020 relative to 2014 and 2016, as measured by our weighted index constructed from panel data collected in 2014, 2016 and 2020. This finding is robust when food security is measured by the number of months with zero, one or two skipped meals (per day). Column 5 shows that the FIES raw scores are also higher in 2020, relative to 2019. Table A3 in the online appendix C provides a breakdown of responses to individual FIES questions.

We are also interested in seeing if households' food security status changes by wealth, gender or remoteness. We estimate equation (2) above where the base-group is comprised of the second, third and fourth asset quintiles based on 2019 asset scores.[4] The results, presented in column 1 of table 2, show that better-off households face less food insecurity in all years, and actually have slightly lower food insecurity (i.e., they are more food secure) in 2020 relative to 2014 and 2016. Households in the bottom asset quintile face a starker increase in food insecurity in 2020, significant at the 10 per cent level. This is consistent with the FIES score results, where the largest increase in food insecurity is observed among poorer households (see figure A2 in online appendix A).

[4] Asset scores were calculated using principal component analysis of items owned by households including household, productive and livestock assets.

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Table 2. Heterogeneity analysis of Food Insecurity Index

Variables	(1) Assets	(2) Remoteness	(3) Gender
2016	0.301 (0.0931)	0.319 (0.117)	0.228 (0.108)
2020	0.568 (0.185)	0.475 (0.202)	0.503 (0.175)
Q1 (Richest, least remote, male head)	–	–	–
2016 X Q1	−0.491 (0.149)	−0.293 (0.228)	–
2020 X Q1	−0.681 (0.224)	−0.122 (0.276)	–
Q5 (Poorest, most remote, female head)	–	–	–
2016 X Q5	0.243 (0.226)	−0.0377 (0.272)	0.101 (0.219)
2020 X Q5	0.385 (0.203)	0.268 (0.287)	−0.0419 (0.220)
Rainfall	0.000699 (0.00150)	0.000553 (0.00152)	0.000570 (0.00158)
Land owned (acres)	−0.0104 (0.00783)	−0.0140 (0.00822)	−0.0149 (0.00769)
Land cultivated (acres)	−0.0442 (0.0200)	−0.0431 (0.0205)	−0.0448 (0.0204)
Constant	1.565 (0.719)	1.649 (0.732)	1.652 (0.763)
Observations	1,585	1,585	1,585
R^2	0.057	0.045	0.041
Number of respondent ID	535	535	535

Notes: The outcome variable is the food insecurity index, which is regressed on year dummies interacted with dummies for highest and lowest quintile of assets, or remoteness, respectively, and includes farmer fixed effects. Q1 refers to the highest quintile, which is the richest 20% in model (1), the least remote 20% in model (2), and male headed households in model (3). Q5 refers to the lowest quintile, which is the poorest 20% in model (1), the most remote 20% in model (2), and female-headed households in model (3). The asset breakdown uses 2019 asset index scores. Remoteness is measured by summing the distance to road plus distance to market, using 2019 distances. Q1 and Q5 are omitted because they are time-invariant. Regressions are weighted to account for attrition. Robust standard errors are clustered at the village level and shown in parentheses.

Similarly, we can look at whether remoteness[5] plays a role in determining the extent to which household food insecurity increased in 2020 relative to previous years. As we see in column 2 of table 2, the remoteness interaction terms are not statistically significant. However, it is worth noting that the most remote households have a slightly larger increase in food insecurity in 2020, but this is not statistically significant. Moreover, when we look at remoteness as a continuous variable instead of broken down by quintile, the interaction term between 2020 and remoteness becomes significant and positive,

[5]Remoteness is defined as the sum of a household's distance to the nearest market and to the nearest road.

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indicating that the more remote households indeed faced more substantial food insecurity increases in 2020, but this trend diminishes for the most remote households (top 20 per cent) – see online appendix E. This could imply that remote households faced additional hurdles to accessing food, such as lacking private transportation to access markets or facing higher transportation costs built in to food prices, which may be further exacerbated by the COVID-19 pandemic due to transportation and shipping bottlenecks. Similarly, the least remote households have a slightly lower increase in food insecurity in 2020, although, again, this is not significant at traditional levels. Finally, we look at heterogeneity in food insecurity by gender of household head, but do not find any significant effects. This lack of effect, however, could result from the low number of female-headed households we observe in our sample, and the fact that we do not ask directly about gender of household head in 2020 (see table A1 in online appendix C), leaving only 87 (or 15.96 per cent) confirmed female-headed households to evaluate.

4.2 Factors impacting household food security in 2020

We are interested in understanding what factors contributed to the decrease in food security in 2020, and the degree to which COVID-19 may have played a role in this change. Below, we explore the degree to which prices and income sources changed relative to previous years.

4.2.1 Income losses

Apart from agricultural production, the primary sources of income reported among our sample group are wages (agricultural and non-agricultural) and remittances. We look at changes in each income source by asking respondents for the average agricultural and non-agricultural wage per day received during this period of 2020, and what they recalled this to be for the same period last year. We also asked about total remittances received in 2020, which we were able to compare to data collected in 2014 and 2016. We estimate equation (1), with Y_{it} representing total remittances, typical agricultural wage and typical non-agricultural wage. For wages, the base year is 2019. For remittances, the base year is 2014. All nominal wages and remittances are reported in 2020 Tanzanian Shillings (Tzs), adjusted using the Tanzania consumer price index taken from World Bank data, allowing us to compare real changes. The results are presented in table 3. We find a decrease in the average agricultural wages in 2020 relative to 2019, significant at the 10 per cent level, and a decrease in non-agricultural wages significant at the 5 per cent level. Total remittances are also lower in 2020, but this is not significant at traditional levels.

Given the heterogeneity in food security impacts by asset group reported in table 2, we look at whether income changes had a differential effect on the richest and poorest households. We estimate equation (2) with Y_{it} taking the value of remittances, agricultural wages, and non-agricultural wages, respectively, and report the results in table 4. The base-group is comprised of the second, third and fourth asset quintiles in 2019 for wages, and 2014 for remittances. We also look at the differential impacts of remoteness and gender, but find no significant results, so we do not report these here.[6]

These results suggest that the richest households saw a steeper decline in agricultural wages (in absolute terms) relative to other asset quintiles. It is worth noting that the mean agricultural wage among the top asset quintile (Q1) was 12,062 Tzs/day in 2020 compared to a mean of just 5,100 Tzs/day among the lower four asset quintiles, implying

[6]Results available upon request from the corresponding author.

Table 3. Changes in income received from various sources in 2020

Variables	(1) Total remittances (Tzs/year)	(2) Agricultural wages (Tzs/day)	(3) Non-agricultural wages (Tzs/day)
2016	81,678 (25,470)	–	–
2020	−1,817 (27,371)	−727.6 (325.9)	−3,359 (1,393)
Rainfall	380.8 (182.3)	−2.294 (9.036)	62.29 (82.12)
Land owned (acres)	−188.8 (2,953)	46.65 (90.53)	−50.38 (157.0)
Land cultivated (acres)	11,481 (8,659)	−4.693 (90.09)	1.499 (280.2)
Constant	−91,265 (88,607)	6,905 (3,835)	−12,487 (35,808)
Observations	402	300	203
R^2	0.179	0.064	0.094
Number of respondent_ID	289	151	102

Notes: Households that do not report receiving income from a given source are dropped from the corresponding regression. The outcome variables in columns 1–3 are regressed on year dummies and include farmer fixed effects. Remittances are winsorised at the 0.05 level. Wage and remittance data are deflated using the Tanzania consumer price index. Robust standard errors are clustered at the village level. Regressions are weighted to account for attrition. Standard errors in parentheses.

that the richest households remained significantly better off in absolute terms despite facing the starkest decline in wages between 2019 and 2020. For non-agricultural wages, the richest households faced less of a decline in 2020 compared to the middle asset quintiles. Interestingly, the bottom asset quintile (Q5) saw almost no decline in non-agricultural wages in 2020 relative to 2019, perhaps suggesting that the poorest households were less connected to labour markets that were affected in 2020.

4.2.2 Higher market prices

We asked respondents to recall the highest price they paid for commonly-purchased staple foods during the past six months (March–August, 2020), and the highest price they paid for these goods during the same period in 2019. We estimate equation (1) above, where the outcome variable, Y_{it}, is the maximum price for maize, salt and sugar, and β_1 measures the change in the maximum price observed in 2020 relative to the base year 2019. As with wages, all nominal prices are adjusted to 2020 values using the Tanzania consumer price index taken from World Bank data.

The results from these regressions, presented in table 5, indicate significantly higher maximum prices for sugar and maize in 2020 relative to 2019, while salt prices remained constant. We corroborate these findings by asking respondents about their perceptions surrounding the price of each good during the months of March–August, 2020 relative to the same period in a typical year. We find these perceptions to be consistent with the maximum price data: 93 per cent of respondents observed a higher price of sugar in March–August 2020 relative to this period in a typical year, and 70 per cent observed higher maize prices. There was no price spike observed for salt, which is

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Table 4. Differential changes in income by asset quintile

Variables	(1) Total remittances	(2) Agricultural wages	(3) Non-agricultural wages
2016	45,173 (27,027)	–	–
2020	−4,965 (27,193)	−328.1 (369.8)	−4,736 (2,013)
Q1 (richest)	–	–	–
2016 X Q1	15,595 (53,980)	–	–
2020 X Q1	45,866 (57,291)	−2,024 (878.1)	2,940 (3,006)
Q5 (poorest)	–	–	–
2016 X Q5	29,960 (58,861)	–	–
2020 X Q5	60,050 (58,012)	−348.2 (435.0)	4,589 (2,292)
Rainfall	407.7 (148.3)	−6.295 (7.967)	46.79 (75.54)
Land owned (acres)	−12.71 (2,321)	84.68 (78.39)	−70.78 (174.5)
Land cultivated (acres)	9,079 (6,875)	−22.25 (80.00)	34.85 (279.3)
Constant	−115,273 (74,497)	8,365 (3,403)	−6,058 (32,962)
Observations	402	300	203
R-squared	0.120	0.090	0.100
Number of respondent ID	289	151	102

Notes: Q1 refers to the highest asset quintile, which is the richest 20%. Q5 refers to the lowest asset quintile, or poorest 20%. The asset breakdown uses 2019 asset index scores. Robust standard errors are clustered at the village level and shown in parentheses. Regressions are weighted to account for attrition. Q1 and Q5 omitted because they are time invariant.

produced domestically and is a net export (TrendEconomy, 2020). Tanzania has four sugar processing plants which produce enough supply to meet approximately half the national demand. The rest is imported, in a process strictly regulated by the Sugar Board of Tanzania. Local news sources reported an artificial sugar shortage shortly after the initial COVID-19 outbreak, as wholesalers bought up the supply on the assumption that imports would be stalled by the pandemic (The Citizen, 2020). Unfavourable climate conditions reduced domestic sugar production, further exacerbating the shortage (The Citizen, 2020). Maize is also produced domestically – Tanzania is a net exporter of maize – and we speculate that prices increased in 2020 due to a combination of unfavourable climate conditions and disruptions in labour supply resulting from the pandemic.

For consistency, we also investigate the differential impact of prices faced by members of each asset quintile, although we would not expect prices faced by households to vary

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Table 5. Changes in maximum price paid for staple goods in 2020

Variables	(1) Max maize price	(2) Max sugar price	(3) Max salt price
2020	78.79 (20.06)	1,399 (192.6)	−242.2 (280.1)
Rainfall	0.0194 (0.484)	4.742 (4.047)	−5.444 (2.966)
Land owned (acres)	6.135 (2.322)	−9.589 (11.50)	−0.445 (6.828)
Land cultivated (acres)	−12.78 (4.700)	−0.531 (12.65)	0.958 (6.454)
Constant	584.6 (219.9)	829.6 (1,777)	3,585 (1,396)
Observations	589	1,001	1,056
R^2	0.190	0.194	0.001
Number of respondent ID	309	505	534

Notes: The outcome variables are regressed on year dummies and include farmer fixed effects. Robust standard errors are clustered at the village level and presented in parentheses. Regressions are weighted to account for attrition. 2019 is the base year, and prices are adjusted for inflation using the Tanzania consumer price index. N is the number of respondents who purchased a given staple good in 2020, respondents who did not purchase the good are omitted. Robust standard errors in parentheses.

by asset group. We run equation (2) with Y_{it} equal to the maximum price paid for each good (maize, salt and sugar), with the base group comprised of the second, third and fourth asset quintiles in 2019. We do not find any heterogeneity in prices; results are available in the online appendix C, table A4.

5. Household perceptions of COVID-19, climate shocks and food security outcomes in 2020

5.1 *Perceptions of climate and yields*

Economic and food security outcomes among agrarian households are highly dependent on climate conditions (Hertel *et al.*, 2010). To understand the extent to which respondents hold climate conditions responsible for poor economic outcomes in 2020, we asked each household to rate the climate between 2014–2019 along four factors: quantity and timing of rainfall, temperatures, and pests. Additionally, we asked farmers about their maize production during the 2020 long rains growing season, which coincided with the pandemic from March–August. The farmers we surveyed overwhelmingly reported that 2020 was a bad year for maize cultivation, primarily due to widespread flooding and the unusual timing of rainfall. Pests and temperatures were also unfavorable this year compared to 2014, 2016 and 2019, highlighting the difficulty in attributing the decline in food security solely to COVID-19. See figure A3 in online appendix A for a figure showing the correlation between unfavorable growing conditions, poor maize yields and high food insecurity.

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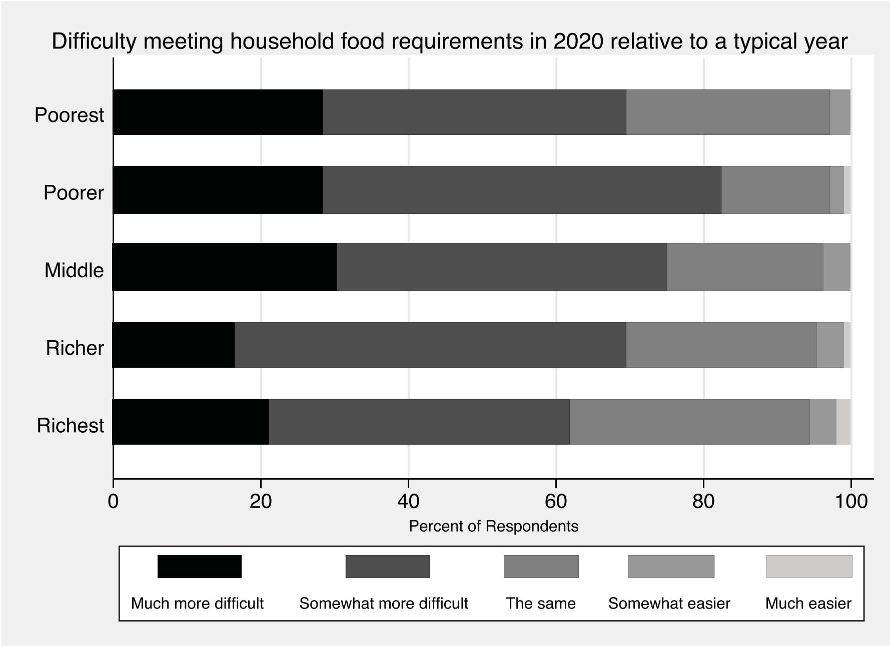

Figure 1. Difficulty meeting household food requirements in 2020 relative to a typical year

5.2 Perceptions of COVID-19

Despite overwhelmingly poor perceptions of climate conditions in 2020, respondents report that the COVID-19 pandemic played a significant role in worsened economic outcomes in this year. We asked households whether their food requirements in 2020 had been met, and how they understood the pandemic to be involved in determining their economic outcomes in 2020. Seventy-two per cent of households perceived it to be more difficult to meet household food requirements during the months of March–August 2020 compared to this period of a 'typical year'. Figure 1 provides a breakdown of perceived changes by quintile,[7] showing that households in the middle three quintiles were more likely to report increased difficulty meeting food requirements in 2020 relative to a typical year. A one-way ANOVA test reveals a significant difference in means between asset groups ($F(4, 540) = [2.96]$, $p = 0.0196$).

Among the 391 households who reported greater difficulty in meeting food requirements, higher prices in markets (42 per cent), reduced income from agricultural production and sales (33 per cent), and loss of wage income (40 per cent) were most commonly cited as contributing factors. Breaking this down by asset quintile, we find that richer households are less likely to state that lost income contributed to increased difficulty meeting food requirements in 2020. A one-way ANOVA confirms that the mean response was significantly different between asset groups ($F(4, 386) = [3.41]$, $p = 0.0094$), and figure 2 illustrates this differential effect. A possible explanation for this

[7]We also looked at the differential impacts by remoteness and gender, but found these were not significant. Results are available upon request from the corresponding author.

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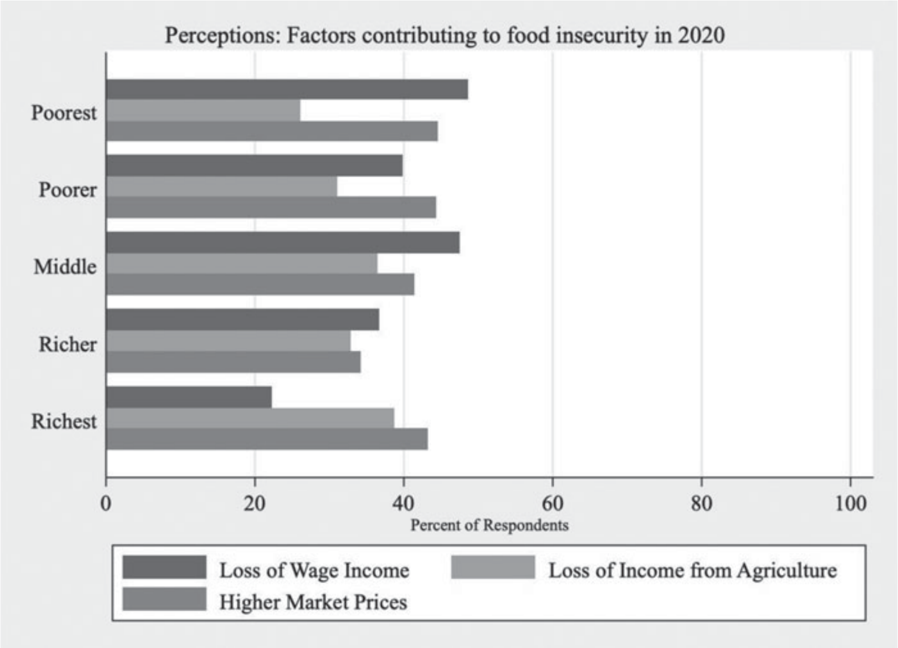

Figure 2. Factors contributing to food insecurity in 2020 – differential impacts by asset quintile

result is that although the richest households saw the starkest decline in wages in absolute terms (see table 4), they still had substantially higher wages relative to other asset groups. We also look at heterogeneity in loss of income from agricultural production or higher market prices as contributing factors to the perceived decline in food security in 2020, but there is no statistically significant difference in means for either factor by asset level. We asked households to describe their experience purchasing staple goods (maize, salt and sugar) during the pandemic months (March–April 2020). Seventy-one per cent of respondents purchased less sugar than usual, and 36 per cent purchased less maize. Salt purchasing remained largely unchanged (see figure A4 in online appendix A). There is no significant heterogeneity in this purchasing behaviour by asset level.

Higher prices and lower incomes were the factors indicated most frequently as contributing to the decrease in quantity purchased of both maize and sugar, with higher prices particularly relevant in the case of sugar. We break this down by asset group, and find that richer households are significantly less likely (relative to all other asset quintiles) to report decreased income as a factor that contributed to their decision to purchase fewer staple goods. This finding is depicted in figure 3, and confirmed by a significant one-way ANOVA ($F(4, 538) = [2.98]$, $p = 0.0197$). Figure 3 also depicts the breakdown by asset group of market price as a contributing factor to households' decisions to purchase fewer staple goods. The graph suggests the poorest households may be less likely to report this factor, perhaps because they are somewhat insulated from market prices due to reliance on subsistence farming, but an ANOVA test indicates that the difference in means is not significant between asset groups.

Finally, we ask respondents directly about their experience and perception of the pandemic, and its effect on their livelihoods and economic outcomes this year. Close

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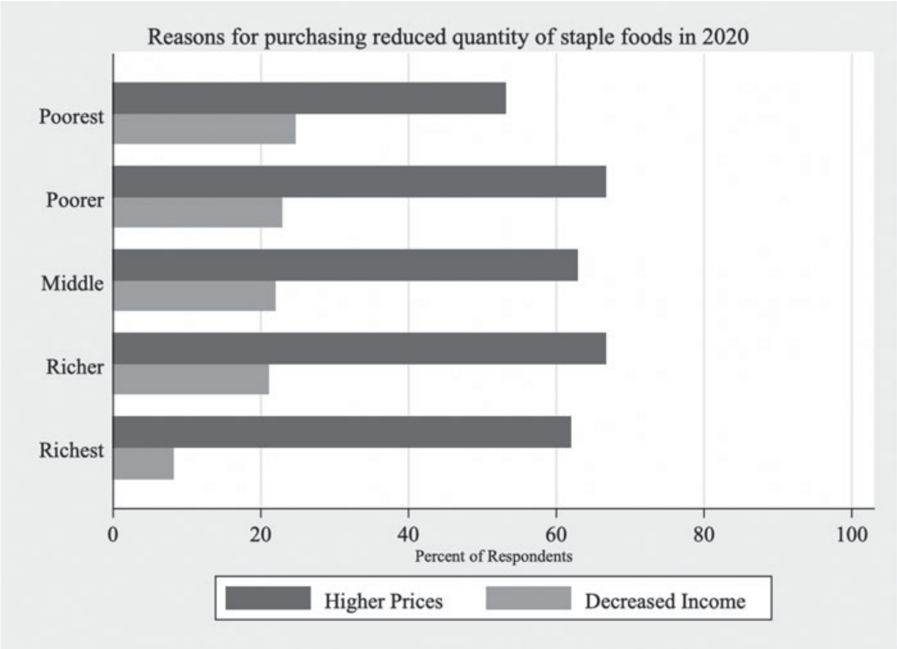

Figure 3. Heterogeneity in purchasing experience by asset quintile
Notes: The bars indicate the percentage of total respondents in each asset quintile who indicated higher prices (decreased income) as a reason for reduced purchasing of staple goods in 2020. Respondents had the option of selecting both categories or neither, so the bars do not necessarily add up to 100.

to 60 per cent of respondents agreed with the statement '*COVID-19 has significantly changed my life*', indicating loss of income (reported by 36 per cent of total respondents, or 194 out of 545), higher market prices (31 per cent), increased difficulty selling agricultural products (30 per cent), and fear of becoming ill (54 per cent) as factors which have affected them. Only two out of 545 respondents indicated sickness of self or a household member as a way in which the pandemic had affected them in 2020. The perceived impact of COVID-19 seems to be strongest among the middle-income quintiles, with the poorest and richest households somewhat less likely to perceive a strong impact of COVID-19. The breakdown of responses to this question is depicted in figure 4, and a one-way ANOVA suggests that the mean response is significantly different (at the 10 per cent level) across asset groups ($F(4, 540) = [2.08]$, $p = 0.0826$). Our analysis throughout has implied that the richest households do not perceive as much of an impact from income losses associated with the pandemic, likely due to a higher initial absolute wage.

6. Conclusion

In 2020, food insecurity among the communities of Morogoro Rural reached the highest levels observed since we began collecting data in 2014. Our results throughout point to reduced incomes and higher food prices as central factors contributing to the decline in food security observed in 2020. Price increases on imported goods like sugar, which resulted from anticipated import bottlenecks and hoarding behaviour triggered by the

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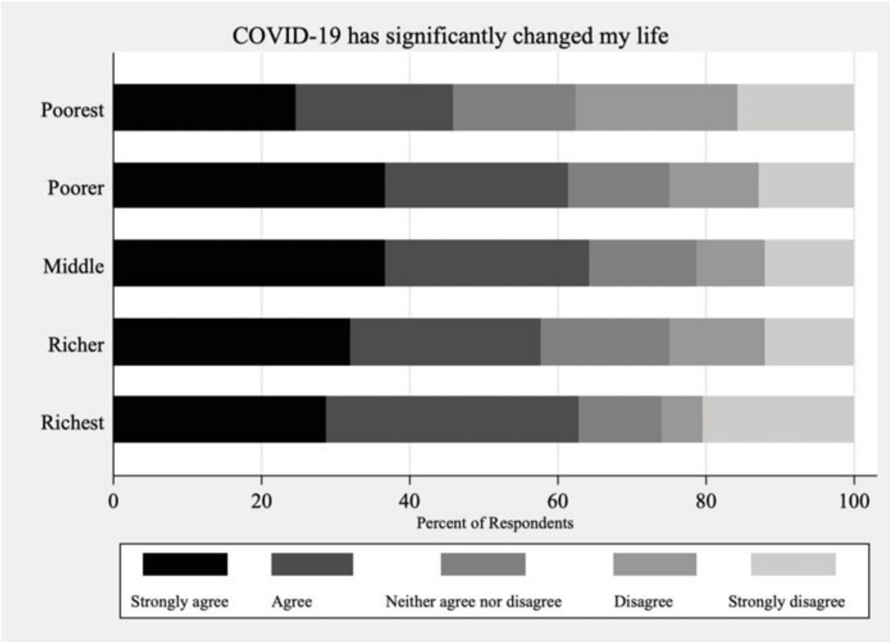

Figure 4. Household perceptions of the felt-impacts of COVID-19.

COVID-19 pandemic, exacerbated the situation from the supply-side, while reductions in income from wages and remittances created additional demand-side obstacles to meeting household food requirements. Price spikes, reduced product availability, and income decreases were all perceived by respondents to be linked to the COVID-19 pandemic. A breakdown of the felt-impacts of the pandemic by asset level suggests that the richest households were less affected by income losses, highlighting the importance of meeting a level of income at which households are buffered from shocks. To some extent we also find that the poorest households were less affected, suggesting that these households which largely rely on subsistence agriculture may be isolated from labour and goods markets and face less fluctuation in income and spending patterns as a result of market shocks. Further work is needed to understand why the poorest households were less impacted from the shocks, and whether remoteness and gender may play a bigger role than we were able to capture in the present study.

Nonetheless, a few important policy implications emerge from this work. First, the pandemic presented a crisis within a crisis for respondents who continuously depend on unpredictable and worsening climate conditions. Social safety nets, as well as tools for increasing the resilience of agrarian communities like Morogoro Rural, are needed to ensure smallholder farming households can adequately cope with simultaneous climate, political, economic and health shocks. Special attention must be made in determining which groups within a population are most affected by different shocks, as targeting the worst-off households may not always be appropriate, if they are more buffered from adverse effects. Second, there has been much optimism for the role of mobile technology in agriculture (Fabregas *et al.*, 2019). However, as the pandemic has made clear, a large proportion of the population in communities like Morogoro still find themselves without

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access to phones or network coverage. These populations, which are often the worst-off and less educated households, are underrepresented in studies like this one. While attempts can be made to minimize this source of bias, alternative means of reaching out to these communities must be considered, whether to collect or to share information (Giulivi *et al*., 2022).

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S1355770X22000225.

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Conflict of interest. The authors declare none.

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