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Poverty and food insecurity during COVID-19: Phone-survey evidence from rural and urban Myanmar in 2020

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ABSTRACT

Myanmar first experienced the COVID-19 crisis as a relatively brief economic shock in early 2020, before the economy was later engulfed by a prolonged surge in COVID-19 cases from September 2020 onwards. To analyze poverty and food security in Myanmar during 2020 we surveyed over 2000 households per month from June–December in urban Yangon and the rural dry zone. By June, households had suffered dramatic increases in poverty, but even steeper increases accompanied the rise in COVID-19 cases from September onwards. Increases in poverty were much larger in urban areas, although poverty was always more prevalent in the rural sample. However, urban households were twice as likely to report food insecurity experiences, suggesting rural populations felt less food insecure throughout the crisis.

1. Introduction

The COVID-19 pandemic triggered a global economic crisis from which few countries were spared. By June 2020 the World Bank (2020b) was already estimating that 119 of 128 low and middle income countries (LMICs) would experience contractions in Gross Domestic Product (GDP) per capita, with an average contraction of 4.3%. Even so, such projections potentially obscure the real scale, scope and speed of a crisis that often involved shutting down large parts of the economy virtually overnight. Case studies of COVID19's impacts on various LMICs using social accounting matrices predicted that economies could shrink by 20–40% during lockdown periods (Arndt et al., 2020; Andam et al., 2020; Diao et al., 2020; Pradesha et al., 2020). However, even when prevention measures are relaxed, fear of contagion can still suppress consumer demand, with adverse multiplier effects rippling through the rest of the economy (Laborde et al., 2020).

The context of this study, Myanmar, is a particularly interesting case study for the objective of quantifying the economic costs of COVID19 at the household level. Myanmar's economy was booming prior to COVID-19, but in 2020 Myanmar effectively experienced two distinct economic shocks. First, as the scale and contagiousness of COVID-19 became apparent in early 2020, Myanmar – like much of the world – imposed stringent prevention measures, including a strict three-week lockdown in April 2020, and a number of prevention measures that continued for several months thereafter. Fig. 1 shows that Oxford COVID-19 Policy Stringency Index (scaled 0–100) for Myanmar, which confirms the sustained stringency of these measures, which were on a par with India's notoriously stringent lockdown (Hale et al., 2021). Household behavior – as reflected by the Google "stay at home" index derived from mobile phone data – further confirms the stringency of these lockdowns (Fig. 1). In April, at the peak of the lockdown, consumers were staying home 30% more than they were prior to COVID-19. However, by mid-2020 Myanmar had one of the lowest headcounts of confirmed COVID-19 cases in the world, with just 303 cases in a population of 50 million (Fig. 1), mostly pertaining to quarantined repatriated individuals. As the disease appeared to be contained, consumer mobility improved, with the

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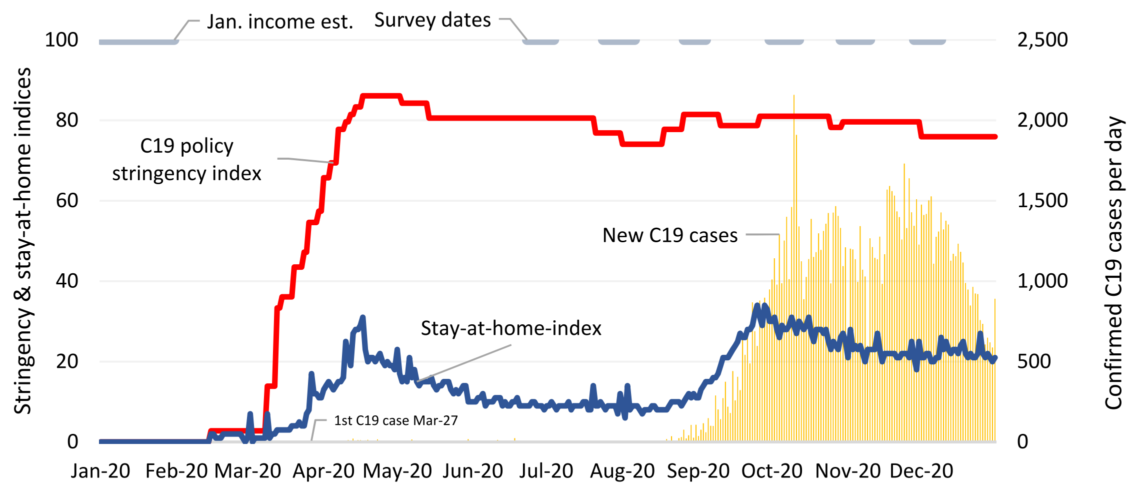


Fig. 1. COVID-19 policy stringency, new COVID-19 cases, and the Google "stay-at-home-index"
Source: The C19 policy stringency index is from the Oxford COVID-19 Government Response Tracker (Hale et al., 2021) and captures a range of policies designed to contain COVID-19, such as mobility restrictions and business closures. Data on new COVID-19 cases are from the same source. The 'stay at home index' refers to the residential mobility index from the Google Mobility Reports (Google™, 2021). The grey bars at the top of the graph refer to the RUFSS survey dates.

stay-at-home index receding from May through to August as economic activity returned to normal. Hence, the first shock induced by the COVID-19 crisis was almost purely economic in nature and relatively short-lived.

However, as Fig. 1 further demonstrates, the COVID-19 situation in Myanmar changed radically in the second half of the year. An outbreak of a new variant in north-western Myanmar in August quickly spread throughout the rest of the country, with particularly rapid growth in the largest city, Yangon. From mid September through mid December the country official reported over 1000 cases per day (Fig. 1) – although this was undoubtedly a vast underestimate given low testing – suggesting that Myanmar was not able to quickly contain the spread of the disease. This second economic shock was therefore accompanied not so much by new policy measures (the stringency index increased only marginally in September 2020) as it was by genuine health impacts and greater fear of contagion, which endured for a prolonged period of time. This is reflected by the sustained increase in the stay-at-home index from September onwards, with conditions only marginally better by December 2020.

How did these successive but quite distinct economic shocks affect household welfare in Myanmar, particularly poverty and food insecurity? While studies from other countries have documented adverse welfare impacts of COVID-19 in a range of countries – see Egger et al. (2021) for a multi-country case study – very few studies have been able to implement high-frequency large-scale panel surveys, and fewer still have attempted to measure household poverty dynamics during the crisis. The present analyzes poverty, food insecurity experiences and other welfare indicators over six rounds of monthly data collection from June 2020 to early December 2020, along with recall-based estimates of household income in January 2020 prior to the COVID-19 crisis (see the grey bars in Fig. 1 for survey timings). Our sample, though not representative of the geographies targeted, is also of special interest from a food and nutrition security standpoint, as each round aimed at covering women from 2000 households evenly split between urban and peri-urban Yangon (Myanmar's largest city) and rural areas of the dry zone, a major population and agricultural production area in the center of Myanmar. Both samples therefore provide good representation of mothers of potentially nutritionally vulnerable young children, but also cover a very diverse array of livelihoods.

We use this survey to first assess the welfare impacts of COVID19 through both quantitative income measures and more qualitative questions on the impacts of COVID19, as well as indicators from the Food Insecurity Experience Scale (FIES), and the coping strategies that households used to deal with these shocks. Through pre-COVID19 income recall as well as long term asset indicators, we show that the urban sample was substantially better off in economic terms prior to COVID-19. However, COVID-19 led to dramatic increases in poverty both in the first "purely economic" wave from April–June and during the "COVID wave" from September–December 2020, with an especially pronounced increase in the urban sample. Moreover, dramatic increases in poverty in the urban sample translate into much more frequent reports of food insecurity compared to the rural sample, despite rural households appearing to be poorer in absolute terms.

We conclude the paper with a discussion of the implications of these findings for social protection and economic recovery in Myanmar. In February 2021, just as the economy appeared to be slowly recovering, the Myanmar military took full control of the government, which has led to prolonged political and economic turmoil, as well as the collapse of the previous government's social protection measures. Furthermore, the Delta variant of COVID-19 has spread rapidly throughout Myanmar in 2020, overburdening a very limited healthcare system. Myanmar therefore faces a triple economic, political and health crisis. The findings of this study suggest that households in Myanmar were already extremely hard hit by the economic shocks of 2020, and that urgent actions will be needed to prevent a large-scale humanitarian crisis in a country of some 55 million people.

2. Data and methods

The Rural-Urban Food Security Survey (RUFFS) was implemented as a panel phone survey on a monthly basis from late June to early December 2020 (see Fig. 1 for survey timings), though since most questions are asked on a 1-month recall we refer to a June–November timeframe. The survey instrument was designed by The International Food Policy Research Institute (IFPRI) Myanmar Office and implemented by Innovation for Poverty Action (IPA). The RUFSS sample drew on two existing survey samples covering predominantly peri-urban or urban areas of Yangon in which non-farm livelihoods dominate, and rural areas of the dry zone in the center of Myanmar where farm-based livelihoods dominate (though non-farm occupations are still important).

The urban sample used contacts from a postponed study of an antenatal care intervention intended to be implemented in 19 peri-urban townships in Yangon Region beginning in February 2020. The sample includes townships largely composed of villages, though most townships have at least a semi-urban layout and most households physically work in urban Yangon. For simplicity we therefore refer to this sample as urban Yangon rather than peri-urban. It is also worth nothing that most female respondents in this sample were giving birth at some stage during the six rounds of RUFSS.

The rural sample drew on an earlier evaluation of a maternal-child cash transfer (MCCT) program implemented over 2017–2019 in rural villages of three states/regions of Myanmar's dry zone (Field and Maffioli 2020). Almost all of these women (94%) still had a child under age 5 at the time of our survey, and all women had stopped receiving MCCTs about 12 months prior to the first round of RUFSS. Although only women respondents were interviewed, the survey also asked questions about household characteristics as described below, including total household income.

The survey was intended to be a panel, although we always anticipated attrition, especially temporary attrition for mothers who had given birth just prior to a survey round. Hence, the survey was designed to achieve a sample size of at least 1000 households per month in each of the rural and urban geographies, resulting in over 2000 households per round and potentially over 12,000 observations over all six rounds. However, in this analysis we use the sub-sample of households whose respondents were able to regularly estimate household income over the path month (see below). In addition to income, respondents were asked about the main impacts of COVID19 on their household, food insecurity experiences in the past month, coping strategies, household assets, occupations and job changes, as well as various nutrition-related indicators analyzed in complementary studies.

2.1. Household assets and livelihoods

We used asset levels and occupation-based livelihood measures both to stratify income and food security results and as explanatory variables in our regression analysis. For assets it is common to construct wealth indices using principal components analysis (PCA), but wealth quintiles are disadvantageous in only providing a ranking and cannot specify how deprived households are in absolute terms. Here we instead first used PCA to look at which assets had sizable and consistent PCA weights (or loadings) across the rural and urban samples. We selected a measure of adequate living space (with no more than four people to a sleeping room), electricity access, flush toilet, piped water, TV, and fridge, and then created an asset count variable as the sum of these six assets. We then examined how incomes and food security indicators varied with asset counts and identified non-linearities that led us to classify households into asset-poor (0 or 1 asset), asset-low (2 or 3 assets) and asset-rich (4–6 assets). Given that we found little evidence of households selling off assets in response to COVID-19 income losses, we consider asset levels an indicator of longer-term socioeconomic status not materially affected by COVID-19.

We also separately measured whether a household rented its home or were squatters. Home rental in urban Yangon is a major expenditure (40% of the urban sample paid rent compared to 4% in the rural sample), and we hypothesized that urban households that lost income would feel more food insecure if they were still required to pay rent. We also measured an indicator of squatter households as this may be an indicator of extreme poverty not necessarily captured by the asset indicators described above.

In addition to asset status we classified households by main income sources in a hierarchical manner to create livelihoods groups. Respondents could list multiple sources of income, but if they listed a salaried occupation they were given this classification irrespective of other occupations. The same strategy was followed hierarchically to classify wholesale/retail trade households, and then farming, skilled labor, unskilled labor households, with a small number of other occupations (about half of whom were dependent on remittance incomes) as a residual.

2.2. Income variables

Gauging the economic impacts of COVID19 in the absence of a baseline survey and in the context of a necessarily short phone survey is challenging. Our strategy involved a mix of qualitative questions about COVID19's impacts on the household and on income losses and the causes of those losses, but also quantitative questions to recall household income in the past month (hereafter June) and in January prior to the COVID19 economic crisis in Myanmar. Respondents could respond that they were unable to estimate monthly income, but around three quarters of the sample gave estimates for both January income and income in the month prior to each survey round. Income estimates were then converted to income per adult equivalent and compared to an updated \$1.90/day poverty line, which was also adjusted for cost of living (CoL) differences between the dry zone and Yangon using a spatial CoL index from a previous national survey.

Clearly, there could be significant mismeasurement with these income estimates. First, around 81% of surveys include income estimates, so there is a potential measurement bias insofar as the inability for a respondent to estimate income may be non-random. Indeed, in Appendix Table A1 we estimate regressions exploring the determinants of the inability to recall income and find that several measured factors are statistically significant. First, demographic factors: having more than two adults in the household, having a larger household, being pregnant and being urban all predict a lower likelihood of reporting income. This last result is more surprising, but may stem from higher rates of off-farm labor force participation in urban areas. Second, compared to salaried households, all other types of households are less able to confidently report total household income. However, while these biases are of potential concern, we also note that the predictive power of these factors is low (R-sq $= 0.05$), suggesting that any selection bias may not be that large in magnitude. Moreover, there was also no bivariate or multivariate association between income-reporting and household asset ownership, suggesting no association between pre-COVID19 asset-poverty and an inability to report income.

Second, respondents are more likely to report rounded income estimates, suggesting that responses are rough approximations only.

Third, there are the usual limitations of income measures for farming and informal sector occupations that may be highly seasonal and require complex revenue and cost calculations, which is why expenditure-based poverty measures are generally preferred to income measures, especially in rural areas. Indeed, it is likely that some of the households we classify as at least temporarily income-poor based on a single month's estimated income may not be poor based on alternative measures of permanent income. Moreover, previous national surveys in Myanmar also measure expenditure-based poverty, so our results can only be qualitatively compared to results of previous surveys.

Given the limitations of these monthly income measures we also closely analyzed more stylized or qualitative indicators of the economic effects of COVID19. First, prior to any income questions, we asked households what the main impacts of COVID19 have been on their household and recorded whether they cited income/job loss or food supply problems. Other possible impacts they could cite included various social problems (not being able to visit family/friends, more arguments) and health-related problems (sickness, fear of sickness, health service disruptions). Second, we asked whether incomes in June were lower than they were at this time last year, which should address seasonality issues (moreover, Myanmar has experienced low inflation in the past 12 months). Third, we ask respondents to list the main reasons their income was lower in June 2020 compared to June 2019 (if it was reported as lower). Clearly, these more qualitative indicators have their own limitations, but they do offer some potential to corroborate quantitative estimates on incomes and income losses.

Table 1
Summary statistics for the main indicators used in the study.

Variable	N	Mean	Std. Dev.	Min	Max
Baseline characteristics (stratifying variables)					
Urban	9972	0.47	0.50	0	1
Asset poor (0–1 assets)	9972	0.35	0.48	0	1
Asset low (2–3 assets)	9972	0.45	0.50	0	1
Asset rich (4–6 assets)	9972	0.20	0.40	0	1
Household rents home	9972	0.22	0.41	0	1
Household are squatters	9972	0.02	0.13	0	1
Farm household	9972	0.19	0.39	0	1
Unskilled labor household	9972	0.23	0.42	0	1
Skilled labor household	9972	0.25	0.43	0	1
Salary household	9972	0.21	0.41	0	1
Trade/retail household	9972	0.10	0.30	0	1
Other livelihood household	9972	0.01	0.10	0	1
Demographic variables					
Female is main income earner	9972	0.05	0.21	0	1
Respondent currently pregnant	9972	0.14	0.34	0	1
household has >6 members	9972	0.18	0.38	0	1
Income, poverty & food insecurity indicators					
household poor in Jan 2020 ($1.90/ day line)	9972	0.17	0.38	0	1
household poor, other months ($1.90/ day line)	9972	0.49	0.50	0	1
FIES: Eating less than you thought you should	9972	0.11	0.32	0	1
FIES: Eating only a few kinds of foods	9972	0.12	0.32	0	1
FIES: Unable to eat healthy foods	9972	0.19	0.40	0	1
FIES: Hungry but did not eat	9972	0.02	0.15	0	1
C19 impact: Income lost from job/ labor loss	9972	0.52	0.50	0	1
C19 impact: Income lost from reduced salary	9972	0.09	0.29	0	1
C19 impact: Income lost from market disruptions	9972	0.16	0.37	0	1
C19 impact: Income lost from travel restrictions	9972	0.22	0.41	0	1
C19 impact: Income lost to low yields/ climate	9972	0.07	0.25	0	1
C19 impact: Lean season	9972	0.05	0.22	0	1
C19 impact: Pregnancy or childbirth	9972	0.06	0.23	0	1
C19 impact: Migrant lost work	9972	0.22	0.41	0	1
Received remittances from overseas	9972	0.01	0.10	0	1
Received remittances from Myanmar	9972	0.03	0.18	0	1

Source: Authors' estimates from RUFSS data. HH refers to household. FIES refers to questions from the Food Insecurity Experience Scale.

2.3. *Food insecurity indicators*

We used Food Insecurity Experience Scale (FIES) indicators to assess food insecurity, which capture a progression of food insecurity experiences ranging from psychosocial questions (such as worrying about not having enough food to eat) to compromising on quality, to reducing quantities or skipping meals, to experiences of hunger (FAO, 2017). We use a recall period of one month for all questions. These questions are obviously subjective and can be biased by cultural norms and other response biases (Headey and Ecker 2013), but they have been validated to a degree, and usefully distinguish between conceptually distinct food insecurity experiences.

2.4. *Coping strategies and government assistance*

For households that reported income losses we asked about their three main coping strategies, including common strategies such as using cash savings, loans or credit, reducing food or non-food expenditures, and selling assets. We also asked households if they had received any kind of cash or in-kind assistance from the government or any non-government sources, although the latter proved very rare.

2.5. *Demographics*

Household characteristics included household composition, ownership of various assets and housing characteristics and major sources of household income. We used six demographic indicators related to pregnancy status and birth in the past month (both more relevant to the urban sample), a dummy variable for large households (7 or more individuals), dependency ratio of the number of 0–14 year olds to the number older than 14, and dummy variables for the main income earner or household head being a woman.

2.6. *Analytical methods*

Our analysis of these indicators involves two steps. First, we examined "baseline" characteristics of households such as asset levels and January 2020 income, stratified by rural/urban status and main livelihood, to understand patterns of incomes and assets prior to the COVID-19 shocks described above. Second, we looked at trends in income-based poverty and FIES indicators stratified in the same way, but additionally stratified by asset levels (asset-poor, asset-low, asset-rich). For both poverty and selected FIES indicators we also used linear probability model regressions to assess the predictors of poverty status or food insecurity in any given month. These regressions use self-reported indicators of COVID19 impacts, asset levels, livelihood type and demographic controls. We used coefficient plots with 95% confidence intervals to examine patterns of results across different dependent and independent variables. Finally, we also examined patterns and trends in coping strategies to get a sense of how different types of households were dealing with these shocks, and which were benefiting from receiving admittedly modest amounts of government assistance promoted in response to the COVID-19 crisis.

2.7. *Descriptive statistics for key variables*

Table 1 reports descriptive statistics for the main indicators used in the analysis. In total, we used a sample of 9972 observations from 2129 households, 47% based in the urban Yangon sample and 53% in the rural sample. Among other baseline characteristics it is notable that our sample has a diverse array of asset levels and livelihoods at baseline. For both assets and livelihoods we use the first observation for each household to classify their livelihoods. At baseline there were a similar proportion of skilled and unskilled labor households, a relatively high proportion of households with salaries (21%) and farm-based incomes (16%), and fewer wholesale/retail households (10%) and a small number of households mainly getting income from other sources such as remittances and other transfers (1%). Among demographics, only 5% of households had females as the main income earner. Unsurprisingly, 14% were pregnant in any given round, mostly in the urban sample, of course, and 18% of households were considered large with more than 6 members.

Income, poverty and food insecurity indicators are discussed more below, but we note a peculiar ambiguity on the migration front. National surveys implemented prior to COVID-19 show that migrant remittances are a major source of household income and that many households have migrants overseas or elsewhere in Myanmar. However, households two sub-samples reported little dependence on remittances from a 1-month recall compared to what we know from nationally representative surveys in Myanmar, even in January 2020; just 3 percent received remittances from elsewhere in Myanmar and just 1% from overseas (likewise, very few – just 4% – sent remittances to other households in Myanmar). On the other hand, 22% of household cited migrant job/ income losses over the course of the six rounds, with higher rates in the Yangon sample (29%) than the rural sample (16%).

Table 2
Household assets, income and poverty status in January 2020 prior to the COVID19 crisis.

	Asset-poor (0–1 assets)	Asset-low (2–3 Assets)	Asset-high (4–6 assets)	Daily income[b] (kyat)	$1.90/day poverty rate
Urban (Yangon)	23%	48%	29%	2626	8%
Rural (Dry Zone)	45%	43%	12%	2119	25%
Farming	44%	45%	11%	2182	30%
Unskilled labor	47%	44%	9%	1758	22%
Skilled labor	32%	44%	24%	2453	11%
Salaried occupation	23%	48%	29%	2828	6%
Trade/retail	21%	48%	31%	2647	21%
Other livelihoods	36%	35%	28%	4053	23%
Full sample	35%	45%	20%	2357	17%

Notes: a. Asset count is the simple sum of the following asset-based binary variables: adequate living space (with no more than four people to a sleeping room), electricity access, flush toilet, piped water, TV, and fridge. b. Daily income is calculated based on a 1-month recall by the respondent converted to January kyat.
Source: Authors' estimates from RUFSS data for households that responded to at least three of the six survey rounds.

Table 3
Income-based poverty trends from January to November 2020.

	Jan.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.
Urban (Yangon)	8%	28%	19%	26%	56%	60%	45%
Rural (Dry Zone)	25%	52%	43%	51%	64%	69%	63%
Farming	29%	57%	52%	66%	77%	80%	72%
Unskilled labor	22%	47%	39%	43%	64%	72%	59%
Skilled labor	15%	39%	26%	31%	64%	65%	55%
Salaried occupation	5%	21%	15%	21%	38%	44%	35%
Trade/retails	13%	43%	30%	39%	61%	58%	52%
Other livelihoods	14%	27%	55%	42%	72%	70%	72%
Asset poor	26%	51%	39%	48%	68%	72%	63%
Asset low	13%	37%	31%	38%	59%	63%	52%
Asset high	6%	31%	22%	26%	52%	55%	45%
Full sample	17%	41%	32%	39%	61%	65%	55%

Source: Authors' estimates from RUFSS data. Data are reported for the income-reporting sub-sample. Results are reported for a pooled sample of households rather than a panel, although results are very similar for the full panel. Sample sizes per month vary between 1700 and 1940.

3. Assessing the economic impacts of COVID-19 in 2020

3.1. Economic status before the onset of the COVID19 crisis

Table 2 reports indicators of the economic status of different kinds of households in January 2020 based on asset counts and recall estimates of income, which we converted to daily income per adult equivalent and poverty headcounts at the $1.90 per day poverty line. Asset counts were higher in urban than in rural areas and 45% of rural households were asset-poor and another 43% asset-low. Far fewer urban households were asset poor (23%) and many more were asset-rich (29%). Asset-poverty was highest among farming (44%) and unskilled labor households (42%), but still relatively high among skilled labor (33%) and even salaried and trade/retail households (22%), as well as other livelihoods who were often dependent on remittances, other transfers or miscellaneous unskilled activities (34%).

Daily income per adult equivalent in January was low overall, but higher in the Yangon sample, and indeed only 8% of the Yangon sample were poor at the $1.90/day poverty line, compared to 25.2% among the rural sample. Income-poverty was highest among farming households at 30% (although this is likely biased upwards by not valuing own-consumption, as well as seasonality factors), and then unskilled labor households (22%). Income-based poverty was surprisingly high among trade/retail households, suggesting many might be involved in petty trades (21%). Very few salary-based households were income-poor (6%). Overall, these poverty differences across geographies and livelihoods are in line with expectations based on the last major national survey conducted in Myanmar, despite the use of an income-based rather than an expenditure-based poverty measure (CSO et al., 2019).

3.2. Incomes and poverty status before and after the onset of the COVID19 crisis

How did income-based poverty change over the course of the two major COVID-19 shocks described in our introduction? Table 3 reports poverty trends by geography, baseline livelihood and asset levels. While the urban sample was rarely income-poor in January 2020 (8%), by June 28% were poor after the initial economic shocks of April and May, a 450% increase. Poverty in the rural sample doubled between January (25%) and June (52%). July showed a modest recovery in both samples, but poverty rates increased again in August as COVID-19 cases started to rise. By September when the COVID-19 cases were rising rapidly and more stringent lockdown measures were re-imposed poverty rates hit 56% in the Yangon sample and 64% in the rural sample. As cases continued to rise into October, poverty rates rose further again, and then started to fall only in November (especially in the Yangon sample).

In terms of baseline livelihoods the most striking feature is how poverty rates rose for all kinds of households. Farm households had the highest prevalence of income poverty in all rounds, although this may be because incomes undervalue own-consumption. Poverty rates among unskilled households reached 64% and 72% in September and October, respectively, although poverty among skilled households was almost as high. Remarkably, given their initial job security, salaried occupation households saw poverty rise from just 5% in January 2020 to 21% in June and 44% in October. As we show below, this is clearly because high proportions of households lost jobs or saw salary reductions. Trade/retail households fared even worse, with 61% estimated to be income-poor in September. The small number of households reporting other livelihoods always saw extremely high poverty rates, perhaps because of declining remittances.

These harsh effects on all kinds of livelihoods are consistent with the trends we see by baseline asset levels. Households that were asset-poor saw the highest increases in both June – after the first economic shocks – and in September and October (after the second shock). But asset-low households were also very badly affected, while asset-high households – just 6% of whom were poor in January – also saw remarkably large increases in income-based poverty. In summary, while the income losses from the first economic shock of April and May were severe, the shock that ensued from September onwards was dire indeed for a large

Table 4
The most common explanations for lower than normal incomes (pooled across all rounds), by location, livelihood and asset levels.

	Lost job or daily labor	Travel was restricted	Markets were disrupted	Reduced salary or wage	Pregnancy or childbirth	Poor weather, low yield	Regular lean season
Urban (Yangon)	53%	21%	12%	12%	10%	1%	1%
Rural (Dry Zone)	50%	21%	18%	5%	1%	14%	11%
Farming	40%	15%	16%	4%	1%	22%	21%
Skilled labor	67%	22%	10%	7%	4%	6%	4%
Unskilled labor	61%	28%	12%	7%	7%	4%	2%
Salaried occupation	40%	14%	9%	16%	8%	3%	3%
Trade/retails	36%	27%	48%	4%	4%	5%	4%
Other livelihoods	61%	24%	6%	16%	15%	6%	2%
Asset poor	51%	21%	16%	8%	5%	8%	6%
Asset low	57%	20%	13%	7%	4%	10%	7%
Asset high	45%	25%	19%	12%	8%	5%	4%
Full sample	52%	21%	15%	8%	5%	8%	6%

Source: Data are reported for the sub-sample of RUFSS respondents/households who say that their income is lower than normal this time of year.

proportion of households across different geographies and livelihoods.

Table 4 reports respondents' explanations of income losses. For brevity we pool all results across the June–November rounds. Respondents could list multiple responses. By far the most commonly cited explanation was losing a job or casual employment, with around half of both rural and urban respondents citing this reason. Notably, high proportions of unskilled labor cited this reason, but so too did skilled labor households, suggesting they too have little job security. Travel restrictions were cited as problematic for around one in five households, on average, with not much variation across location, livelihood or asset levels. Other patterns are closely tied to livelihoods. Market disruptions affected trade/retail households the most (48%), while reductions in salary affected salaried households more frequently (16%). Loss of income from pregnancy or childbirth was, unsurprisingly, more common in the urban sample because of the sample selection, but this loss of income is still notable given the vulnerability of pregnant mothers and young children to nutritional insults. Finally, poor weather, low yields or regular lean season income problems were much more common among the rural sample and among farm households in particular.

Overall, the results in Table 3 show that different kinds of households have been affected by the economic crisis in different ways, although job losses and reduced casual labor opportunities stand out as the most common explanation of lower than normal incomes. We also asked respondents more open-ended questions about the main economic, psychosocial and health impacts of COVID-19 on their households. While respondents often cites health fears, and sometimes mentioned food supply problems or shop closures (especially in urban areas), by far the most commonly cited problem was loss of income, with responses

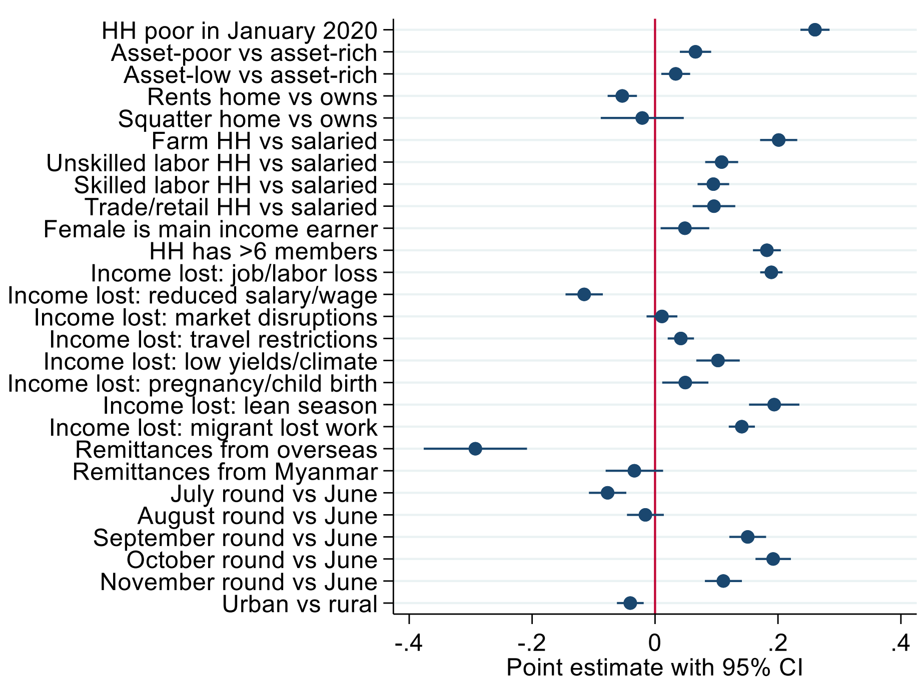


Fig. 2. Linear probability model estimates of the predictors of income-based poverty in the full sample over June–November 2020.
Notes: These are linear probability model coefficients with 95% confidence intervals. The sample size for this regression model is 9972 observations, with an R-squared of 0.34.

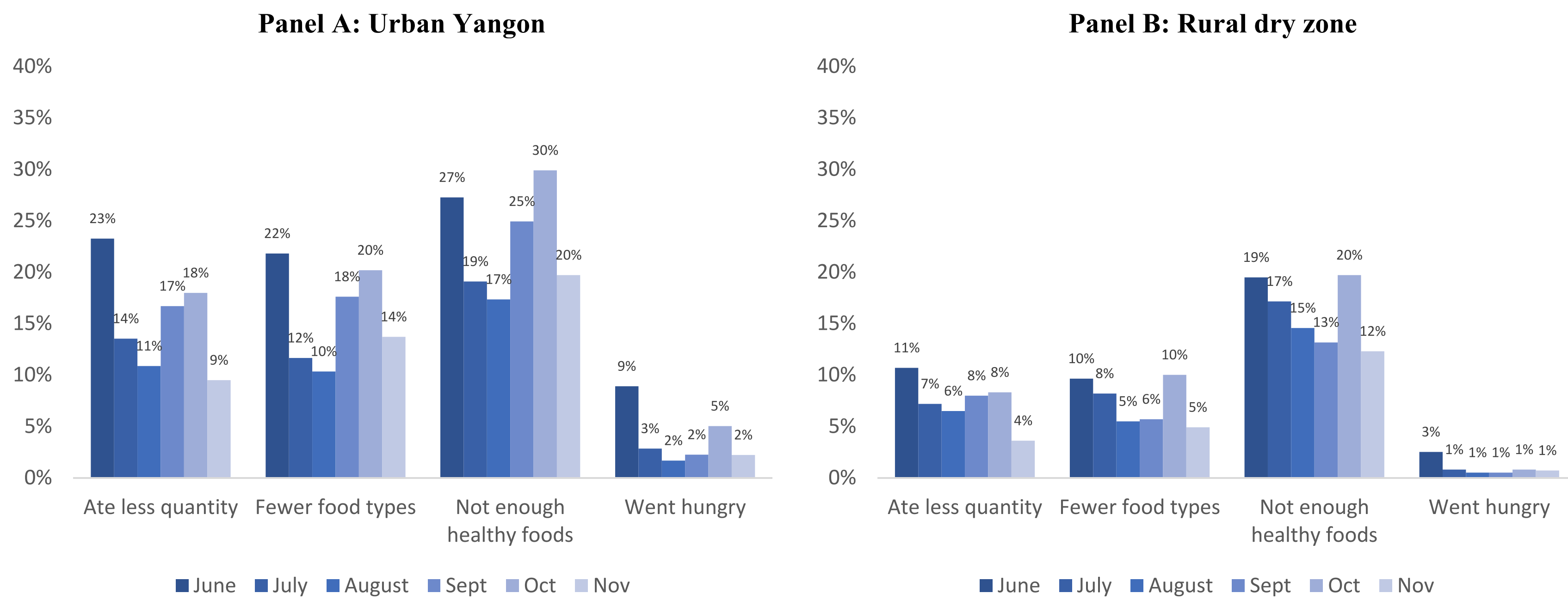


Fig. 3. Trends in selected food insecurity experience indicators in the rural and urban samples (N = 2017).
Source: Authors' estimates from RUFSS data.

Table 5
Trends in the FIES indicator of "times consumed fewer food types", July to November 2020, by location, livelihood and asset levels.

	June	July	August	September	October	November
Urban (Yangon)	22%	11%	11%	18%	21%	14%
Rural (Dry Zone)	10%	8%	5%	6%	10%	5%
Farming	10%	4%	5%	2%	6%	4%
Unskilled labor	22%	15%	11%	16%	20%	13%
Skilled labor	17%	9%	7%	13%	20%	8%
Salaried occupation	14%	6%	6%	9%	9%	7%
Trade/retails	12%	7%	4%	4%	7%	5%
Other livelihoods	17%	16%	12%	16%	21%	16%
Asset poor	18%	10%	10%	13%	18%	9%
Asset low	18%	12%	8%	12%	16%	11%
Asset high	8%	5%	6%	7%	11%	6%
Full sample	16%	10%	8%	12%	16%	9%

Source: Authors' estimates from RUFSS data.

varying between 69% and 86% across all six survey rounds (results not reported).

3.3. Predictors of poverty

To look more systematically at predictors of poverty during 2020 we ran linear probability models with poverty status over June–November as the dependent variable and a series of correlates that refer to both baseline characteristics (poverty status in January, asset levels, livelihoods, demographics) and contemporaneous characteristics (explanations of income losses, remittances), as well as dummy variables. Note that we could also have estimated household fixed effects models, although that would have precluded the estimation of coefficients on baseline characteristics, which are clearly of interest. Nevertheless, for time-varying variables we found that fixed effects models yielded similar coefficients (results not reported).

The results point to some key predictors of poverty (see Fig. 2). Among baseline characteristics, poverty status in January 2020 has a large and precise point estimate, increasing the probability of being poor in any given month by 26 percentage points. However, although asset-poor and asset-low households are more likely to be poor than asset-high households, the marginal effects are not large, confirming that even better off households faced major income losses during 2020. Among livelihoods, farm households were 20 points more likely to become poor compared to salaried households. While some of this may be related to seasonality and under-reporting of own-consumption, other research documents major disruptions to agricultural marketing during the pandemic and relatively poor rainfall and issues with pests (Boughton et al., 2021). Moreover, as noted above, many farm households reported income losses due to low yields or climate, and the coefficient on that variable is also large (0.10) and highly significant. Farm households clearly did poorly in 2020, perhaps refuting the common suggesting that the farming sector was generally more robust during the pandemic. All other livelihoods were around 10 points more likely to be poor in any given month compared to salaried households, except the very small group of other livelihood households (16 points). Households where women were the main income earners were 5 points more likely to be poor, although only 5% of respondents said they were the main earner. Larger households (18% of the sample) were 18 points more likely to be poor.

Among explanations for income losses, job/labor loss had the large coefficient (19 points), but income losses due to regular lean season factors was equally important (20 points), while climatic factors or low yields was also a strong predictor (10 points). Income lost due to pregnancy/childbirth had a small marginal effect on poverty status (5 points) as did income losses due to travel restrictions (4%), although the effects of travel restrictions may have been more indirect than direct (e.g. reduced demand for labor and goods and services).

Migration impacts also seem important. Job/income losses of migrants predicted a 14 point increase in the risk of being income-poor, and as noted above, 22% of households cited this problem. The very few (1%) of households that still received remittances from overseas were also 30 points less likely to be poor. Overall, these combined results suggest that shocks to migration-based income were likely an important negative impact channel for many households, as many overseas migrants in Thailand, Malaysia and elsewhere lost work, and repatriated to Myanmar.

Finally, we note that some of the survey round dummy variables are still significant – poverty is substantially higher in the second round of shocks of September–November than it is in June – most likely because of the more prolonged nature of the COVID-19 contagion and low levels of consumer activity. We also note the strikingly small coefficient on the urban sample dummy; although urban respondents were much less likely to be poor in January 2020, they were only 4 points less likely to be poor after controlling for all other factors. Separate regression results for the urban and rural samples are also reported in Appendix Figures A1 and A2 respectively, although there are few notable differences. Another notable feature of these regressions is their quite strong explanatory power, with an R-squared suggesting the model explains around one third of the variation in poverty status across all six rounds.

3.4. Food insecurity experiences

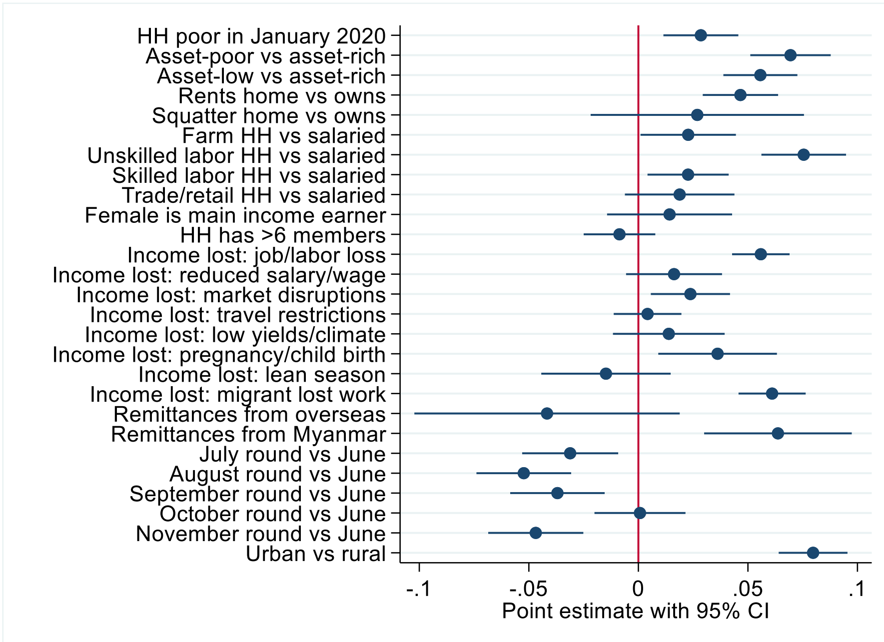
Fig. 3 reports trends in four selected FIES indicators related to experiences of eating lower quantities, fewer food types, not enough healthy foods, or going hungry (a more extreme experience), split across the urban and rural samples. Several striking facts emerge. First and foremost, food insecurity experiences are reported around twice as frequently in the urban sample of women as they are in the rural sample, despite the rural sample being more likely to be income-poor (though rural-urban income differences are marginal over September–November). In June 2020, for example, 23% of urban women said they had experiences of eating lower quantities compared to just 11% of rural women. Similar differences are observed for eating fewer food types, although the differences for not eating enough healthy foods are smaller.

Second, as expected, food insecurity experiences broadly track trends in poverty dynamics (Table 3) and consumer mobility (Fig. 1), though more so in the urban sample. Food insecurity experiences were quite common in June 2020 after the first "pure economic" shock, but then improved substantially in July and August, before becoming more frequent again in September, October and November. Overall, June and October were the worst months in terms of reported food insecurity.

Finally, the proportion of respondents reporting going hungry was relatively small, peaking at 9% in June 2020 in the urban sample, then 5% in October 2020. In the rural sample it is striking that very few respondents reported going hungry (1% in all months except June). This suggests that rural respondents rarely felt extremely food insecure, because of better access to food through access to farming activities.

Table 5 reports trends for the specific indicator of experiences of consuming too few foods, stratified by household types, since this indicator may reflect reduced dietary diversity, which is commonly expected in the wake of major income shocks (Headey and Ecker 2013). As above, consuming too few foods is reported much more frequently among urban respondents in all rounds. Strikingly, very few farm household respondent report consuming too food (2–6% from July onwards), despite being income-poor. Consuming too few foods is much

Panel A. Times consumed fewer food types



Panel B. Times when I went hungry

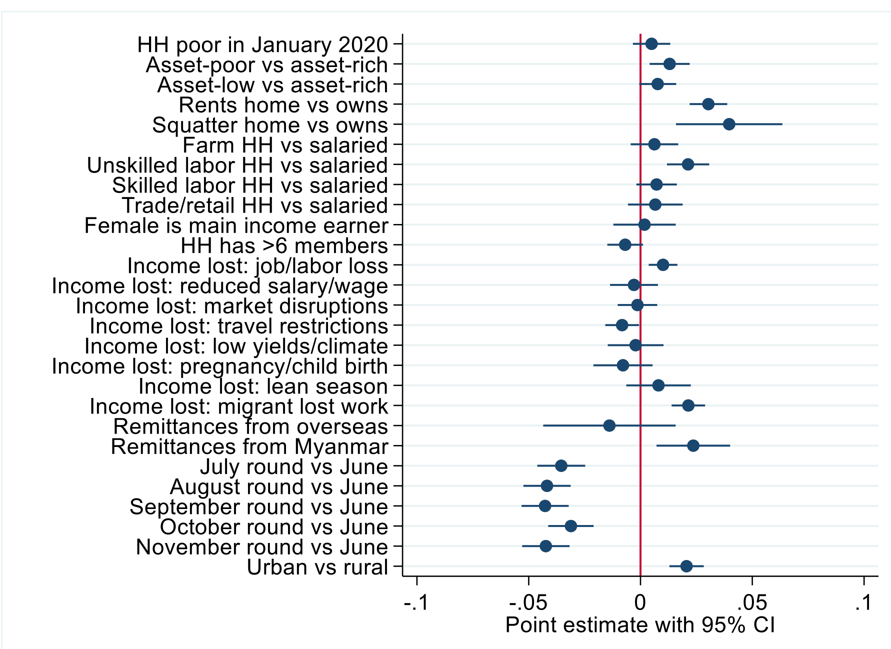


Fig. 4. Linear probability model estimates of the predictors of FIES indicators of consuming fewer food types (Panel A) and experiencing hunger (Panel B), with 95% confidence intervals.

Notes: These are linear probability model coefficients with 95% confidence intervals. The sample size for this regression model is 9972 observations, with an R-squared of 0.05 for the regression in Panel A and 0.03 for the regression in Panel B.

more common among unskilled and skilled labor households as well as other livelihoods, but less common among salaried occupations and trade/retail households. As expected, asset-poor and asset-low household respondents were much more likely to experience food insecurity than asset-high households. Also of note is that June stands out as an exceptional month with high rates of food insecurity experiences, perhaps because of greater anxiety about food security earlier on in the pandemic.

In Fig. 4 we look at predictors of two of these FIES indicators - "fewer food types" and "went hungry" – using the same specifications used to predict poverty status. One notable feature of both regressions is less precision on the coefficient estimates and much lower explanatory power of the model overall, with R-squared coefficients of 0.06 and 0.03, respectively. Even so, we still observe a number of statistically significant predictors of consuming fewer food types. Respondents from asset-poor households are 7 points more likely to report eat fewer food types compared to asset-high households, while asset-low households are 6 points more likely. Respondents that rent a home instead of owning it (which is a major financial expenditure) are 5 points more likely to report food insecurity, and respondents that were poor in January were 3 points more likely. Among livelihoods, respondents from unskilled labor households clearly feel much more food insecure relative to salaried households (8 points), but the differences for other livelihood types are much smaller (just 2 points). Neither larger households nor those

Table 6
Coping mechanisms in response to income losses and the share of respondents who reported receiving special COVID-19 government transfers.

	Self-reported coping mechanisms in response to income losses[a]							Special C19 Govt transfer[b]
	Used cash savings	Took loans	Reduced non-food spending	Reduced food spending	Sold assets	Other	No coping strategy	
Urban (Yangon)	23%	31%	30%	8%	4%	10%	2%	46%
Rural (Dry Zone)	24%	37%	33%	6%	4%	4%	2%	46%
Farming	27%	35%	30%	6%	5%	4%	2%	38%
Unskilled labor	20%	44%	33%	9%	4%	8%	2%	52%
Skilled labor	24%	36%	36%	8%	3%	9%	2%	52%
Salaried	21%	25%	26%	5%	3%	7%	3%	39%
Trade/retails	32%	29%	33%	6%	6%	7%	5%	45%
Other livelihoods	33%	25%	27%	9%	8%	13%	3%	42%
Asset poor	23%	35%	33%	7%	3%	8%	2%	45%
Asset low	20%	42%	30%	7%	5%	6%	2%	49%
Asset high	32%	22%	32%	7%	4%	8%	3%	43%
Full sample	24%	35%	32%	7%	4%	7%	2%	46%

Source: Authors' estimates from RUFSS data. a. Only respondents who stated that income is lower at this time of year than in the previous year were asked for coping mechanisms. Other respondents were assumed not to have adopted any coping mechanisms. b. Respondents were asked whether they received any special assistance due to COVID-19 responses, and were asked the source of the transfer. Virtually all respondents only cited government assistance, mostly in the form of 20,000 Kyat cash transfers.

with women as the main income earners report more food insecurity. In terms of COVID-19 shocks, job/labor losses predict a 6 point increase in consuming fewer food types, as does loss of jobs/labor for migrants, and market disruptions a 3 point increase. However, poor weather, low yields and lean season effects – all likely to influence rural households more – are insignificant predictors of consuming fewer food types. Relative to June, all months but October predict lower food insecurity, suggesting that respondents in June felt exceptionally insecure. Moreover, even after controlling for all these covariates, urban respondents were 8 points more likely to report consuming fewer food types than rural respondents. Appendix Figure A3 estimates regressions for each sub-sample. By and large, there are few differences in coefficients, though one notable difference is that renting a home is only a positive predictor of food insecurity in the urban Yangon sub-sample, consistent with expectations of this being an added economic stress for urban households.

Panel B of Fig. 4 looks at the "times when I went hungry" indicator, which was less commonly observed but denotes a more extreme form of food insecurity. For this indicator respondents with fewer assets are slightly more likely to report going hungry, but a striking result is that both renting a home and being a squatter are strong predictors of experiencing hunger. We also find that respondents from unskilled labor households and households that had a migrant lose work were more likely to report experiences of hunger. Unexpectedly, receiving remittances also increased the probability of experiencing hunger. The survey month dummies again suggest that June was an exceptional month, and the urban dummy remains significant, suggest the model does not completely explain why urban respondents are more likely to report experiencing hunger. Appendix Figure A4 reports separate regression estimates for each sub-sample. Results for the urban sub-sample remain similar to the results of Panel B in Fig. 4, but the rural model performs poorly, with fewer indicators being able to predict hunger experiences.

3.5. *Coping mechanisms and government and non-government assistance*

How did respondent cope with income losses, and what share were able to access special government transfers as part of the COVID-19 Economic Recovery Plan (CERP)?

Table 6 examines coping mechanisms for the approximately three quarters of households that reported lower than normal income across survey months, as well as a separate question on whether the household receive a special government transfer in the past month. There are several distinct patterns in coping mechanisms. Most strikingly, poorer households are much less likely to use cash savings compared to households with more assets, and far more likely to take loans. Around 32% of asset-high households use cash savings, for example, compared to 23% and 20% of asset-poor and asset-low households, whereas 35% and 42% of those poorer households take loans. Unskilled labor households are especially likely to take loans (44%), as are skilled labor households (36%) and farm households (35%). With such a prolonged crisis the frequency of this coping mechanisms raises concerns of serious indebtedness and falling into poverty traps that are difficult to escape from. There are few differences in the use of reduced non-food spending across household types, with around one third of households pursuing this strategy. Reducing food spending was much less common (just 7%), as was selling off assets (4%).

As the depth of the economic crisis became more apparent in Myanmar, the democratically elected government initially implemented food transfers to poorer households before quickly turning to modest monthly cash transfers of 20,000 kyat (or 12 USD per month), to be identified by local officials. However, the data in Table 6 show that the targeting of these transfers was evidently quite poor. Among asset-poor households 45% received transfers in an average survey month,

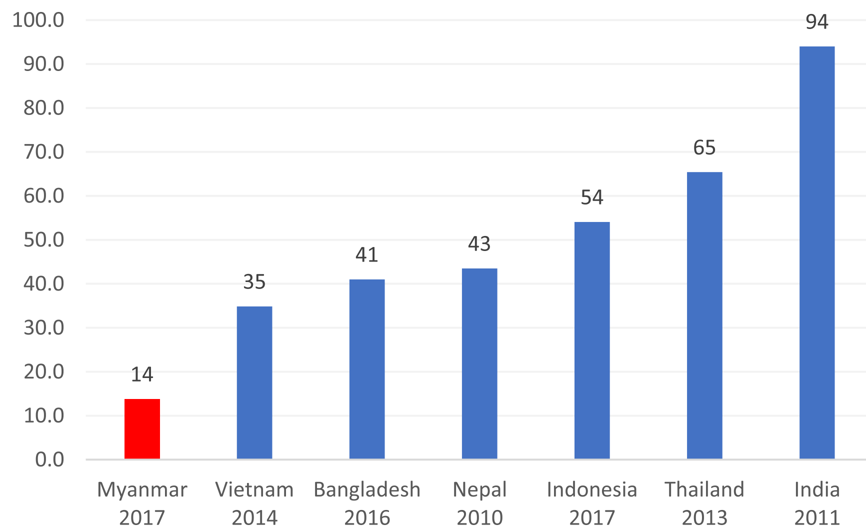


Fig. 5. Percentage of population participating in Social Protection and Labor programs in Myanmar and various comparator countries (including direct and indirect beneficiaries).
Source: Authors' estimates from *The Atlas Of Social Protection Indicators Of Resilience And Equity* (ASPIRE) database (World Bank, 2020a).

compared to 43% for asset-high households and 49% for asset-low households. Unskilled labor households were more likely to receive transfers (52%) but farm households – clearly quite poor – were much less likely (38%).

4. Discussion

We implemented a high frequency panel survey over the course of two distinct economic shocks in Myanmar, the first related to preventative measures and trade disruptions (March–June 2020) and the second related to growing COVID-19 cases (August–December 2020). Somewhat uniquely, we are able to report respondents' estimates of monthly household income and use those to estimate income-based poverty, in addition to reporting FIES indicators, coping mechanisms and other more qualitative indicators of the impacts of COVID-19 and other shocks.

We find truly dramatic increases in poverty between January and June 2020 in response to the first of these shocks, brief signs of recovery in mid 2020, before even starker increases in poverty. While our samples were clearly economically vulnerable to begin with, by September and October 2020 around two thirds of the rural sample was poor, and just under two-thirds of the urban sample. The latter fact is all the more remarkable given that only 8% of sampled urban households were poor in January 2020.

While rural populations are typically poorer than urban populations in normal times, and likely also more food insecure, our survey reveal a striking converse disparity, with urban respondents generally around twice as likely to state they had a variety of different food insecurity experiences in the previous month. Here we offer several potential explanations of this unusual phenomenon.

First, it is possible that farming households have been less affected economically by COVID-19 shocks because the agricultural sector is expected to experience significantly less economic harm than other sectors (Diao et al., 2020). Our income-based poverty measure is not consistent with that hypothesis – farm households had the highest poverty headcounts in all months – but this may stem from the nature of an income-based poverty measure that excludes the value of own-consumption. The scope for farm households to rely on their own farm produce, including potentially substantial grain stocks, may given them a much greater sense of food security.

Second, a substantial proportion of the rural respondents had previously been exposed to a maternal and child cash transfer program, perhaps giving them greater food security and greater knowledge or empowerment to effectively manage food resources. Unpublished analysis of the RUFSS dataset suggests this may be the case.

Third, while we have no pre-COVID estimates of FIES indicator, some dietary and nutrition indicators were quite poor in Yangon even prior to COVID19; the 2015 Demographic Health Survey (DHS), for example, showed that child dietary diversity in Yangon was much lower than the rural dry zone (MoHS and ICF International, 2017).

Fourth, while the urban sample is always slightly less likely to be income-poor in any given month during the pandemic, the change in urban poverty headcounts from January onwards is much larger in proportional terms than it is in the rural sample. And in addition to experience dramatic income shocks, around 40% of urban respondents reporting still having to pay rent, which we show to be a strong predictor of food insecurity. The general cost of living is also higher in urban areas, adding further financial stress, and urban households – many of whom may be migrants from rural areas – may have more limited proximate social networks to deal with economic insecurity.

This study has several limitations, including several concerns about the income-based poverty measure, mentioned in the Methods section. Our results section also showed that FIES indicators are clearly noisier than poverty status in our regression models, and previous reviews have noted they may behave erratically in the context of economic shocks (Headey and Ecker 2013). Our samples are also not representative of the geographies surveyed, but do cover an interesting and nutritionally important demographic.

Despite these limitations, both quantitative and qualitative measures consistently suggest that the economic impacts of COVID19 have been severe and widespread. Moreover, our June estimates of poverty status are consistent with the income losses projected by Diao et al. (2020) and Diao and Mahrt (2020) using ex ante economic simulation models, and our results and those of Diao et al. (2020) suggest that loss of employment is one of the main channels of impact. Moreover, a nationally representative phone survey conducted in September/October 2020 found that over four-fifths of households reported a drop in income since the beginning of the year and that estimates reductions in household income were larger for urban (49%) than rural households (41% reduction). Both results are consistent with the findings in this study.

These results have significant policy implications for building resilience to economic shocks, both in Myanmar and other countries with high degrees of economic vulnerability. As a fledgling democracy in 2020, Myanmar had only recently started to expand social protection. As the global COVID-19 crisis unfolded with alarming speed in early 2020, Myanmar social protection system was unprepared to provide significant protection of incomes. Indeed, prior to COVID19, just 14% of Myanmar's population benefiting from any form of social protection, compared to much higher rates in comparator countries (Fig. 5). As a result, the democratically elected government in 2020 scrambled to scale up social protection measures, albeit with imperfect targeting (Table 5) and some critical delays. Worse still, in the wake of the military takeover in 2021, the World Bank has projected an 18% contraction in GDP and notes that the social protection measures introduced in 2020 have been stopped entirely. While Myanmar's broader economic and political future is clearly highly uncertain, the rebuilding of social protection programs will be critical for restoring some measure of economic resilience at the household level, and for aiding longer term economic recovery.

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.

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Appendix

Table A1
Linear probability model estimates predicting whether a respondent was able to report total household monthly income in any given month over June–December

	Coefficient	p-value
Multiple adults (more than 2)	−0.053***	0.000
HH has >6 members	−0.053***	0.000
Currently pregnant	−0.038***	−0.001
Asset-poor vs asset-rich	−0.002	−0.882
Asset-low vs asset-rich	−0.008	−0.390
Rents home vs owns	0.001	−0.913
Squatter home vs owns	0.071**	−0.014
Farm HH vs salaried	−0.118***	0.000
Unskilled labor HH vs salaried	−0.135***	0.000
Skilled labor HH vs salaried	−0.093***	0.000
Trade/retail HH vs salaried	−0.136***	0.000
Other livelihood HH vs salaried	−0.354***	0.000
Female is main income earner	−0.031*	−0.053
Remittances from overseas	−0.035	−0.300
Remittances from Myanmar	0.000	−0.981
Urban vs rural	−0.108***	0.000
July round vs June	0.017	−0.154
August round vs June	0.027**	−0.025
September round vs June	0.021*	−0.097
October round vs June	0.013	−0.296
November round vs June	0.001	−0.939
Observations	11,874	
R-squared	0.05	

Source: Authors' estimates from RUFSS data. *, **, *** indicate significant at the 10%, 5% and 1% level respectively.

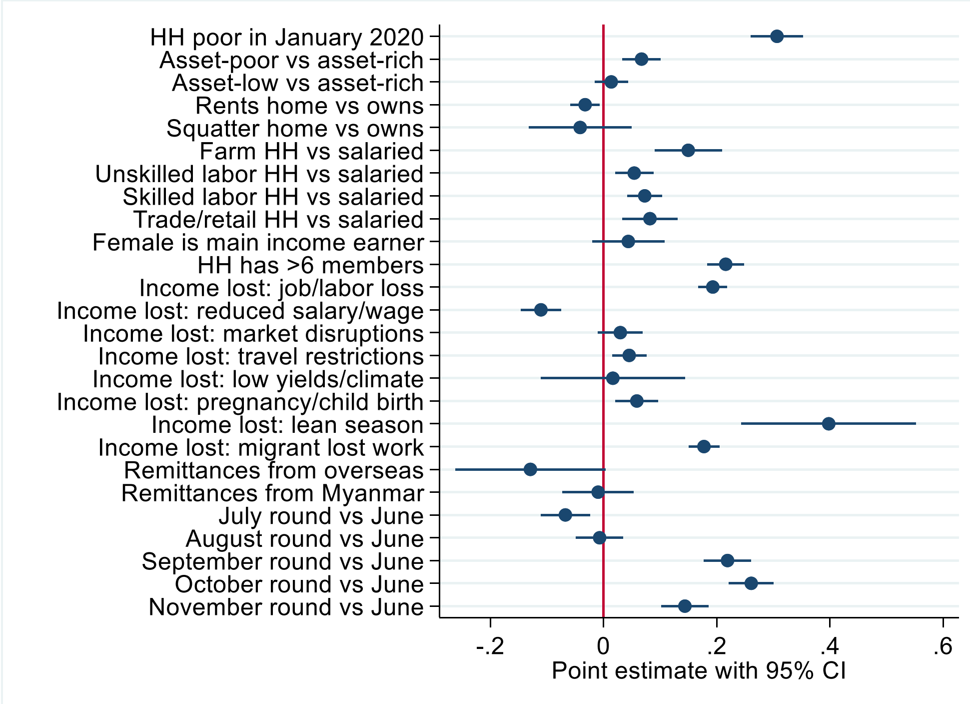


Fig. A1. Linear probability model estimates of the predictors of becoming poor at the $1.90/day poverty status between January and June 2020 in the urban and peri-urban Yangon sub-sample (with 95% confidence intervals)
Source: Authors' estimates from RUFSS data using linear probability model regressions with 95% confidence intervals.

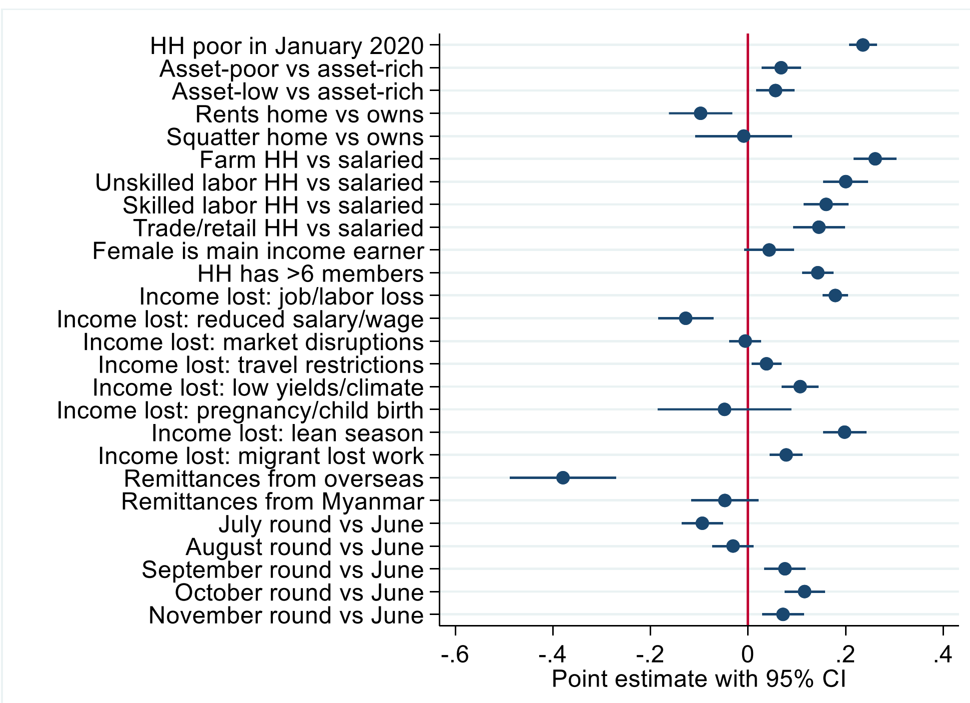
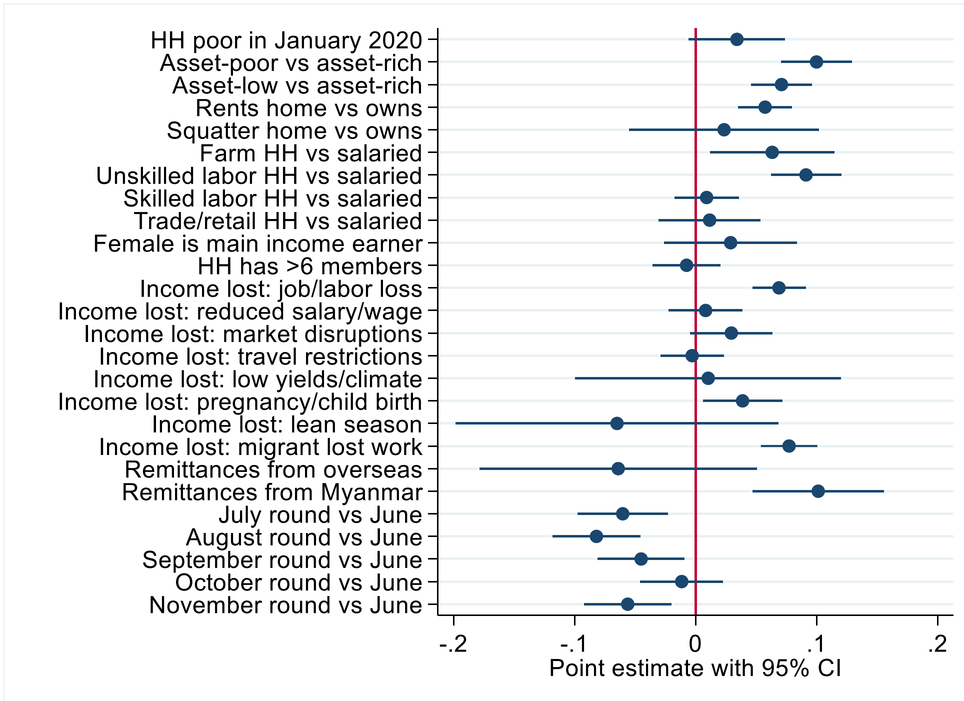


Fig. A2. Linear probability model estimates of the predictors of becoming poor at the $1.90/day poverty status between January and June 2020 in the rural dry zone sub-sample (with 95% confidence intervals)
Source: Authors' estimates from RUFSS data using linear probability model regressions with 95% confidence intervals.

Panel A. Urban Yangon sample



Panel B. Rural sample

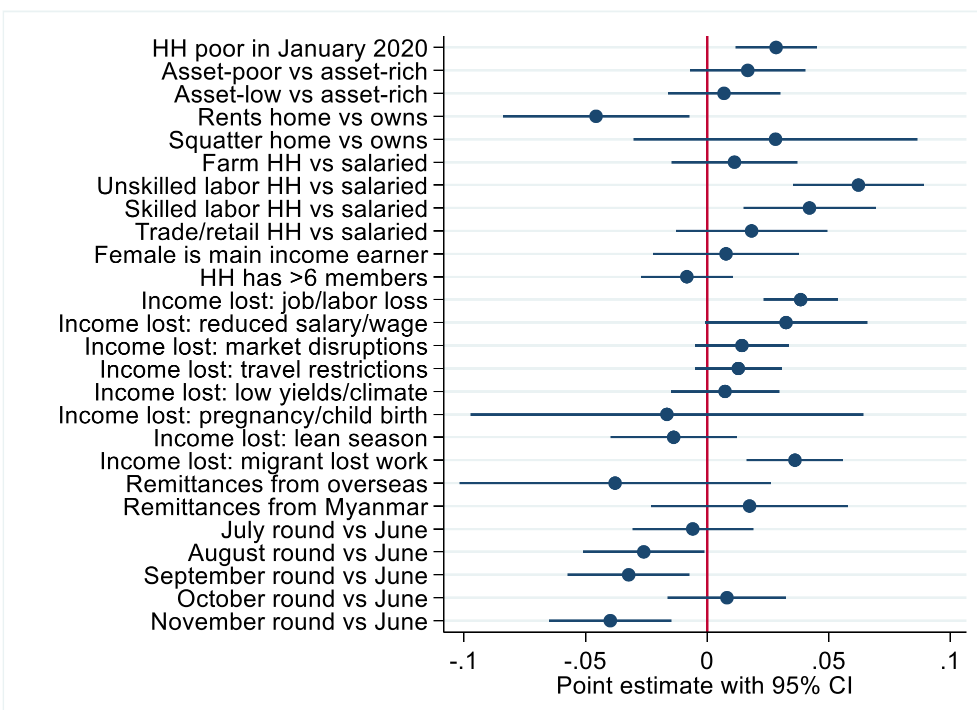
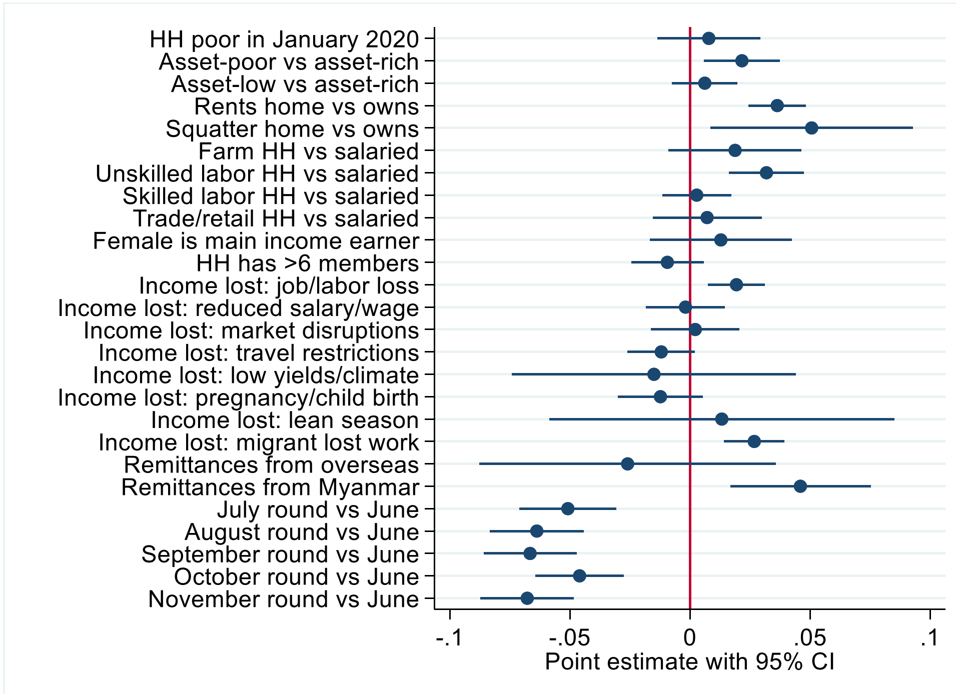


Fig. A3. Linear probability model estimates of the predictors of the FIES indicator of consuming fewer food types in the Yangon and rural dry zone sub-samples, with 95% confidence intervals

Source: Authors' estimates from RUFSS data using linear probability regressions with 95% confidence intervals.

Panel. A. Urban Yangon sample



Panel B. Rural dry zone sample

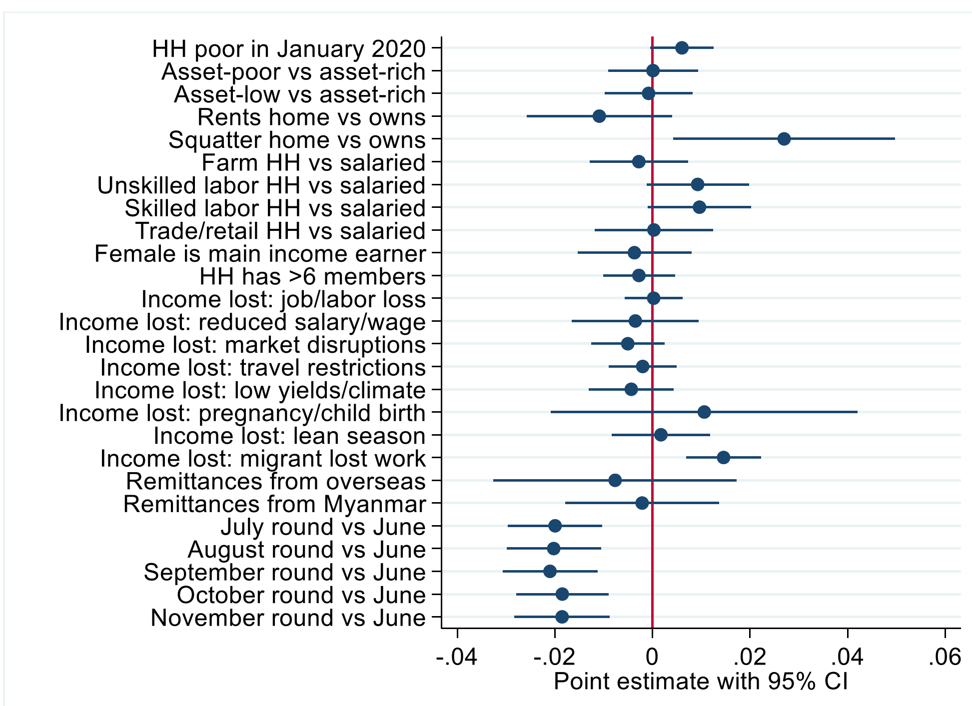


Fig. A4. Linear probability model estimates of the predictors of the FIES indicator of experiencing hunger in the Yangon and rural dry zone sub-samples, with 95% confidence intervals

Source: Authors' estimates from RUFSS data using linear probability regressions with 95% confidence intervals.

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