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Poverty measurement by phone

Developing and testing alternative poverty metrics from the nationally representative Myanmar Household Welfare Survey (MHWS), Round 1 (December 2021-January 2022)

CONTENTS

TABLES

FIGURES

ABSTRACT

Poverty measurement in low and middle income countries (LMICs) has always been challenging, especially among rural households whose incomes are characterized by seasonality, informality and some degree of subsistence consumption. During the COVID-19 pandemic poverty measurement became even more challenging as research had to resort phone surveys, who necessary brevity precludes the use of detailed household expenditure modules preferred in rural settings. Phone surveys instead typically resorted to qualitative questions on income losses and other welfare impacts of economic shocks. Here we use the new nationally representative Myanmar Household Welfare Survey (MHWS) to experiment with three kinds of poverty measures: (1) Asset poverty (10 questions); (2) Income poverty (a maximum of 17 questions); and (3) Food expenditure poverty (based on 4 questions). We first describe the methods for constructing these three indicators – including the poverty lines used for income and food poverty – and their conceptual strengths and weaknesses, before turning to a descriptive analysis of their geographical patterns, their associations with each other and with expenditure-based poverty in the last national survey in 2017. We then test their ability to predict poor diet quality and experiences of hunger, which – based on previous studies – are outcomes that ought to be highly sensitive to household poverty. We draw three important conclusions for measuring poverty in phone surveys. First, asset poverty and income poverty are strongly associated with each other, and with state/region poverty patterns of expenditure-based poverty in 2017. Second, asset poverty was consistently the strongest predictor of poor diet diversity among adults and children, as well as food insecurity at the household level, but income poverty also predicted these outcomes even after controlling for asset poverty. Third, we argue that phone surveys should measure both asset and income poverty, but should likely steer clear of food expenditure measures, which will either require overly long survey instruments, or very short questionnaires susceptible to underestimate of expenditure and overestimation of poverty. However, asset and income poverty are relatively quick and easy to measure, and conceptual complements to each other: income poverty is likely to be sensitive to shocks and seasonality, while asset poverty is insensitive to these fluctuations but captures long-term wealth. Finally, another important benefit of measuring income poverty is its ability to capture the effects of inflationary shocks, as inflation can affect both nominal incomes (e.g. through unemployment) as well as through the analyst's price adjustments to the real food poverty line.

1.INTRODUCTION

Poverty measurement in low and middle income countries (LMICs) has always been challenging, especially among rural households whose incomes are characterized by seasonality, informality and some degree of subsistence consumption (Deaton and Zaidi, 2002). During the COVID-19 pandemic poverty measurement became even more challenging as researchers had to switch to phone or other online surveys, who necessary brevity precludes the use of detailed household expenditure modules preferred in rural settings.

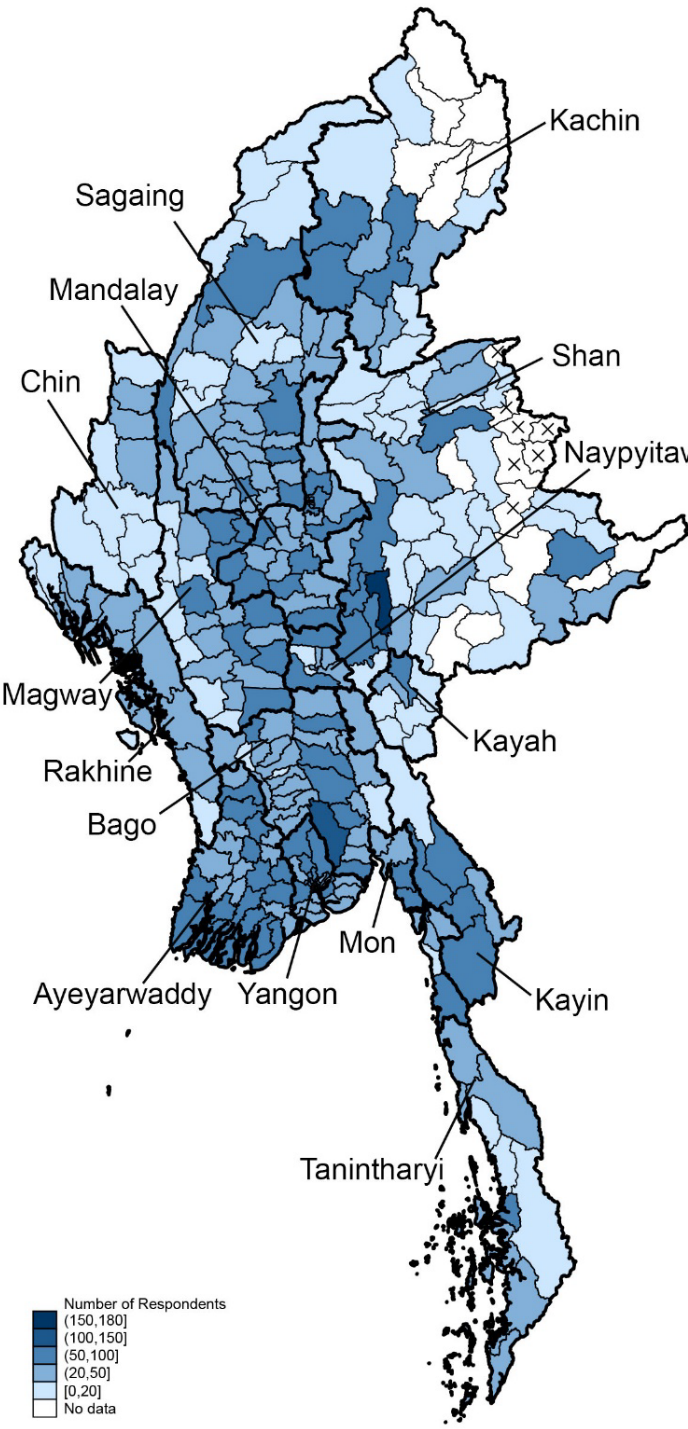
Monitoring poverty via phone surveys is very challenging, however, especially as the preferred expenditure-based modules for measure poverty in more rural settings are prohibitively long for phone surveys (Deaton and Zaidi, 2002). Asset-based wealth measures (Filmer and Pritchett, 2001) and multi-dimensional poverty meausres (Alkire and Foster, 2011) are relatively short and easy to measure, but are generally not sensitive to shocks (e.g. people do not give up housing characteristics when economic conditions deteriorate), and cut-off lines for describing a household as income-poor or multi-dimensionally poor are somewhat arbitrary. Asset-based poverty measures and multi-dimensional poverty measures therefore tend to be good proxies for long term wealth or socioeconomic status, but not for short term variations in economic conditions in the wake of the kinds of severe economic shocks that have hit LMICs in recent years, including COVID-19 shocks but also conflict, political instability and inflation.

As a result of these poverty measurement challenges, most phone surveys conducted during COVID-19 only asked qualitative questions about whether the household experienced income changes relative to pre-COVID periods (Amare et al., 2020; Egger et al., 2021; Gourlay et al., 2021). Qualitative questions on income losses offer limited information, however, because they say little about the specific depth of income losses, or whether a household is poor after the event of an income loss (i.e. a wealth household could lose more than 20 percent of its income but would clearly avoid becoming poor).

However, a previous 10-round panel phone survey of approximately 2000 households conducted in Myanmar by The International Food Policy Research Institute (IFPRI) from June 2020 to December 2021 used both a simple asset-count measure of poverty (the number of different assets owned by a household) and an even simpler income-based measure asking each respondent to estimate total household income in the past month (Headey et al., 2022). Asset-based poverty from that survey was a strong predictor of child diet quality and food insecurity experiences, and the income-based poverty measure also showed plausible variation with the timing of various COVID shocks as well as disastrous economic impacts of the military takeover in February 2021. Indeed, another study based on that survey showed that inter-round fluctuations in this income-based poverty measure were strongly correlated with Google's consumer mobility index (Headey et al., 2021), suggesting this very simple poverty measure did a reasonably good job of tracking poverty, though perhaps more so in urban areas (Yangon).

In this study we use new data from the sub-nationally representative Myanmar Household Welfare Survey (MHWS) conducted between December 2021 and February 2022 (Figure 1) to describe and test three alternative measures of poverty: (1) a new asset-based poverty measure based on a count of 10 statistically "relevant" assets; (2) an income-based poverty estimated from an expanded module on different income sources, including net remittances received; (3) a food expenditure-based poverty measure based on four questions on estimates of four types aggregated food expenditures (e.g. purchased, own-farm, et cetera).

Figure 1: Interviews conducted in the first round of MHWS, by township



Note: Crosses indicate townships in Wa SAZ which were avoided for interviewing.

The objectives of the research are threefold. First, we set out to describe spatial patterns of the three poverty measures in order to inform policymakers about poverty and vulnerability in different regions, and gauge the correlations between the three measures, as well as their correlations with official poverty rates in 2017 (based on an in-person survey and expenditure-based poverty calculations). Second, we set out to test the explanatory power of the three MHWS poverty measures by assessing their ability to predict poor diet diversity among adults and young children, as well as experience-based household food insecurity indicators. The rationale for this test of predictive power is that we know from extensive previous research that as incomes increase, households and individuals diverse their diets (Choudhury et al., 2019; Subramanian and Deaton, 1996); and conversely, as incomes decline due to shocks, people cut back on consumption of high-value nutrient dense foods (Block et al. 2004). Thus, we argue that a good poverty indicator should be able to predict whether or not individuals have poor diets, or whether households report food insecurity experiences.

The remainder of this paper is structured as follows. Sections 2, 3 and 4 respectively describe the construction of asset-, income- and food expenditure-based poverty measures, as well as their distributions and geographical patterns. Section 5 looks at the question of "validation", albeit very imperfect validation based on associations and predictive power rather than true validation per se. This section firstly examines correlations between the three MHWS poverty measures, as well as their basic state/region level correlation with expenditure-based poverty in 2017 from the last national in-personal survey conducted in Myanmar. It then uses multi-variate regressions to see how well the three MHWS poverty measures predict inadequate diet diversity for adults and young children, as well as household food insecurity (hunger) experiences. Section 6 concludes with remarks on the implications of our findings for poverty measurement in the context of phone surveys. In short, we conclude that phone surveys should try to measure both asset-poverty (or multi-dimensional poverty) as well as income-based poverty, as the two are likely complements to one another. Assets capture long-term wealth that is relatively insensitive to short term shocks, where as real income and income-based poverty captures seasonal fluctuations, the impacts of recent income shocks, including inflationary shocks to disposable income. Both measures are also practical in that they can be measured with relatively short modules.

2.ASSET POVERTY

We measure the poverty of households by a simple count of the number of "assets" they own, with ten assets in total: flush toilet, improved water source (piped into house or bottled water), improved housing (semi-pucca, bungalow/brick, apartment/condominium), grid-based electricity (not solar), rice cooker, fridge, TV, wardrobe, car/motorcycle/tuk-tuk and working computer/laptop/iPad. These assets were selected for the survey based on principal components analysis (PCA) of two previous national in-person surveys in Myanmar, the 2015-16 Demographic Health Survey (MOHS and ICF-International, 2017) and the 2017 Myanmar Living Conditions Survey (CSO et al., 2019). We then identified which assets or housing characteristics had the highest weights (or "loadings) in the PCA for each survey, implying that these were variables with strong power for explaining latent wealth. We also tried to choose a range of assets that would distinguish extreme poverty from moderate poverty, but also moderate wealth from higher household wealth (with the latter more likely to own computers/iPads, for example). As expected, given our pre-MHWS analyses on the DHS and MLCS assets, when we conduct a PCA on the 10 assets chosen for the MHWS we find relatively high loadings (weights) on the first principal component, which explains 33 percent of the total variance (Table 1).

Table 1: Loadings (weights) on the first principal component of the ten selected assets in the MHWS

Variable	Loading	Variable	Loading
Improved house	0.29	Fridge	0.40
Flush toilet	0.22	TV	0.36
Improved water	0.22	Wardrobe	0.30
Electricity	0.40	Vehicle	0.19
Rice cooker	0.43	Computer/iPad	0.23
Variance explained			33.0%

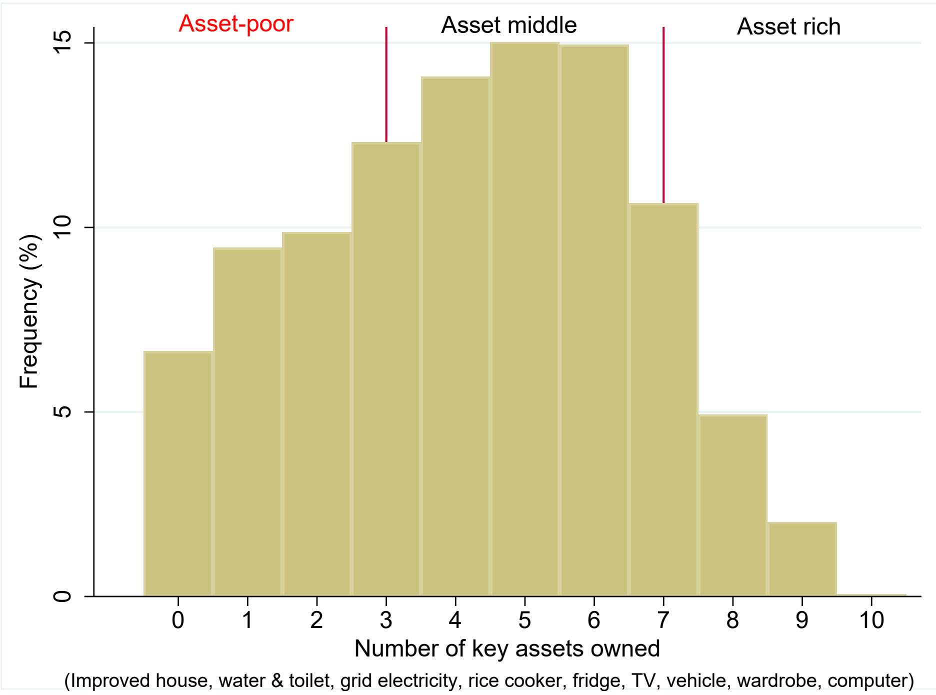
Notes. Sample size is 12,100 households from the MHWS

While the PCA results reported in Table 1 could be used to construct a wealth index and wealth quintiles, wealth quintiles only offer an ordinal ranking of wealth, whereas our goal here was to offer an indicator of asset poverty in more absolute terms. However, the relative similarity of loadings in Table 1 arguably provides a justification for constructing a simple count measure of assets owned, even though we make no assumption about the monetary value of these assets.

After constructing a simple count of the ten assets, the households were categorized into three groups based on the number of assets: asset-poor (0-3 assets), asset-low (4-6 assets) and asset-rich (7-10 assets). The cut-offs are somewhat arbitrary and there may be few observable differences between a household that owns three assets and a household that owns four assets, but the same is true of monetary poverty lines in income or expenditure-based poverty measures.

Figure 2 shows a histogram of the distribution of asset ownership. Income or expenditure distributions are typically log normal. The distribution of assets owned also has a thin tail – there are not many asset-rich households – but the bulk of the distribution is in the asset-middle grouping of 4-6 assets, although there are still larger number of Myanmar households owning 0-3 assets.

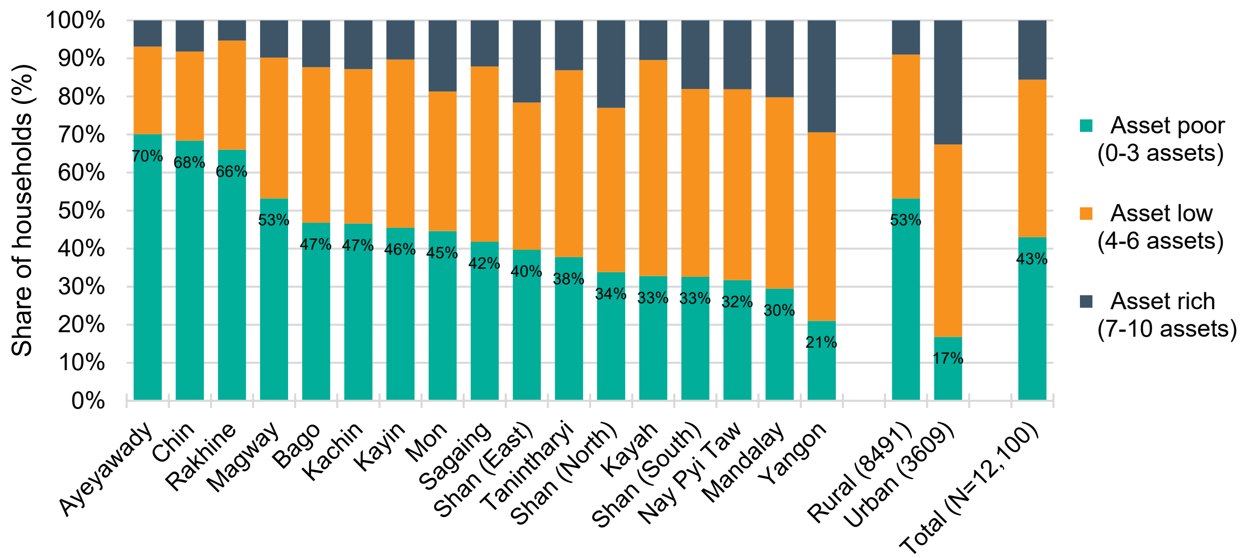
Figure 2: A histogram of the frequency of ownership of 10 assets, with cut-off lines for asset-poor, asset-middle and asset-rich



Notes. Sample size is 12,100 households from the MHWS

Figure 3 shows the distribution of asset poverty levels by state/region and rural/urban. Nationally, 43 percent of households are asset-poor and 42 percent are asset-low while only 15 percent of households are asset-rich. Among the states and regions, we found that Ayeyarwady is poorest, with 70 percent of households in Ayeyarwady asset-poor. Similarly, asset-poor states are Chin and Rakhine. At the other extreme, households in Yangon region are much less likely to be asset-poor (21 percent) though half of the households were asset-low and Yangon had by far the largest share of asset-rich households (29 percent). Mandalay (which includes rural Mandalay) also had relatively low poverty, as did Nay Pyi Taw. Unsurprisingly, then, urban households are much less likely to be asset-poor (33 percent) than rural households at the national level (53 percent). Overall, the spatial distribution of asset-poverty in Figure 2 looks very plausible, although one potential concern is that asset-indices tend to be “urban biased” because the assets measured may not reflect farm-based wealth (Rutstein and Staveteig, 2013). Also, five of the 10 assets are electricity-dependent, so not having reliable access to electricity could potentially exacerbate inter-household differences in wealth.

Figure 3: Distribution of asset levels by state/regions, rural/urban and national



Source: Estimates from round 1 of MHWS conducted over December 2021-February 2022. See text for definition of asset-poverty. Sample size is 12,100 households.

3.INCOME-BASED POVERTY

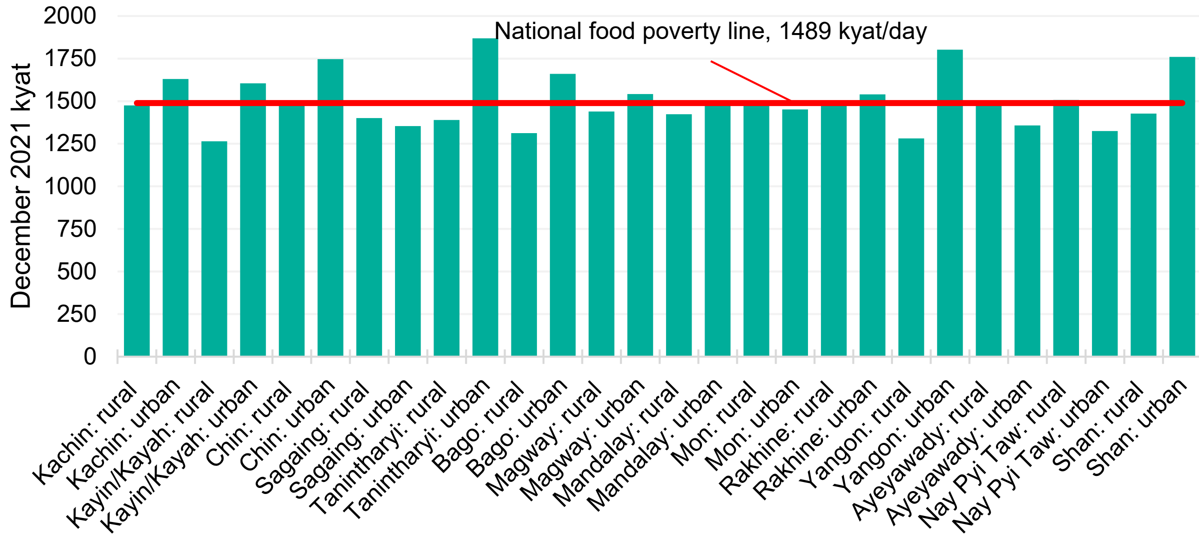
We measured income-based poverty status through five steps. First, we asked respondents to estimate total household income in the past month from 15 different economic activities[1] plus net remittances received. Second, daily income per adult equivalent was estimated from the total monthly income aggregate and household size adjusted for demographic composition using standard adult equivalency scales. Third, the national food-based poverty line from the first quarter of 2017 – which was 1,037 kyat (CSO et al., 2019) – was updated first with the official food CPI until mid-2020, and then with a MAPSA food price index from a national survey of food vendors (MAPSA, 2022a). The resulting updated food poverty line for December 2021 was 1,489 kyat per person per day. Fourth, we applied a spatial deflator to adjust food prices for rural and urban areas within each state/region based on price information from the MAPSA food vendor survey.[2] Results for this food poverty line are shown in Figure 4, which confirms the generally much higher price of food in urban areas. Not making this adjustment could therefore seriously bias poverty comparisons across states/regions and different types of households. Finally, we applied the ratio of the 2017 nonfood poverty (533 kyat) to the 2017 food poverty line (1,037) kyat to the updated food poverty lines in Figure 4. In effect, we assume – through necessity – that the relationship between food and non-food prices in spatially the same in 2021/2022 as it was in

[1] These economic activities are described in the survey design report (MAPSA 2022), but are: 1 = wage work– crop farming; 2 = wage work– livestock; 3 = wage work – fishing/aquaculture; 4 = wage work – non-agriculture; 5 = salaried work– crop farming; 6 = salaried work– livestock; 7 = salaried work – fishing/aquaculture; 8 = salaried work– non-agriculture; 9 = work on household crop farm (seasonal/perennial crops); 10 = own or household livestock business; 11 = own or household fishing or aquaculture business; 12 = own or a household non-farm enterprise (including any small business activities); 13 = renting out of land / properties; 14 = gifts, donations, pensions, assistance; 15 = remittances. Remittances were further adjusted for any money sent by the household to individuals outside the household to generate net remittances received.

[2] Due to small sample sizes in the MAPSA Food Vendor Survey for Kayin and Kayah, price indices were merged for these two regions, separately for rural and urban areas.

2017. At the national level the result is total (food + non-food) poverty line of 2,234 kyat per adult equivalent per day.

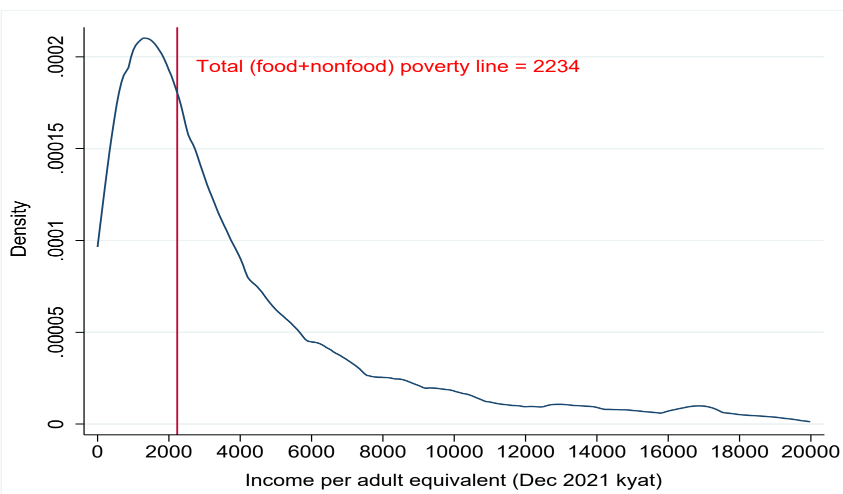
Figure 4: Food poverty lines at the national level and by rural/urban area of each state/region



Source: Estimates from round 1 of MHWS conducted over December 2021-February 2022. See text for definition of asset-poverty. Sample size is 12,100 households. See text for the derivation of food poverty lines for each region.

Figure 5 reports a kernel density plot of the distribution of income per adult equivalent. As expected, the distribution is log-normal with a long thin tail of higher income households, but the bulk of the distribution relatively poor, earning less than 8,000 kyat per day (or about USD 4.50).

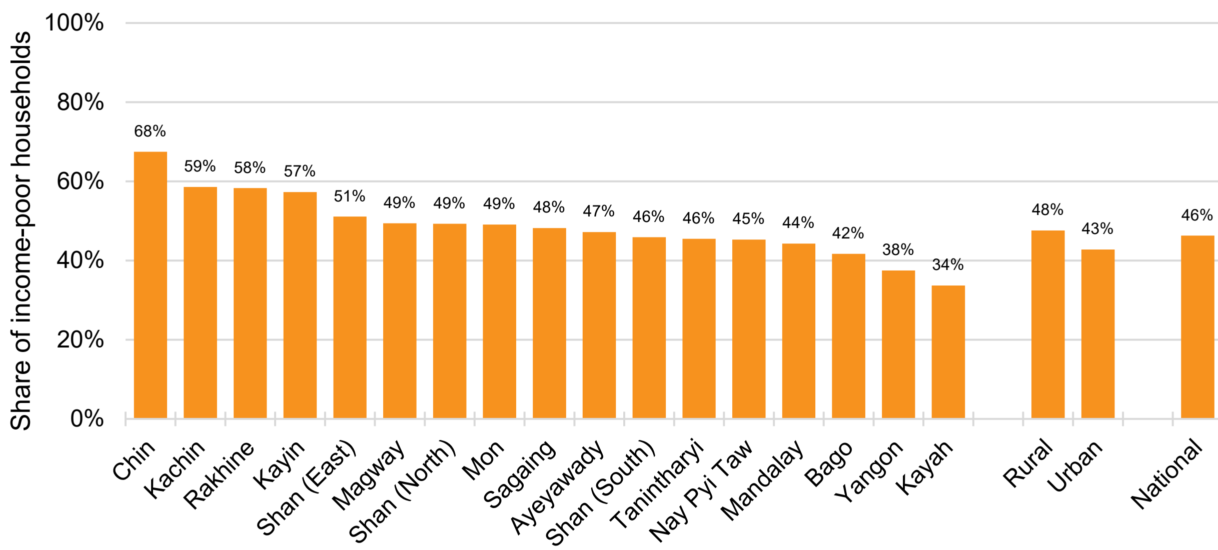
Figure 5: A Kernel density plot of the distribution of income per adult equivalent per day (December 2021 kyat) against the total poverty line of 2,234 kyat



Source: Estimates from round 1 of MHWS conducted over December 2021-February 2022. See text for definition of asset-poverty. Sample size is 12,100 households. See text for the derivation of the total (national) poverty line.

Figure 6 reports spatial patterns in this income-based poverty indicator. Nationally, nearly half of households (46 percent) are income-poor by this measure. Chin state (68 percent of households) is the poorest followed by Kachin (59 percent), Rakhine (58 percent), Kayin (57 percent) and Shan (East) states (51 percent). Ayeyarwady – which had the highest asset-poverty – is also income-poor (47 percent). Although Yangon and Kayah are much less likely to income-poor compared to other states/regions, one-third of households are still poor (38 percent and 34 percent respectively). Rural households (48 percent) are more likely to be income-poor compared to urban households (43 percent), but the rural-urban poverty gap for the income measure is much smaller than it is for the asset measure. However, it should be noted that this first round of MHWS was conducted just after Myanmar's main harvest season, so farmer incomes may be relatively high at this time of year, and subsequent rounds in 2022 may shed light on how rural-urban income gaps vary by season.

Figure 6: Share of income-poor households with daily income per capita less than poverty line



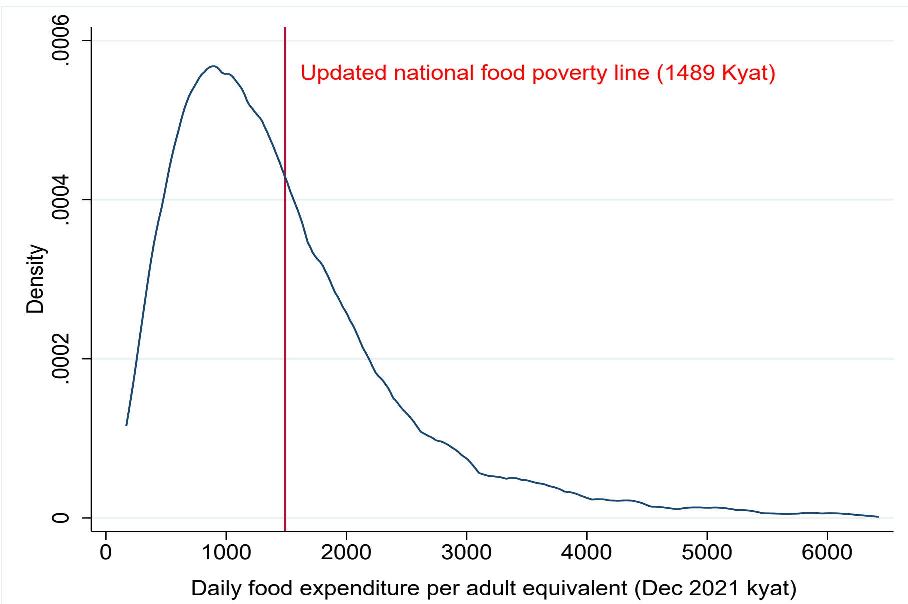
Source: Estimates from round 1 of MHWS conducted over December 2021-February 2022. See text for definition of income-based poverty. Sample size is 12,100 households. See text for the derivation of poverty lines for each region.

4.FOOD EXPENDITURE POVERTY

For in-person surveys in heavily agrarian economies expenditure-based poverty measurement is preferred, but this usually entails as many as 100 or more questions on spending for a detailed list of food and nonfood items. Since this was clearly not feasible in a phone survey, we experimented with a very abridged module based of 7-day recall estimates for the total household expenditure on four means of acquiring food: (1) markets and stores; (2) food from restaurants and other prepared meals; (3) food from their own farm; and (4) food obtained as in-kind wage or free. The same food poverty line, as described above, was used to define food expenditure poverty. The household was defined as food-poor if they spent less than the food poverty line defined above, which was 1,489 kyat at the national level but adjusted for rural and urban areas within each state/region (as reported above in Figure 3).

Figure 7 reports a kernel density plot of the distribution of food expenditure per adult equivalent along with the 1,489 kyat per day food poverty line. Like the income estimates, food expenditure has a log-normal distribution, and the majority of households appear to spend less on food than the 1,489 khat poverty line. Also, as expected, the right tail of distribution is shorter than the income distribution.

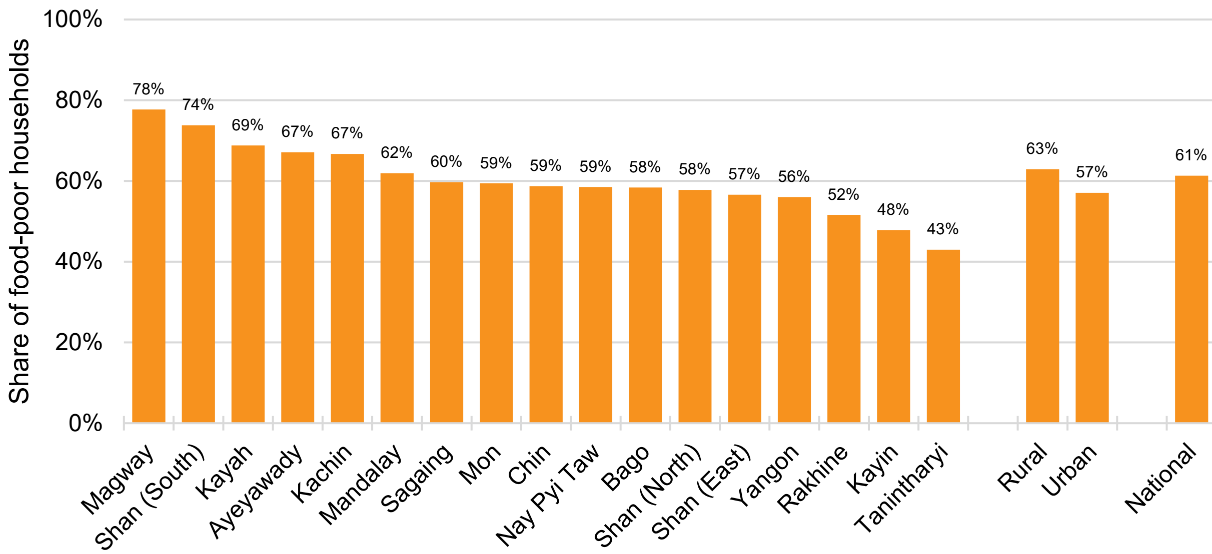
Figure 7: A Kernel density plot of the distribution of food expenditure per adult equivalent per day (December 2021 kyat) against the total poverty line of 1,489 kyat



Source: Estimates from round 1 of MHWS conducted over December 2021-February 2022. See text for definition of food expenditure poverty. Sample size is 12,100 households. See text for the derivation of food poverty lines for each region.

Estimates of food poverty expenditure poverty are reported in Figure 5, and are strikingly high: more than half of households (61 percent) are food-poor. Like income-based poverty, rural households (63 percent) are more likely to food-poor than urban households (57 percent). Magway region (78 percent) experienced food-poverty most, followed by Shan (South) (74 percent), Kayah (69 percent) and Ayeyarwady (67 percent). Though households in Kayin State and Tanintharyi region are less food-poor than other states and regions, nearly half experienced food-poverty (48 percent and 43 percent correspondingly). It is also notable that the pattern of food expenditure poverty across states/regions is quite different to the patterns observed for asset poverty and income poverty. That, together with the very high levels of food poverty observed, casts some doubt on the accuracy of the food expenditure poverty measure. With such aggregated food categories (just four), it is likely that it is computationally difficult for respondents to recall all food expenditures, and convert own farm consumption into value terms, leading to under-estimation of food expenditures.

Figure 8: Share of food-poor households with food expenditure per adult equivalent per day less than food poverty line



Source: Estimates from round 1 of MHWS conducted over December 2021-February 2022. See text for definition of food expenditure poverty.

5. ASSOCIATIONS BETWEEN POVERTY MEASURES AND THEIR SCOPE TO PREDICT POOR DIET QUALITY AND FOOD INSECURITY

5.1 Associations, predictions and "validation" questions

It is challenging to "validate" any particular poverty measure, especially in the current Myanmar context, for several reasons.

First, validation requires comparison to a gold standard, but there is neither any conceptual agreement among poverty economists on what constitutes "true" poverty nor any real empirical gold standard. On the conceptual front, for example, the World Bank and others have historically advocated monetary poverty measures, but other research and institutions have advocated multi-dimensional poverty indices, and there are many disagreements and debates on the virtues of both measures (Alkire and Foster, 2011; Ravallion, 2010, 2011). Since monetary and multi-dimensional indices are conceptually very different from other, it is also not necessarily the case that they should be highly correlated with each other, especially in the context of seasonal income variations.

Second, in the context of phone surveys – which have limitations related to selection biases but perhaps also other response biases (Brubaker et al., 2021; Gourlay et al., 2021) – it would be ideal to "validate" phone-based poverty indicators against indicators derived from in-person surveys. However, the last national in-person survey in Myanmar was the 2017 Myanmar Living Conditions Survey (MLCS). The MLCS was itself imperfect in terms of spatial coverage and sampling (particularly in Rakhine), but more importantly Myanmar has experienced severe COVID shocks in 2020 followed by an economic collapse in the way of the February 2021 military takeover, with the economy projected to have collapsed by almost 20 percent in 2022. These shocks were profound, destroying livelihoods, businesses and even whole sectors (e.g. tourism), as well as catalyzing large scale internal and international migration. Thus, patterns of poverty in 2022 could be very different from patterns of poverty in 2017, even with the same sample and the same poverty indicator.

Third, different poverty measures may be useful for different purposes. Asset-based indices were developed to measure latent wealth (Filmer and Pritchett, 2001), which is likely quite fixed in the short to medium term, but assets/wealth was shown to be a strong predictor of other outcomes, like educational attainment and health and nutrition outcomes (Choudhury et al., 2019; Filmer and Pritchett, 2001; Filmer and Scott, 2012; Harttgen et al., 2013; Hjelm et al., 2016; Sahn and Stifel, 2003). However, as noted in the introduction, asset ownership/scores rarely decline, and are unlikely to be appropriate for gauging the impacts of shocks. More shock-sensitive poverty measures are therefore desirable in many contexts, particularly in Myanmar's very volatile economic and political situation.

Bearing in mind that it is impossible to engage in any strict validation of these measures, we still consider it important to pose three questions of them:

1. Howe well do different MHWS poverty indicators correlate with each other?
2. How well do these different MHWS poverty indicators correlate with the expenditure poverty measure of the MLCS 2017? And
3. How well do these different MHWS poverty indicators predict other (conceptually distinct) welfare indicators, such as individual diet diversity (quality) and food security?

One might reasonably conjecture that a poverty indicator that was weakly correlated with other indicators is suspicious, while one would also expect well-performing indicators of poverty to be strong predictors of inadequately diverse diets or food security. Previous research has shown, for example, that asset indicators are strong predictors of inadequate diet diversity in children (Choudhury et al., 2019), but also that in the face of severe income shocks – such as the 1998 Indonesian financial crisis – household and individual dietary diversity declines sharply (Block et al., 2004). The ability of different kinds of poverty or socioeconomic measure to predict experience-based food indicators is less well understood (Headey and Ecker, 2013; Hjelm et al., 2016), but also worthy of further exploration.

5.2 How strongly are different poverty measure correlated with each other?

Table 2 compares state/region and rural/urban poverty headcounts for the three MHWS measures for 2021-2022 and the 2017 MLCS expenditure-based measure derived from a detailed expenditure module applied to a nationally representative in-person survey (CSO et al., 2019). There is no particular reason to expect levels of poverty to be similar across surveys, for the reasons outlined above, including the severe deterioration in living standards in Myanmar over 2020-2022. That said, expenditure poverty in the 2017 MLCS is much lower than it is for the three MHWS measures (25 percent), but also shows a striking disparity in rural (30.2 percent) and urban (11.3 percent) poverty rates. That disparity remains true for the asset-based poverty indicator, though much less so for the income and food poverty measures from MHWS.

Table 2: Comparisons of the three MHWS poverty measures and the 2017 MLCS expenditure poverty measure, by state/region and rural/urban area

	Asset poverty % (MHWS 2021-22)	Income poverty % (MHWS 2021-22)	Food Poverty % (MHWS 2021-22)	Expenditure poverty % (MLCS 2017)
Ayeyarwady	70.1	47.2	67.1	31.7
Bago	46.8	41.7	58.4	17.4
Chin	68.4	67.5	58.7	58.0
Kachin	46.6	58.6	66.7	36.6
Kayah	32.8	33.7	68.8	32.0
Kayin	45.5	57.3	47.8	24.2
Magway	53.2	49.4	77.7	35.6
Mandalay	29.5	44.3	61.9	13.2
Mon	44.6	49.1	59.4	19.2
Nay Pyi Taw	31.7	45.3	58.5	22.1
Rakhine	66.0	58.3	51.6	41.6
Sagaing	41.8	48.2	59.7	30.7
Shan	33.8	47.5	67.2	28.6
Shan (East)	39.7	51.1	56.6	
Shan (North)	33.8	49.3	57.8	
Shan (South)	32.6	45.9	73.8	
Tanintharyi	37.8	45.5	43.0	13.2
Yangon	21.0	37.5	56.0	13.7
Rural (8491)	53.2	47.6	62.9	30.2
Urban (3609)	16.8	42.8	57.1	11.3
Total (N=12,100)	43.0	46.3	61.3	24.8

Source: MHWS poverty headcount estimates are from round 1 of MHWS conducted over December 2021-February 2022. See text for definitions. The MLCS 2017 expenditure poverty headcount is drawn from the MLCS poverty report, which also details the methods involved in measuring this indicator (CSO et al., 2019).

Patterns across states/regions are also interesting. Table 3 reports correlations between the four indicators at the state/region level (albeit from a very small sample of 15-17 states/regions). Asset-based and income-based poverty headcounts at the state-region level are highly correlated with each other (0.66) and also with MLCS 2017 expenditure-based poverty (0.72 and 0.70), but food poverty patterns by state/region share no significant correlation with other measures.

Table 3: Correlations between state/region level poverty headcounts for the three MHWS poverty indicators and the MLCS 2017 expenditure-based poverty indicator

		MHWS 2021-22 indicators			MLCS 2017
		Asset poverty	Income poverty	Food poverty	Expenditure poverty
MHWS 2021-22	Asset poverty	1.00			
	Income poverty	0.66***	1.00		
	Food poverty	0.02	-0.19	1.00	
MLCS 2017	Expenditure poverty	0.72***	0.70***	0.31	1.00

Source: MHWS poverty headcount estimates are from round 1 of MHWS conducted over December 2021-February 2022. See text for definitions. The MLCS 2017 expenditure poverty headcount is drawn from the MLCS poverty report, which also details the methods involved in measuring this indicator (CSO et al., 2019).

Table 4 reports correlations at the household level (N=12,100) for the three MHWS poverty measures. Asset and income-based poverty have a moderately strong correlation (0.22), but asset poverty and food poverty are more weakly correlated (0.09), though food poverty and income poverty are more strongly correlated (0.24). In summary, the MHWS food poverty measure seems to have weaker associations with other poverty measures compared to the asset and income-based poverty measures.

Table 4: Correlations between the three MHWS poverty indicators at the household level

	Asset poverty	Income poverty	Food Poverty
Asset poverty	1.00		
Income poverty	0.22***	1.00	
Food poverty	0.09***	0.24***	1.00

Source: MHWS poverty estimates are from round 1 of MHWS conducted over December 2021-February 2022. See text for definitions. The sample size is 12,100.

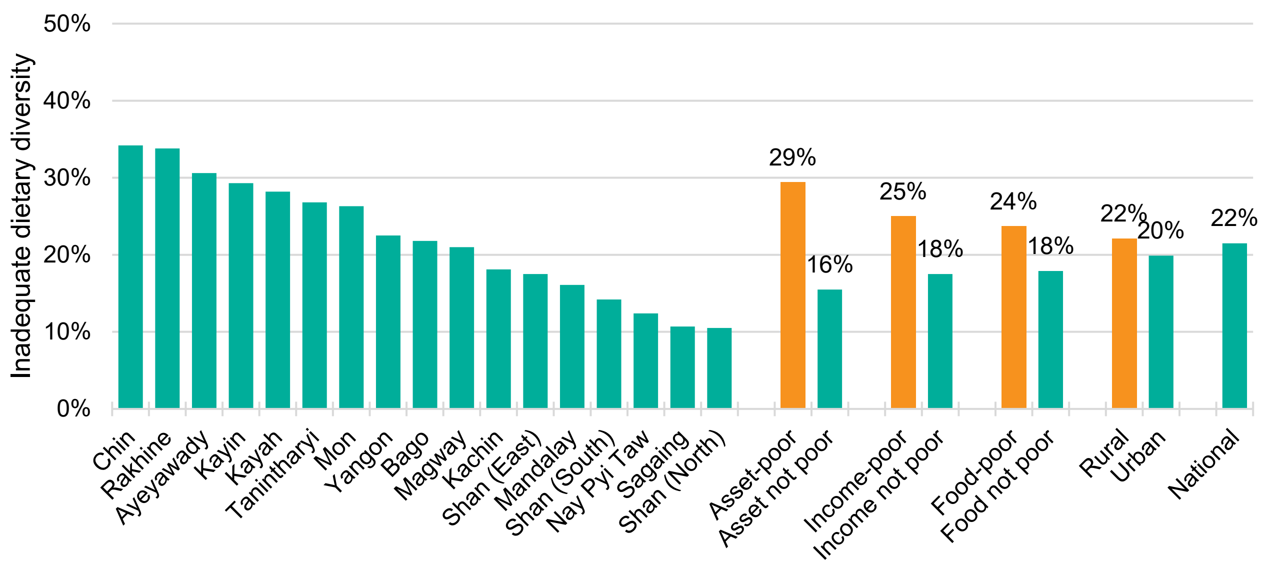
5.3 Do poverty measures predict poor dietary diversity?

Each adult respondent was asked about the foods they consumed in the past 24 hours using the Minimum Dietary Diversity for women (MDD-W) module (Arimond et al., 2010), while caregivers of infants 6-23 months (if present in a household) were also asked about food groups consumed in the past 24 hours (FANTA, 2006). MDD-W was asked of men and women (with approximately equal sample sizes) and poor diet diversity was defined as <5 of 10 food groups, while poor diet diversity in infants 6-23 months was defined as <4 of 7 food groups.

Figure 9 reports regional patterns of inadequate diet diversity in adults, but also differences by poverty status for each of the three poverty indicators. Notably, the regional patterns broadly resemble the patterns of asset poverty and to some extent income poverty. The highest prevalence of inadequate diet diversity was found in asset-poorest states/regions such as Chin, Rakhine and Ayeyarwady. Consistent with that pattern, asset-based poverty does the best in identifying poor adult diets, followed by income-based poverty. The prevalence of adult poor diets in asset-poor households (29 percent) is almost double of those in asset not poor households (16 percent). Similarly, income-poor adults (25 percent) are more likely to have poor diets than income not poor adults (18 percent). Differences between food-poor and food-nonpoor are more modest (24 vs 18 percent).

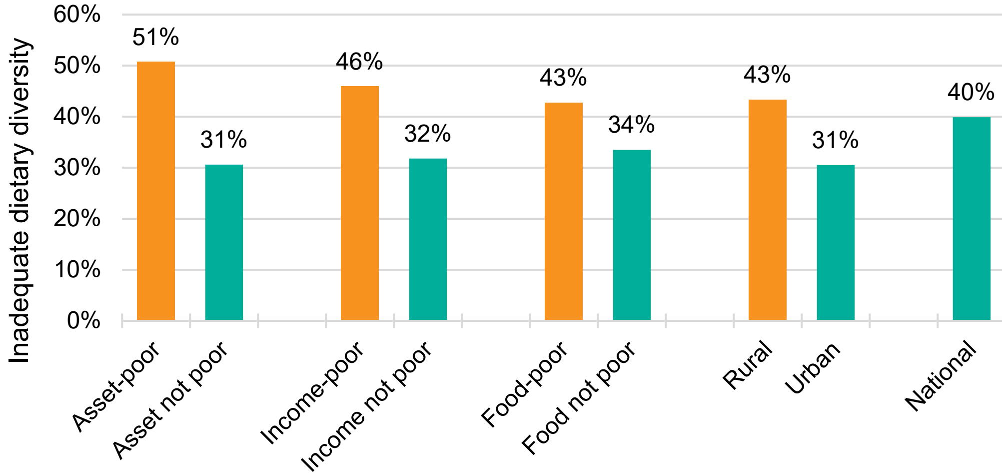
In case of youngest children, Figure 10 shows that 2 out of 5 children have inadequate diets and rural children (43 percent) had much worse dietary diversity than urban children (31 percent). Similar as adults, children in asset-poor households were far more likely to have poor diets than those in nonpoor households. The prevalence of child poor diets in income-poor households (46 percent) was 14 points higher than those in income-not-poor households (32 percent), while children from food-poor households were 9 points more likely to have poor diets than children from non-poor households.

Figure 9: Percentage of adults with inadequate dietary diversity by states/regions, poverty status and rural/urban



Source: MHWS poverty estimates are from round 1 of MHWS conducted over December 2021-February 2022. See text for definitions. The sample size is 12,100.

Figure 10: Percentage of children with inadequate dietary diversity (<4 out of 7 food groups)

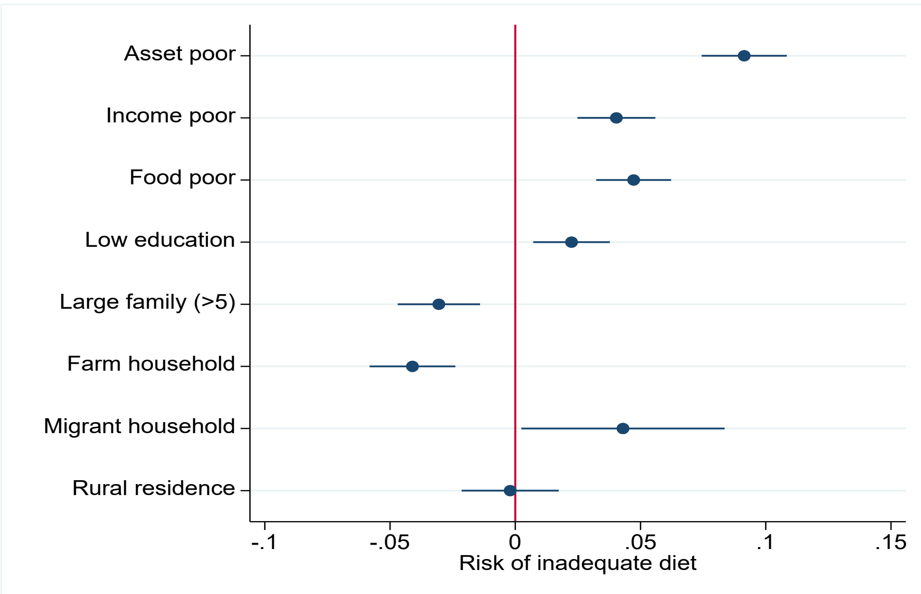


Source: MHWS poverty estimates are from round 1 of MHWS conducted over December 2021-February 2022. See text for definitions. The sample size is 12,100.

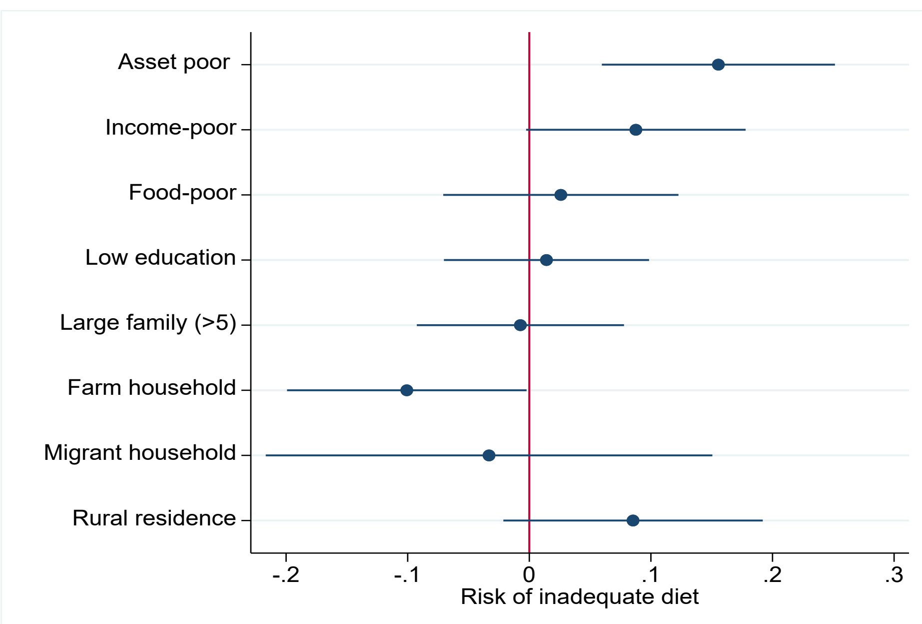
While these bivariate relationships between poverty status and inadequate diet diversity are interesting, it is also important to assess their predictive power in a multivariate regression framework. We therefore estimated linear probability models or inadequate dietary status against poverty status and other expected predictors of diet quality, including state/region fixed effects. Panel A shows that asset poverty status is the single strongest predictor of inadequate diet diversity among adults, increasing the risk by almost 10 percentage points. However, even in the same regression model both income poverty and food poverty predict 4-5 point increases in the risks of adequate diets. The effects are stronger than that of low education. Individuals from households that migrated in the last 2 years are also at higher risk of poor diets, but perhaps surprisingly, individuals from farm households and larger families are at lower risk.

Figure 11: Coefficients plots with 95 percent confidence intervals from linear probability models predicting inadequate dietary diversity among adults (Panel A) and infants 6-23 months of age (Panel B)

Panel A. Risk factors for poor diet diversity among adults



Panel B. Risk factors for poor diet diversity among infants 6-24 months of age



Source: The sample size for Panel A is 11,250 adults, while the sample size in Panel B is 668 children 6-23 months of age. Both regression models control for state/region fixed effects.

In Panel B we observe that asset poverty is again a very strong predictor of poor dietary diversity among infants 6-24 months of age, predict a 16-point risk increase. Income poverty predicts a 9-point increase (significant at the 4 percent level), but food poverty is not significantly associated with inadequate diets. Interestingly, farm households again have a lower risk of having infants with poor diet diversity.

5.4 Do poverty measures predict hunger?

Table 5 reports the share of households reporting food insecurity experiences from the Household Hunger Scale by poverty status and rural/urban status. The HHS asks the respondent whether any individual in the household experienced no food to eat, going to sleep without eating at night, or going to sleep without eating a whole day and night, and these measures have been validated for cross-cultural use (Deitchler et al., 2011). These measures capture increasingly severe food insecurity experiences.

Consistent with that intention, 12 percent of households reported experiences of having no food to eat in the past 4 weeks, while 5 percent and 2 percent reporting members sleeping without eating at night or going a whole day without eating. Consistent with results for the inadequate dietary diversity measures, we observe large differences in food insecurity between asset-poor and non-poor households, but also income-poor and non-poor households. In contrast, food poverty differentials are very modest.

Table 5: Share of households with selected food insecurity experiences in the past 4 weeks, by poverty and rural/urban status

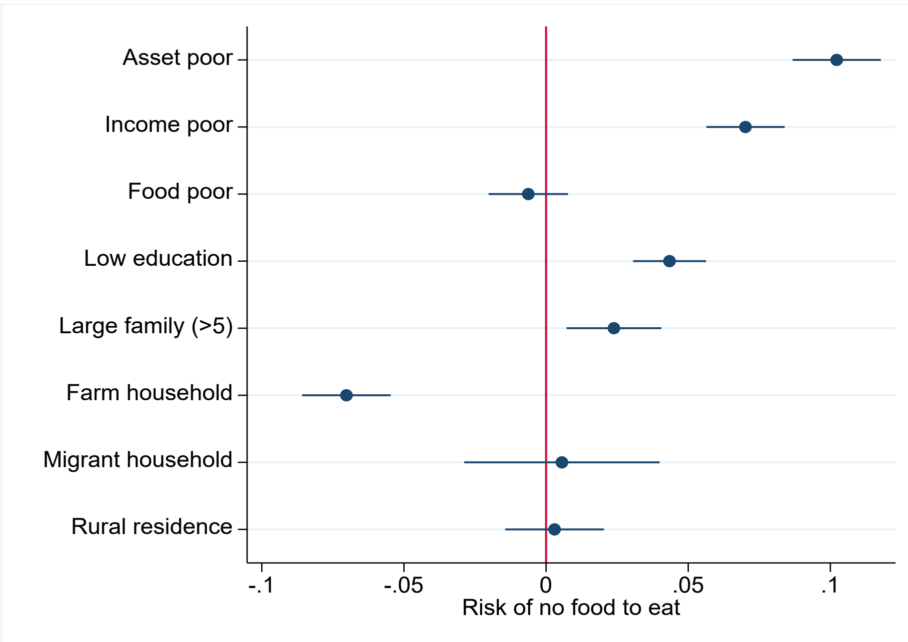
	No food to eat	Slept without eating at night	Slept without eating whole day and night
Asset-poor (%)	19	9	4
Asset-not poor (%)	6	2	1
Income-poor (%)	18	8	3
Income-not poor (%)	6	2	1
Food-poor (%)	13	6	3
Food-not poor (%)	10	4	2
Rural (%)	12	5	2
Urban (%)	10	4	2
National (%)	12	5	2

Source: MHWS poverty estimates are from round 1 of MHWS conducted over December 2021-February 2022. See text for definitions. The sample size is 12,100.

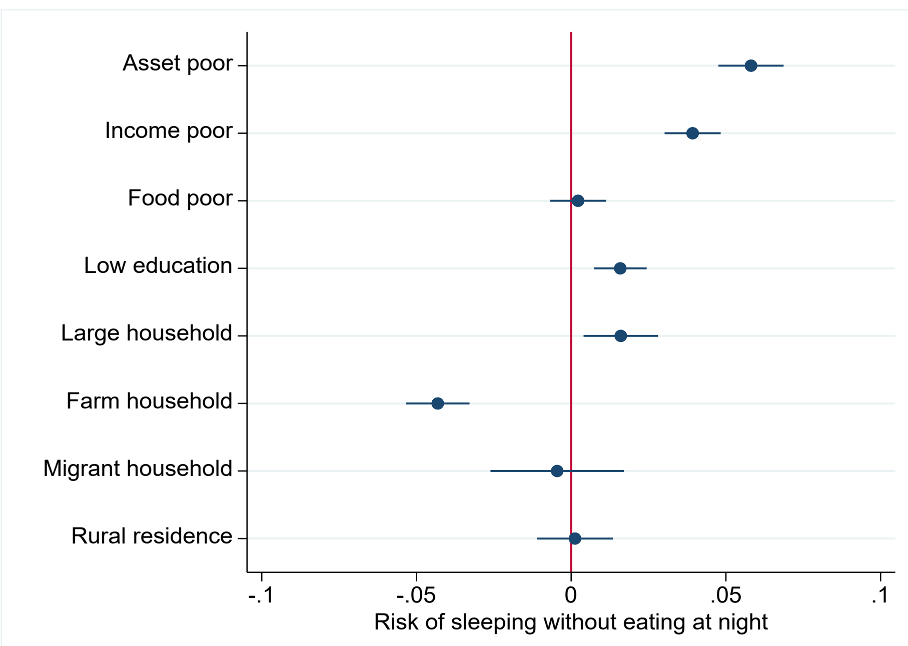
Figure 12 reports coefficient plots with 95 percent confidence intervals for the same regression models used for inadequate diet diversity, but with experiences of hunger as the dependent variables. Similar patterns emerge: asset poverty is the strongest predictor of poverty, but income poverty also has highly significant predicted effects on hunger experiences, while food poverty coefficients are never statistically significant. We also again find that, controlling for rural residence, farm households are less likely to experience food insecurity.

Figure 12: Coefficients plots with 95 percent confidence intervals from linear probability models predicting experiences of hunger

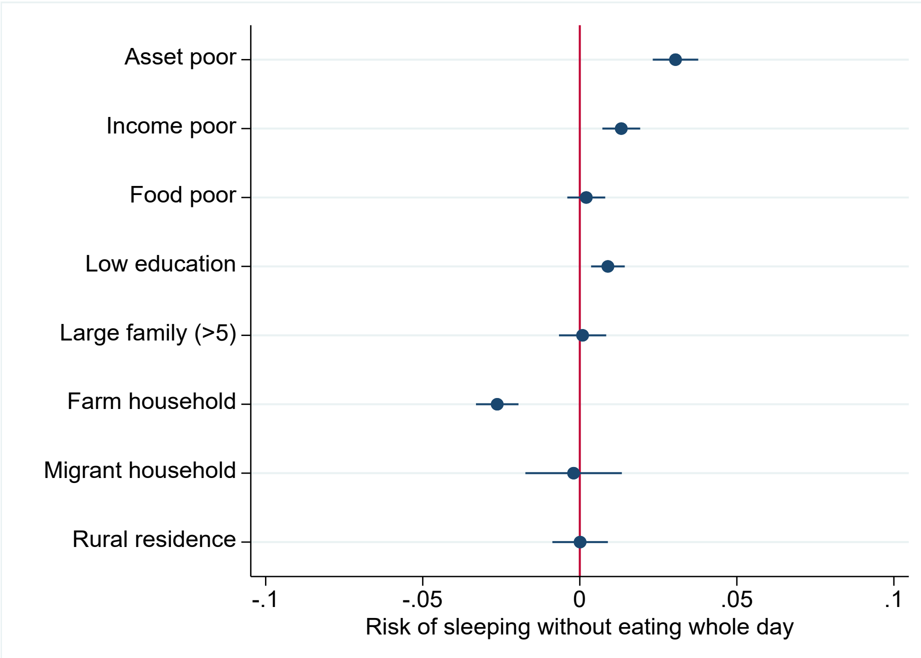
Panel A. Risk factors for any household member having no food to eat



Panel B. Risk factors for any household member having slept without eating at night



Panel C. Risk factors for any household member sleeping without eating for a whole day



Source: The sample size for Panel A is 11,241 adults. All three regression models control for state/region fixed effects.

6. CONCLUSIONS

COVID-19 was a catalyst for a vast number of phone surveys aimed at tracking the welfare impacts of an unprecedented global economic shock. However, while phone surveys have some advantages, the shorter nature of phone surveys limits their ability to conduct detailed modules on many facets of household welfare, including the household expenditure modules preferred for poverty measurement (Gourlay et al. 2021). COVID-19 phone surveys instead relied shorter qualitative questions on income losses, employment impacts or patterns of consumption changes. Qualitative questions on income losses provide an idea of the prevalence of income losses but not the depth of loss, or the poverty status of households in the wake of income losses. Another limitation – particularly in the context of Myanmar, which has experienced two years of multiple economic shocks – is that qualitative questions on income relative to 12 months ago, for example, are of little use, since the economic situation 12 months ago was also bad.

Given these limitations, this study experimented with three types of alternative poverty measures. The first was an adaptation of asset or wealth indices, which typically use principal components analysis to create ordinal wealth quintiles. We used an alternative approach by first using previous surveys to identify relevant assets, and then creating a simple country measure and imposing an arbitrary poverty line. While this approach is simple, simplicity and brevity are a virtue in phone surveys, and we show – consistent with many other studies of asset-based measures (cited above) – that this simple measure is consistently the strongest predictor of poor diets and experiences of hunger. The reasons are likely twofold. First, asset questions (and asset counts) are effectively unaffected by measurement error, so there is little or no scope for attenuation bias, especially when the assets were in some sense pre-tested within previous surveys. Second, assets are indeed likely to be a good predictor of long-term latent wealth, and assets and wealth are understandably a source of resilience even if incomes are falling or fluctuating.

We also tried – perhaps naively – to follow another longstanding convention in household surveys in high rural settings: to measure expenditure, rather than income, as a basis for identifying the poor. However, the time limitations of a phone survey meant that we could only measure food expenditure through a series of four questions that likely required an excessive amount of mental arithmetic on the part of respondents. Moreover, short expenditure lists from in-person surveys are known to lead to under-estimation of total expenditure, so it is not surprising that highly aggregated questions on food expenditure in MHWS led to significant underestimation of total food expenditure and over-estimation of food poverty, as well as white noise-type error. We recommend avoiding this kind of measure, and instead focusing on the simpler dietary diversity and experiential food insecurity questions to capture issues related to food consumption.

However, although income-based poverty measures are typically unfavored with in-person surveys (Deaton, 1997; Deaton and Zaidi, 2002), this study found that they are likely quite well suited to phone surveys as a second-best measure, even in rural settings. For despite the predictive power of the asset count measure, we found that an income poverty measure also had significant predictive power in explaining poor diets and hunger experiences. In that sense, income poverty – which we expect to fluctuate over time, especially in rural areas, and in the face of multiple economic shocks – may be a relevant complement to longer term asset-based indicators. Another virtue was this measure of income was also reasonably quick to implement, and the module used to measure different income sources can also be used to identify different types of livelihoods, and measure income diversification, which may also be important for resilience to shocks.

Finally, a truly critical virtue of income-based poverty is that it can factor in the effects of inflation (which asset-based measure cannot) through the updating of the poverty line as well as any indirect effects on nominal incomes. This feature is extremely important given that nominal food prices in Myanmar have risen by 41% between March 2021 and March 2022 (MAPSA 2022c). More generally, though, many other developing countries are also facing very high rates of inflation on the back of high fuel prices and the tailwinds of COVID-19 disruptions (Vos et al. 2022). On these grounds we recommend that income and income-based poverty be more regularly incorporated into phone surveys, especially since phone surveys are cost-effective enough to be implemented at a higher frequency compared to in-person surveys. In those circumstances, the volatility of household income over seasons and aftershocks are a virtue, not a limitation, of income-based indicators.

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