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Updating Poverty in Afghanistan Using the SWIFT-Plus Methodology

Oscar Barriga-Cabanillas
Parth Chawla
Silvia Redaelli
Nobuo Yoshida

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Abstract

Close to half of the population of Afghanistan was living below the national poverty line prior to the regime change in August 2021, with no additional information on poverty collected in the country since the last official household survey in 2019/20. This paper fills this knowledge gap through survey-to-survey imputation using a SWIFT-plus methodology. The analysis trains a predictive model on data from the 2019/20 Expenditure and Labor Force survey and imputes poverty in the latest Afghanistan Welfare Monitoring Survey. The analysis accounts for seasonality in welfare patterns and implements several tests to assess the model's predictive capacity. The results show that 48.3 percent of the Afghan population was poor as of April–June 2023, a relative decline of 4 percentage points compared to poverty levels observed over the same months in 2020. The reduction in poverty was concentrated among rural households, with a decline from 51 to 44 percent, while it stagnated in urban areas at around 58 percent. Although no poverty data exists since 2020, the evolution of self-reported welfare and food security makes it reasonable to conclude that poverty first increased during the immediate economic contraction following the regime change and has progressively declined since then.

This paper is a product of the Poverty and Equity Global Practice. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at obarriga@worldbank.org.

Updating Poverty in Afghanistan Using the SWIFT-Plus Methodology[1]

Oscar Barriga-Cabanillas	Parth Chawla	Silvia Redaelli	Nobuo Yoshida
The World Bank Group	UC Davis	The World Bank Group	The World Bank Group

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Introduction and context

Since the change of administration in August 2021, there has been a critical need for timely and frequently updated information on welfare in Afghanistan. While macroeconomic data shows a large economic contraction, the evolution of poverty levels over the last two years remains uncertain since no additional household expenditure survey has been conducted. The latest official estimates based on the 2019-2020 Expenditure and Labor Force Survey (IE-LFS) conducted by the National Statistics and Information Authority (NSIA) placed the national poverty rate at 47.1 percent, meaning that close to half of the country's population was already living in poverty before 2021. Data collection for a new IE-LFS started in April 2021 (IE-LFS 2021-22) but fieldwork was suspended in June 2021 due to the deteriorating security situation. Poverty estimates based on first quarter data (spring season) of the IE-LFS 2021 showed that poverty for that period was 52 percent, very close to that reported for the same period in 2020.

The lack of comparable household budget survey data limits the ability to directly estimate the evolution of monetary poverty. We fill this knowledge gap by implementing a survey-to-survey imputation method using a SWIFT-plus approach. After the NSIA halted regular collection and reporting on key socio-economic indicators in 2021, the World Bank continued welfare monitoring using phone surveys, and implemented the third round of the Afghanistan Welfare Monitoring Survey (AWMS) between April and June 2023. This round was expanded to include a module that allows estimating current monetary poverty levels through survey-to-survey imputation techniques.

We use the IE-LFS 2019-20 as it represents the last full-year household survey the NSIA conducted. Considering the strong seasonal dimension of poverty in Afghanistan and the timing of the AWMS R3 (April to June 2023), we trained the model using a quarter-representative sample of the IE-LFS 2019-20 corresponding to the same months of 2020. That is, we used data from the spring quarter of the IE-LFS 2019-20 to calibrate a model that predicts household expenditure and used this model to impute poverty in the AWMS R3. The SWIFT-plus methodology includes fast-changing consumption variables to better capture welfare changes in a context where large economic shocks have occurred. We implemented additional estimation steps to minimize model overfitting, account for estimation error through multiple imputation techniques, and improve out-of-sample performance. In line with previous SWIFT-plus tests done on Afghanistan, we trained separate models for urban and rural samples.

Our results show that poverty in Afghanistan has remained roughly the same as that observed in the spring of 2020 before the regime change. Overall, about 48.3 percent of the Afghan population was poor as of April-June 2023, representing a four-percentage point decline compared to poverty levels observed over the same months of 2020. Poverty trends differ between urban and rural areas. In rural areas, monetary poverty is estimated to have declined from 51 to 44.2 percent while marginally increasing in urban areas from 55.2 to 58 percent, although not statistically significant. These projected poverty rates are robust to in-sample and out-of-sample tests and potential biases from the AWMS R3 sampling.

The estimated change in poverty is conservative with respect to the contraction of the Afghan economy between 2021 and 2023. The political crisis in Afghanistan on August 15, 2021, caused a sizeable economic contraction, with GDP per capita dropping 23 percent between 2020 and 2021. The reduction in economic activity in the aftermath of the political crisis was caused by lower aggregate demand fueled by the cessation of aid flows, which sustained a large part of the service sector, and supply constraints have forced the scale-down of business operations. Economic contraction presented different sectoral dynamics, with the service and industry sectors contracting by 32.7 and 14.1 percent, respectively. The political crisis also hurt agricultural production, which fell by 3 percent during the year. Since then, the economy has experienced a slow recovery in agriculture and stabilization in the service and industry sectors.

Reconciling poverty estimates with macroeconomic trends requires understanding the combined effects of a reduction of conflict and overall economic stabilization after the regime change, the significant dependence of households on agriculture, and their usage of coping mechanisms. Prior to 2021, high conflict in rural areas and a constant threat of attacks in cities depressed overall economic output. With the regime change, conflict is at a historical minimum, which has helped stabilize economic activity in what appears to be a new equilibrium. Welfare monitoring shows that households mobilized extra labor by women and youth to cope with the economic instability of post-August 2021. Mobilization of additional labor has allowed households to maintain consumption levels, even with a lower GDP.

The lack of data makes it impossible to measure poverty trends between 2021 and April/June 2023. While no data were collected in R1 and R2 of the AWMS survey to directly assess how monetary poverty evolved during the first two years of the interim Taliban administration, emerging trends in self-reported welfare and food security make it reasonable to expect that poverty increased in the immediate aftermath and declined progressively afterward to the current level.

The rest of the paper continues as follows: Section 2 expands on the SWIFT-plus methodology, the imputation model, and its internal and external validity; Section 3 presents the poverty imputation result, an overview of welfare trends in the country since the regime change, and how they support poverty evolution trends.

Data

We implement poverty imputation on the AWMS R3 using a SWIFT-plus module trained using 2019–20 IE-LFS data, the survey contains information for 18,139 households and has the official consumption vectors used for estimating the official poverty rates in the country. It was conducted between October 2019 and September 2020, matching the year’s four seasons and being representative at the quarterly and urban/rural levels. Households are considered poor if their expenditures are insufficient to satisfy basic needs, defined by the national poverty line.[2] A new IE-LFS was started in April 2021 (IE-LFS 2021-22). However, due to the rapidly deteriorating security situation, fieldwork was suspended in June 2021. Data collected between April and June 2021 cover a total of 4,871 households. Information from the IL-LFS 2021 provides an additional baseline and benchmark model performance.

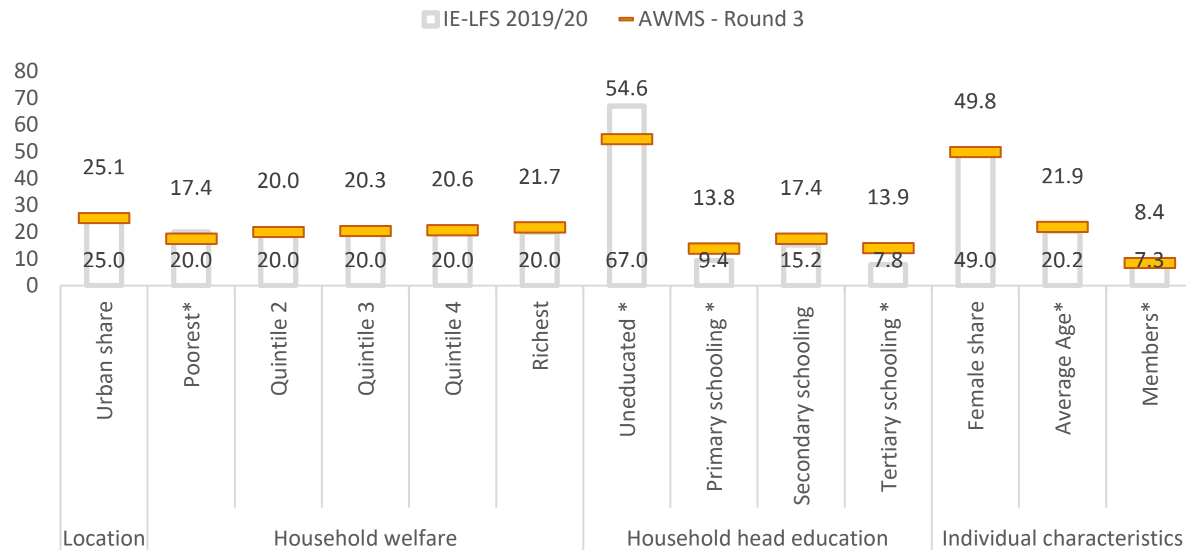
The regime change brought a halt to data collection in the country. To understand the evolution of welfare, the World Bank implemented three rounds of the Afghanistan Welfare Monitoring Survey (AWMS), a phone survey covering a wide range of indicators, including employment and labor earnings, food security and access to safety nets, school attendance, and health services. The phone surveys are administered on the subsample of the original IE-LFS 2019/20 and IE-LFS 2021 participants for which phone numbers were available.

As expected from a phone survey, the sample of phone owners includes some expected biases, given that (i) not all of the households from IELFS provided telephone numbers, and those who do are, on average, better off; and (ii) not all of the available numbers could be reached.[3] Sampling differences in the AWMS are adjusted by reweighting to match the original full IE-LFS 2019/20 distributions. These adjustments reduced the biases, although the final sample is still slightly more educated. Additionally, as found in previous AWMS rounds, household size is relatively larger, possibly reflecting internal migration dynamics and/or household consolidation. Overall, the differences in welfare and education levels are not large enough to introduce crippling biases to the results, and every category considered has substantial representation (Figure 1). The next section further discusses the comparability of the IE-LFS 2019/20 and AWMS R3 samples.

[2] In line with best international practices, the poverty line for Afghanistan is estimated following the Cost of Basic Needs (CBN) methodology. There are no PPP conversion factors available in Afghanistan to convert the value of the national line into international lines.

[3] In order to correct for these possible sources of selection bias and to preserve the national representativeness of the sample of completed interviews, we implemented a four-step process. First, the sampling weights for all households interviewed in the two IELFS rounds were harmonized so that the consolidated sample could match the population size and distribution coming from the original sampling frame. Second, the new sampling weights for the households that provided a telephone number in the IELFS rounds were adjusted so that this sub-sample could be used to estimate nationally representative estimates. This adjustment was based on the probabilities of each household providing a telephone number in the IELFS rounds, as predicted by their socioeconomic characteristics (such as region, urban/rural, access to electricity, and household assets). Third, a readjustment was conducted on the sample of households with completed interviews accounting for the panel status of the household and the probabilities of completing the interview (again, as predicted by sociodemographic characteristics). Finally, post-stratification of the sampling weights by regions trimmed excessively large weights to reduce their impact on estimate standard errors.

Figure 1: Contrast of IELFS 2019–20 and AWMS sociodemographic variables, various rounds



Note: An asterisk (*) indicates that differences in means are significant at 1%. AWMS R2 only collected information on the household head.
Source: Elaboration based on IELFS 2019–20 and AWMS round.

The SWIFT-plus approach

Over the past decade, significant advances have been made in the research on survey-to-survey imputation techniques. Lack of household survey data during or after a crisis is not unique to Afghanistan. Not surprisingly, the research on how to fill knowledge gaps on welfare has been growing considerably over the past decade in response to a growing need for real-time welfare monitoring data and the cost and time challenges involved in implementing standard household expenditure surveys. The Survey of Well-Being via Instant and Frequent Tracking (SWIFT) methodology (Yoshida et al., 2015) provides poverty estimates in situations where no expenditure and consumption surveys are available.

SWIFT-plus trains a model to predict household expenditure using data from past household expenditure surveys. It was developed to address two major methodological challenges: model stability over time and model capacity to capture shocks. The model identifies key poverty correlates and uses the model coefficient and errors to impute household expenditures in a survey where no household expenditure data was collected. Additionally, the SWIFT-plus approach integrates Machine Learning (ML) and Cross-Validation (CV) steps to improve the stability of the estimated model and expand the list of variables for poverty modeling/data collection to include dummies on consumption of key items.[4]

[4] See Yoshida et al (2022). The Concept and Empirical Evidence of SWIFT Methodology. World Bank.

The SWIFT methodology has been tested extensively, not only using *within-sample tests*—that is, testing how well it predicts poverty using the same data on which the model is trained—but also using *between-sample tests*—that is, using two rounds of comparable household surveys with complete consumption data and using one round for model training and another round for model testing. Among other countries, the methodology was tested using data from Afghanistan in its development stages. The SWIFT-plus model, trained on NRVA 2011-12 data, predicted a poverty rate of 53.5 percent in 2016-17, outperforming traditional Proxy Means Testing (PMT) approaches (see Table 1). To date, the methodology has been applied in more than 75 countries, where SWIFT-plus predictions are proven to be within +/- 2 percentage points of those from actual consumption data, even when large changes in the poverty rate have occurred. The results are available in the annex A.

Table 1: Past implementation of SWIFT-plus in Afghanistan to predict poverty changes, 2011 to 2016

	Afghanistan (2011 - 2016)		
	Official Estimates	Original PMT	SWIFT Plus
2011	38.3%		
2016	54.5%	39.4%	53.5%

Note: *PMT estimates exclude fast-changing consumption dummies.*
Source: *Modified from* Yoshida et al (2022).

Model training in the IE-LFS 2019/20

The SWIFT-plus identifies variables that best predict household expenditure. Candidate variables include household characteristics, education levels, asset ownership, dwelling conditions, and fast-changing consumption variables. The SWIFT-plus approach relies on a regression model to estimate a welfare-generating function on the data where both a welfare vector and household characteristics are available. In contrast with traditional PMT approaches, it implements several steps to control for the correlation and stability of the variables used to predict welfare, cross-validation of the variable selection process to account for potential model overfitting, and multiple imputations to account for the model's error (see annex B for details on the SWIFT-plus algorithm). A key innovation of the SWIFT-plus approach compared to traditional PMT is that it includes fast-changing consumption variables to better capture welfare changes during shocks. This is important because evidence shows that changes in household assets and dwelling conditions lag changes in household expenditure. Table 2 shows the full list of variables we used to train the SWIFT-plus module.[5,6]

[5] Not all the variables were included as part of the SWIFT-plus module. For instance, household composition variables were already part of previous AWMS rounds. Additionally, models from the IE-LFS 2019/20 and 2021 differ.

[6] Questions on shocks were excluded from the training steps since they referred to the past year and not only to the current quarter used in the prediction. Additionally, employment variables were excluded as evidence suggested that employment status was not a good proxy for household generating capacity. Robustness tests show that excluding these variables has no impact on model performance.

TABLE 2: List of Explanatory Variables for Prediction of Poverty Levels

CATEGORIES	AMWS candidates
Household characteristics	*1. Household Size* *2. Ratio of household members (<15 & >65) over working age males* 3. Number of dependents (grouped by <5, 5-10m 10-15)
Household head characteristics	*1. Age (grouped by 15-25, 26-35, 36-45, 56+)* *2. Education Attainments by level (No education, primary, lower secondary, upper secondary)* *3. Illiterate* 4. Any women adult women with primary *5. Working more than one job* *6. Work agricultural sector*
Livestock ownership	*1. Ownership large livestock (horses, goats, sheep)* *2. Ownership poultry*
Asset ownership	*1. Refrigerator* *2. TV* *3. Bicycle* *4. Motorcycle* *5. Car* *6. Washing Machine* *7. Vacuum Cleaner* *8. Iron* *9. Electric Fan* *10. Stove*
Dwelling characteristics	*1. Wall material* *2. Roof material* *3. Toilet condition*
Food consumption dummies (last 7d)	*1. Beans and pulses* *2. Meat* *3. Milk* *4. Apple* *5. Egg* *6. chocolate*
Region dummies	*Region dummies*

Note: Variables that were identified as relevant in any model are marked in italics.

We trained separate models for both urban and rural areas to ensure they effectively capture household welfare in each setting. Moreover, considering the high seasonality in welfare levels, the model leverages the third quarter of the IE-LFS 2019/20 since it matches the data collection schedule of the AWMS R3. It is reasonable that the income-generating process varies by location. For example, correlation between wall materials and household expenditure differs between urban and rural households. Additionally, poverty in Afghanistan has a strong seasonal character, with welfare deteriorating in winter when agricultural income-generating opportunities are fewer, and less food is available in local markets. However, during 2019/20, the spring season coincided with the onset of the COVID-19 crisis, which put pressure on urban households. This cyclical variation in poverty rates implies that a quarter-specific model provides the best predictive performance. Considering the AWMS R3 was collected between April and June 2023, the preferred model specification uses a model trained on the respective IE-LFS 2019/20 quarter.

Table 3 shows the model coefficients and the mean of the regressors in third quarter IE-LFS 2019/20 and AWMS R3. Overall, the training process identified different variables for the urban and rural models, even when the variables available during variable selection process were the same.[7] When both models identify the same variable, their coefficients differ, further validating the decision to estimate independent models. Consumption dummies are an important component of the models, comprising five out of seventeen variables in the urban model, and seven out of twenty-five in the rural model. Changes in the distribution of variables between the third quarter IE-LFS survey and the AWMS R3 indicate the direction of the poverty estimates. In the urban sample, there is a noticeable increase in average household size and a decrease in certain asset holdings, except for small livestock ownership. However, there is an uptick in the consumption of key items. Typically, the patterns observed in the first two categories are indicative of declining household welfare, whereas the trend in the third category suggests an improvement in welfare. In rural areas, the household demographic trends hint at a slight decrease in welfare. In contrast, the data related to asset ownership, dwelling conditions, and consumption patterns indicate significant improvements in welfare between the two surveys.[8]

[7] Given the urban population is concentrated in the Kabul region, region 1 in table 3, that was the only regional dummy available during the tuning of the model.

[8] An additional model was estimated, which included quarter-average satellite measures of rainfall, temperature, NDVI, and nightlights at the province level. Meteorological variables were included as shocks, using 2 standard deviations from the historical mean, while nightlights were used as levels. The model estimates and predictions are qualitatively the same. Results are available upon request.

Table 3: Swift Plus model estimates in urban and rural samples.

PANEL A. URBAN MODEL

Variables	Coeff.	IELFS Q3 Mean	AWMS R3 Mean
Household Characteristics			
Log Household Size	-0.500	0.83	0.88
Ratio of household members (<15 & >65) over working age males	-0.020	2.3	2.1
Region 1	-0.103	63.8	55.9
Household Head Education			
Lower Secondary	0.127	25.5	23.4
Upper Secondary or Above	0.158	16.8	16.9
Asset Ownership			
Car	0.224	12.6	8.3
Refrigerator	0.066	44.4	39.9
TV	0.062	71.9	68.7
Vacuum Cleaner	0.109	25	19
Washing Machine	0.158	40.1	36.8
Small Livestock	0.127	6.5	29
Consumption in the last 7 days			
Apples	0.156	10.3	13.9
Chocolate	0.172	64.4	74.5
Meat	0.194	57.3	60.1
Milk	0.117	25.7	34.6
Fuel for Car	0.075	14.2	20.2
Dwelling Characteristics			
Wall material is Concrete	0.100	53.7	33.5
Performance metrics			
R-squared		0.669	
Constant		8.575	
Observations		988	

PANEL A. RURAL MODEL

Variables	Coeff.	IELFS Q3 Mean	AWMS R3 Mean
Household Characteristics			
Log Household Size	-0.410	0.86	0.93
Ratio of household members (<15 & >65) over working age males	-0.022	2.7	2.5
Region 2	0.141	14.3	13.7
Region 5	0.192	11.3	7.1
Region 6	-0.173	15.6	17.8
Region 7	-0.136	9.1	6.2
Region 8	-0.210	8.5	11.4
Household Head Education			
Primary	-0.079	7.9	12.2
Household Head age			
Age 46-55	0.040	16.2	19.5
Labor Market Participation (household head)			
Multiple Jobs	-0.105	23.6	8.7
Asset Ownership			
Bicycle	0.117	8.8	19.3
Car	0.329	7.9	6.9
Motorcycle	0.058	26.4	25.8
TV	0.088	25.6	32.1
Consumption in the last 7 days			
Apples	0.131	4.6	12
Eggs	0.112	32	60
Beans/Pulses	0.122	72.4	77.3
Chocolate	0.129	51.7	73.3
Meat	0.228	48.1	61.5
Milk	0.095	42.6	49.8
Fuel for Car	0.104	30.1	30.6
Dwelling Characteristics			
Wall material is Concrete	0.115	10	12.7
No Toilet	-0.055	16	3.9
Performance metrics			
R-squared		0.582	
Constant		8.091	
Observations		2,986	

Source: World Bank estimations using 2019/20 IE-LFS and AWMS R3 surveys.

We assess the model's in-sample performance using five-fold cross-validation to determine the subset of variables that best perform across folds.[9] In-sample performance tests show that both urban and rural models display a high R-square, low Mean Square Error (MSE), and can predict welfare ranking well (Spearman rank correlation). Overall, in-sample tests show very small differences between observed and predicted poverty levels of between 1.6 and 2 percent in urban and rural models, respectively. The higher predictive capacity in the urban samples is likely the result of the lower variability in income levels and a limited number of variables to fully model rural households' income-generating processes, particularly assets used in agricultural production (Table 4).

Table 4: SWIFT-Plus model validation tests

		R2	Mean MSE	Spearman correlation	In-sample prediction IE-LFS 2019/20			Out-of-sample prediction IE-LFS 2021		
					Observed poverty	Predicted Poverty	Difference (%)	Observed poverty	Predicted Poverty	Difference (%)
IE-LFS 2020/19 Quarter 3	Urban	66.9	0.083	84.2	55	54.1	1.6%	51.1	52.8	3.3%
	Rural	58.2	0.083	72.4	51	52.0	2.0%	52.3	54.4	4.0%

Source: World Bank estimations using 2019/20 IE-LFS and 2019/20 and AWMS R3 surveys.

Validity of the results

The validity of the survey-to-survey imputation model relies on two main assumptions**.** First, sampling must be comparable across the surveys. Second, the predictors for poverty imputations should be key determinants of the intertemporal variations in household expenditure and be stable over time. This section discusses these assumptions in detail.

Assumption 1: The survey sampling process must be comparable across surveys. To estimate comparable poverty measures, survey-to-survey imputation techniques require that information in both surveys was collected following similar protocols. Doing this requires that both surveys follow the same sampling process. If that is not the case, poverty imputations can be biased and over/underestimate the true poverty rate, even if the model correctly predicts the relation between household characteristics and expenditure in training data. This is a particularly valid concern in the case of phone surveys since phone ownership positively correlates with higher expenditure.

The comparability of the AWMS sample with the IE-LFS 2019-20 sample relies on the reweighting process that corrects a possible sampling bias induced by phone ownership and differences in survey response. As stated in the data section, the AWMS R3 listing comes from households that provided a cellphone number

[9] To avoid over-fitting, Cross-validation (CV) is a standard empirical test in machine learning literature. The Q3 urban and rural samples of the IE-LFS 2019-20 are randomly split into five subsamples each; then, the model is estimated on four folds (training dataset) and evaluated on the remaining one (testing dataset). Since the remaining fold is not included when the model is trained, all performance indicators in the remaining fold are not subject to the over-fitting problem. This exercise is repeated iteratively for different levels of statistical significance to maximize model performance.

in the IE-LFS surveys. As expected, the sample of phone owners comprises households more likely to be urban, with higher expenditure levels and lower poverty rates (Table 5, panel b). To adjust for this sampling bias, the AWMS R3 relies on a reweighting process to adjust sampling differences between the AWMS and the original full IE-LFS 2019/20 surveys. Panels a and c show that, to a great extent, the reweighting process narrows sampling differences in the spatial distribution, asset ownership, and dwelling conditions of the AWMS R3 and the IE-LFS sample. Additionally, Panel b shows that the weighted AWMS R3 sample closely reflects the expenditure distribution of the full IE-LFS 2019/20 sample.

Table 5: Sample composition AWMS rounds

Panel a. Sample size and household spatial distribution of IE-LFS and AWMS R3 round						
	Full IE-LFS 2019/20		**Quarter 3 IE-LFS 2019/20**		**AWMS R3**	
Fieldwork	October19-September 2020		June-August 2022		April-June 2023	
Households	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
Central	22.2	24.6	23.1	28.2	27.1	26.2
East	11.7	9.2	11.7	10.8	14.9	11.2
North	13.6	13.8	14.6	15.6	15.4	16.1
North-East	11.8	13.9	12.2	13.3	12.8	12.5
South	11.0	10.7	10.2	8.9	7.7	5.7
South-West	13.3	11.7	11.3	9.5	5.2	6.2
West	7.4	10.5	6.6	6.9	7.1	11.1
West-Central	9.0	5.7	10.4	6.8	9.7	11.0

Panel b. Welfare differences between original IE-LFS sample and AWMS R3 round								
Source sample		**Poor**	**Urban**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
Weighted	Full sample	47.1	25.1	20.0	20.0	20.0	20.0	20.0
	With a phone	43.0	30.4	16.6	18.9	19.8	20.8	23.9
	Full sample Q3	52.2	29.4	21.5	21.0	22.2	19.0	16.3
	AWMS R3 participants *	46.2	24.9	17.9	21.2	20.3	21.1	19.5

Panel c. Comparison of key characteristics at baseline: IELFS 2019/20 information				
	Full sample (IE-LFS weights)	**Phone owners (IE-LFS weights)**	**AWMS R3 panel* (IE-LFS weights)**	**AWMS R3 panel* (AWMS weights)**
Household Characteristics				
Household Size	7.25	7.39	7.59	7.52
Asset Ownership				
Refrigerator	16.7%	22.7%	25.9%	20.1%
TV	40.5%	49.2%	52.2%	48.0%
Bicycle	12.4%	13.7%	13.6%	12.3%
Motorcycle	21.3%	20.7%	18.2%	20.7%
Car	9.4%	10.8%	11.9%	10.7%
Washing Machine	13.0%	17.7%	19.1%	15.4%
Vacuum Cleaner	7.1%	9.2%	9.6%	7.7%
Small livestock	33.6%	31.4%	30.5%	34.3%
Large livestock	44.2%	39.4%	38.7%	42.8%
Dwelling Characteristics				
Roof material: Concrete	22.5%	27.7%	29.1%	25.1%
Wall material: Concrete	20.3%	25.6%	27.2%	22.1%
No Toilet	10.5%	6.3%	5.2%	7.8%

Source: World Bank estimations using IE-LFS households surveys and AMWS rounds.

*Note: *Includes households that participated in both the IE-LFS 2019 and the AWMS R3. Shows characteristics at baseline using the AWMS R3 panel weights.*

The panel component of the AWMS R3 further reinforces that the trends in the assets and consumption variables between the IE-LFS and AWMS R3 reflect actual changes in living conditions. An advantage of the AWMS R3 compared to other phone surveys is that about 82 percent of the sample comprises the same households that participated in the original household surveys.[10] Using the pure panel component, it is possible to validate the observed changes in the household's living conditions and isolate any changes as stemming from the reweighting process. Table 6 shows the living conditions for the same households in the IE-LFS and AWMS R3 with and without weights. Changes in the variables between the IE-LFS and the AWMS R3 hold even in the absence of weights, further supporting that the imputed poverty rates are the results of actual changes in living conditions and are not driven by sampling bias toward households with better-off initial conditions.

Table 6: Unweighted trends on key household model variables between IELFS and AWMS R3

	IELFS (1)	Panel households AWMS R3 *panel* (2)	Ratio (2)/(1)
Household Characteristics			
Household Size	7.8	8.4	1.1
Asset Ownership			
Refrigerator	18.3	18.2	1.0
TV	48.3	42.3	0.9
Bicycle	11.2	23.1	2.1
Motorcycle	19.1	20.9	1.1
Car	12.2	7.1	0.6
Washing Machine	15.1	16.8	1.1
Vacuum Cleaner	7.7	7.7	1.0
Small livestock	36.3	48.6	1.3
Large livestock	45.8	45.6	1.0
Dwelling Characteristics			
Roof material: Concrete	23.4	23.4	1.0
Wall material: Concrete	22.6	18.0	0.8
No Toilet	6.8	2.9	0.4
Consumption in the last 7 days			
Beans/Pulses	78.7	80.8	1.0
Meat	57.5	60.2	1.0
Milk	41.1	48.3	1.2
Apples	22.6	11.4	0.5
Eggs	42.6	65.3	1.5
Chocolate	58.9	75.1	1.3
Fuel for Car	24.7	26.0	1.1

Source*: World Bank estimations using IE-LFS households surveys and AMWS rounds.*
Note: Shows characteristic of households that participated in both the IE-LFS 2019/20 and IE-LFS 2021, and those AWMS R3 participants whose identity match original IE-LFS respondents.

[10] For the sample from the IE-ELFS 2019/20, the identity of the original respondents was done directly as the name of the household head was available in the information the NSIA shared. In the case of the IE-LFS 2021, no information on the names of previous respondents was available. Instead, we used information on the household head— including age, gender, location, and number of members—to assess if the respondent household was the same that participated in the IE-LFS 2021.

Assumption 2: The predictors for poverty imputations should be key determinants of the intertemporal variations in household expenditure and be stable over time. Large shocks between surveys may compromise the model's stability by changing what variables are meaningful predictors of household expenditure, and/or their respective coefficients. Violations to this assumption can go in two directions: first, poverty correlates might not change immediately after a big shock, such as dwelling conditions or household asset ownership; and second, some variables present a natural evolution over time and, if included, can mask the true evolution of well-being.[11] The large economic and social disruptions in Afghanistan since the IE-LFS survey was collected raise concerns about the validity of the survey-to-survey imputation model. However, the empirical assessment shows that models using the SWIFT-Plus approach can project poverty rates accurately even after a large economic or climate shock.

The estimation approach mitigates these risks by including dummies for consumption of certain food and non-food items as they respond to shocks quickly**.** The inclusion of consumption dummies in the model allows for a more direct measure of the current expenditure levels of households in the presence of structural changes in the economy. The SWIFT-plus models used to impute poverty in the AWMS R3 include several of these variables as they are to be more "reactive", although the size of the shock—especially in urban areas—could also imply sufficient changes in terms of assets. Lastly, to limit concerns related to the change in the relation between expenditure and poverty correlates, we excluded labor market variables as changes in economic structure are likely to have had a significant effect on returns.

Out-of-sample tests using the IE-LFS 2021 data confirm the relative precision of model-based estimates and their superior predictive capacity compared to asset-only models. As an additional test, a model was calculated excluding consumption dummies with data from the IE-LFS 2021 survey to assess the predictive performance of the models. The urban and rural models were further tested for out-of-sample performance using the spring quarter of IE-LFS 2021-22 survey.[12] While more demanding, this test further confirms the relative precision of the estimates, showing only a 3.3 and 4 percent difference compared to the poverty levels directly measured in Spring 2021 (last three columns Table 4). This improved performance holds when benchmarking the model against one that excludes consumption dummies (Annex C).

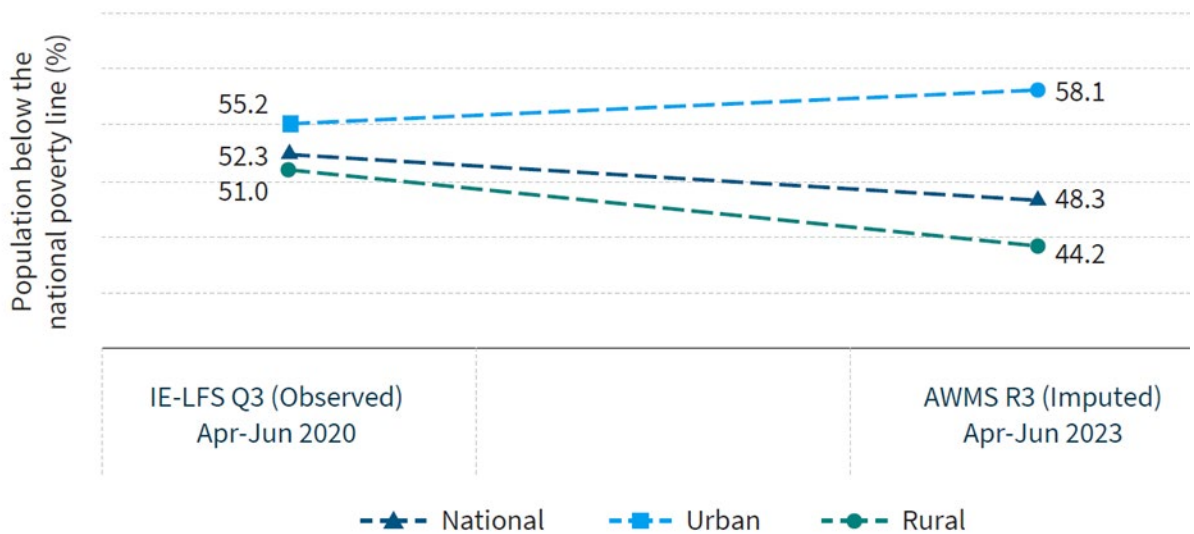
[11] A typical example is mobile phone ownership, which has increased rapidly as a consequence of the prices of cell phones and service fees going down, and not, necessarily, cellphone users becoming richer.

[12] Data collection of the IE-LFS 2021-21 started in March 2021 and continued until the end of June, before being suspended due to the collapsing security situation in the country.

Results

Poverty projections based on round three of the AWMS survey indicate that the current level of monetary poverty in Afghanistan is comparable in magnitude to the one observed in the spring of 2020. Overall, we estimate that 48.3 percent of the Afghan population is poor as of April-June 2023, a 4-percentage point decline compared to poverty levels observed over the same months of 2020. Figure 2 shows diverging trends emerging between urban and rural areas: in rural areas, monetary poverty is estimated to have declined from 51 to 44.2 percent, while in urban areas poverty is estimated to have marginally increased from 55.2 to 58 percent, although this change is not statistically significant.

Figure 2: Poverty projections as of April-June 2023, by urban and rural areas



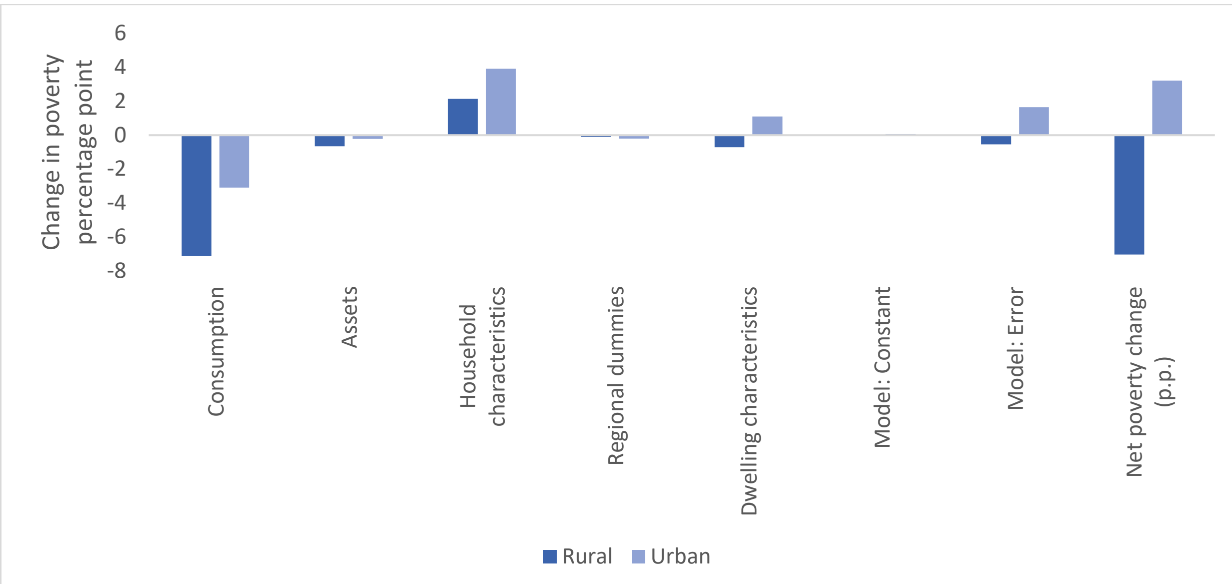
Note: The probability of differences in poverty between April-June 2023 and April-June 2020 being different from zero is 95.4 percent at the national level, 99.6 percent at the rural level and less than 25 percent at the urban level.
Source: IE-LFS 2019-20 and AWMS 2023 (R3).

To better understand the drivers of the poverty changes, we implement a Shapley decomposition on the predicted household expenditure between quarter three of the IE-LFS 2019/20 and the AWMS R3. Considering the computational intensity of the decomposition increases with the number of components of the welfare vector, we aggregate the variables into five categories: consumption dummies, asset holdings, household characteristics, regional distribution, and dwelling conditions (see Azevedo et al., 2012).[13] The variables in these categories result from aggregating the model's coefficients times its respective variables. Since we work with the predicted welfare vector, the decomposition includes the model's constant and error. We present results for the urban and rural models independently. As Figure

[13] The Shapley decomposition provides a measure of the marginal contribution of each factor to the total change in poverty. The decomposition has a combinatory nature that follows the number of components to decompose and equals $n!$. This implies that for a model such as the rural one here, with 26 components to decompose, the total number of combinations equals more than $403\text{x}10^{24}$, making it computationally unfeasible. Therefore, we aggregate variables into larger components. Shorrocks et al. (2012)

3 shows, for rural areas, the main driver for the almost 7 percentage point reduction in poverty was the increase in consumption of food and non-food items, while higher asset ownership and improvement in dwelling characteristics played a minor role. In urban areas, consumption of food and non-food items contributed to a lesser extent to reduce poverty. However, the higher household consumption could not compensate for the increase in average household size, nor the deterioration of dwelling conditions. Further validating the urban results, we see that no change in an individual component of the model would alter the net poverty increase.

Figure 3: Decomposition of changes in welfare using Urban and Rural models



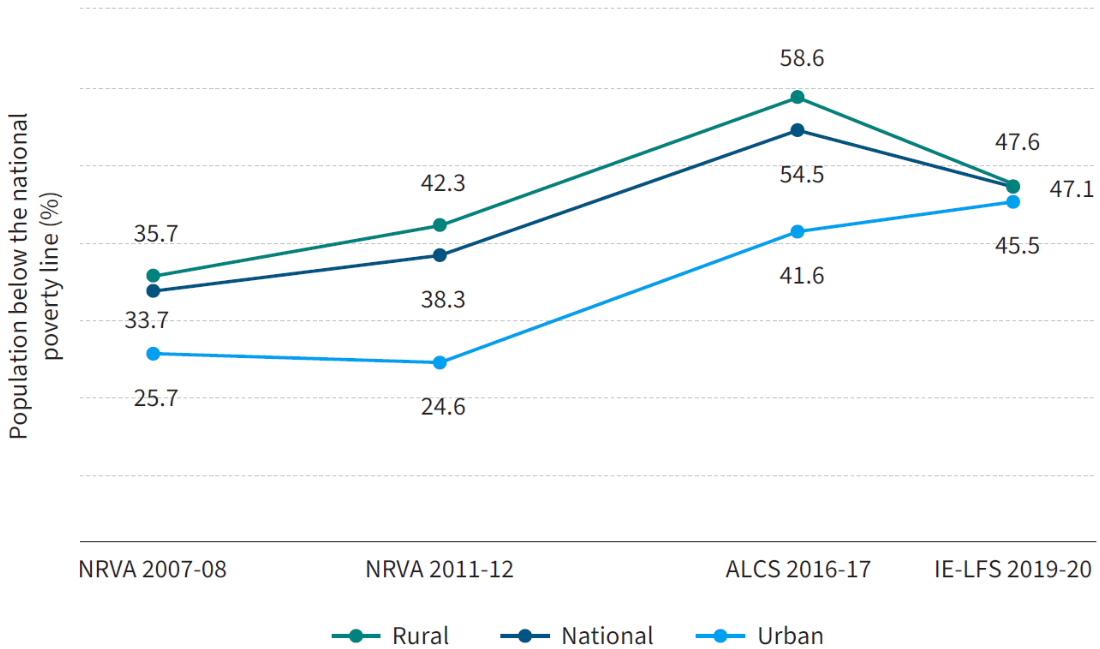
Note: Results use a Shapley decomposition on the different components of the prediction of the welfare vector. The different categories include the variables of the urban and rural model independently as shown in Table 3. Model error is the average error across the multiple imputations.
Source: IE-LFS 2019-20 and AWMS 2023 (R3).

Discussion of economic trends in Afghanistan and their effect on poverty levels

Before socioeconomic data stopped being collected, close to half of the population in Afghanistan was living below the national poverty line. As shown in Figure 4, while the national poverty rate in 2019-20 was lower than the 55 percent estimated in 2016-17,[14] poverty trends were showing diverging patterns in urban and rural areas. In urban areas, the observed increase in poverty is the result of the compounding effect of the progressive decline in aid as well as the onset of the COVID-19 crisis, while in rural areas, poverty was on a declining path spurred by strong agricultural production in the 2019 and 2020 seasons.

[14] World Bank (2018) *Poverty in Afghanistan : Results based on ALCS 2016-17.* Washington, D.C. : World Bank Group.

Figure 4: Poverty trends in Afghanistan, by urban and rural areas. Official estimates.

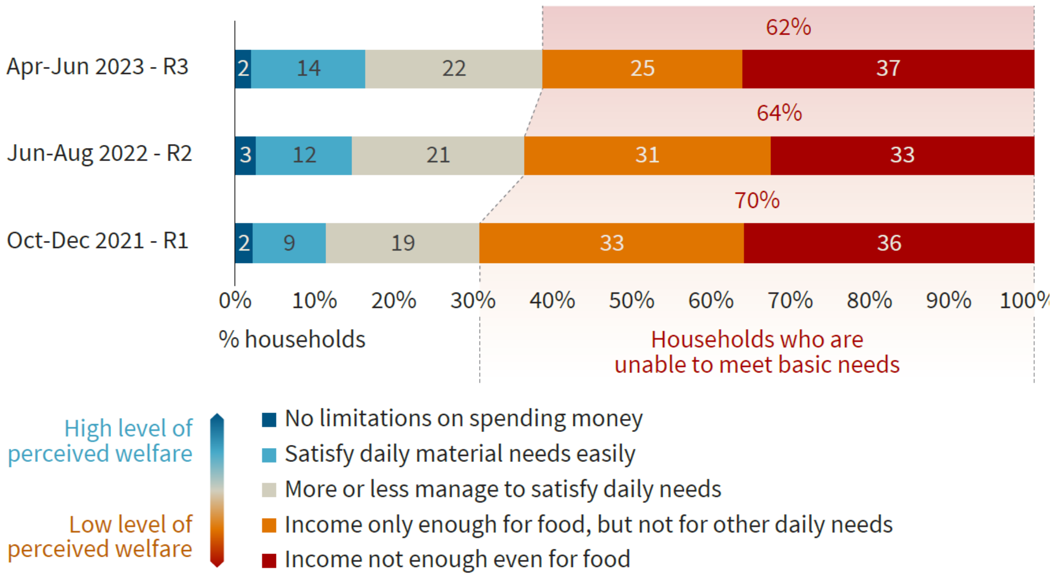


Source: National Statistics and Information Authority (NSIA) – formerly Central Statistical Organization (CSO), survey reports.

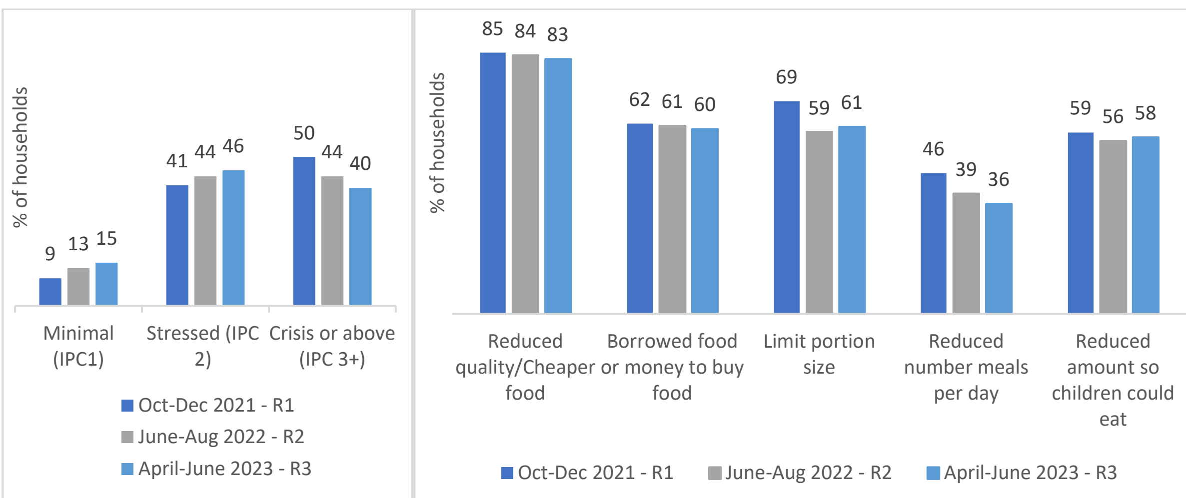
In the first two rounds of the AWMS surveys, households show a trend of marginal improvements in self-reported capacity to satisfy basic needs and food security. By the spring of 2023, the third round of the AMWS shows that 40 percent of the households report having enough income to satisfy basic needs. This constitutes an improvement from the reported share in summer 2022 (36 percent) and winter 2021 (30 percent). Considering that spring and winter data correspond to the periods of the year furthest from the harvest, the improving living conditions are in line with an improvement (even if marginal) in the country's living conditions since the regime change (Figure 5, panel a). Progressive improvement in Afghan households' welfare is mirrored by a decline in the share of households reporting crisis levels of acute food insecurity. Since the height of the crisis captured in R1 of the AWMS survey, the share of households experiencing crisis levels of acute food insecurity (IPC phase 3 or above) has progressively declined, particularly in rural areas. Still, the observed improvement in food security occurred in a context characterized by persistently high levels of vulnerability, with more than 80 percent of households still having to rely on at least one negative coping strategy to make ends meet. Reflecting on this evidence, it seems reasonable to expect that poverty increased in the immediate aftermath of the regime change to progressively decline afterward, in line with emerging trends in self-reported welfare and food security.

Figure 5: Evolution of non-monetary welfare indicators

panel a: Self-reported household capacity to cover food and non-food expenses.



Panel b. Acute food insecurity and household reliance on negative coping strategies



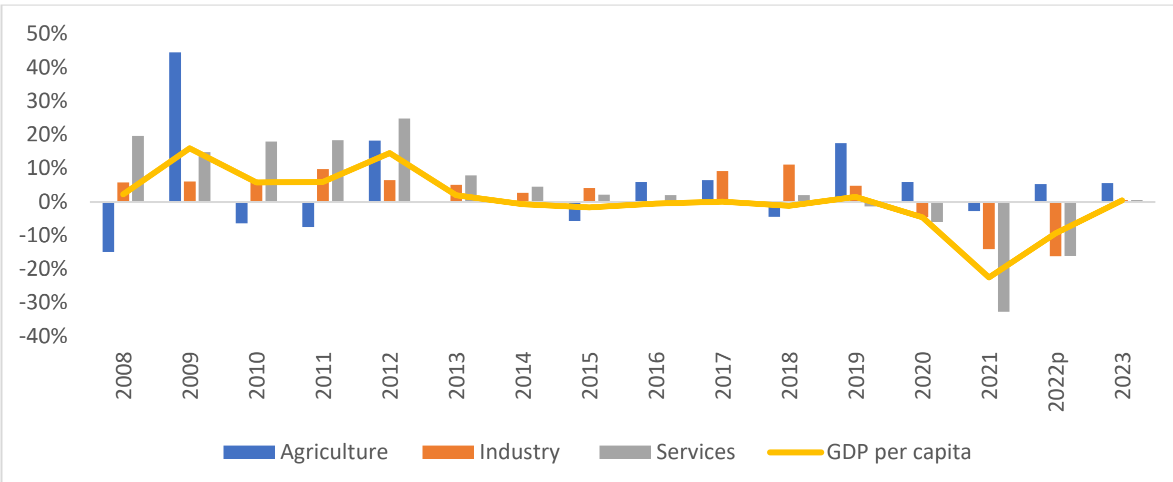
Note: IPC Phase 1 is associated to rCSI 0 to 3, IPC Phase 2 corresponds to rCSI 4-18, and IPC Phases 3-5 correspond to rCSI 19 and above.
Source: AWMS 2021 (R1); AWMS 2022 (R2) and AWMS 2023 (R3).

The predicted poverty changes from a survey-to-survey imputation imply that the large macroeconomic contraction had less effect in terms of lowering welfare than expected. The Afghan economy has experienced volatile growth in the two decades prior to the change in administration, characterized by aid-boosted aggregate demand in the industry and service sector and volatile agricultural productivity due to vulnerability to climate fluctuations (Figure 6).[15] Moreover, the prevalence of conflict in rural areas has

[15] See Kochhar, Nishtha, and Erwin Knippenberg. "Droughts and Welfare in Afghanistan." (2023) for details on the extent weather shocks impact consumption and poverty in the country.

depressed agricultural productivity and reduced incentives for improving productive techniques. The political crisis in Afghanistan starting August 15, 2021, caused a large economic contraction, with GDP per capita dropping 23 percent between 2021 and 2022. Since then, the economy has seen slow recovery in agriculture and stabilization in the service and industry sectors. Using the macroeconomic data on a non-neutral distribution, projections of poverty in 2023 are between 63 and 59 percent (See Annex D for details).

Figure 6: Evolution of sectoral growth

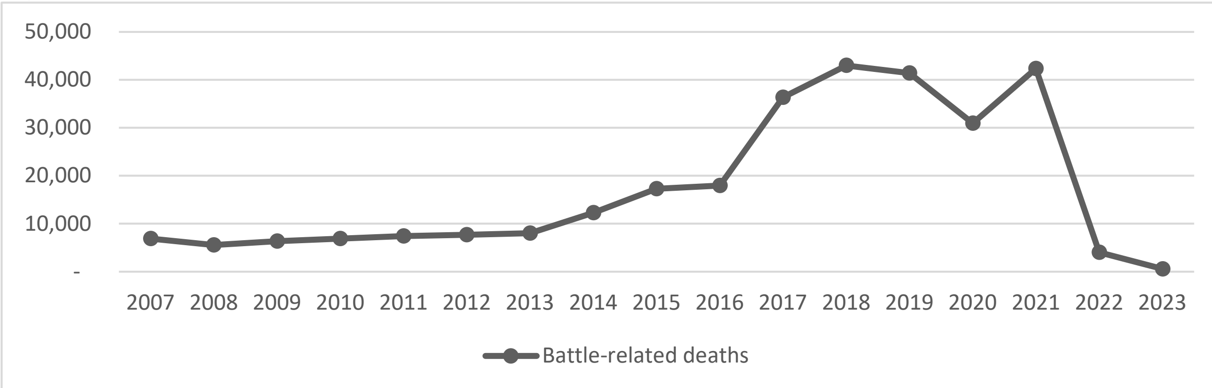


Source: NSIA and World Bank projections

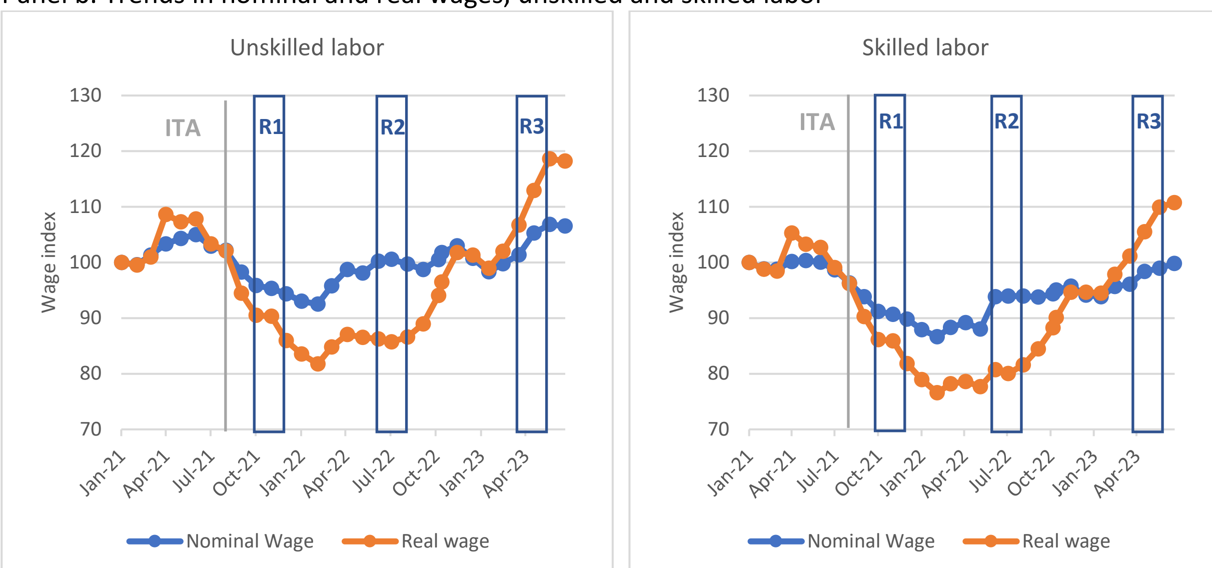
Note: Macroeconomic data up to 2021 come from the NSIA, while 2022 and 2023 data are World Bank projections. After 2021, the NSIA stopped producing official national accounts data. GDP data for 2022 and 2023 are projected information produced by World Bank staff using information from different monitoring sources.

Poverty projections using economic growth do not account for household adaptation strategies, economic stabilization, or conflict reduction. These conditions make it feasible for rural areas to experience lower poverty rates in Q3 2023 than in the corresponding periods in 2019/20 and 2021. In the case of Afghanistan, welfare monitoring shows that to cope with the economic instability after August 2021, households mobilized extra women and youth labor. This has resulted in structurally higher labor force participation and unemployment compared to 2020, especially among women and youth. Increasing wages and recent deflationary dynamics contribute to the observed improvement in Afghan households' capacity to satisfy basic needs. After an initial decrease in real wages following the regime change, nominal wages have started to recover to pre-crisis levels. Since April 2023, a sustained negative inflation rate has driven the value of real wages for both skilled and unskilled workers above pre-crisis levels, supporting improvement in household welfare (Figure 7, panel b). The mobilization of additional labor and rising wages has allowed households to maintain consumption levels, even with a lower GDP. Moreover, rural areas' reliance on agriculture, where 70 percent of the population lives, has acted as a shield against the large contraction experienced in the industry and service sectors, in particular in a context where conflict, a large drag in the capacity of rural areas to produce income, is at historically low levels, see Figure 7 panel a.

Figure 7, Panel a: Conflict: Battle related deaths



Panel b. Trends in nominal and real wages, unskilled and skilled labor



Source: World Bank based on ACLED and WFP food monitoring data
Note: conflict 2023 data reported as in March.

Conclusion

Afghanistan has experienced significant economic and social changes since the regime change in late 2021. However, how these multiple shocks have affected monetary poverty has yet to be assessed since up-to-date household and budget survey data has not been available, a situation unlikely to change in the short term. Under these circumstances, round 3 of the AWMS phone survey was expanded to include questions to predict monetary poverty through survey-to-survey imputation techniques. The resulting imputation models take account of the country's seasonal and urban/rural dimensions of poverty and provide the first estimated measures of poverty since the regime change in Afghanistan.

Estimates show that the current level of monetary poverty in Afghanistan is comparable to the one observed in the spring of 2020. At the national level, 48.3 percent of the Afghan population was poor as of April-June 2023, a 4-percentage point decline compared to poverty levels observed over the same months of 2020. The national average reflects diverging trends between urban and rural areas. Rural poverty is estimated to have declined from 51 to 44 percent, while poverty has stagnated in urban areas. Although it is not possible to assess the evolution of monetary poverty during the first two years of the interim Taliban administration, it seems reasonable to expect that poverty increased at first and then progressively declined, in line with emerging trends in self-reported welfare and food security.

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Annex A. Reliability of SWIFT-Plus approach

Many machine learning models and techniques are only performance tested using *within-sample* tests, meaning that the data used to train the models is also the same data used to test the performance of the models. Within-sample tests are prone to miss problems of over-fitting and model-instability. Yoshida et al. (2022) go beyond within-sample tests and test multiple applications of SWIFT-Plus with *out-of-sample* tests, providing empirical evidence that SWIFT-Plus is a reliable methodology for poverty estimation. Unlike a within-sample test, an out-of-sample test shows the performance of a model within a dataset that was *not* used to train the model. These out-of-sample tests help to identify whether models are vulnerable to model instability.[16]

Yoshida et al. (2022) conducted an out-of-sample test introduced by Christiaensen et al. (2012), hereafter referred to as the "Christiaensen test." The Christiaensen test uses the last two rounds of a comparable household survey, both of which include household expenditure and poverty correlates. Models are trained using the first round of the survey and then used to impute household expenditure into the second round. Since there are actual household expenditure data in the second round of the survey, poverty rates can be produced based on the actual and the imputed household expenditure and then compared to see the model's performance. The table below shows the results of this performance test for 12 country examples.

Table. Comparison of poverty rates – actual consumption and SWIFT imputed expenditures (%)

Countries & years	Actual consumption		SWIFT Imputation
	First-year	Second year	(second year)
Vietnam (1992/93 - 97/98)*	60.6	37.4	36.7
Inner Mongolia (2000 - 2004)*	19.0	6.2	7.8
Kenya (1997 - 2005/6)*	50.8	46.6	45.5
Russia (1994 - 2003)*	11.4	11.1	9.2
Morocco (2001-2007)**	15.3	8.9	8.4
Afghanistan (2011 - 2016)	38.3	54.5	53.5
Albania (2005-2008)	17.7	12.1	13.0
Malawi (2005-2011)	51.6	50.2	49.7
Romania (2011-2012)	22.6	21.7	22.3
Rwanda (2005-2008)	56.7	44.9	43.3
Sri Lanka (2009-2012)	8.7	6.5	7.0
Uganda (2009-2012)	24.5	19.5	23.3

Source: Christiaensen et al. (2012), Douiditch et al. (2013), and Yoshida et al. (2022).

For this test, it is necessary that the two survey rounds be fully comparable. Unfortunately, in many developing countries, it is not uncommon to find that two household surveys are not comparable due to government changes to the questionnaire, survey logistics, or enumerator training for newer surveys. Because of this, Yoshida et al. (2022) selected surveys for countries and years where two subsequent household surveys are confirmed to be comparable by the World Bank's country poverty economists.

[16] As mentioned above, the SWIFT methodology incorporates a Cross-Validation exercise to prevent the over-fitting problem during each application of SWIFT, so these out-of-sample performance tests are instead meant to address proof of model-stability.

Except for Uganda (2012), all poverty rates based on household expenditures imputed by SWIFT models are within +/- 2 percentage points of those from actual consumption data. This comparison includes three countries (Vietnam, Afghanistan, and Rwanda) with large changes in the poverty rate between the first and second survey round (+/-10 percentage points), showing that SWIFT can estimate poverty rates well even when there is a large change in the poverty rate.

Annex B: SWIFT-plus model training steps.

The first part of this exercise implements a cross-validation process separately for both the urban and rural (excluding Kuchi households) areas. In detail, it follows the following steps:

1. Since highly correlated variables tend to lead to model instability, in a first stage, we use variance inflation to reduce the number of indicators to those that present lower correlation levels.
2. Randomly partition the data sample (i.e. urban sample) into five folds of equal size.
3. Choose one of the five cross-validation folds to serve as the test set, while using the other four (combined) as the training set.
4. Use a stepwise regression for variable selection over the training set. We use a grid that varies over the significance levels of removal and inclusion into the model. Using each optimal model, we predict the poverty rate and estimate the absolute difference and MSE between the actual and predicted poverty rates on the test set.
5. An optimal model is identified where we minimize the absolute bias and MSE.
6. The optimal model is applied to the surveys where no welfare data was collected. To account for the distribution of errors, we use multiple imputations to obtain point estimates of poverty.

Annex C: Asset only model performance

Table B.1: Performance metrics, Model trained on the IE-ELFS 2019/20

		R2	mean MSE	Spearman correlation	In-sample prediction IE-LFS 2019/20			out-of-sample prediction IE-LFS 2021		
					Observed poverty	Predicted Poverty	Difference (%)	Observed poverty	Predicted Poverty	Difference (%)
Panel a. AMWS R3 models (with consumption variables)										
IE-LFS 2020/19 Quarter 3	Urban	65.3	0.083	84.2	55	54.1	1.6%	51.1	52.8	3.3%
	Rural	56.1	0.083	72.4	51	52.0	2.0%	52.3	54.4	4.0%
Panel b. AMWS R3 models (without consumption variables)										
IE-LFS 2020/19 Quarter 3	Urban	57.9	0.113	75.8	55	53.9	2.0%	51.1	51.6	1.0%
	Rural	42.8	0.106	62.4	51	51.4	0.8%	52.3	49.6	5.2%

Source: World Bank estimations using 2019/20 IE-LFS and AWMS R3 surveys.

Table B.2: Poverty projections using the AWMS R3 survey.

		Projection into AMWS R3 IE-LFS 2019/20 quarter 3 model	
	Apr-Jun 2020 Baseline	With consumption variables	Without consumption variables
Urban	55.2% [49.3, 61.2]	58.1% [52.3, 63.8]	59.9% [52.6, 67.2]
Rural	51.0% [47.4, 54.6]	44.2% [40.2, 48.2]	52.7% [48.9,56.2]
National	52.3% [49.5, 54.9]	48.3% [45.5, 50.9.2]	54.7% [52.1, 57.5]

Source: World Bank estimations using 2019/20 IE-LFS surveys .
Note: Model was trained in the quarter 3 of the IE-LFS 2019/20 at the urban and rural level, independently. Poverty imputed into the AWMS R3 data. Preferred specification includes consumption variables.

Annex D: Macroeconomic projections

Several methods are available to nowcast poverty using macroeconomic data. These methods combine aggregate measures of national welfare, such as GDP per capita, to predict poverty levels. A key assumption of this approach is that poverty and aggregate measures of national welfare are intertwined. Following Caruso et al. (2017), this document focuses on neutral and non-neutral projections approaches. The transmission from economy/sectoral to income and then expenditure is not one-to-one since factors such as measurement errors, labor market power, labor market transitions, home production mediate the extent growth in the economy impacts households. To account for this, a pass-through is often used. For validation purposes, 2016 poverty rates were back-casted. Results indicate that, at least for the 2016-2020 period, the pass-through rate for both neutral and non-neutral was closer to 0.3.

Distributional neutral poverty projection methodology assumes that the real per capita consumption of all households is identically affected by GDP per capita growth. The nowcasting of the welfare vector $y_{1,\,i}$ is made by using the real GDP growth g between the period that will be predicted and the baseline level $y_{0,\,i}$ following the formula $y_{1,\,i} = (1+\vartheta g)y_{0,i}$. The pass-through accounts for the extent that GDP per capita transfers to household consumption expenditures. The validity of poverty estimates using macroeconomic data depends on the quality of GDP data, the level of similarity of income growth across households (the more similar the growth is the more accurate is the poverty estimate), and the level of knowledge about the passthrough (Caruso et al., 2017).

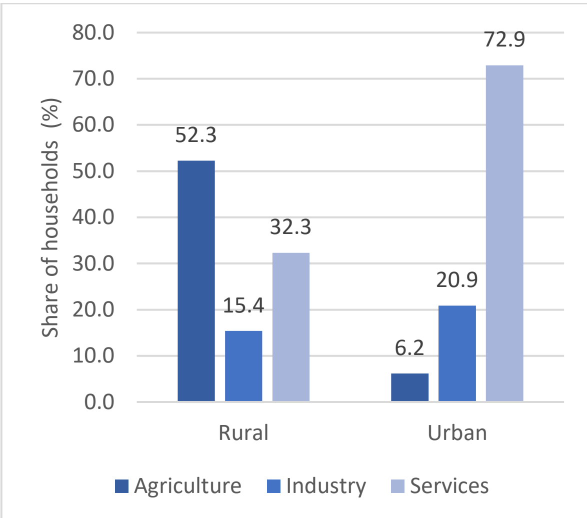
Non-neutral projections use information on sectoral growth to account for household income generation processes. The heterogeneity of income growth among households is a crucial factor that GDP per capita growth fails to capture as it differs across sectors of the economy and, therefore, does not translate into similar income growth rates across the income distribution. In practice, sectoral models impute following the formula $y_{1,\,i,j} = (1+\vartheta g_j)y_{0,i,j}$, where the sector of employment of the household head *j* determines the growth path of household expenditure. For this note, the sector of employment of the household is used to map sector economic growth with household expenditure.[17] Additionally, a key assumption is that households remain in the same employment sector. Figure D.1 displays the distribution of employed household heads across the agriculture, industry, and service sectors as in the IE-LFS 2019/20 survey. Employment distributions vary by area of residence, with agriculture employing a larger percentage of household heads in rural than urban areas (52 Vs 6.2 percent, respectively), see Figure D.1. Additionally, there were preexisting welfare differences across employment sectors with households that depend on agriculture being more likely to be poor. For instance, in rural areas, the poverty rate for those employed

[17] When the household head is not employed or economically active, the sector of employment of the oldest employed member is used. For the instances where no household member is employed the growth of GDP per capita is used.

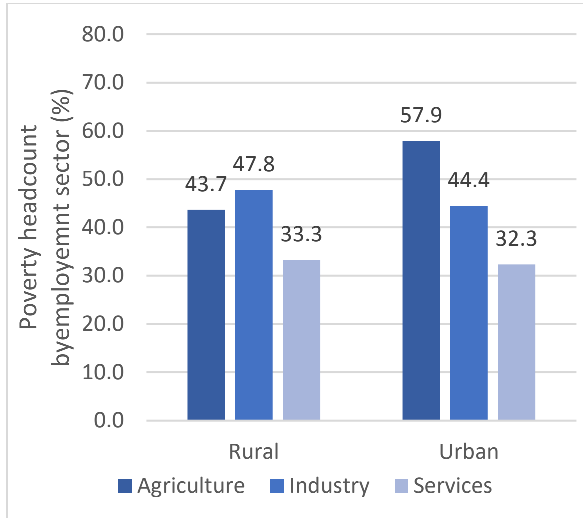
in agriculture is 43 percent while it is only 33 percent for those rural households with a household head employed in services. A similar trend occurs in urban areas, see Figure D.1, panel b.

Figure D.1: Sectoral employment and welfare of household heads

Panel a. Sector of employment



Panel b. poverty rate and sector of employment of the household head



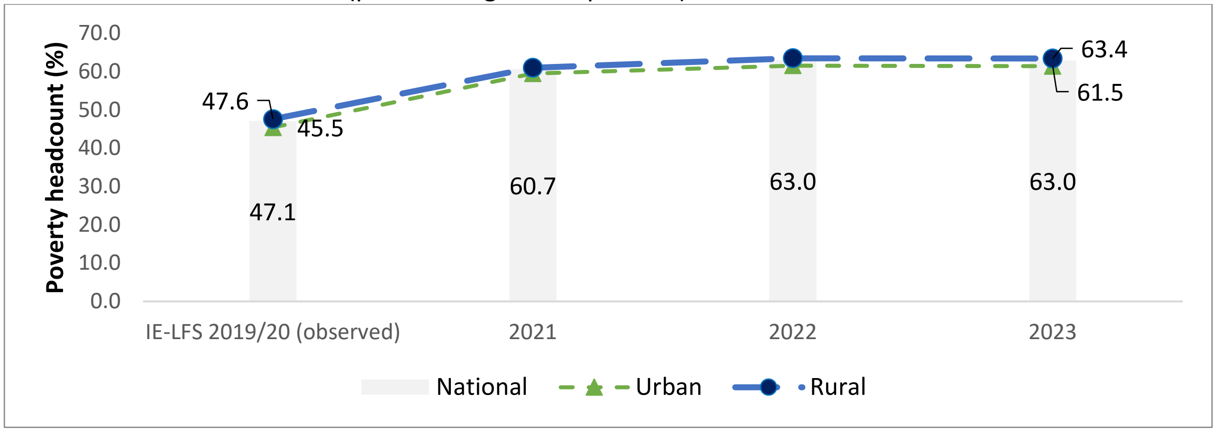
Source: World Bank calculations using 2019/20 IE-LFS
Note: Includes only household heads 2023

Neutral and non-neutral models assume growth in macroeconomic variables translates into household expenditures through labor markets. A main assumption in the usage of macroeconomic data to nowcast poverty rates is that changes in economy/sectoral growth translate into changes in household income, which then drive changes in consumption. Considering poverty in Afghanistan is measured using expenditures, this is the variable which, ultimately, is of interest to evaluate poverty impacts. Moreover, it is important to highlight that economic growth relies on projections produced under uncertainty regarding the actual GDP dynamics, the evolution of factor prices, and changes in the economic structure, which add additional challenges when mapping sectoral growth to the evolution of household income.

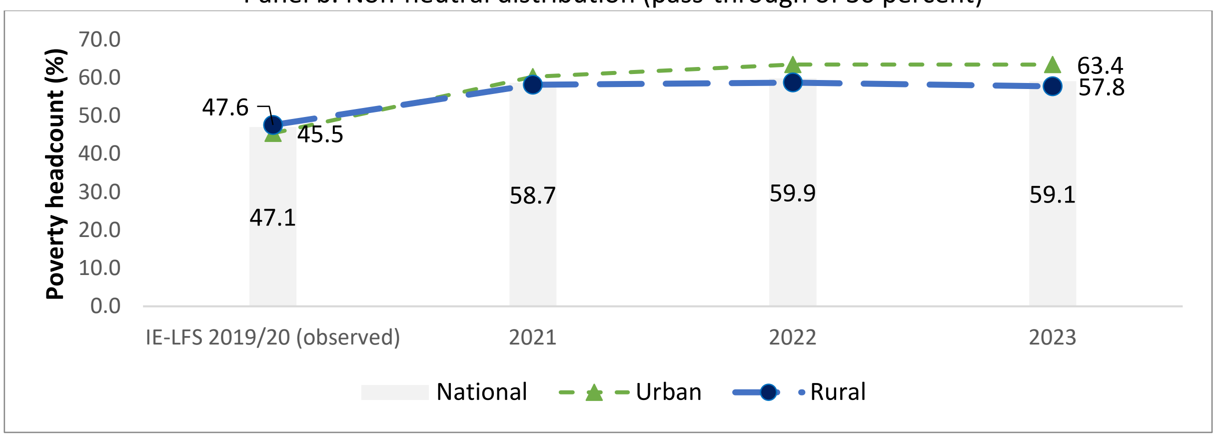
Given the relatively better performance of the agriculture sector, non-neutral distribution models predict lower poverty increment, especially in rural areas. The national poverty rate in 2023 is expected to be between 63 percent in the neutral distribution model, and 59 percent when accounting for differential sector growth (Figure D.2, panels a and b, respectively). The main difference arises from the better performance of the agriculture sector, where almost half of the employed population was working in 2019/20 and is the only sector with positive growth with respect to 2021 levels. Panel c presents the projected poverty rates in 2023 under different pass-through rates.

Figure D.2: Poverty projections using macroeconomic data

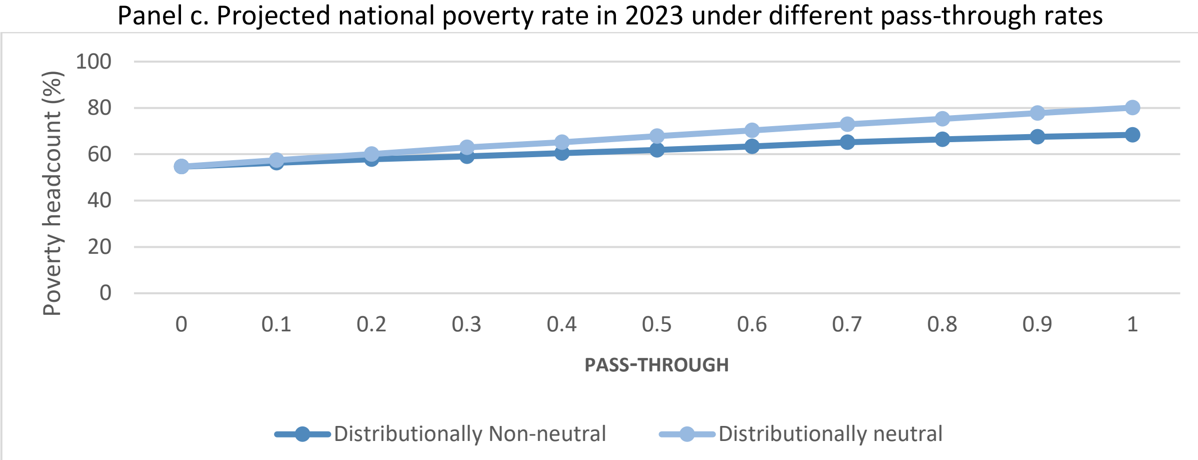
Panel a. Neutral distribution (pass-through of 30 percent)



Panel b. Non-neutral distribution (pass-through of 30 percent)



Panel c. Projected national poverty rate in 2023 under different pass-through rates



Source: World Bank estimations using 2019/20 IE-LFS surveys .

Note: A passthrough of 0.3 was used. Macroeconomic data projected by World Bank staff for the 2022-2023. When the household head is not employed, the sector of the oldest employed member is used. When every member is employment average GDP per capita growth is used.