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Estimating the food security impact of cuts in WFP assistance

A look at the highly affected operations using micro-data

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Abstract

With food insecurity numbers ramping up in many countries, WFP life-saving assistance has significantly increased thanks to growing donor contributions in 2022. However, the current global economic context does not allow us to believe that WFP's budget can keep pace with mounting needs. It is therefore crucial to understand what the impact of reduced assistance would be in terms of global food security numbers. We apply a household impact model in four countries to estimate the number of additional people that will become acutely food insecure due to projected assistance cuts. These are Afghanistan, Haiti, Iraq, and Yemen, where in 2022 WFP assisted 31 million people with food transfers and 12 million with cash transfers. In each country we simulate budget cuts of 50 and 30 percent from 2022 operations by reducing the number of people assisted or the transfer value. Our results show that in the worst-case scenario up to 6.6 million people will be added to the 13.9 million people already at emergency or worse levels of acute food insecurity. Depending on the country, results from our study show that different ways to implement assistance cuts may influence the magnitude of the impact depending on the package of assistance provided by WFP, its share in the overall household income and the prevailing depth of food insecurity.

Introduction

There are only few years left before 2030 and the world is moving away from the goal of achieving zero hunger. As a result of conflicts, climate change and economic downturns, "it is estimated that nearly 670 million people will still be undernourished in 2030 – 8 percent of the world population, which is the same percentage as in 2015 when the 2030 Agenda was launched" (FAO, 2022). Across the countries where WFP operates, 345 million people are acutely food insecure and require urgent food and livelihood assistance in 2023, more than doubling the number in 2019. Up to 40.4 million people across 51 countries are estimated to be in emergency or worse levels of acute food insecurity – without urgent life-saving action, these populations will be at risk of falling into catastrophe or famine conditions. (WFP, 2023.a). The food security situation is likely to deteriorate further in 18 hunger hotspots during the outlook period from June to November 2023 (WFP and FAO, 2023), where Afghanistan and Yemen remain regions of highest concern for the June to November 2023 outlook, with recent addition of Haiti due to increasing level of concern.

As a result of aforementioned growing needs, WFP provided assistance to 160 million people in 2022, 109 percent more than in 2015 (76.7 million people), thanks to tripling donor contributions (from US$4.7 to US$14.1 billion) (WFP, 2023.b). However, it's unlikely that funding levels will continue to keep pace. The world is just out of the Covid-19 pandemic, and most economies are still recovering. At the same time, inflation reached record heights in 2022, while the impact of the conflict in Ukraine spreads additional instability globally, compounding the effect of an increasing frequency of agroclimatic shocks affecting the livelihoods of agricultural communities.

In the first six months of this year alone, WFP has already put in place cuts to assistance in Afghanistan, Bangladesh, Burundi, Chad, Ecuador, Mali, Palestine, Syria, Tanzania, and Uganda, with further cuts on the horizon for operations in Ethiopia, Jordan, Haiti, Nigeria, Rwanda, Somalia, and Yemen – among others.

It is therefore crucial to understand what the impact of WFP budget cuts would be in terms of additional people at emergency or worse levels of acute food insecurity. We attempt to answer this question by leveraging the wealth of data collected by WFP. Specifically, WFP uses household surveys to assess needs and inform operations, obtaining granular information about household conditions such as demographics, expenditures, food consumption and coping strategies.

In the past few years, WFP has developed a simulation approach that uses household data to forecast food security. We simulate how assistance cuts can affect households' income and expenditure decisions using a household impact model.[1] The model estimates price elasticities and expenditures to food and non-food goods, thereby enabling food security outcomes to be estimated along with other measures of household welfare.

Through this model we simulate two sets of scenarios, with budget cuts worth 30 and 50 percent of the actual transfers delivered by WFP in 2022. For each scenario, we distinguish between two prioritization strategies: a) all the current recipients continue to receive assistance with a reduced transfer value, and b) WFP withdraws assistance to 30 and 50 percent of the recipients, while the remaining continue to receive the full transfer value. Food and cash assistance modalities are considered separately.

Our results indicate that budget cuts may lead to substantial increases in the food insecure population and shed further insight into the *'breadth vs. depth'* debate around humanitarian assistance: With a fixed budget, is it more effective to assist a higher number of people with less transfers or a lower number of people with more.

The rest of the paper is organized as follows: the first section describes the data; the second section provides an overview of the simulation approach; and the third section describes the results. The concluding remarks summarize the findings. The annex provides a formal description of the model, along with additional outputs.

Data

While our approach is potentially applicable in all the countries where a recent household survey exists, there are limitations due to a lack of standardization of data collection practices. Details on the household surveys used for this analysis are provided in Table 1[2]. Results cover four countries, namely Afghanistan, Haiti, Iraq, and Yemen, for which one standardized dataset was built covering 65 relevant household characteristics, for a total of 93,574 households interviewed, which is representative of 85.1 million people. Almost half of them are classified in food security crisis or worse (phase 3 or above) situation based on the Integrated Food Security Phase Classification (IPC) / Cadre Harmonisé (CH) (IPC, 2023). In Iraq, the WFP household survey covered asylum seekers and internally displaced people in Dahuk, Erbil and Sulaymaniyah governorates, while for the remaining countries the survey coverage was nationally representative.

[1] WFP's Shock and Assistance Platform for Economic Simulations (SHAPES) simulates the impact of negative shocks on households and the local economy, and assesses the direct and indirect benefits of assistance provided to households to offset those shocks. We here apply a reduced version of the model, modeling the effects of budget cuts thorugh a household impact model. The full approach comprises also a climate impact model to predict seasonal weather-related shocks to crop yields; and a general equilibrium model whereby households in a local community are allowed to trade with each other generating spillover impacts to non-assisted households.

[2] Given the sensitivity of some information, survey data can be requested in the WFP-VAM Data Library for specific scopes https://datalib.vam.wfp.org/

Table 1- Population, IPC/CH and equivalent data, and WFP household survey summary statistics by country

	Country	Population *(million)*	People in IPC/CH PHASE 3 and above (or equivalent) *(million)*	WFP beneficiaries as a share of population	Household survey			
					Name	**Date**	**Coverage**	**Households**
AFG	Afghanistan	41.7	15.3 (φ)	55.1%	PLAS	January 2022	All country	11,345
HTI	Haiti	11.9	4.9 (φ)	15.5%	ENNSAN	August 2022	All country	6,877
IRQ	Iraq (*)	0.9	0.2 (ψ)	52.9%	FSOM	March 2022	Partial	2,699
YEM	Yemen	30.6	16.9 (φ)	57.8%	FSLA	November 2021	All country	72,653
	Total	**85.1**	**37.3**					**93,574**

Source: IPC/CH (or equivalent) from (ψ) FSIN Global Report on Food Crises 2023, (φ) WFP Global Operational Response Plan Update #8 – June 2023. Population figures from IPC/CH website. Note that column 'WFP beneficiaries as a share of total population' uses WFP beneficiaries presented in Table 2 without considering that some beneficiaries may receive both food and cash transfers. Surveys from WFP. (*) Iraq IPC/CH figures cover only returnees and internally displaced people in Dahuk, Erbil and Sulaymaniyah governorates, while the household survey covers asylum seekers and refugees in several camps in the same governorates.

These four countries are chosen because the number of people in need of food assistance is extremely high and thereby WFP operations particularly sizeable and the data availability responds to the model requirements. Table 2 documents WFP's footprint in 2022, with 31 million people receiving food and 12 million people receiving cash transfers,[3] thereby making potential budget cuts very impactful. In total, WFP distributed almost 2 million metric tons of food and US$538 million in cash-based transfers in these four operations. Food transfers in metric tons are monetized at average 2022 retail market prices available in WFP Dataviz and for this study are estimated to be equivalent to US$1,448 million. Per capita average yearly transfers change significantly between transfer modalities and from country to country. In three out of four countries, most WFP beneficiaries received food transfers: 77 percent in Yemen (KG56 equivalent to US$50), 71 percent in Afghanistan (KG70 equivalent to US$45), 55 percent in Haiti (KG10 equivalent to US$25), and only 12 percent in Iraq (KG67 equivalent to US$68). On the other hand, per capita average cash transfers vary less between countries, US$49 in Afghanistan, US$39 in Haiti, US$51 in Iraq, and US$40 in Yemen. These differences can reflect operational funding gaps, diverse household needs, and different cost of living in these countries.

Depending on the transfer modality, these average transfers represent between 15 to 20 percent of per capita income in Yemen, suggesting that assistance cuts are likely to be more detrimental there as compared to other countries, where they are typically below 10 percent.

[3] Source: WFP Comet. Some beneficiaries may receive both food and cash transfers.

Table 2 - WFP beneficiaries and transfer values in 2022

Country	Food transfers					
	Metric tons (thousand)	Value in USD (million)	Beneficiaries (million)	Average transfer in KG (year, per capita)	Average transfer in USD (year, per capita)	Average transfer share of per capita income
Afghanistan	1,144.6	732.4	16.3	70.2	44.9	8.5%
Haiti	10.2	25.5	1.0	10.0	25.2	4.5%
Iraq (*)	3.8	3.9	0.1	66.5	68.4	8.9%
Yemen	760.1	686.3	13.6	55.9	50.5	19.6%
Total	**1,918.6**	**1,448.1**	**31.0**			

Country	Cash transfers			
	Value in USD (million)	Beneficiaries (million)	Average transfer in USD (year, per capita)	Average transfer share of per capita income
Afghanistan	326.9	6.7	48.9	9.2%
Haiti	28.2	0.8	33.8	6.0%
Iraq (*)	20.8	0.4	50.9	6.5%
Yemen	162.0	4.1	39.7	15.4%
Total	**537.9**	**12.0**		

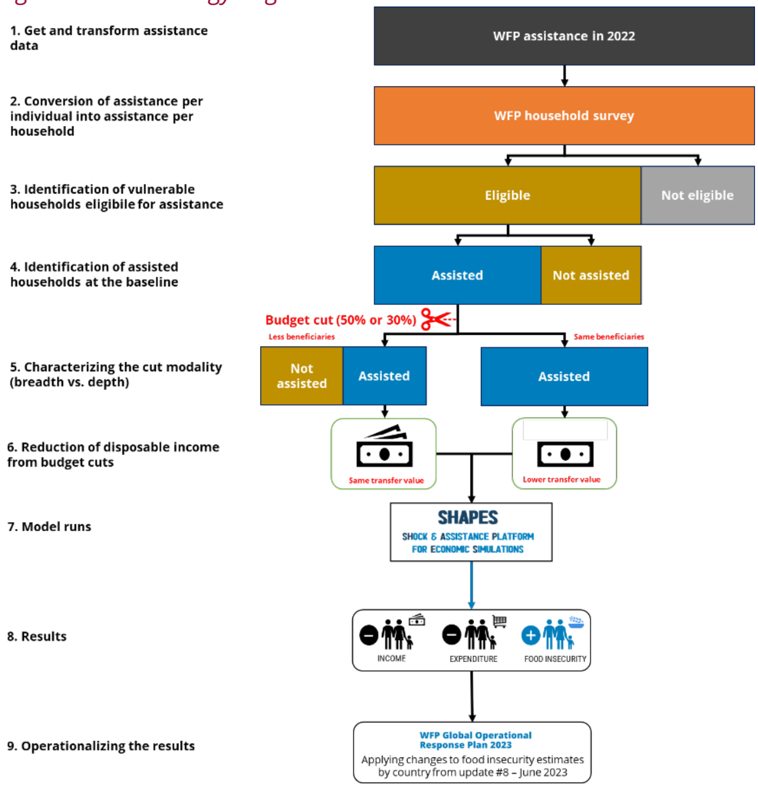
Source: WFP, available at https://www.wfp.org/annual-country-reports-2022 in section 'beneficiary by modality'. Note that some beneficiaries may receive both food and cash transfers. Cash transfers include both cash-based transfers and commodity vouchers. (*) Iraq figures cover only asylum seekers and internally displaced people in Dahuk, Erbil and Sulaymaniyah governorates.

Methodology at a glance

Figure 1 details the process used to run the simulations and what happens at each step.

1. **Get and transform assistance data.** We retrieve yearly assistance numbers by country from WFP's COMET (Country Office Tool for Managing programme operations Effectively), which reports the total number of individuals assisted with food in metric tons and cash in US dollars in a year. Metric tons are monetized at average 2022 retail market prices, and everything is transformed into local currencies using official or parallel exchange rates. This transfer value is further divided into monthly per capita entitlements for both food and cash transfers.

Figure 1: Methodology at glance



2. **Conversion of assistance per individual into assistance per household**. WFP's corporate system reports the number of beneficiaries as individuals while the surveys are at the household level, therefore approximation errors exist when applying the budget cuts from individuals to households (and then return the simulation results back to individuals in step 8). We rescae the number of beneficiaries against the number of individuals eligible in the sample considering the number of people living in the household and how many people in the total population each household represents. In the last two columns of Table 6 in the annex we detail approximation errors both in terms of percentage and absolute numbers.

3. **Identification of vulnerable households**. This is based on country specific Vulnerability-Based Targeting (VBT) approaches employed to identify and assist households who qualify for food assistance. With this strategy WFP operations chooses observable socio-demographic indicators that correlate with a household's food insecurity. Correlation measures are further analysed on a country-by-country basis running a combination of a range of statistical tests, including the T-Test, ANOVA test, Pearson's Chi-squared test, Wilcoxon rank sum test, Fisher's exact test and logistic regression. The identified proxies are used to define targeting criteria, classifying eligibility to food assistance with a dummy variable. Thanks to this, food assistance can be directed towards those who are most in need, thereby optimizing the impact of WFP's interventions.

4. **Identification of assisted households at the baseline**. Household sampling is by design not representative of those receiving assistance and the structure of the data collection does not allow for identification of the modality of the transfer or who receives assistance from WFP. We therefore assign a pseudo-random draw between zero and one to each household that meet the targeting criteria and then we randomly chose the households up to the n^{th} unit corresponding to the number of assisted households at the baseline. By repeating this procedure 20 times in a Monte Carlo simulation we partially offset the randomness of this choice and reduce bias. This step also defines the assistance modality that each household receives, be it food, cash or a combination thereof.

5. **Characterizing the cut modality, breadth versus depth.** In each simulation, we reduce actual assistance numbers in 2022 by 50 and 30 percent either in of the number of beneficiaries assisted or transfer value. We present two scenarios through which the assistance budget cut affects households:
    a. **Reduced beneficiaries.** With a second Monte Carlo procedure, we randomly remove the per capita transfer value multiplied by the household size to half or thirty percent of the recipient households by modality, thereby moving them in the group of those who are eligible but not assisted.
    b. **Reduced transfer value.** In this case, all beneficiaries assisted at the baseline continue to receive assistance but with a reduction of income corresponding to the reduced entitlement.

6. **Reduction of disposable income from assistance budget cuts**.
    a. **Direct reduction to assisted households.** Since some of the households interviewed already receive various forms of assistance, those identified as assistance recipients in the previous steps already incorporate assistance as part of household disposable

income and its impact is reflected in their expenditure patterns. Consequently, we subtract part of their income to simulate a reduction of assistance.

b. **Indirect reduction to all households.** We also consider a reduction of the indirect economic effects generated from WFP assistance. These apply to all households, irrespective if they were receiving assistance or not. The justification for this comes from a growing body of literature that emphasizes how transferring resources to vulnerable households generates positive spillover effects both to direct beneficiaries and indirectly to the entire economy. These effects are different depending on the context. A recent meta-analysis reviewing 34 studies conducted in 13 countries in Sub-Saharan Africa found demand-side income multipliers from 1.21 to 1.32 (Filipski, et al., 2022), while a study in the eastern Africa region found an average income multiplier of 1.42 as WFP delivered 1.1 million metric tons of food (Corong, Kagin, Taylor, & Van Der Mensbrugghe, 2022). Several studies looked at spillover effects in refugee contexts: for example, providing refugees with access to cultivable land generates income multipliers in the range of 1.49-2.32 with food and cash transfers (Zhu, et al., 2023). Similarly, income multipliers from 1.37 to 1.89 are estimated in four refugee settlements in Uganda (WFP, 2023.c), in line with similar earlier studies conducted in Uganda (Taylor, et al., 2016) and Rwanda (Taylor, et al., 2016), with income multipliers of 2.47 and 1.51-1.95, respectively. In this study we apply the most conservative estimate (21 percent) to the average budget cuts by region or governorate.[4] This is removed from disposable income to all households and represents the loss for the entire local community.

7. **Model runs.** The execution of the Monte Carlo procedure delivers 20 draws of the dataset, from which we obtain aggregate estimates, smoothing the probability of extreme combinations at steps 4 and 5.a that might bias the results. At each iteration, a non-linear seemingly unrelated regression (SUR) estimates a linear expenditure system (LES) of equations that allocates household budget into food and non-food expenditure. The equation for total expenditure is estimated as a function of household income, controlling for household social and demographic characteristics. The model determines the percentage change in each food item consumed from a percentage change in (own and cross) price elasticities and income (see Table 7 in the annex). We use this estimated expenditure to derive the Food Consumption Score (FCS) components in a constrained regression with lower and upper bounds respectively set to 0 and 7. The coefficients from this regression are used to predict the frequency of consumption of food items from specific commodity groups in a week.[5] Predicted values are used to construct a simulated FCS as a result of the decrease in assistance. See the Annex for more detailed information of the model.

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[4] This is done because indirect effects are estimated in the local economy, which we here assume correspond to the highest Administrative level.

[5] When data allows, we normally use a Linear Almost Ideal Demand System (LAIDS) instead of this constrained regression. LAIDS allocates household food expenditure over food subgroups which include rice, wheat, other cereals, potatoes, meat, fish and eggs, milk products, vegetables and fruits, fats and oils, spices and sugar, and non-alcoholic beverages. At this point, quantities are converted into calorie intake by using a food composition table. Since household food expenditures (but not quantities) are commonly available in surveys, we derive the quantities by linking these expenditure shares to human food consumption as described in FAO's Food Balance Sheet and expressed in terms of daily caloric consumption per person for each item (group). The final step transforms the estimated food quantities into food security outcomes by converting consumption shares into grams using NutVal data.

8. **Results.** At this stage indicators obtained from the model predictions are aggregated to the national level to presenting the final results. We use the Consolidated Approach for Reporting Indicators of Food Security (CARI) as our main indicator for measuring food security changes (Rose, 2012; WFP, 2021). This approach combines different food security indicators[6] into one index that categorizes households into food secure, marginally food secure, moderately food insecure and severely food insecure, and is typically used to inform the IPC phase classification process.[7] The indicators used for CARI in this paper are:
    a. For **food consumption** we use FCS, which measures the number of days in which food items from a commodity group have been consumed by most of the household members. FCS classifies a household's food consumption into poor, borderline and acceptable based on the index's thresholds set at 21 and 35.[8,9]
    b. For **economic capacity** we use the economic capacity to meet essential needs (ECMEN) indicator that identifies the percentage of households whose expenditures exceed a minimum expenditure basket defined as what a household requires to meet essential needs (WFP, 2023.d). Instead of the MEB, we use the international poverty line set to US$2.15 per-person-per-day, duly rescaled by the prevalent exchange rate in the country or unofficial market rates where relevant (Duflo & Banerjee, 2007). Normally, this is the threshold for extreme poverty. The second threshold that we set is at US$1, which here represents a survival minimum expenditure basket (SMEB) or "dollar-a-day" absolute extreme poverty (Ravallion, Datt, & Van de Walle, 1991). We categorize households as non-poor, poor or extremely poor if the estimated expenditure after the budget cut remains respectively below, in between, or above the US$1 and US$2.15 thresholds.
    c. For **asset depletion** we use the livelihood coping strategy index (WFP, 2023.e) that classifies household coping strategies into three severity groups – stress, crisis, and emergency – depending on which coping strategy they have adopted in the past 30 days or exhausted within the past 12 months. In the model, we conservatively estimate no change in the number of coping strategies adopted.

9. **Operationalizing the results.** We apply the percentage changes reported in Table 3 to IPC4+ estimates from WFP Global Operational Response Plan 2023 (WFP, 2023.a). This last step acknowledges the need to align the results to the situation at the time of writing to make them usable for early warning by addressing the time gap since the survey. There are three main reasons for doing so:
    a. in most of the countries where WFP operates the time validity of a baseline becomes shorter as the situation in the country deteriorates (or perhaps improves). Take for example the case of Haiti: in the last year increasing gang violence and political

[6] Namely, Food Consumption Score, reduced Coping Strategy Index, Livelihood coping strategies, Economic Capacity to meet essential needs, and Food Expenditure share.

[7] "The manner in which CARI is utilized during IPC analyses may vary, depending on the wider body of evidence available. If the CARI console, i.e., the aggregated results, is included within the IPC analysis, WFP recommends that the food security groups translate to the IPC phases as illustrated", whereby the moderately food insecure category corresponds to IPC/CH Phase 3 (Crisis), and the severely food insecure category corresponds to IPC/CH Phase 4 (Emergency) and 5 (Famine). See CARI & IPC Factsheet: Technical Annex for further details.

[8] Note that we use the very same FCS thresholds in all the countries for the sake of comparability of the results. However, we are aware that some countries have different thresholds, for example Afghanistan uses 28 and 42. Next interations of the simulations may fine-tune the scenario settings for each country.

[9] The reduced coping strategy index, which is normally combined with the FCS in the 2022 CARI methodology, is conservatory held constant.

instability have made movement of people, goods, and humanitarian aid difficult, forcing massive displacement and limiting access to food, water, and fuel, harming the functioning of markets, as well as slowing down all economic activities and basic services. In this situation, headline inflation was 31 percent year-on-year at the time of the data collection in August 2022, and kept growing to 48 percent in March 2023.[10] In a year, IPC4+ estimates increased from 1.3 million (WFP, 2022) to 1.8 million (WFP, 2023.a).

b. we use survey data to model how budget cuts affect income, expenditure, and food consumption for each household. After we classify households using the CARI approach, we aggregate the model estimates to derive how many people would be severely food insecure. Yet, for operation purposes, where available, WFP uses IPC aggregate estimates not available at the household level. In all the cases of this study, CARI values were below IPC estimates,[11] and thus reporting absolute values based on CARI might have resulted in an underestimation of the impact of assistance cuts.

c. By applying this alignment to IPC figures at the end of the process, we hope to isolate the effect of assistance cuts from possible other shocks, e.g., inflation. We are aware that by doing this we are not fully capturing the impacts of assistance cuts, because the affected beneficiaries might have already experienced rising inflation and other shocks that affected their capacity to consume even before WFP's assistance scale back.

Results

We estimate that, in the four countries analyzed, between 5.1 and 6.6 million additional people would experience emergency or worse levels of acute food insecurity from a 50 percent budget cut to WFP assistance. This comes on top of the fourteen million already there. These two figures represent respectively whether the cut is applied either to the number of beneficiaries or to the transfer value. This means that in the worst-case scenario, almost one out of four people in the four countries will be classified in IPC4+, i.e., more than twenty million people. With a 30 percent budget cut, the additional people would remain in the range of 3 and 4.1 million.

The worst outcomes stem from the simulation with a 50 percent budget cut applied equally to all beneficiaries, while the least impactful scenario comes from a 30 percent budget cut where WFP maintains the same transfer value to a reduced number of beneficiaries. Yet, as shown later, reducing the number of beneficiaries and preserving the transfer value doesn't necessarily result in the least impactful situation in all the countries. Instead, a case-by-case analysis is crucial. Table 3**Error! Reference source not found.** presents results by simulation and country as per step 8 of the methodology, while Table 4 presents the number of people in IPC4+ after step 9.

[10] Data from the *L'Institut Haïtien de Statistique et d'Informatique (IHSI)* retreived from Trading Economics website.

[11] Looking back at the time of the data collection, the number of people in IPC4+ was higher than the number of people severely food insecure estimated with the CARI approach respectively by 3 percent in Afghanistan (IPC projected in Nov 2021-March 2022 8.7 million vs. CARI 8.5 million), 53 percent in Haiti (IPC projected in March-June 2022 1.3 million vs. CARI 0.9 million), and 10 percent in Yemen (IPC projected in January-June 2021 5.1 million vs. CARI 4.6 million).

Table 3 - Percentage changes in the number of severely food insecure people

Country	Simulation scenario: 30 percent – Less beneficiaries Same transfer value	Simulation scenario: 30 percent – Same beneficiaries Lower transfer value	Simulation scenario: 50 percent – Less beneficiaries Same transfer value	Simulation scenario: 50 percent – Same beneficiaries Lower transfer value
Afghanistan	11%	7%	20%	18%
Haiti	4%	3%	6%	6%
Iraq (*)	17%	8%	35%	36%
Yemen	37%	60%	63%	89%

Source: Authors' calculation. Changes are calculated against the baseline data using WFP's CARI approach.

Naturally, the most sizeable impact is in the two countries where WFP assists more than half of the total population. In Afghanistan the number of additional (total) people in IPC4+ ranges between 0.4 (6.1) and 1.2 (7.3) million depending on the simulation, whereas in Yemen these are between 2.2 (8.3) and 5.4 (11.5) million. However, the share of assistance in income is quite different in these two countries and hence the expected impact of budget cuts. In fact, food and cash transfers in 2022 represented respectively 7.6 and 8.2 percent of per capita income in Afghanistan, and 18.7 and 14.7 percent in Yemen. This is visible in Table 5, where average per capita expenditure for the people affected by the budget cut in Yemen drops more prominently across the four simulations. As a result, in the worst-case scenario, there are 20 percent more people at emergency or worse levels of acute food insecurity in Afghanistan, and 89 percent more in Yemen.

In the camps hosting asylum seekers and internally displaced people in the governorates of Dahuk, Erbil and Sulaymaniyah in Iraq we find that a combined effect of reduced food consumption and economic capacity, as reported by the CARI indicator, brings the number of people severely[12] food insecure up by 36 percent in the worst-case scenario. We do not estimate the additional number of people living at emergency or worse levels of acute food insecurity because none is currently reported to be in that condition at the time of writing. This is because most of the households have an acceptable FCS and just a few have a Poor FCS status. Note that this case study is different from the others presented in this paper because it only covers a specific sub-set of the population living in Iraq, i.e., 900,000 individuals, out of which around 500,000 receive WFP's assistance.

[12] Note that we refer to 'severely' food insecure people when we use CARI estimates, and to 'acutely' food insecure people when we use IPC estimates.

Table 4 – Estimated additional and total people in IPC Phase 4+ after assistance cuts

Country	IPC4+	Simulation scenario: 30 percent – Less beneficiaries Same transfer value	30 percent – Same beneficiaries Lower transfer value	50 percent – Less beneficiaries Same transfer value	50 percent – Same beneficiaries Lower transfer value
Afghanistan	Baseline	6,080,000	6,080,000	6,080,000	6,080,000
	Additional	+ 695,000	+ 422,000	+ 1,189,000	+ 1,090,000
	Total	6,775,000	6,502,000	7,269,000	7,170,000
Haiti	Baseline	1,808,000	1,808,000	1,808,000	1,808,000
	Additional	+ 70,000	+ 46,000	+ 115,000	+ 99,000
	Total	1,878,000	1,854,000	1,923,000	1,907,000
Yemen	Baseline	6,061,000	6,061,000	6,061,000	6,061,000
	Additional	+ 2,235,000	+ 3,640,000	+ 3,800,000	+ 5,390,000
	Total	8,296,000	9,701,000	9,861,000	11,451,000
Total	Baseline	13,949,000	13,949,000	13,949,000	13,949,000
	Additional	+ 3,000,000	+ 4,108,000	+ 5,104,000	+ 6,579,000
	Total	16,949,000	18,057,000	19,053,000	20,528,000

Source: Authors' calculation based on IPC data to which we apply percentage changes as per Table 3**Error! Reference source not found.**. Note that Iraq estimates are not presented because there are no people living in IPC4+ phase in the camps hosting asylum seekers and internally displaced people in Dahuk, Erbil and Sulaymaniyah governorates.

WFP assistance represents 8 percent of per capita income in Haiti. In the case of budget cuts, the model estimates up to 2 million people in IPC4+, with changes from the baseline in the order of 3 to 6 percent. However, this is the country with the least number of people assisted as a share of total population (15.5 percent, see Table 1), and therefore the impact is smaller within the entire population. Still, for those affected, the average FCS drops by approximately 9 percent in the worst-case scenario (Table 5).

As expected, the worst-case scenario is not consistent across countries. In Afghanistan and Haiti, providing the same transfer value to less beneficiaries results in the least impactful scenario, whereas in Iraq and Yemen the opposite is true. Looking at average per capita expenditure at the baseline, the share of people living with less than $2.15 per day is 84 percent in Afghanistan, 71 percent in Haiti, 57 percent in the refugee camps in Iraq, and 92 percent in Yemen (see Annex), with Yemen being the country where the severity of poverty[13] is highest, followed by Afghanistan, Haiti and Iraq. The number of people whose FCS is below the poor threshold is 26 percent in Afghanistan, 8 percent in Haiti, less than 1 percent in Iraq, and 14 percent in Yemen. In this study, these two indicators representing economic capacity and food consumption determine the food security changes (holding constant asset depletion) that are then applied to the latest IPC estimates. While budget cuts directly reduce household's economic capacity, they have a larger impact on food consumption, emphasizing how these budget cuts would be more of a driver for food insecurity rather than poverty.

[13] Measured with the Poverty Gap Index derived with the Foster-Greer-Torbecke index with alpha equal to 1 (Foster, Greer, & Thorbecke, 1984). This measure is the mean shortfall from the poverty line divided by the value of the poverty line itself. When multiplied by the population and the poverty lines it indicates the total amount of money ideally needed to move everyone out of extreme poverty and up to the poverty line, assuming perfect targeting of transfers.

Table 5 - Average expenditure and FCS for people affected by assistance cut

Simulation		Country	expenditure in US$ (per capita/month)	change	FCS	change
Budget cut	Scenario					
50%	Less beneficiaries Same transfer value	Afghanistan	40.4	-8.0%	22.0	-14.2%
		Haiti	45.1	-5.0%	34.3	-8.1%
		Iraq	60.9	-5.9%	66.5	-3.1%
		Yemen	16.9	-21.5%	17.9	-37.6%
50%	Same beneficiaries Lower transfer value	Afghanistan	42.0	-4.5%	24.0	-6.2%
		Haiti	45.9	-3.3%	36.2	-3.1%
		Iraq	62.7	-3.0%	68.5	-0.2%
		Yemen	18.9	-11.9%	22.9	-20.2%
30%	Less beneficiaries Same transfer value	Afghanistan	40.8	-7.2%	22.1	-13.8%
		Haiti	45.1	-5.1%	34.0	-8.9%
		Iraq	60.9	-5.9%	66.8	-2.7%
		Yemen	16.9	-21.4%	18.1	-37.0%
30%	Same beneficiaries Lower transfer value	Afghanistan	42.8	-2.7%	25.0	-2.5%
		Haiti	46.5	-2.0%	36.9	-1.2%
		Iraq	63.5	-1.8%	68.6	0.0%
		Yemen	19.9	-7.2%	25.4	-11.3%

Source: Author's calculation based on WFP's data. (*) Iraq estimates cover only asylum seekers and internally displaced people in Dahuk, Erbil and Sulaymaniyah governorates.

In summary, it is challenging to derive a rule of thumb for the 'breadth vs. depth' assistance conundrum. Analysis of more household surveys in other countries would be required. However, looking only at the two extreme cases where WFP assistance is higher can provide some valuable insight: 26 percent of the people in Afghanistan already had a poor food consumption with actual assistance making up around 8.5 percent of their income, whereas 14 percent of the population in Yemen have a poor food consumption with assistance making up 20 percent of income. When we simulate a 50 percent cut, poverty measures do not change significantly while poor food consumption goes up from 26 to 30 percent in Afghanistan and from 14 to 25 percent in Yemen. For the latter, it means that the current level of assistance allows many people to have a borderline food consumption score, but without external aid most of these people would be severely food insecure. Despite Afghanistan being the top recipient country in the study, needs are so vast that current assistance level fails to prevent that many people from living with poor food consumption. In this case, the budget cut would push them further into food insecurity, but the CARI approach is not sensitive to this.[14] Given these two situations, it is not surprising that Afghanistan would have a lower impact with budget cuts equally divided on all the current beneficiaries, while in Yemen this would be the most harmful scenario. As a note of caution to interpret these findings, we stress that our approach does not involve any prioritization exercise where those most in need among the vulnerable population continue to get assistance from WFP.

[14] Differently, the IPC/CH classification has a Phase 5 that could perhaps better capture the real effect of assistance budget cuts in this country.

Concluding remarks

WFP provided life-saving assistance to 160 million people in 2022, which is the highest number ever assisted by the organization. Every year since 2015 marked a new record in terms of the number of people assisted, thanks to contributions from donors that have tripled in the same period up to US$14.1 billion. While this is an enormous operational budget, it is far from the needs-base plan that instead would have required US$21.4 billion (WFP, 2023.b). More so, it is uncertain if donors can maintain the same level of contribution post Covid-19 pandemic and the consequent slowdown of the world economy.

This study investigates the impact of WFP assistance cuts on food insecurity numbers using a simulation model based on household microdata collected in four countries where assistance is particularly important. These are Afghanistan, Haiti, Iraq (refugees camps near Erbil), and Yemen, where in total WFP assisted 31 million people with food transfers and 12 million people with cash transfers in 2022. The scenarios simulated include budget cuts worth 50 and 30 percent of the budget of the same year. For each simulation, we present two scenarios, one where assistance cuts consist of reduced transfers equally applied to all beneficiaries vis-à-vis the other where full assistance is withdrawn to some beneficiaries while the others continue to receive the same transfer value. Provided we are using household data collected approximatively one year ago, we first derive our results in terms of percentage changes using WFP's CARI approach and then apply these changes to the latest IPC estimates to make our results more operational. The worst outcomes are with cuts worth 50 percent of the budget that lowers the transfer value to every WFP's beneficiary. Results show that an additional 6.6 million people will experience acute food insecurity, for a total of 20.5 million in the four countries. Most of these additional people live in Yemen (5.4 million), followed by Afghanistan (1.1 million), Haiti (99,000), while in the refugee camps in Iraq there are no people in IPC4+.[15]

The majority of the increase in food insecurity is driven by Yemen, where reducing assistance means almost doubling the number of people at emergency or worse levels of acute food insecurity. Looking at Afghanistan and to a lesser extent Haiti, the simulations do not return results of similar magnitude, and the most impactful scenario is the one where only some beneficiaries are affected by budget cuts (with respectively 1.2 million and 115,000 people). This is due to the different level of assistance that WFP can provide in each country and how sizeable it is as compared to household income. On a per capita basis, when assistance share of disposable income is relative lower, many people are already in IPC4+ and therefore removing that assistance will not necessarily add a proportional number of additional people. However, when assistance is relative higher, any cut to the transfer value will trigger a change in the food security classification.

Additional case studies would be required to generalize the findings around the breath vs. depth assistance debate. However, based on these preliminary insights, we recommend a case-by-case analysis before reducing either the transfer value or the number of people enrolled in the assistance scheme (or a combination thereof). From this study, we highlight it's important to understand the share of WFP assistance in household budgets and how the eligible population is distributed in various food security categories. Specific attention should be paid to how the population is distributed around food security classification thresholds and to sub-national

[15] Looking at CARI estimates, some 500 additional people would be severely food insecure in the worst-case simulation.

specificities. In any case, strengthening targeting approaches and monitoring the impacts of such cuts remain critical.

We acknowledge the following limitations: this model does not consider prioritization exercises that may partially ease the described negative impacts. Additionally, we are aware that withdrawing assistance from some beneficiaries is likely to create social tension within communities and may be challenging to implement in certain contexts. The results of this study relate only to the effects of cuts in assistance, without considering other shocks that may have compounding effects on household's food security. Finally, using threshold-based classifications for food security allows us to model how many additional people are pushed into a worse food security classification, but does not account for how severe the deterioration is for those that remain in their original classification phase.

Annex

Estimating consumption

Obtaining usable information abouton household income from surveys is a challenge. Typically, respondents either tend to under-report income or simply refuse to answer (Mancini & Vecchi, 2022) and finding a good enough alternative variable becomes the only option. Normally, this alternative comes from household expenditure (Deaton & Zaidi, 2002), collected in WFP household surveys with a recall period of one month for both food and non-food goods. In most cases,[16] household expenditure is further broken down in diverse groups, for example cereals, tubers, pulses, and so on when it comes to food items, and hygiene, transportation, energy, education fees and so on when it comes to non-food goods. In addition to expenditure, we add a fixed share of savings as a percentage of GDP calculated as the difference between total income in the country net from private and government consumption. This is a workaround to differentiate between income and expenditure, and income data could improve by asking households how much they are able to save as a percentage of their expenditures in a month.

To understand how the assistance cut shock passes through from household income to expenditure, we estimate the propensity to consume defined as the ratio of a household's spending to its disposable income. Therefore, the equation for the natural logarithm of per capita total expenditure E_h for household h is specified as a function of household income, controlling for households social and demographic characteristics such as household size, location, and gender of household head:

$$\ln E_h = f(\ln Y_h, s_h, g_h, l_h) \qquad [1]$$

where $\ln Y$ is the natural logarithm of per capita income, g the gender of the household head, s the number of people living in the household and l is a dummy variable indicating either urban or rural dwellers.

At this point it is possible to allocate their reduced budget using expenditure data. This data is typically available in WFP's household surveys aggregated at food group rather than food item level. Using expenditure data to derive household consumption measures will require some assumptions on how to disaggregate the data, and how to apply price information. We run a non-linear seemingly unrelated regression (SUR) to estimate how household allocate budget into food and non-food expenditures, based on the behaviour of other households falling within the same income quartile (Burger, Coetzee, Kreuser, & Rankin, 2015). This linear expenditure system (LES) is a widely used functional form derived from maximization of a utility function subject to an expenditure constraint (Stone, 1954). It provides an intuitive economic interpretation despite its strong separability assumption (Blundell & Robin, 2000), i.e., that net impact on household food consumption depends on the importance of the commodity group in terms of both consumption and profit. In formal terms:

$$\ln E_{i,h} = \alpha_i \cdot P_i + \beta_i \cdot \left[\ln E_h - \left(\sum_i \alpha_i \cdot P_i\right)\right] \qquad [2]$$

[16] With the exception of Afghanistan, within the four assessments used in this study, which does not include further disaggregation of food expenditures.

where the suffix i indexes food and non-food goods, and P is the aggregated price for commodities within group i calculated from each country's Consumer Price Index and commodity group weight. The estimated parameters α and β represent the direct impact on consumption and the profit/income effect of price change, respectively, (Ulimwengu & Ramadan, 2009; Fang & Sanogo, 2014) and are subject to the following constraints: $\sum_i \alpha_i = 0, 0 < \beta_i < 1$, and $\sum_i \beta_i = 1$ (Clements, Mariano, & Verikios, 2020). These parameters are used to derive a set of elasticities by income quartile that are used for the simulation.

Own price elasticity: $$\eta_{ii} = (1 - \beta_i) \cdot \frac{\alpha_i \cdot P_i}{\overline{E_\iota}} - 1 \qquad [3]$$

Cross price elasticity: $$\eta_{ij} = -\beta_i \cdot \frac{-\alpha_j \cdot P_j}{\overline{E_\iota}} \qquad [4]$$

Income price elasticity: $$\eta_i = \beta_i \cdot \frac{\overline{E}}{\overline{E_\iota}} \qquad [5]$$

$\overline{E}$ and $\overline{E_\iota}$ are the average expenditure by income quartile and the suffix j represent non-food goods when i is food and vice versa.[17] The estimated elasticities by country are available in Table 7 in the annex.

At the end of this process, the model returns for each households a reduced income Y_h^{t1} and an estimated expenditure E_h^{t1}, where the super-scripts $t1$ refer to the post simulation results as compared to the baseline $t0$.

Estimating Food Consumption Score

We utilize expenditure function estimates to predict FCS levels. The procedure adopted implicitly assumes an average portion size for each of the eight food types used in the FCS score; Additionally, it is assumed that the food types are normal goods. The relationship between food expenditure at the household level and household income is first estimated via a reduced form equation converted to natural logs.[18]

$$\ln E_h = \gamma_1 \cdot \ln Y_h + e_h \qquad [6]$$

The estimated parameter γ_1 is the marginal percent increase in food expenditures, corresponding to a one-percent increase to household incomes.

To predict food consumption scores using expenditure, let $c_{g,h}$ be a vector of goods consumed (cereals, tubers etc.,), measured in "days consumed per week", i.e., $c_{g,h} \in [0,1,2,3,4,5,6,7]$ in discrete steps, with the sub scripts h representing household and g food groups. Let U^h denote the utility function for household h. For the sake of simplifying the notation hereinafter, we assume one household group only. Similarly, let Y_h denote total income and $E_{i,h}$ denote total expenditures on food items. As such, the household faces the following maximization problem:

$$Maximize\ U^h(c_{g,h}) \qquad subject\ to \sum_{\forall g} c_{g,h} \leq E_{i,h} \equiv \theta^h \cdot Y_h \qquad [7a]$$

[17] For simplicity, we omit the country and income group notations henceforth.

[18] An inverse hyperbolic sine transform specification can also be adopted, should the share of 0 expenditures in each category be higher.

where $0 < \theta^h < 1$ is the share of income used for expenditure on consumption items. Applying a Cobb-Douglas specification, we have the Lagrange constrained optimization model of:

$$Max \prod_{\forall g} (c_{g,h})^{\delta_g} - L \cdot (\sum_{\forall g} c_{g,h} - E_{i,h}) \qquad [7b]$$

The functional form of the Cobb-Douglas gives the solution:

$$c^*_{g,h} = E_{i,h} \cdot {}^{\delta_g}\!\Big/_{\sum_{\forall g} \delta_g} \qquad [8a]$$

Without loss of generality, we can normalize the sum of coefficients to equal 1 (this is specific to Cobb-Douglas when constant returns to scale is applied):

$$c^*_{g,h} = E_{i,h} \cdot \delta_g \qquad [8b]$$

For each of the eight food types in the FCS, we regress a double-log model of portions consumed in a week against expenditures, with the log-log specification resulting in estimates that can be interpreted as percent change. This model is estimated for all goods g in the list of FCS items, for all household group types within the income groups.

$$\ln FCS_{g,h} = \delta_0 + \delta_1 \cdot \ln E_h + \varepsilon_h \qquad \forall g \in \{FCS\} \qquad [9a]$$

The estimated parameters, together with the residual ($\hat{\delta}_o$, $\hat{\delta}_1$, $\hat{\varepsilon}_h$) are stored and used to predict FCS levels for each of the food items individually. Point estimates from the regression are validated by checking whether results are a) consistent with a normal good, and b) statistically significant at the two-tailed 10% level. Should either of the two conditions fail, the resulting predictions (for that specific good and household group) are dropped at the end and replaced with a backup procedure.

The prediction uses estimated expenditures from equation [2] with previous parameter estimates from [9a] to construct and predict the new FCS levels for each of the g items and household h, as shown in equation [9b]:

$$\ln FCS^{t1}_{g,h} = \hat{\delta}_0 + \hat{\delta}_1 \cdot \ln E^{t1}_{i,h} + \hat{\varepsilon}_h \qquad [9b]$$

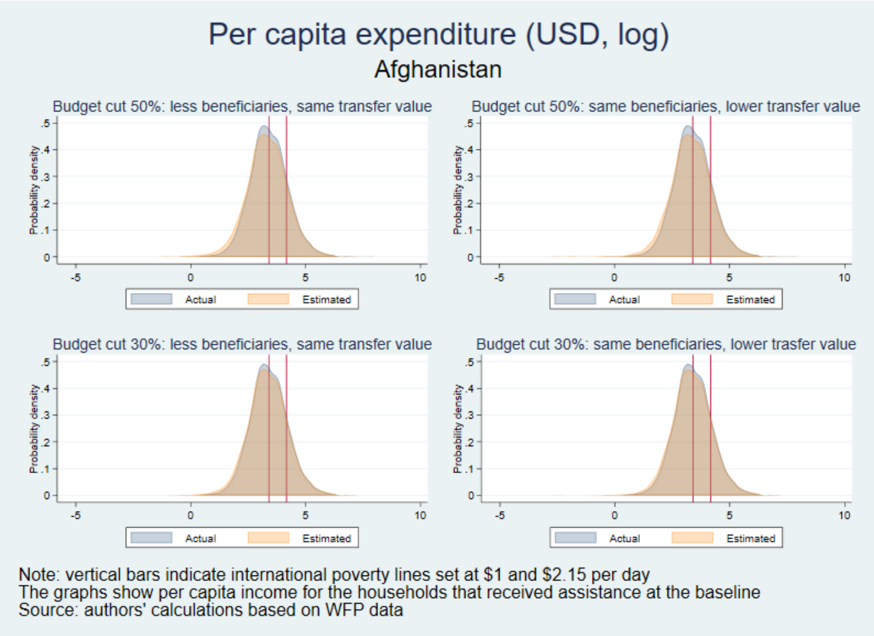
The resulting predictions are then converted back to levels and adjusted for out of bounds predictions.[19] Replacement of missing estimates is done via a simple expansion of the observed FCS count, proportionally scaled by the percent changes of incomes. This replacement calculation assumes that Engel curves of the food items are linear and radiate from the origin.

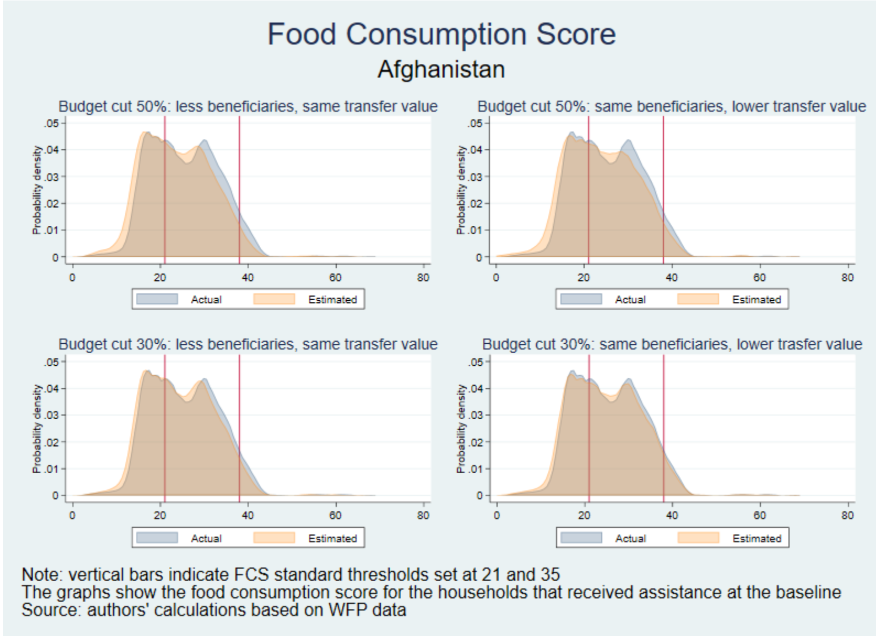
$$FCS^{t1}_{g,h} = FCS^{t0}_{g,h} \cdot \left[1 + \left(E^{t1}_{i,h}/E^{t0}_{i,h} - 1\right)\right] + \hat{\gamma}_1 \qquad [10]$$

[19] The bounds for the prediction are [0,7] inclusive, as there are only 7 days in 1 week, the timeframe for the question in the survey.

Once the replacement has been done, a final replacement is done for predicted values of consumption that fall outside the physical bounds (>7 days a week). These adjusted values are the final predicted FCS consumption levels for the food items.

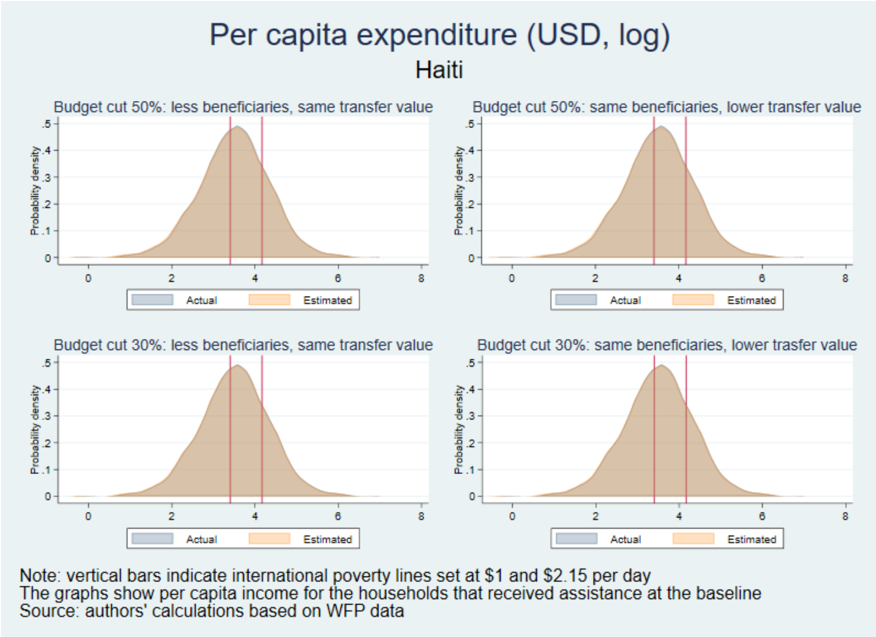
Simulations output: Afghanistan

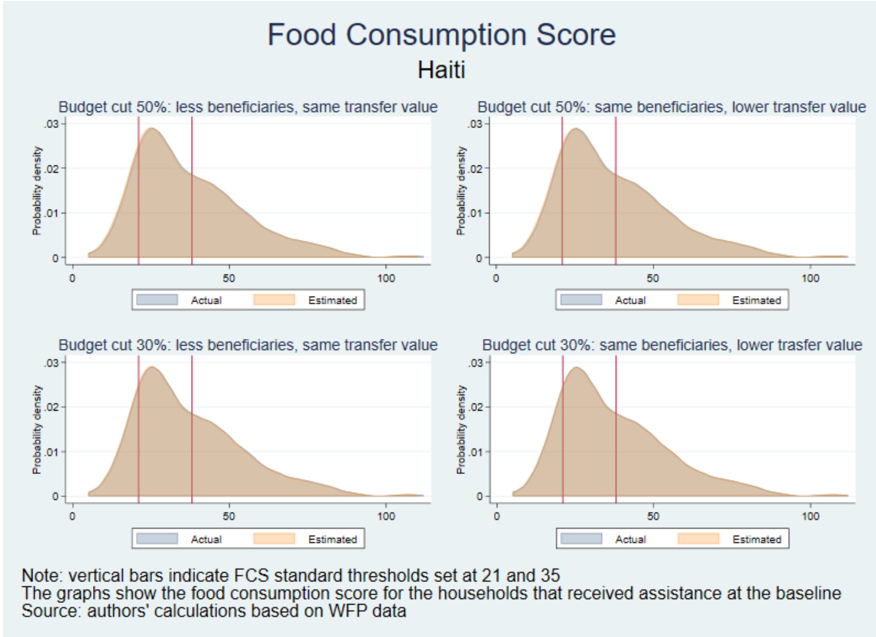




		Percentage of people with expenditure below international poverty lines		Severity of poverty		Percentage of people with FCS below the thresholds	
Budget cut	**Scenario**	**$ 1.00**	**$ 2.15**	**$ 1.00**	**$ 2.15**	**21**	**35**
	Baseline	51.61%	83.51%	21.46%	47.80%	26.09%	76.69%
50%	Less beneficiaries - Same transfer value	53.38%	84.01%	23.53%	49.33%	30.33%	78.69%
50%	Same beneficiaries - Lower transfer value	53.44%	84.05%	23.50%	49.32%	29.78%	78.49%
30%	Less beneficiaries - Same transfer value	52.68%	83.82%	22.70%	48.72%	28.54%	77.84%
30%	Same beneficiaries - Lower transfer value	52.69%	83.82%	22.67%	48.71%	27.57%	77.28%

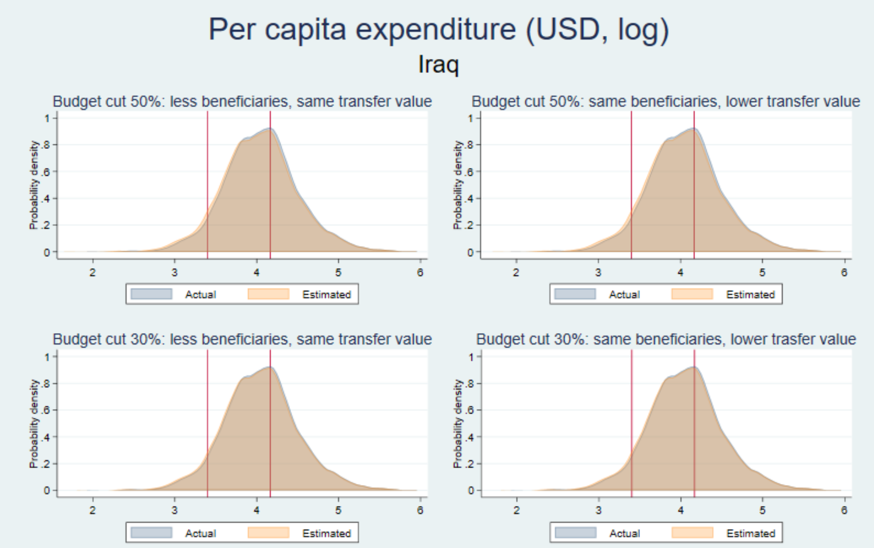
Simulations output: Haiti



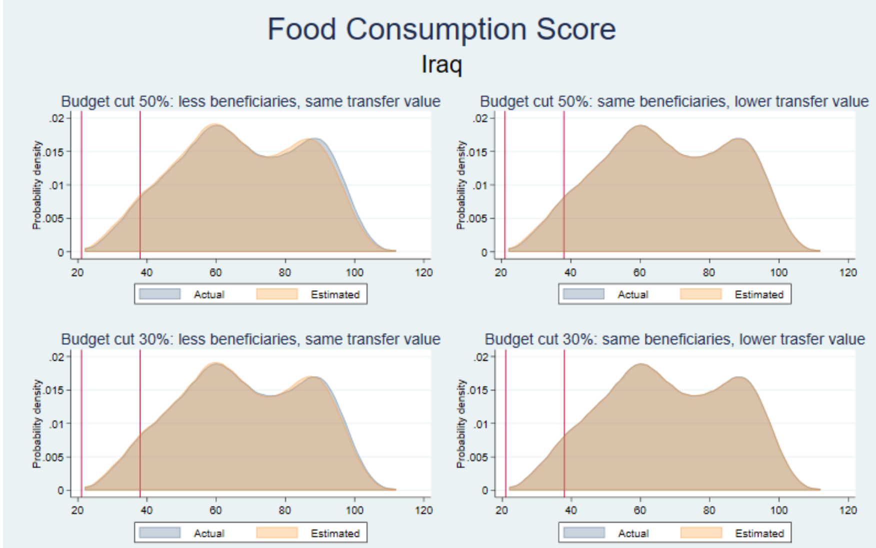


		Percentage of people with expenditure below international poverty lines		Severity of poverty		Percentage of people with FCS below the thresholds	
Budget cut	**Scenario**	**$ 1.00**	**$ 2.15**	**$ 1.00**	**$ 2.15**	**21**	**35**
	Baseline	34.40%	70.86%	13.30%	35.66%	7.55%	36.45%
50%	Less beneficiaries - Same transfer value	34.75%	71.01%	13.63%	35.94%	8.16%	36.86%
50%	Same beneficiaries - Lower transfer value	34.79%	71.03%	13.63%	35.94%	8.09%	36.74%
30%	Less beneficiaries - Same transfer value	34.63%	70.96%	13.50%	35.83%	7.92%	36.70%
30%	Same beneficiaries - Lower transfer value	34.68%	70.98%	13.50%	35.83%	7.79%	36.56%

Simulations output: Iraq



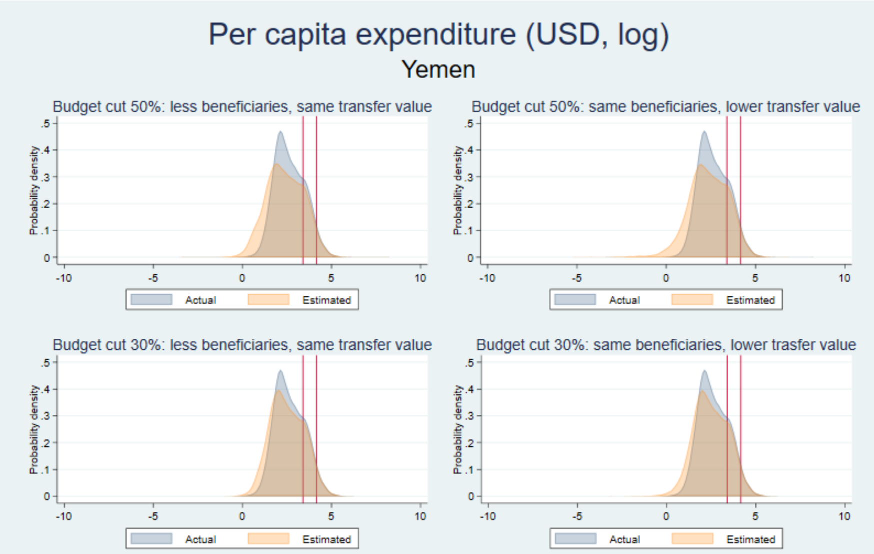
Note: vertical bars indicate international poverty lines set at $1 and $2.15 per day
The graphs show per capita income for the households that received assistance at the baseline
Source: authors' calculations based on WFP data



Note: vertical bars indicate FCS standard thresholds set at 21 and 35
The graphs show the food consumption score for the households that received assistance at the baseline
Source: authors' calculations based on WFP data

		Percentage of people with expenditure below international poverty lines		Severity of poverty		Percentage of people with FCS below the thresholds	
Budget cut	**Scenario**	**$ 1.00**	**$ 2.15**	**$ 1.00**	**$ 2.15**	**21**	**35**
	Baseline	5.34%	57.32%	1.15%	16.31%	0.07%	2.59%
50%	Less beneficiaries - Same transfer value	6.43%	58.94%	1.41%	17.37%	0.10%	2.87%
50%	Same beneficiaries - Lower transfer value	6.28%	58.81%	1.39%	17.35%	0.10%	2.74%
30%	Less beneficiaries - Same transfer value	5.92%	58.30%	1.30%	16.95%	0.08%	2.76%
30%	Same beneficiaries - Lower transfer value	5.89%	58.20%	1.28%	16.93%	0.07%	2.60%

Simulations output: Yemen



Note: vertical bars indicate international poverty lines set at $1 and $2.15 per day
The graphs show per capita income for the households that received assistance at the baseline
Source: authors' calculations based on WFP data

Note: vertical bars indicate FCS standard thresholds set at 21 and 35
The graphs show the food consumption score for the households that received assistance at the baseline
Source: authors' calculations based on WFP data

		Percentage of people with expenditure below international poverty lines		**Severity of poverty**		**Percentage of people with FCS below the thresholds**	
Budget cut	**Scenario**	**$ 1.00**	**$ 2.15**	**$ 1.00**	**$ 2.15**	**21**	**35**
	Baseline	70.61%	92.24%	39.85%	63.41%	14.00%	55.30%
50%	Less beneficiaries - Same transfer value	71.93%	92.51%	43.44%	65.44%	25.05%	58.00%
50%	Same beneficiaries - Lower transfer value	71.95%	92.52%	43.50%	65.49%	29.02%	58.65%
30%	Less beneficiaries - Same transfer value	71.39%	92.41%	42.00%	64.63%	20.45%	56.83%
30%	Same beneficiaries - Lower transfer value	71.40%	92.41%	42.03%	64.66%	23.66%	57.27%

Table 6 - Percentage of beneficiaries affected by budget cut by simulation

Simulation		Country	Change from the baseline					Error (percent)	Error (number of people)
			Not assisted		Assisted				
Budget cut	Scenario		Non eligible	Eligible	Food	Cash	Food and Cash		
50%	Less beneficiaries Same transfer value	Afghanistan	0%	363%	-50%	-50%	0%	-0.01%	-4,420
		Haiti	0%	14%	-50%	-50%	-50%	0.00%	0
		Iraq	0%	145%	-50%	-50%	0%	0.00%	0
		Yemen	0%	552%	-50%	-50%	-50%	0.01%	1,804
50%	Same beneficiaries Lower transfer value	Afghanistan	0%	0%	0%	0%	0%	0.00%	0
		Haiti	0%	0%	0%	0%	0%	0.00%	0
		Iraq	0%	0%	0%	0%	0%	0.00%	0
		Yemen	0%	0%	0%	0%	0%	0.00%	0
30%	Less beneficiaries Same transfer value	Afghanistan	0%	218%	-30%	-30%	0%	0.00%	-452
		Haiti	0%	9%	-30%	-30%	-30%	0.00%	0
		Iraq	0%	87%	-30%	-30%	0%	0.00%	0
		Yemen	0%	332%	-30%	-30%	-30%	0.01%	1,804
30%	Same beneficiaries Lower transfer value	Afghanistan	0%	0%	0%	0%	0%	0.00%	0
		Haiti	0%	0%	0%	0%	0%	0.00%	0
		Iraq	0%	0%	0%	0%	0%	0.00%	0
		Yemen	0%	0%	0%	0%	0%	0.00%	0

Table 7 - Estimated elasticities

Country	Income group	Food			Non-food		
		Own	Cross	Income	Own	Cross	Income
Afghanistan	1	-0.971	0.052	0.910	-1.057	-0.032	1.088
	2	-0.788	0.160	0.628	-1.127	-0.168	1.295
	3	-0.709	0.141	0.568	-1.076	-0.157	1.233
	4	-0.212	0.051	0.162	-1.012	-0.194	1.206
Haiti	1	-0.999	0.012	0.974	-1.036	-0.003	1.022
	2	-0.997	0.035	0.961	-1.101	-0.009	1.110
	3	-0.990	0.084	0.906	-1.211	-0.026	1.236
	4	-0.986	0.090	0.896	-1.171	-0.027	1.197
Iraq	1	-0.996	0.065	0.930	-1.068	-0.005	1.072
	2	-1.000	-0.005	1.005	-0.995	0.000	0.995
	3	-0.987	0.156	0.831	-1.157	-0.013	1.171
	4	-0.986	0.152	0.834	-1.133	-0.013	1.146
Yemen	1	-0.984	0.117	0.868	-1.389	-0.053	1.418
	2	-0.950	0.187	0.763	-1.381	-0.101	1.482
	3	-0.997	0.018	0.979	-1.030	-0.005	1.035
	4	-0.932	0.185	0.747	-1.256	-0.093	1.349

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