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Can Unconditional Cash Transfers Mitigate the Impact of Civil Conflict on Acute Child Malnutrition in Yemen?

Evidence from the National Social Protection Monitoring Survey

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ABSTRACT

Hunger and acute child malnutrition are increasingly concentrated in fragile countries and civil conflict zones. According to the United Nations, Yemen's civil war has caused the world's worst humanitarian crisis in recent history. We use high-frequency panel data and district fixed-effects and household fixed-effects models to estimate the impact of civil conflict on child nutrition. Our results indicate that an increase by one standard deviation in civil conflict intensity translates into an increase in the prevalence of acute child malnutrition by at least 0.7 percentage points if measured by weight-for-height z-scores and by at least 1.7 percentage points if measured by mid-upper arm circumference z-scores.

In mid-December 2018, Yemen's main warring parties agreed to a ceasefire for the contested port city of Hodeida and to allow humanitarian aid to be shipped in and distributed through protected corridors. While the recent agreements are an important, first step to tackle the humanitarian crisis, the road to a sustainable peace agreement will certainly be long and bumpy. Relative stability could soon open a window of opportunity for targeted interventions to support recovery in Yemen. Against this background, our analysis suggests that unconditional cash transfers can be an effective tool in situations of complex emergencies. Our estimation results show that cash transfers can mitigate the detrimental impact of lingering civil conflict on child nutritional status in Yemen on a large scale. Our results also reveal that the regularity of transfer payments influence the magnitude of the mitigation effect, as regular assistance allows beneficiary households to smoothen their food consumption and other demands influencing child nutrition outcomes.

Keywords: acute child malnutrition, unconditional cash transfers, civil conflict, fixed-effects

1. INTRODUCTION

Hunger and acute child malnutrition are increasingly concentrated in fragile countries and civil conflict zones (IFPRI 2018; von Grebmer et al. 2015). About 1.35 billion children and adolescents under the age of 18 live in a country affected by civil conflict, and almost 357 million of them live in a conflict zone (Bahgat et al. 2017). Currently, the most dramatic case in point is Yemen. Conservative estimates suggest that the death toll has reached nearly 50,000 people among active participants in battles between January 2018 and July 2018, and that there were at least 6,500 civilian casualties, including more than 1,600 children, between March 2015 and July 2018 (Fahim 2018). More than two million people were forced to flee their homes (UNHCR 2018). In October 2018, the United Nations Office for the Coordination of Humanitarian Affairs (UN-OCHA) warned that half the population—some 14 million people—could soon be on the brink of famine and completely relying on humanitarian aid for survival (Reuters 2018). According to the international NGO Save the Children, 84,700 children under the age of five may have died from acute malnutrition between April 2005 and October 2018, as a result of the conflict (BBC 2018a). Although the precise estimates are contestable, there is broad consensus that Yemen's current situation is extremely alarming in terms of widespread starvation, especially among young children.

Evidence on the detrimental consequences of civil conflict on human capital, particularly when exposed at early ages, is strong (e.g., Alderman et al. 2006; Bundervoet and Verwimp 2009; Akresh et al. 2012a, 2012b; Minoiu and Shemyakina 2012; Domingues and Barre 2013; Dagnelie et al. 2018). However, rigorous empirical research on how to mitigate the adverse impact of civil conflict is limited. An exception is Tranchant et al. (2018), who assessed the effectiveness of food assistance in Mali. Using a quasi-experimental impact evaluation method, the authors find that food assistance has a protective effect among food-insecure population in conflict settings. Other researchers discussed the role of different interventions in fragile contexts. For example, Rossi et al. (2006) explore the role of health and nutrition interventions in the Democratic Republic of Congo, but the lack of baseline data or credible counterfactuals make causal inference about the effectiveness of the interventions examined difficult, if not impossible.

Despite common concerns of cash diversion, including for war purposes, unconditional cash transfer programs have become increasingly popular in fragile contexts, including in active conflict zones, and have been employed in Afghanistan, Chechnya, Democratic Republic of Congo, Nigeria, Pakistan, Somalia, Syria, and Yemen (e.g., Economist 2018a; HPN 2012). The spread of mobile phones and mobile-money transfer systems, such as through the traditional Muslim *hawala* networks, has helped to leverage the implementation of cash transfers in conflict-prone settings. Operational evaluations of cash transfers in fragile and conflict-affected areas suggest that the risks of diversion, corruptible behavior, and insecurity concerns are largely overstated or at least are not greater than in the case of in-kind transfers, such as food assistance (Chene 2010; Gordon 2015; Bailey and Harvey 2015; Doocey and Tappis 2016). Moreover, cash transfers have been found to facilitate the reintegration of ex-combatants into their local communities (Gilligan et al. 2012; Annan and Blattman 2016) and, in some settings, reduce the risk of civil conflict in fragile communities (Crost et al. 2016). However, there is little scientific evidence on the effectiveness of unconditional cash transfers on food security and nutrition outcomes in fragile contexts and conflict zones. Increasing experience among program implementers suggests that cash transfers do have a substantial mitigation effect, counteracting the detrimental impact of civil conflict (ODI 2015; World Bank 2011).

The objective of this paper is twofold. First, we quantify the detrimental impact of civil conflict increasing acute child malnutrition in Yemen. We exploit quarterly variation in conflict events at the district level to assess the impact on weight-for-height z-scores (WHZ) and mid-upper arm circumference z-scores (MUACZ) of children under five years of age. According to our knowledge, despite the alarming nutritional emergency, the detrimental impact on child nutrition has not been rigorously quantified. Our results indicate that an increase by one standard deviation in civil conflict intensity translates into an increase in the prevalence of acute child malnutrition in our sample by at least 0.7 percentage points, if measured by WHZ, and by at least 1.7 percentage points, if measured by MUACZ.

Second, we assess the mitigation effect of the national cash transfer program of the Social Welfare Fund (SWF). Although our data do not offer an experimental design, the longitudinal nature of the dataset allows us to control for unobserved household-level heterogeneity and seasonal variations. We use data from the 2012-13 National Social Protection Monitoring Survey (NSPMS) that provides observations from four survey rounds over a period of one year. Households' beneficiary status was determined prior to the observation period of our study and remains fixed throughout that period, independent of the households' living conditions and the nutritional status of children in the household. The results of our household fixed-effects (FE) model estimations suggest that the cash transfer program mitigates the detrimental impact of civil conflict on child nutrition. This holds for children both in households that have been beneficiaries for a long time and in households that were newly enrolled. Modifications of our model estimations further suggest that the regularity of transfer payments matters for the size of the mitigation effect. Finally, we discuss the policy implications of our findings that may strengthen the mitigating role of cash transfers in fragile countries and civil conflict zones and particularly in Yemen.

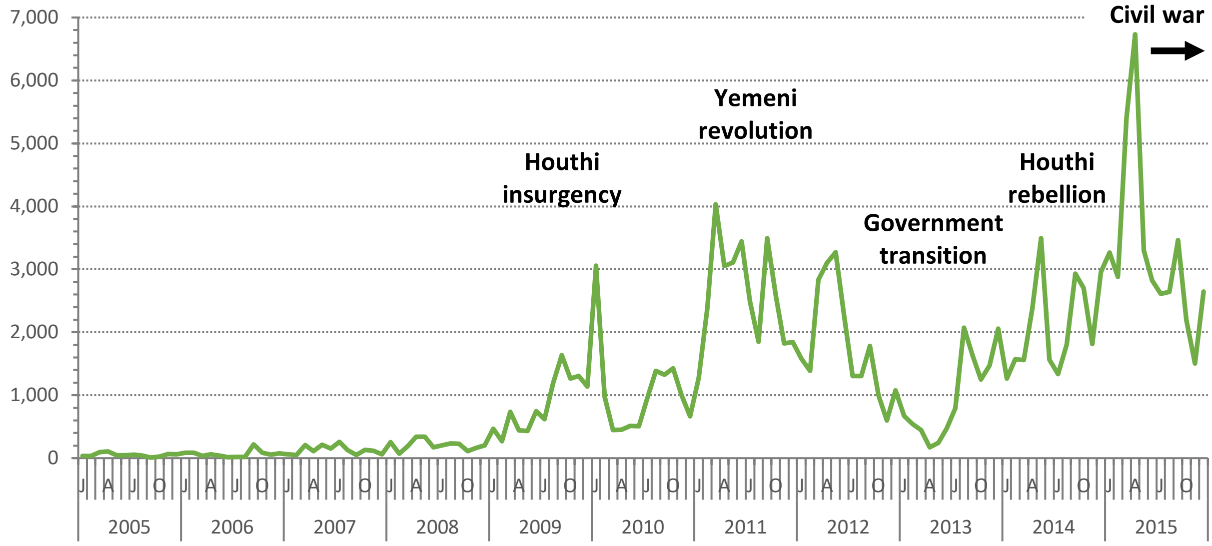
The rest of the paper proceeds as follows. Section 2 provides the context of our study. Section 3 presents the data and descriptive statistics. Section 4 explains the methods of the econometric analysis, and Section 5 presents and interprets the estimation results. Section 6 concludes and discusses the policy implications of our findings.

2. STUDY CONTEXT: EMERGENCE OF YEMEN'S CURRENT CIVIL WAR

Yemen's current civil war began with the 2011-12 revolution against President Ali Abdullah Saleh, who became the first president of a unified north and south Yemen in 1990. The Yemeni revolution shortly followed the Tunisian and Egyptian revolutions and other "Arab Spring" protests throughout the Middle East and North Africa (MENA) region. In Yemen, mass protests in early 2011 demanding better governance, people's voice, and economic opportunities evolved into civil conflict, including armed clashes between protesters and government security forces (WFP 2012). Political resistance and mass protests quickly spread from the capital, Sana'a, throughout the country, melding with three ongoing prolonged conflicts (Economist 2013; 2014; 2015; 2017a). First, since 2004 military troops frequently battled rebels from the Houthi clan to regain full control over Yemen's northwest. The Houthi insurgency heated up in 2009 but quieted the following year after a ceasefire was signed (Taylor 2015). Second, in the south, since 2008 clashes of government security forces with protesters demanding political reform and partial secession (anew) from the north became more frequent. In parallel, government also struggled to control a range of jihadist groups, lawless tribes, secessionist efforts, and bandits in parts of the rural south (WFP 2012). Third, from 2009 Al-Qaeda in the Arabian Peninsula (AQAP) gained influence and launched terrorist attacks across Yemen, including in Sana'a.

The 2011-12 revolution ended with the signature of a power transition agreement in early 2012 (World Bank et al. 2012). Abdrabbuh Mansur Hadi, who was Saleh's former vice president, was hastily elected as president in February 2012. The new government struggled to unite Yemen's fractious political landscape and to fend off threats both from Houthi militants and AQAP (Economist 2017a, 2017b, 2017c). Although the number of conflict events declined in the second half of 2012 and in the first half of 2013, political instability remained, terrorist attacks continued, and violent clashes between different militia groups and with government security forces flared across the country in the second half of 2013 (Figure 2.1).

Figure 2.1: Number of conflict events per month in Yemen, 2005 to 2015



Source: Own representation based on GDELT 1.0 and GDELT 2.0 data.

In the fall of 2014, Houthi fighters swept into Sana'a and quickly gained control over strategic points in the city (Economist 2014; El-Naggar 2015). The Houthis refrained from an immediate coup d'état, but forced President Hadi to negotiate a 'unity government' with other political factions. In early 2015, Hadi along with his ministers resigned after his presidential palace and private residence came under attack. The Houthis declared themselves in control of the government, dissolved the Parliament, and installed the interim Supreme Revolutionary Committee. Hadi first escaped to the port city of Aden in Yemen's south, before fleeing to Riyadh in Saudi Arabia (BBC 2015). In Aden, Hadi declared that he remained the legitimate president of Yemen, proclaimed the city as the temporary capital, and called on loyal government officials and military officers to rally to him. Subsequently, Yemen's civil war erupts between loyalists of Hadi's government and the Houthis. A coalition of Arab countries led by Saudi Arabia began military operations against the Houthi fighters. Since early 2018, the Southern Transitional Council—a secessionist organization with its headquarters in Aden—joined the conflict in fighting against Hadi's government (Dahlgren 2018; Economist 2018).

The Yemeni civil war has lasted for over three years and has had devastating consequences for the population, particularly for young children. The United Nations declared the crisis in Yemen as "the world's worst humanitarian crisis" (UN 2018) and warned of a looming large-scale famine. Basic infrastructure, including sanitation and drinking water systems, collapsed. A severe cholera epidemic began in September 2016, the largest documented cholera epidemic of modern times. Between September 2016 and March 2018, there were more than 1.1 million suspected cholera cases with 2,400 deaths due to the disease (Camacho et al. 2018).

On 13 December 2018, Yemen's main warring parties agreed to an immediate ceasefire for the contested port city of Hodeidah, which is the gateway for the bulk of humanitarian aid coming into the country (Wintour and McKernan 2018). After skirmishes immediately following the agreement, the ceasefire was reported to have taken effect on 18 December (BBC 2018b).

3. DATA AND DESCRIPTIVE STATISTICS

The observation period of our empirical analysis is from July 2012 to October 2013. This falls within the transitional period of Yemen's government, when civil conflict was less intense before the outbreak of the current civil war (Figure 1). It was also the time when a window of opportunity opened for increasing and expanding public assistance to disincentivize individuals to engage in civil conflict for economic reasons and to protect people's living conditions from the impact of possible conflict intensification and other shocks (e.g., Berman et al. 2011; Blattman and Ralston 2015; Maystadt and Ecker 2014).

In this analysis, we combine high-frequency, longitudinal household survey data with georeferenced conflict event data. The survey data are from the Yemen National Social Protection Monitoring Survey (NSPMS). The conflict event data were compiled by the GDELT Project (2013; 2015).[1] We merged the conflict event data to the household survey data at the administrative district level and by survey round.

National Social Protection Monitoring Survey and the Social Welfare Fund program

The NSPMS was implemented by the United Nations' Children Fund (UNICEF), the International Policy Centre for Inclusive Growth (IPC-IG); Yemen's Ministry of Planning and International Cooperation; and Interaction in Development, with support from the Yemen NSPMS Technical Committee (IPC-IG et al. 2014a). The survey had two main objectives: (1) to examine the living conditions of poor households in Yemen after the 2011-12 revolution, and (2) to assess the targeting of the national cash transfer program of the Social Welfare Fund (SWF) and the program's impact on a variety of development indicators, including child nutrition.

The SWF cash transfer program is an unconditional cash transfer program of the Government of Yemen, supported by the World Bank. It provides financial assistance to citizens who are temporarily or permanently unable to sustain themselves and whose families are not able to support them financially. The beneficiaries include socially-disadvantaged people, such as the elderly, disabled people, and orphans, and economically-disadvantaged people, such as unemployed men and single, widowed, or divorced women (IPC-IG et al. 2014a).

Survey sample

The NSPMS was designed to provide nationally representative estimates of key indicators of households' living conditions (when using survey sampling weights) and to accommodate the assessment of the SWF cash transfer program (IPC-IG et al. 2014a). The survey oversampled at the district level both the poor population and SWF beneficiaries and potential beneficiaries. Data collection for the NSPMS started in October 2012 and was completed in September 2013. The survey provides data for a balanced sample of 6,396 households. Each of these households were interviewed on a quarterly basis over the 12 months of the survey period. The balanced sample provides household data from 19 governorates out of the 21 mainland governorates and for 218 districts out of the 331 mainland districts. Districts in the two northern governorates of Sa'ada and

[1] https://www.gdeltproject.org/

Al-Jawaf—the stronghold of the Houthi rebels—suffered complete attrition, as the enumerator teams were unable to visit the enumeration areas in later survey rounds because of serious security concerns (IPC-IG et al. 2014a). A detailed description of the sample design and sampling procedures can be found in IPC-IG et al. (2014b).

The balanced sample includes 3,644 beneficiary households, who were defined as households that had ever received a SWF cash transfer payment, and 2,752 non-beneficiary households, who were never enrolled in the cash transfer program. The beneficiary households include 2,188 “old beneficiary” households and 1,175 “new beneficiary” households. These beneficiary groups were defined using a district-based census of poor people in 2008. Old beneficiaries are those who were already enrolled in the program at the time of the census, while new beneficiaries are those who did not receive benefits at that time, but were identified as potential beneficiaries. New beneficiaries were gradually enrolled in the program from 2011 onward. Some of the new beneficiaries received a first cash transfer payment in early 2011, but their payments were suspended during the 2011-12 revolution due to a lack of funds. Their payments resumed during the observation period of our study. Other new beneficiaries received their first payment after the first round of NSPMS data collection (IPC-IG et al. 2014a). Transfer payments for old beneficiaries were generally not suspended during the 2011-12 revolution.

The beneficiary status of 281 beneficiary households (7.7 percent) is not specified in the released NSPMS dataset. However, our data checks strongly suggest that these households were misclassified as beneficiaries in the survey sample design or excluded from the program after the sample selection and during the survey. About one-fourth of them (24.6 percent) reported to have not received any transfer payment during the observation period; most of them (59.8 percent) received only one payment; and none of them received all four regular payments throughout the observation period of the survey. We therefore drop these households from our sample to reduce estimation biases from “contamination” of our beneficiary groups.

Child nutrition

Our analysis uses indicators of acute child malnutrition (i.e., “wasting”), as our study focus is on the immediate nutritional impact of civil conflict. Moreover, the observation period of the underlying data is too short to credibly track the impact on long-term child nutrition indicators that measure linear growth faltering (i.e., “stunting” or low height-for-age). There are two common child nutrition indicators of wasting: (1) weight-for-height and (2) mid-upper arm circumference (MUAC). Wasting implies a recent or continuing severe process of weight loss, which is often associated with acute starvation or severe disease (WHO 1995). Weight-for-height and MUAC measures are accurate predictors of mortality among children with severe acute malnutrition (Chiabi et al. 2017). The two indicators should be used as complementary—rather than alternative—measures to diagnose the prevalence of acute malnutrition (Grellety and Golden 2016a).

For all survey rounds, the NSPMS included an anthropometry module that provides measurements of the body height and weight of all children who permanently lived in the interviewed households and were aged between 0 and 59 months at the time of the survey rounds. The module also provides MUAC measurements for these children if they were 6 months or older. Hence, these anthropometric data allow the tracking of the nutritional status of individual children over the 12-month observation period.

We used the height and weight measurements in combination with information on child sex, age, edema signs, and positioning for height measurement to compute weight-for-height z-scores (WHZ) by applying a routine developed by Leroy (2011) for the Stata software package. We dropped children from our sample if they had missing WHZs in any survey round; if their WHZ in any round was outside a biologically plausible range (defined as -5 ≤ WHZ ≤ 5, following the classification of outlier measurements recommended by the World Health Organization); or if their height in any round was lower than in any previous survey round (as shrinking in children is biologically impossible). We use MUAC z-scores (MUACZs) as provided by the released NSMPS dataset. We do not consider the MUACZs of children if they had missing MUACZs in any survey round or their MUACZ in any round was outside a biologically plausible range (defined as -5 ≤ MUACZ ≤ 5). Children are classified as wasted if their WHZ or MUACZ is below -2; they are severely wasted if their WHZ or MUACZ is below -3.

WHZ and MUACZ are the outcome variables of our econometric analysis. We therefore restrict our sample to households who have children under five years of age with valid WHZs in all survey rounds. Our final sample includes 36.5 percent of the households in the original balanced household sample (after dropping misclassified/terminated beneficiary households). It has four rounds of observations for 3,176 children (aged 0-59 months) from 2,232 households, of which 2,687 children (aged 6-59 months) from 1,905 households have valid MUACZ scores.

Table 3.1 presents the prevalence of acute malnutrition and severe acute malnutrition among pre-school children in our sample for both indicators.[2] Note that the standard deviations (SD) of WHZ and MUACZ in all rounds are near or even below 1.0, which gives us confidence in the quality of the anthropometric data (Grellety and Golden 2016b; Mei and Grummer-Strawn 2007). The average SD—across all four survey rounds—is 1.03 for WHZ and 0.95 for MUACZ.

Table 3.1. Prevalence of acute and severe acute malnutrition among pre-school children

	Children aged 0-59 months				Children aged 6-59 months			
	Weight-for-height z-score (WHZ)		Wasting (%)		Mid-upper arm circumference z-score (MUACZ)		Wasting (%)	
Survey round	Mean	SD	Moderate & severe (WAZ<-2)	Severe (WAZ<-3)	Mean	SD	Moderate & severe (MUACZ <-2)	Severe (MUACZ <-3)
1	-0.69	1.24	12.8	3.7	-1.19	1.00	19.4	3.5
2	-0.54	0.96	6.6	0.9	-1.02	0.91	13.0	1.9
3	-0.56	0.94	6.8	1.1	-0.96	0.91	12.7	1.2
4	-0.65	0.98	8.7	1.5	-1.00	0.95	14.5	1.3
Observations:	3,176				2,687			

Source: Own estimated based on 2012-13 Yemen NSPMS data.

Social Welfare Fund program beneficiaries

Our final sample has 1,084 beneficiary households, made up of 448 new beneficiary and 636 old beneficiary households, and 1,148 non-beneficiary households. The selection of beneficiary households based on eligibility criteria differed between old and new beneficiaries due to a series of reforms of the SWF cash transfer program that started in 2008. The most important reforms were (1) the enactment of an SWF law in early 2008 that specifies the eligibility criteria of the cash transfer program, and (2) the (re)assessment of all SWF beneficiaries and potential beneficiaries based on the above-mentioned census of poor people and the use of a proxy means test (PMT) formula that accounts for these criteria. While the eligibility criteria had been considered in part for

[2] WHZ and MUACZ are strongly correlated (for children aged 6-59 months): The Pearson correlation coefficient is 0.443 for Round 1, 0.537 for Round 2, 0.589 for Round 3, and 0.600 for Round 4.

the selection of beneficiary households before 2011, the PMT formula was first implemented in 2011 to select new beneficiaries. Due to the political sensitivity of excluding beneficiaries from the program, especially after the 2011-12 revolution, the reclassification of old beneficiaries through the use of PMT screening were not effectively enforced (IPC-IG et al. 2014a). Given these classification issues, our analysis mainly focuses on all beneficiary households, but we will show that the results are robust to both new and old beneficiary households considered separately.

As a first data check, we used information from the NSPMS data to test mean differences in variables corresponding to the SWF cash transfer program eligibility criteria between the different groups of beneficiaries and non-beneficiaries. Annex 1 describes the eligibility criteria and presents the results of our analysis in detail. The results confirm that for most eligibility criteria beneficiary households are socially and economically disadvantaged compared to non-beneficiary households, on average. They also suggest that there are many households in the non-beneficiary group that appear to fulfill the eligibility criteria. Most importantly, the results indicate that there are no statistically significant differences in the means of most eligibility criteria variables between old and new beneficiary households, despite the selection of new beneficiaries through the PMT method. On average, old beneficiaries appear to be better targeted with respect to some social criteria, particularly for households with elderly people and single, widowed, or divorced women, whereas new beneficiaries appear to be better targeted in terms of total chronic poverty. Overall, the findings imply that the introduction of the PMT method has slightly shifted the targeting focus towards economic eligibility criteria rather than social eligibility criteria, while it appears not to have substantially improved general targeting effectiveness (IPC-IG et al. 2014a).

Social Welfare Fund cash transfer payments

The NSPMS provides information on the payment modalities of the SWF cash transfer program. By law, transfer payments were to be made quarterly (IPC-IG et al. 2014a). While cash transfers were administered to individual beneficiaries, beneficiaries of the same households typically received their payments at the same time. In 85.3 percent of all beneficiary households in our sample, there is only one registered beneficiary per household. The percentage is 90.8 percent for new beneficiary households and 81.4 percent for old beneficiary households.

Table 3.2. Frequency of Social Welfare Fund cash transfer payments received by households between July 2012 and October 2013

Transfer payments received	All beneficiaries	New beneficiaries	Old beneficiaries
1	1.7	4.7	3.0
2	19.0	22.3	20.4
3	43.7	46.2	44.7
4	35.5	26.8	31.9
Observations	1,084	448	636

Source: Own estimated based on 2012-13 Yemen NSPMS data.
Note: The frequencies are reported in percentage. The frequency is calculated by household as the count of the survey rounds when the interviewed household reported to have received a payment since the last interview and, for the first round, over the three-month period prior to the first interview.

Table 3.2 shows the frequency of the received transfer payments among beneficiary households. It suggests that many beneficiary households received their payments irregularly. While all beneficiary households in our sample reported having received cash transfers, more than one in five households received only one or two payments during the observation period of our study. On average, new beneficiaries received 2.95 payments and old beneficiaries received 3.13 payments.

The mean difference is statistically significant and reflect that some new beneficiaries were enrolled in the program after the first survey round.

Since the 2008 SWF program reforms, the maximum monthly transfer amount per beneficiary was YER 4,000 (IPC-IG et al. 2014a), or about USD 18.64 in early October 2012. This is equivalent to USD 0.10 per day in a typical six-person household with one registered beneficiary. While this amount is small, focus group discussions revealed that beneficiaries valued the regularity of the transfer payments to cover regular expenses for basic needs, including food purchases, and to repay debts for purchases made on credit (IPC-IG et al. 2014a).

Conflict event data

The conflict event data are taken from the GDELT 1.0 Event Database, which provides data through 31 March 2013 (GDELT 2013) and the GDELT 2.0 Event Database, which provides data from 1 April 2013 onward (GDELT 2015). The GDELT Project compiles news media records of conflict events from countries around the world. The databases provide the number of conflict events per day, the "importance" (as proxy of the significance) of the event, and the location of the event, among other variables. We consider only conflict events that are classified as important events and for which the administrative district of the event location can be identified. For almost all reported events, the location is specified by the precise geographic coordinates of the event or at least the geographic coordinates of the capital of the district where the event took place.

We used the GDELT event coordinates and a geographic map for Yemen to identify the districts of the event locations. We were able to identify the district of the event location for 99.5 percent of all important events in Yemen between 2005 and 2015. Then, we aggregated the number of events at the district level and by month per year. Finally, we merged this dataset with our NSPSMS sample at the district level and by year and month.

Table 3.3 shows summary statistics for the exposure of the households in our sample to civil conflict and the intensity of civil conflict experienced by survey round. We report the statistics for the different groups of SWF cash transfer program beneficiaries and non-beneficiary households.

Table 3.3. Summary statistics of civil conflict exposure and intensity

	All households		All beneficiaries		New beneficiaries		Old beneficiaries		Non-beneficiaries	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Conflict exposure during study observation period										
Conflict event in own district, 0/1	0.410	0.492	0.414	0.493	0.408	0.492	0.418	0.494	0.405	0.491
Conflict intensity: Number of conflict events in own district by survey round										
Round 1	12.32	73.01	13.44	76.20	11.36	70.16	14.90	80.21	10.85	67.38
Round 2	9.36	41.19	9.25	41.57	7.69	37.18	10.35	44.40	9.26	39.78
Round 3	4.14	18.02	4.16	18.06	3.73	17.53	4.47	18.43	4.07	17.35
Round 4	5.99	22.65	6.52	25.29	5.56	21.68	7.20	27.55	5.47	19.78
Observations	2,232		1,084		448		636		1,148	

Source: Own estimated based on 2012-13 Yemen NSPMS and GDELT data.
SD = standard deviation

Table 3.4 shows the results of mean difference tests for conflict exposure and intensity between the different household groups. The estimates clearly show that, although conflict exposure and intensity slightly vary among the different household groups, there are no statistically significant differences in these variables between the groups on average. This finding provides suggestive evidence that the coverage of the SWF cash transfer program is not correlated (positively or negatively) with the occurrence or intensity of civil conflict in our sample.

Table 3.4. Mean difference tests between household groups for civil conflict exposure and intensity

	All vs. non-beneficiaries		New vs. non-beneficiaries		Old vs. non-beneficiaries		New vs. old beneficiaries	
	Differ-ence	Signi-ficance	Differ-ence	Signi-ficance	Differ-ence	Signi-ficance	Differ-ence	Signi-ficance
Conflict exposure during study observation period								
Conflict event in own district, 0/1	-0.009		-0.003		-0.013		0.010	
Conflict intensity: Number of conflict events in own district by survey round								
Round 1	-2.59		-0.51		-4.05		3.54	
Round 2	0.01		1.57		-1.09		2.66	
Round 3	-0.09		0.34		-0.40		0.74	
Round 4	-1.05		-0.09		-1.73		1.64	

Source: Own estimated based on 2012-13 Yemen NSPMS and GDELT data.
Note: ***, **, * Per a two-sided t-test for unpaired data with unequal variance, mean difference is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively.

4. METHODS

Identification strategy

The econometric analysis exploits the panel structure of our dataset. We use fixed-effects (FE) regression models to first estimate the nutritional impact of civil conflict and then the mitigation effect of the SWF cash transfer program. Hence, our analysis includes two main steps. First, we test our hypothesis that acute child malnutrition in Yemen increases with the number of conflict events that children experience. Second, we examine if unconditional cash transfers can help to mitigate the detrimental impact of conflict intensification on children's WHZ and MUACZ—the most common child nutrition indicators used for diagnosing acute child malnutrition. Specifically, we explore the mitigation effect of SWF cash transfer program for all beneficiaries compared to non-beneficiaries. We then check the robustness of our estimation results by separately considering only new and old beneficiaries in the treatment variable, given the changes in selection and enrollment modalities discussed above. In addition to exploring the mitigation effect that is associated with program participation, we estimate the marginal mitigation effect that is associated with changes in the regularity of received transfer payments among all beneficiaries.

We estimate regression models with district FE and household FE, together with survey round FE. These models address potential endogeneity problems due to unobserved (time-constant) heterogeneity across district and households, respectively, as well as time-variant factors, such as seasonality. Introducing district or household FE helps to minimize potential estimation biases from spatial or inter-household correlations between child nutritional status and civil conflict or the SWF cash transfer program that may occur by coincidence or from unobserved or omitted factors driving both outcomes. The household FE model is more restrictive and can be expected to yield more robust estimation results, as it allows only for variations in variables at the household level or higher levels (such as district) over time. In all estimations, standard errors of the parameter estimates are clustered at the district level, relaxing the usual requirement that the observations be independent within clusters.

Estimating the nutritional impact of civil conflict intensity

The specifications of the district and household FE models have the following estimation form:

$$y_{ir} = \beta_1 x_{dr} \, [+Z'_{ir}\,\gamma_1 + Z'_h\,\gamma_2 + \, W'_{dr}\,\delta\,] \, + \Omega_d \, [+\Psi_h] \, + \Phi_r \, + \, \varepsilon_{ir} \qquad (1)$$

where i refers to the individual child, h refers to the child's household, d refers to the district where the household is located, and r refers to the survey round. y_{ir} denotes the child's nutritional status per survey round, measured by WHZ or MUACZ. x_{dr} denotes the number of conflict events per district and by survey round that occurred since the last interview to the current interview or, for the first round, over the three-month period prior to the baseline interview. The variable measures the civil conflict intensity that the child experiences. For ease of interpretation of estimation results, we standardized the values of the variable to yield a standard deviation equal to one in our full sample. District FE enter the estimation through Ω_d. Alternatively, household FE, denoted Ψ_h, are used. Survey round FE, denoted Φ_r, are introduced in all specifications. β_1 is the parameter to be estimated, and ε_{ir} is the residual.

Fixed effects control for unobserved heterogeneity likely to be correlated with the dependent variable, i.e., children's nutritional status, and the independent variable(s), i.e., civil conflict intensity in the first estimations and SWF cash transfers in following specifications. These controls are important for several reasons.

First, survey round FE are crucial to account for seasonality effects in both household food insecurity—and hence child nutrition outcomes—and civil conflict (Abay and Hirvonen 2017; Shah and Steinberg 2017; Guardado and Pennings 2017). They also capture external shocks that affect all Yemenis similarly, such as food price spikes in the world market (Breisinger et al. 2011; Ivanic et al. 2012).

Second, civil conflict events are likely to occur more frequently in poor areas where malnutrition is likely to be concentrated and where the opportunity costs to fight are expected to be low (Miguel at al. 2004; Dube and Vargas 2013; Maystadt and Ecker 2014). District FE control for such unobserved spatial heterogeneity. Because we may be concerned about possible changes in the sample population over time and household-level factors that influence child nutrition, we stepwise augment the basic estimation specification by introducing vectors that control for individual characteristics, Z_{ir}, and household characteristics at baseline, Z_h.

Third, civil conflict violence has been shown to be targeted at wealthier households in countries like Burundi (Bundervoet 2010), Rwanda (Verpoorten 2009), Uganda (Blattman and Annan 2010), and the Democratic Republic of Congo (Dagnelie et al. 2018), implying a bias that may push the estimated response of socioeconomic outcomes to conflict toward zero. Household FE control for such unobserved, time-constant heterogeneity across households.

Naturally, we cannot exclude that (unobserved) time-varying factors may act as confounding factors, provided they are correlated with both child nutrition outcomes and civil conflict. Weather shocks, for example, have been found to affect the risk of civil conflict violence (Hsiang et al. 2013; Maystadt and Ecker 2014; Maystadt et al. 2015) and children's nutritional status (Hoddinott and Kinsey 2001; Zivin and Neidell 2013; Kadamatsu et al. 2016). Therefore, weather shocks, denoted by W_{dr}, are introduced as one step of our augmentation of the basic specification. The additional parameters to be estimated in the augmented specifications are γ_1, γ_2, and δ.[3]

The vector Z_{ir} controls for individual characteristics in each survey round. It includes variables identifying the child's sex and his/her age (in months) as linear and squared terms. The vector Z_h controls for time-constant, standard household characteristics that were measured in Round 1 of the NSMPS. It includes variables identifying household wealth, household size (as measured by the number of household members who permanently live in the household), and the

[3] Parameter estimates for the control variables are not discussed in the main text of the paper but are presented for the model estimating the nutritional impact of civil conflict intensity in Tables A2.1 and A2.2 in Appendix II.

sex, the age (in years), and the literacy status of the household head. Household wealth is measured by a household asset-based wealth index. To construct the index for our sample, we used principal component analysis and a large set of household asset variables, following the procedure proposed by IPC-IG et al. (2014c). All other variables are directly available from the NSMPS without considerable transformation.

The vector W_{dr} controls for weather shocks at the district level. It includes either temperature and precipitation anomalies, in one estimation specification, or the Standardized Precipitation Evapotranspiration Index (SPEI), in another specification. Both the anomalies and the SPEI indicate extreme weather events, such as droughts and floods. We constructed these extreme weather indicators from two weather data sources and merged them to our dataset at the district level and by survey round. We used georeferenced land surface temperature and precipitation data from the Moderate Resolution Imaging Spectroradiometer (MODIS) database of the US National Aeronautics and Space Administration (NASA) (Wan 2015) and georeferenced precipitation data from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) database of the Climate Hazards Group at the University of California Santa Barbara (Funk 2015). To obtain one monthly observation per district from the georeferenced data, we applied a series of geoprocessing procedures. Most notably, we used the Spline spatial interpolation method (Mitas 1988) to impute missing observations at the spatial raster level, and the Zonal Statistics function in the ArcGIS software package to calculate district-level averages from the spatial raster data.[4]

We used the monthly, district-level MODIS data to calculate average temperature anomalies and the monthly district-level CHIRPS data to calculate cumulative precipitation anomalies over a three-month observation period. The three-month observation period includes the observation of the survey month of the NSPMS and the preceding two months. Anomalies are generally calculated as the deviation of the current month value from the long-term monthly mean, divided by the monthly long-term standard deviation over the same time period (Dell et al. 2014; Marchiori et al. 2012; Barrios et al. 2010). Our reference period is 2001 to 2015. We also used monthly district-level MODIS data to construct the SPEI based on three-month periods. SPEI is a multi-scalar drought indicator that includes both rainfall and temperature observations and has emerged as one of the most comprehensive drought indexes over recent years (Begueria et al. 2010; Cook et al. 2014).[5] The index is based on a monthly weather-water balance, i.e., precipitation minus potential evapotranspiration (PET). SPEI measures the monthly difference between precipitation and PET and is expressed as a standardized Gaussian variate with a mean of zero and a standard deviation of one.

Estimating the mitigation effect of the Social Welfare Fund cash transfer program

To estimate the mitigation effects of participation in the SWF cash transfer program and the regularity of cash transfer payments on child nutrition, we augment the specifications of the district FE model and household FE model by stepwise introducing a respective treatment variable and an interaction term of the treatment variable with civil conflict intensity. The specifications of the district FE model have the following estimation form:

$$y_{ir} = \beta_1 x_{dr} + \beta_2 t_h \, [+\beta_3 x_{dr} * t_h] \, [+Z'_{ir}\,\gamma_1 + Z'_h\,\gamma_2 + W'_{dr}\,\delta\,] + \Omega_d \, [+\Psi_h] + \Phi_r + \varepsilon_{ir} \quad (2)$$

[4] Information on the precise data sources and computation procedures can be obtained from the authors upon request.

[5] Unlike other water balance-based drought indexes such as the Palmer Drought Severity Index, SPEI does not rely on the water balance of a specific soil system. Because the effect of the evaporative demand is considered in the calculation of SPEI, the index is better suited to account for the effect of warming temperatures on drought occurrence (Begueria et al. 2010).

where t_h is the treatment variable that is time-constant throughout all survey rounds. The additional parameters to be estimated are β_2 and β_3.

In a first set of estimations, the treatment variable, t_h, identifies the program beneficiary status of a household. This variable is binary, and its parameter estimate, β_2, indicates the general effect of program participation on child nutrition independent of the intensity of civil conflict experienced. As explained in the previous section, the beneficiary status of households is defined prior to the observation period of our study. Replacing district FE by household FE in the estimations controls for unobserved selection into the program. We augment both the district FE model and household FE model with a term that captures the interaction between the treatment variable and the conflict events variable, $x_{dr} * t_h$. The parameter estimate of the interaction term, β_3, if positive, indicates a mitigation effect of program participation on child nutrition which counteracts the negative nutritional impact of civil conflict intensification.

An identification concern might be the possibility that beneficiaries and non-beneficiaries are on different development paths in the absence of the SWF cash transfer program. However, given the very low level of pro-poor economic growth and human capital investment in Yemen and the relatively good targeting of beneficiaries in terms of total chronic poverty documented in the previous section, we can reasonably conjecture that improvements in living conditions among beneficiaries is much slower than those among non-beneficiaries, even with the benefits from the SWF cash transfer program. Furthermore, given our focus on the mitigation effect of the program, it is even less obvious to conjecture opposite trend differentials between beneficiaries and non-beneficiaries in conflict affected and non-affected districts. The lack of correlation between the coverage of the SWF cash transfer program and the occurrence or intensity of civil conflict in our sample corroborates this identifying assumption (Table 3.4). Finally, we show that our estimation results for the effect of program participation among all beneficiaries compared to non-beneficiaries are robust to restricting the group of beneficiaries to only new beneficiaries and old beneficiaries, respectively.

In a second set of estimations, we replace the binary treatment variable with a continuous variable that counts the number of SWF cash transfer payments that a household received over the observation period of our study. Hence, the parameter estimate, β_2, indicates the marginal general effect of a change in the regularity of cash transfer payments independent of the intensity of civil conflict experienced. The parameter estimate of the interaction term, β_3, if positive, indicates, at a given payment frequency, the marginal effect of changes in the payment regularity on child nutrition that mitigates the negative nutritional impact of civil conflict intensification. The second set of estimations is motivated by anecdotal evidence on the beneficial effects of regular transfer payments among SWF program beneficiaries (IPC-IG et al. 2014a). Irregularity of payments can potentially affect how beneficiary households spend the cash transfers, with implications for child nutrition outcomes.

5. ESTIMATION RESULTS

In the following, we first establish that there is a robust detrimental impact of civil conflict increasing acute child malnutrition in Yemen. Then, we explore the mitigation effects of the SWF cash transfer program and the regularity of cash transfer payments.

Nutritional impact of civil conflict intensity

Table 5.1 shows that increasing civil conflict intensity is associated with deteriorating child nutrition, increasing the risk of acute child malnutrition. The parameter estimates of the conflict event count variable are highly statistically significant in all estimations for child WAZ and MUACZ. The estimated effect sizes for both nutrition outcomes are similar across the different specifications, which indicates the robustness of our estimation results. The estimated effect of civil conflict on child WAZ ranges from -0.033 in the household FE model estimation (with SPEI) to -0.038 in a district FE model estimation. The estimated effect of civil conflict on child MUACZ is larger. It ranges from -0.056 in the household FE model estimation to -0.064 in a district FE model estimation.

Table 5.1. Estimated impact of civil conflict intensity on child nutrition

Specification	1	2	3	4	5	6	7
Panel A: Weight-for-height z-score (WHZ)							
Conflict events count (std.)	-0.037***	-0.037***	-0.038***	-0.038***	-0.037***	-0.034***	-0.033***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
R-sq.	0.130	0.135	0.138	0.138	0.138	0.524	0.524
Panel B: Mid-upper arm circumference z-score (MUACZ)							
Conflict events count (std.)	-0.064***	-0.064***	-0.064***	-0.062***	-0.061***	-0.058***	-0.056***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
R-sq.	0.140	0.142	0.149	0.150	0.151	0.601	0.601
Controls							
Individual characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	No	No	Yes	Yes	Yes	Dropped	Dropped
Precipitation & temperature anomalies	No	No	No	Yes	No	Yes	No
SPEI	No	No	No	No	Yes	No	Yes
Fixed effects							
District	Yes	Yes	Yes	Yes	No	Dropped	Dropped
Household	No	No	No	No	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own estimation based on 2012-13 Yemen NSPMS and GDELT data.
Note: std. = standardized; SPEI = Standardized Precipitation Evapotranspiration Index.
***, **, * parameter is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively. Standard errors are reported in parenthesis.
Estimations of Panel A are based on 12,704 observations (from 3,176 children aged 0-59 months). Estimations of Panel B are based on 10,748 observations (from 2,687 children aged 6-59 months). In all estimations, standard errors are clustered at the district level. The number of clusters is 218 in Panel A estimations and 215 in Panel B estimations.
Parameter estimates for the control variables are presented in Tables A2.1 and A2.2 in Appendix II.

These estimates imply that an increase in the conflict event count variable by 1 SD decreases children's WAZ by at least 0.033 SDs and their MUACZs by at least 0.056 SDs, on average. One SD in the non-standardized conflict event count variable varies by around 40 conflict events per quarter (from 64 events prior to Round 1 to 16 events prior to Round 3). To put this number into perspective, the average child in our sample was exposed to about seven conflict events in his/her home district per quarter—or 28 events over the entire observation period of this study (July 2011 to October 2012). More than 4 percent of all children were exposed to more than 47 conflict events in at least one quarter. The average number of conflict events per quarter across Yemen was 6,579 events during the observation period; it was almost twice that much during the first two quarters of 2015 (12,209 events), which marked the onset of the current civil war.

An average decrease in child WHZ by 0.033 SDs and child MUACZ by 0.056 SDs translates into an increase in the prevalence of child wasting among the sampled children by 0.7 percentage points, if measured by WHZ, and 1.7 percentage points, if measured by MUACZ. A decrease in average child WHZ and MUACZ by 0.1 SDs translates into an increase in the child wasting prevalence by 1.7 percentage points and 2.8 percentage points, respectively. The prevalence of child wasting in our sample averaged across all four survey rounds is 8.7 percent for WHZ and 14.9 percent for MUACZ (see also Table 3.1).

Mitigation effect of the Social Welfare Fund cash transfer program

Our estimation results in Table 5.2 suggest that the SWF cash transfer program indeed mitigates the detrimental impact of civil conflict on child nutrition. The parameter estimates of the term that captures the interaction between the conflict intensity variable and the program participation variable are positive and highly statistically significant (with p-values smaller or equal to 0.001) in the district FE model estimations with child WHZ as dependent variables and the household FE model estimations with child MUACZ as dependent variables. The parameter estimates of the interaction term in the household FE model estimations for child WHZ and the district FE model estimations for child MUACZ are also positive, but just above the highest conventional statistical significance level of asterisking at a p-value of 0.1; all are statistically significant at least at a p-value of 0.15. The parameter estimates of all variables of interest are quite similar across the different specifications of both the district FE and household FE models (within each estimation panel). These results further increase our confidence in the robustness of these estimation results. The estimates indicate that the mitigation effect is considerably larger for MUACZ as an indicator of child nutrition outcomes than for WHZ.

Table 5.2. Estimated effects of Social Welfare Fund program participation on child nutrition among all beneficiaries compared to non-beneficiaries

Specification	1	2	3	4	5	6	7	8
Panel A: Weight-for-height z-score (WHZ)								
Conflict events count (std.)	-0.037***	-0.061***	-0.060***	-0.059***	-0.059***	-0.058***	-0.053***	-0.052***
	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.020)	(0.020)
Beneficiary (1=yes, 0=no)	-0.003	-0.004	-0.002	-0.010	-0.010	-0.010	.	.
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)		
Interaction term		0.046***	0.044***	0.041***	0.041***	0.041***	0.036	0.036
		(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.024)	(0.024)
R-sq.	0.130	0.131	0.136	0.138	0.138	0.139	0.524	0.524
Panel B: Mid-upper arm circumference z-score (MUACZ)								
Conflict events count (std.)	-0.064***	-0.081***	-0.080***	-0.081***	-0.078***	-0.077***	-0.080***	-0.078***
	(0.007)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.011)	(0.011)
Beneficiary (1=yes, 0=no)	0.024	0.024	0.023	0.039	0.039	0.039	.	.
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)		
Interaction term		0.037	0.035	0.034	0.034	0.034	0.045***	0.045***
		(0.024)	(0.024)	(0.023)	(0.023)	(0.023)	(0.012)	(0.013)
R-sq.	0.140	0.140	0.142	0.150	0.151	0.151	0.601	0.601
Controls								
Individual characteristics	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	No	No	No	Yes	Yes	Yes	Dropped	Dropped
Precipitation & temperature anomalies	No	No	No	No	Yes	No	Yes	No
SPEI	No	No	No	No	No	Yes	No	Yes
Fixed effects								
District	Yes	Yes	Yes	Yes	Yes	Yes	Dropped	Dropped
Household	No	No	No	No	No	No	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own estimation based on 2012-13 Yemen NSPMS and GDELT data.
Note: std. = standardized; SPEI = Standardized Precipitation Evapotranspiration Index.
***, **, * parameter is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively. Standard errors are reported in parenthesis.
Estimations of Panel A are based on 12,704 observations (from 3,176 children aged 0-59 months). Estimations of Panel B are based on 10,748 observations (from 2,687 children aged 6-59 months). In all estimations, standard errors are clustered at the district level. The number of clusters is 218 in Panel A estimations and 215 in Panel B estimations.

These estimation results are also robust to restricting the group of beneficiaries to new and old beneficiaries, shown in Tables 5.3 and 5.4, respectively. The parameter estimates of the interaction term consistently suggest that the mitigation effect is somewhat larger among new beneficiaries than old beneficiaries. Moreover, the parameter estimates are statistically significant in the estimations of the household FE model—the methodologically most robust one—for both child WHZ and MUACZ at least at the 10 percent level. Thus, our estimation results provide strong statistical evidence for a mitigation effect of the SWF cash transfer program that counteracts the detrimental impact of civil conflict on child nutrition.

Table 5.3. Estimated effects of Social Welfare Fund program participation on child nutrition among new beneficiaries compared to non-beneficiaries

Specification	1	2	3	4	5	6	7	8
Panel A: Weight-for-height z-score (WHZ)								
Conflict events count (std.)	-0.042***	-0.059***	-0.058***	-0.057***	-0.057***	-0.056***	-0.055***	-0.054***
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.019)	(0.020)
Beneficiary (1=yes, 0=no)	-0.006	-0.006	-0.005	-0.011	-0.011	-0.011	.	.
	(0.041)	(0.040)	(0.039)	(0.040)	(0.040)	(0.040)		
Interaction term		0.062***	0.060***	0.056***	0.055***	0.056***	0.058*	0.059*
		(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.033)	(0.032)
R-sq.	0.143	0.144	0.150	0.153	0.153	0.153	0.516	0.516
Panel B: Mid-upper arm circumference z-score (MUACZ)								
Conflict events count (std.)	-0.072***	-0.087***	-0.087***	-0.086***	-0.083***	-0.082***	-0.079***	-0.077***
	(0.013)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
Beneficiary (1=yes, 0=no)	0.024	0.025	0.027	0.046	0.046	0.046	.	.
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)		
Interaction term		0.067*	0.064	0.061	0.062	0.062	0.049***	0.050***
		(0.040)	(0.041)	(0.039)	(0.040)	(0.040)	(0.016)	(0.017)
R-sq.	0.172	0.173	0.178	0.183	0.184	0.184	0.614	0.615
Controls								
Individual characteristics	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	No	No	No	Yes	Yes	Yes	Dropped	Dropped
Precipitation & temperature anomalies	No	No	No	No	Yes	No	Yes	No
SPEI	No	No	No	No	No	Yes	No	Yes
Fixed effects								
District	Yes	Yes	Yes	Yes	Yes	Yes	Dropped	Dropped
Household	No	No	No	No	No	No	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own estimation based on 2012-13 Yemen NSPMS and GDELT data.
Note: std. = standardized; SPEI = Standardized Precipitation Evapotranspiration Index.
***, **, * parameter is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively. Standard errors are reported in parenthesis.
Estimations of Panel A are based on 9,116 observations (from 2,279 children aged 0-59 months). Estimations of Panel B are based on 7,696 observations (from 1,924 children aged 6-59 months). In all estimations, standard errors are clustered at the district level. The number of clusters is 212 in Panel A estimations and 207 in Panel B estimations.

Table 5.4. Estimated effects of Social Welfare Fund program participation on child nutrition among old beneficiaries compared to non-beneficiaries

Specification	1	2	3	4	5	6	7	8
Panel A: Weight-for-height z-score (WHZ)								
Conflict events count (std.)	-0.044***	-0.060***	-0.059***	-0.058***	-0.058***	-0.057***	-0.052**	-0.051**
	(0.010)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.020)	(0.020)
Beneficiary (1=yes, 0=no)	-0.002	-0.003	-0.000	-0.014	-0.014	-0.014	.	.
	(0.039)	(0.039)	(0.039)	(0.041)	(0.041)	(0.041)		
Interaction term		0.038***	0.036***	0.034***	0.033***	0.034***	0.026	0.026
		(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.021)	(0.021)
R-sq.	0.147	0.148	0.152	0.154	0.155	0.155	0.523	0.523
Panel B: Mid-upper arm circumference z-score (MUACZ)								
Conflict events count (std.)	-0.069***	-0.080***	-0.079***	-0.080***	-0.078***	-0.077***	-0.080***	-0.078***
	(0.006)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.011)	(0.011)
Beneficiary (1=yes, 0=no)	0.023	0.023	0.019	0.034	0.034	0.034	.	.
	(0.048)	(0.048)	(0.049)	(0.048)	(0.048)	(0.048)		
Interaction term		0.028	0.026	0.027	0.026	0.026	0.043**	0.043**
		(0.022)	(0.021)	(0.022)	(0.022)	(0.022)	(0.018)	(0.018)
R-sq.	0.159	0.159	0.161	0.168	0.169	0.170	0.606	0.606
Controls								
Individual characteristics	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	No	No	No	Yes	Yes	Yes	Dropped	Dropped
Precipitation & temperature anomalies	No	No	No	No	Yes	No	Yes	No
SPEI	No	No	No	No	No	Yes	No	Yes
Fixed effects								
District	Yes	Yes	Yes	Yes	Yes	Yes	Dropped	Dropped
Household	No	No	No	No	No	No	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own estimation based on 2012-13 Yemen NSPMS and GDELT data.
Note: std. = standardized; SPEI = Standardized Precipitation Evapotranspiration Index.
***, **, * parameter is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively. Standard errors are reported in parenthesis.
Estimations of Panel A are based on 10,196 observations (from 2,549 children aged 0-59 months). Estimations of Panel B are based on 8,632 observations (from 2,158 children aged 6-59 months). In all estimations, standard errors are clustered at the district level. The number of clusters is 217 in Panel A estimations and 213 in Panel B estimations.

The parameter estimates of the program participation variable are small and far from being statistically significant in all model estimations. This provides suggestive evidence that the SWF cash transfer program is not targeted at malnourished children and hence that our identification strategy is not violated by a potential bias associated with such (unobserved) targeting. Further, this finding is consistent with the results of the impact assessment of the SWF cash transfer program by IPC-IG et al. (2014a). That research team used a quasi-experimental impact evaluation method, i.e., propensity score matching, to estimate the general effect of household program participation on children's nutritional status and the prevalence of child malnutrition among all beneficiary households, i.e., the 'average treatment effect on the treated'. They find no statistically significant result for any indicator of nutritional status or malnutrition prevalence, considering measures of short-term, long-term, and composite nutrition outcomes. However, their analysis does not account for children's exposure to civil conflict intensity. The mitigation effect of the program that we found remained undetected and possibly was averaged out in their analysis as it ignored spatial and temporal heterogeneity in conflict occurrence and intensity.

Furthermore, our estimation results in Table 5.5 suggest that the regularity of SWF cash transfer payments matters for the mitigation effect. The parameter estimates of the term that captures the interaction between the conflict intensity variable and the payment frequency variable are positive and statistically significant in the district FE model estimations for child WHZ and the household FE model estimations for child MUACZ, like in the estimations of the models having the binary program participation variable as treatment variable. Thus, these estimates indicate that the mitigation effect tends to be larger if transfer payments are received more regularly. Regular assistance allows beneficiary households to smoothen their food consumption and other demands, influencing child nutrition outcomes.

Table 5.5 Estimated effects of payment regularity of Social Welfare Fund cash transfers on child nutrition

Specification	1	2	3	4	5	6	7	8
Panel A: Weight-for-height z-score (WHZ)								
Conflict events count (std.)	-0.037***	-0.055***	-0.054***	-0.054***	-0.054***	-0.053***	-0.048***	-0.047***
	(0.007)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.017)	(0.018)
Beneficiary (1=yes, 0=no)	-0.002	-0.002	-0.001	-0.004	-0.004	-0.004	.	.
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)		
Interaction term		0.011***	0.011***	0.011***	0.010***	0.011***	0.009	0.009
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)
R-sq.	0.130	0.131	0.136	0.138	0.138	0.138	0.524	0.524
Panel B: Mid-upper arm circumference z-score (MUACZ)								
Conflict events count (std.)	-0.064***	-0.077***	-0.077***	-0.077***	-0.075***	-0.074***	-0.070***	-0.068***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.009)	(0.008)
Beneficiary (1=yes, 0=no)	0.007	0.007	0.007	0.011	0.011	0.011	.	.
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)		
Interaction term		0.010	0.009	0.010	0.010	0.010	0.008***	0.008**
		(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.003)	(0.003)
R-sq.	0.140	0.140	0.142	0.150	0.151	0.151	0.601	0.601
Controls								
Individual characteristics	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	No	No	No	Yes	Yes	Yes	Dropped	Dropped
Precipitation & temperature anomalies	No	No	No	No	Yes	No	Yes	No
SPEI	No	No	No	No	No	Yes	No	Yes
Fixed effects								
District	Yes	Yes	Yes	Yes	Yes	Yes	Dropped	Dropped
Household	No	No	No	No	No	No	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own estimation based on 2012-13 Yemen NSPMS and GDELT data.
Note: std. = standardized; SPEI = Standardized Precipitation Evapotranspiration Index.
***, **, * parameter is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively. Standard errors are reported in parenthesis.
Estimations of Panel A are based on 12,704 observations (from 3,176 children aged 0-59 months). Estimations of Panel B are based on 10,748 observations (from 2,687 children aged 6-59 months). In all estimations, standard errors are clustered at the district level. The number of clusters is 218 in Panel A estimations and 215 in Panel B estimations.

6. CONCLUSIONS

The findings of our analysis stress the detrimental impact of civil conflict on child nutrition in Yemen. Our estimation results show that conflict intensification decreases weight-for-height z-scores (WHZ) and mid-upper arm circumference z-scores (MUACZ) of children under five years of age and, hence, increases the risk of acute child malnutrition. An increase by one standard deviation in conflict intensity translates into an increase in the prevalence of wasting in our sample by at least 0.7 percentage points, if measured by WHZ, and by at least 1.7 percentage points, if measured by MUACZ.

Finding a political resolution of the current civil war in Yemen is an absolute priority to tackle what has been recognized as currently the world's worst humanitarian crisis. Although the latest agreements signed under UN oversight in mid-December 2018 to halt fighting in the contested port city of Hodeida and to allow the future deployment of UN-supervised neutral forces and the establishment of humanitarian aid corridors constitute a first important step, the road to a sustainable peace agreement will certainly be long and bumpy. Civil conflict can be expected to continue for some time, although, hopefully, with declining intensity. Building resilience to civil conflict and violence-facilitating shocks in fragile states is challenging (Breisinger et al. 2015), but the recent political development could open a new window of opportunity for targeted interventions to support recovery in Yemen.

Against this background, our analysis suggests that unconditional cash transfers can be an effective tool in complex emergencies. This finding confirms the practical experience of program implementers in several fragile countries and civil conflict zones (e.g., HPN 2012; ODI 2015). Despite the institutional and logistical challenges encountered after the 2011-12 revolution in Yemen, the SWF cash transfer program was able to reach vulnerable households. Beneficiary households on average were more socially and economically disadvantaged compared to non-beneficiary households. Program coverage could certainly have been improved, as it was found that some of the non-beneficiary households in our study appear to have been eligible for the assistance. Nonetheless, being able to target the most in need, especially due to the program expansion started in 2011, was a notable achievement in such challenging conditions. A major implementation challenge seen throughout the observation period of our study was the irregularity of payments.

Perhaps the most critical opportunity that was missed during the period of a transition in government between 2012 and 2014, preceding the onset of the current civil war, was the inability to increase and expand public assistance to disincentivize individuals to engage in civil conflict for economic means and to protect people's living conditions from the impact of conflict intensification and other shocks (e.g., Berman et al. 2011; Blattman and Ralston 2015; Maystadt and Ecker 2014). International donors could have played a greater role in providing financial support. Instead, SWF stopped cash transfer payments at the end of 2014 due to a lack of funds. After 2½ years of civil war, the World Bank stepped in to restart payments in October 2017 (ReliefWeb 2018).

While the observation period of our study falls within the post-revolution transitional period, our findings are highly relevant for designing and implementing interventions what will hopefully be an upcoming post-war transitional period. Given the humanitarian crisis, there has never been a more urgent need for assistance in Yemen's recent history than today. Another window of opportunity for intervention should not be missed, as the consequences for Yemen's population will be even more devastating.

Our estimation results also suggest that unconditional cash transfers can mitigate the detrimental impact of lingering civil conflict on child nutrition in Yemen on a large scale. This is consistent with findings from a forthcoming impact evaluation study of a pilot program of conditional cash transfers with a nutrition training component in three districts of Hodeidah governorate. Kurdi et al. (2018) document that household food security and child nutrition deteriorated between January 2015 and July 2017, plausibly as a result of the civil war. The authors find statistically significant and positive program effects on the consumption of a range of nutritious foods. These effects were largest among the poorest tercile of beneficiary households. They also find statistically significant and positive effects on the reduction of children diagnosed with moderate and severe malnutrition and on child weight-for-height z-scores and height-for-age z-scores (identifying child stunting) among the poorest tercile of beneficiary households.

Finally, our estimation results suggest that the regularity of cash transfer payments matters for the mitigation effect to effectively counteract the detrimental impact of civil conflict. The mitigation effect tends to be larger the more regular payments are received, as regular assistance allows beneficiary households to smooth their food consumption and other demands influencing child nutrition outcomes. This finding implies that payment regularity, such as on a monthly or at least on a quarterly basis, should be given high priority in the implementation of cash transfer programs by addressing the institutional and logistical challenges associated with irregular payments.

More broadly, our findings provide additional evidence of the beneficial role of cash transfers in civil conflict settings found in other contexts, such as in India (Fetzer 2018) or Iraq (Crost et al. 2016). Our study also complements recent work by Tranchant et al. (2018), who find that food assistance has a protective effect among food insecure populations experiencing civil conflict in Mali. Understanding the relative efficiency of food assistance versus (both unconditional and conditional) cash transfers in fragile countries and during civil conflict is an important area of future research that can help humanitarian and development assistance organizations in strategizing and further improving their support to affected populations.

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ANNEXES

Annex 1: Social Welfare Fund cash transfer program eligibility criteria and differences between household beneficiary groups

The 2008 SWF law defines household eligibility for SWF cash transfer payments according to social and economic categories (IPC-IG et al. 2014a). In the social category, a household is eligible if a household member fulfills one of the following criteria:

1. Disabled, which can be fully and permanently; partially and permanently; and fully or partially temporarily. The common, practical identification is that the person is unable to work either permanently or temporarily due to a physical or mental disability or chronic disease;
2. Orphaned, for children and adolescents less than 18 years of age and college students or students of technical education between 18 and 25 years and whose parents are either dead or disappeared (and therefore cannot support them financially);
3. Elderly, for women above 55 years of age and men above 60 years of age.

In the economic category, a household is eligible if a household member fulfills one of the following criteria:

4. Single and widowed or divorced, not remarried women aged 18 years and older and widowed or divorced, not remarried women younger than 18 years with a child, whose breadwinner is absent from the household for any reason and does not provide financial support;
5. Unemployed man aged 18-60 years, who does not have a job in the public or private sector and whose total income is below the SWF cash transfer level (see above).

In addition to these individual-based eligibility criteria, household eligibility is assessed based on legal conditions for assistance and household chronic poverty status (IPC-IG et al. 2014a). The legal conditions are that the individual or any other family member has (a) currently no other source of income that can compensate for not receiving SWF assistance and (b) no relative who is legally obliged to provide financial support. Household chronic poverty status was determined by relating information on household assets and wealth-related characteristics of the household head from the 2008 census of poor people with corresponding information of a previous, representative household budget survey to obtain income-based poverty classifications. Households were classified into poor and non-poor, and, within the group of poor households, into extremely poor, moderately poor, and vulnerable to poverty.

We used information from the NSPMS data to create variables that correspond to the eligibility criteria for the SWF cash transfer program, while the categorical variable of household chronic poverty was directly available from the obtained dataset. Table A1.1 shows summary statistics for these variables among all households, all beneficiary households, new and old beneficiary households, and non-beneficiary households in our sample in Round 1—the baseline of our study. Table A1.2 shows results of mean difference tests for the eligibility criteria variables between the different household groups, which provide indication of the accuracy of program targeting.

Table A1.1. Summary statistics of Social Welfare Fund cash transfer program eligibility criteria at baseline

	All households		All beneficiaries		New beneficiaries		Old beneficiaries		Non-beneficiaries	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Household has a …										
Disabled person, 0/1	0.191	0.393	0.253	0.435	0.237	0.425	0.264	0.441	0.138	0.345
Orphan, 0/1	0.038	0.191	0.043	0.204	0.038	0.191	0.047	0.212	0.035	0.183
Elderly, 0/1	0.349	0.477	0.481	0.500	0.386	0.487	0.547	0.498	0.226	0.419
Single/widowed/divorced woman, 0/1	0.240	0.427	0.355	0.479	0.281	0.450	0.407	0.492	0.132	0.338
Unemployed man, 0/1	0.069	0.253	0.081	0.273	0.087	0.282	0.077	0.267	0.057	0.233
Household current per capita income quintile, from non-SWF sources										
Quintile 1	0.205	0.404	0.232	0.423	0.234	0.424	0.231	0.422	0.184	0.387
Quintile 2	0.200	0.400	0.230	0.421	0.228	0.420	0.231	0.422	0.173	0.379
Quintile 3	0.200	0.400	0.198	0.399	0.190	0.393	0.204	0.404	0.199	0.399
Quintile 4	0.200	0.400	0.186	0.390	0.192	0.394	0.182	0.386	0.213	0.410
Quintile 5	0.194	0.396	0.153	0.360	0.156	0.363	0.151	0.358	0.231	0.422
Household chronic poverty status										
Poor, 0/1	0.655	0.476	0.736	0.441	0.768	0.423	0.714	0.452	0.585	0.493
Extreme poor, 0/1	0.180	0.384	0.244	0.429	0.239	0.427	0.247	0.432	0.119	0.324
Moderately poor, 0/1	0.304	0.460	0.331	0.471	0.346	0.476	0.321	0.467	0.287	0.452
Vulnerable to poverty, 0/1	0.170	0.376	0.161	0.368	0.183	0.387	0.146	0.354	0.179	0.384
Observations	2,232		1,084		448		636		1,148	

Source: Own estimation based on 2012-13 Yemen NSPMS data.

Table A1.2. Mean difference tests between household groups for cash transfer program eligibility criteria at baseline

	All vs. non-beneficiaries		New vs. non-beneficiaries		Old vs. non-beneficiaries		New vs. old beneficiaries	
	Difference	Significance	Difference	Significance	Difference	Significance	Difference	Significance
Household has a …								
Disabled person, 0/1	-0.115	***	-0.099	***	-0.127	***	0.028	
Orphan, 0/1	-0.009		-0.003		-0.012		0.009	
Elderly, 0/1	-0.254	***	-0.160	***	-0.321	***	0.161	***
Single/widowed/divorced woman, 0/1	-0.224	***	-0.150	***	-0.276	***	0.126	***
Unemployed man, 0/1	-0.024	**	-0.030	**	-0.020		-0.010	
Household current per capita income quintile, from non-SWF sources								
Quintile 1	-0.049	***	-0.051	**	-0.047	**	-0.003	
Quintile 2	-0.056	***	-0.054	**	-0.058	***	0.003	
Quintile 3	0.000		0.009		-0.006		0.015	
Quintile 4	0.027		0.021		0.031		-0.010	
Quintile 5	0.078	***	0.075	***	0.080	***	-0.005	
Household chronic poverty status								
Poor, 0/1	-0.151	***	-0.182	***	-0.128	***	-0.054	**
Extreme poor, 0/1	-0.124	***	-0.120	***	-0.128	***	0.008	
Moderately poor, 0/1	-0.045	**	-0.059	**	-0.034		-0.025	
Vulnerable to poverty, 0/1	0.018		-0.004		0.033	*	-0.037	

Source: Own estimation based on 2012-13 Yemen NSPMS data.
Note: ***, **, * Per a two-sided t-test for unpaired data with unequal variance, mean difference is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively.

The statistics confirm that, for most eligibility criteria, beneficiary households are socially and economically disadvantaged compared to non-beneficiary households, on average. The only exception are households with orphans, for which there is no statistical difference between the means of beneficiary and non-beneficiary households. This finding also holds for the groups of new and old beneficiaries separately. Compared to non-beneficiary households, both new and old beneficiary households are more likely to have disabled, elderly, or single female household members; to have less income from non-SWF sources; and to be poor or extreme poor. In addition, new beneficiary households are more likely to have an unemployed male household member than non-beneficiary households. Old beneficiary households are more likely to have above-average income from non-SWF sources and are more likely to be vulnerable to poverty—instead of moderately poor—than non-beneficiary households. Both results point to targeting issues in terms of economic eligibility criteria. Moreover, the summary statistics suggest that there are many households in the non-beneficiary group that may be eligible for SWF program benefits. For example, 22.6 percent of the non-beneficiary households in our sample have an elderly person, and 11.9 percent were classified as extremely poor and 28.7 percent as moderately poor.

Finally, the results also suggest that there are no statistically significant differences in the means of most eligibility criteria variables between old and new beneficiary households, despite the selection of new beneficiaries through the PMT method. On average, old beneficiaries appear to be better targeted with respect to some social criteria—specifically households with elderlies and single, widowed, or divorced women. In contrast, new beneficiaries appear to be better targeted in terms of total chronic poverty. Overall, the findings imply that the introduction of the PMT method seems to have only slightly shifted the targeting focus toward stronger weights on economic eligibility criteria rather than social eligibility criteria, while it appears to not have substantially improved overall targeting effectiveness (IPC-IG et al. 2014a).

Annex 2: Complementary estimation results

Table A2.1. Parameter estimates of control variables in the model estimating impact of civil conflict intensity on child weight-for-height z-score (WHZ)

Specification	1	2	3	4	5	6	7
Panel A: Weight-for-height z-score (WHZ)							
Individual characteristics							
Female child, 0/1		0.082***	0.083***	0.083***	0.083***	0.051	0.051
		(0.029)	(0.029)	(0.029)	(0.029)	(0.038)	(0.038)
Child age, months		0.017***	0.018***	0.018***	0.018***	0.026***	0.026***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Child age squared, months		-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household characteristics							
Household wealth index (std.)			0.082***	0.082***	0.082***	.	.
			(0.029)	(0.029)	(0.029)		
Household size, persons			0.001	0.001	0.001	.	.
			(0.004)	(0.004)	(0.004)		
Female head of household, 0/1			-0.061	-0.061	-0.061	.	.
			(0.075)	(0.075)	(0.075)		
Age of household head, years			0.001	0.001	0.001	.	.
			(0.001)	(0.001)	(0.001)		
Literate household head, 0/1			-0.052	-0.052	-0.052	.	.
			(0.039)	(0.039)	(0.039)		
Weather shocks							
Precipitation anomaly				0.009		0.007	
				(0.010)		(0.010)	
Temperature anomaly				-0.008		0.007	
				(0.029)		(0.029)	
SPEI					0.017		0.011
					(0.020)		(0.021)

Source: Own estimation based on 2012-13 Yemen NSPMS and GDELT data.
Note: The table complements Table A5 in the main text. Specification 1 included no control variables.
std. = standardized; SPEI = Standardized Precipitation Evapotranspiration Index.
***, **, * parameter is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively. Standard errors are reported in parenthesis.
Estimations of Panel A are based on 12,704 observations (from 3,176 children aged 0-59 months). Estimations of Panel B are based on 10,748 observations (from 2,687 children aged 6-59 months). In all estimations, standard errors are clustered at the district level. The number of clusters is 218 in Panel A estimations and 215 in Panel B estimations.

Table A2.2. Parameter estimates of control variables in the model estimating impact of civil conflict intensity on child mid-upper arm circumference z-scores (MUACZ)

Specification	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Panel B: Mid-upper arm circumference z-score (MUACZ)							
Individual characteristics							
Female child, 0/1		0.053*	0.052*	0.052*	0.052*	0.111**	0.111**
		(0.030)	(0.030)	(0.030)	(0.030)	(0.044)	(0.044)
Child age, months		-0.002	-0.001	-0.001	-0.001	0.005	0.005
		(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Child age squared, months		-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household characteristics							
Household wealth index (std.)			0.136***	0.136***	0.136***	.	.
			(0.030)	(0.030)	(0.030)		
Household size, persons			-0.002	-0.002	-0.002	.	.
			(0.004)	(0.004)	(0.004)		
Female head of household, 0/1			-0.167**	-0.168**	-0.166**	.	.
			(0.073)	(0.073)	(0.073)		
Age of household head, years			-0.000	-0.000	-0.000	.	.
			(0.001)	(0.001)	(0.001)		
Literate household head, 0/1			-0.043	-0.043	-0.043	.	.
			(0.042)	(0.042)	(0.042)		
Weather shocks							
Precipitation anomaly				-0.008		-0.010	
				(0.010)		(0.010)	
Temperature anomaly				-0.091**		-0.083**	
				(0.040)		(0.039)	
SPEI					0.065***		0.070***
					(0.022)		(0.022)

Source: Own estimation based on 2012-13 Yemen NSPMS and GDELT data.
Note: The table complements Table A5 in the main text. Specification 1 included no control variables.
std. = standardized; SPEI = Standardized Precipitation Evapotranspiration Index.
***, **, * parameter is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively. Standard errors are reported in parenthesis.
Estimations of Panel A are based on 12,704 observations (from 3,176 children aged 0-59 months). Estimations of Panel B are based on 10,748 observations (from 2,687 children aged 6-59 months). In all estimations, standard errors are clustered at the district level. The number of clusters is 218 in Panel A estimations and 215 in Panel B estimations.

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