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Abstract

The “ignored” civil war in Yemen has caused the world’s worst humanitarian crisis in recent history. Little is known about how to mitigate the detrimental consequences of such protracted violence. We use quarterly panel data to estimate the impact of armed conflict on child nutrition in Yemen and the role of unconditional cash transfers in mitigating the adverse nutritional impact. Our results show that a one-standard-deviation increase in armed conflict intensity reduces the weight-for-height z-scores (WHZ) and mid-upper arm circumference z-scores (MUACZ) of children by 9.6% and 4.4%, respectively, on average. We also find that the studied cash transfer program reduces the nutritional impact by 35.8% for WHZ and 20.4% for MUACZ. Our analysis suggests that if relative stability is restored, unconditional cash transfer programs can be an effective tool to curb rising acute child malnutrition in situations of complex emergencies.

Keywords: Armed conflict, child nutrition, cash transfers, fixed effects regression, panel data, Yemen.

JEL Classifications: D74, I15, O15.

1. Introduction

Hunger and acute child malnutrition are increasingly concentrated in fragile countries and armed conflict zones (FAO et al., 2017; von Grebmer et al., 2015). In 2016, about 1.35 billion children and adolescents younger than 18 years lived in a conflict-ridden country, and almost 357 million of them lived in a conflict zone (Bahgat et al., 2017). Armed conflict substantially and persistently increases child mortality, with effect sizes several times greater than common estimates of the mortality burden of conflict (Wagner et al., 2018). Armed conflict increases child mortality by exacerbating malnutrition, infectious diseases, and maternal health impairments, in addition to deaths from direct injuries and harm to the parents of young children. For example, the number of infant deaths related to armed conflict in Africa between 1995 and 2015 exceeded the number of direct infant fatalities from armed conflicts by 3.2–3.6 times (Wagner et al., 2018). As the most extreme outcome, the child death toll marks only the "tip of the iceberg" of the much greater impact of armed conflict on child health.

One of the most dramatic cases of armed conflict in recent history is Yemen's current civil war—"the war the world ignores" (*The Economist,* 2017). By the end of October 2019, more than 100,000 people had been killed in direct violence—including more than 12,000 civilian casualties—since the outbreak of civil war in 2015 (ACLED, 2019). According to the United Nations, more than 2,600 children had been verified as killed between April 2015 and December 2018 (UNICEF, 2019), and the international NGO Save the Children estimates that about 85,000 children younger than five may have died from acute malnutrition during the same time period, as a result of the conflict (Save the Children, 2018). The United Nations warns that more than 20 million Yemenis (more than two-thirds of the country's total population) are food insecure, including nearly 10 million people who suffer from extreme hunger. An estimated 7.4 million people require services to treat or prevent malnutrition, including two million children younger than five years who are in need of treatment for acute malnutrition (UN, 2018a).

In this paper, we quantify the adverse impact of armed conflict on child nutrition in Yemen. To that end, we use four rounds of panel survey data from 2012-13 and exploit quarterly variation in violent conflict intensity at the district level to estimate the effects on child anthropometric indicators commonly used to identify acute child malnutrition. Despite the alarming humanitarian emergency, the nutritional impact of armed conflict has not been rigorously assessed. Our results show that an increase by one standard deviation in conflict intensity reduces child weight-for-age z-scores (WHZ) by at least 0.06 and child mid-upper arm circumference z-scores (MUACZ) by at least 0.05 in our sample. For a child at the mean of the distributions, the estimated effects translate into a deterioration of nutritional status by about 9.6% if measured by WHZ and 4.4% if measured by MUACZ. By estimating the adverse impact of armed conflict on child nutrition in Yemen, we contribute to a growing literature seeking to quantify the detrimental consequences of protracted violence for child health and development outcomes (e.g., Akbulut-Yuksel, 2017; Akresh et al., 2012; Bundervoet et al., 2009; Lee, 2014; Minoiu and Shemyakina, 2012).

Our second contribution is to assess whether unconditional cash transfers can mitigate the adverse impact of armed conflict on child nutrition in Yemen and to estimate this mitigation effect. Specifically, we look at 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), which provides household and individual child anthropometry observations from four survey rounds over a period of one year. Households' beneficiary status was determined prior to the observation period of our analysis and remains fixed throughout that period, independent of the households' changing living conditions and the nutritional status of children in the household. The results of our household fixed effects model estimations suggest that the unconditional cash transfers do mitigate the adverse impact of armed conflict on child nutrition. The SWF cash transfer program reduces the nutritional impact by 35.8% for WHZ and 20.4% for MUACZ across all beneficiary households. We find a mitigation effect for children both in households that have been beneficiaries for a long time and in households that were newly enrolled before the start of the analysis period. Modifications of our estimation model specifications further suggest that the regularity of transfer payments matters for the size of the mitigation effect.

Thus, our paper also contributes to the literature on the effectiveness of cash transfer programs in civil conflict settings and humanitarian crises (e.g., Doocy and Tappis, 2017; HPN, 2012; ODI and CGD, 2015). While the literature has recently made considerable progress in understanding how cash transfer programs can be used to reduce the risk of conflict outbreak and intensification (e.g., Crost et al, 2016; Willibald, 2006; Pena et al., 2017), there is little systematic evidence on the effectiveness of cash transfers in mitigating the impact of armed conflict on food security and nutrition outcomes. Our paper helps to fill this knowledge gap in particular. The transferability of findings from available studies evaluating the effectiveness of food assistance programs may be limited, because the use of cash is more flexible than that of food vouchers and handouts; food shortages in local markets may be constraining; and program implementation modalities tend to be considerably different. Nevertheless, in a recent evaluation of World Food Programme food assistance interventions in a conflict-affected region in Mali, Tranchant et al. (2019) find protective effects of general food distribution on household calorie and micronutrient consumption.

The medical literature also offers little evidence on the effects of cash transfers on people's health conditions in conflict-affected areas.[3] In a systematic review by Balhara et al. (2017) on the impact of nutrition interventions (including food assistance and cash transfer programs) on pediatric mortality and nutrition outcomes in humanitarian emergencies, only seven out of the 31 selected

[3] A literature search on the PubMed search engine (https://www.ncbi.nlm.nih.gov/pubmed, accessed 1 April 2020) with the keywords "cash transfer" and "conflict" yields 14 articles. We deem only two articles as relevant in the context of our study (Edmond et al., 2019; Grijalva-Eternod et al., 2018).

studies take place in a conflict setting. None of them explores the role of food assistance or cash transfers for health outcomes. More recently, Edmond and colleagues used cross-sectional data from six Afghan districts to examine the effects of a conditional cash transfer program on the use of maternal and child health services (Edmond et al., 2019). The authors find increases in the use of antenatal and postnatal care services in the intervention villages relative to the comparison villages, but they did not investigate associations between program interventions and maternal and child health indicators. In a non-randomized cluster trial in internally displaced person camps in Somalia, Grijalva-Eternod and colleagues do not find an association between unconditional cash transfers and reduced risk of acute child malnutrition among beneficiary households (Grijalva-Eternod et al., 2019). However, the lack of a valid control group or a credible counterfactual in the two studies make analyzing causal inference about the effectiveness of the interventions difficult, if not impossible.

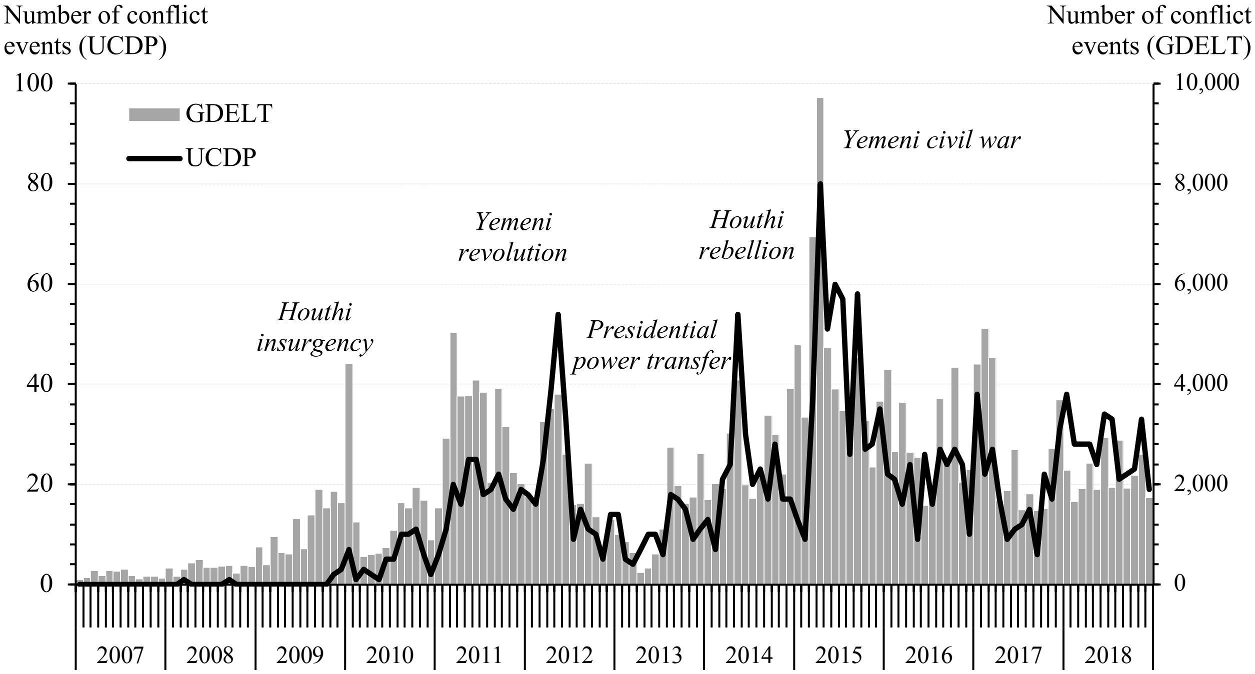
The rest of the paper proceeds as follows. Section 2 provides the context of our study. Section 3 presents the data and descriptive analysis. Section 4 explains the empirical strategy of the econometric analysis. Section 5 presents the main estimation results, and Section 6 provides robustness checks of the estimation results and validity tests of our empirical strategy. Section 7 concludes this paper by discussing policy implications of the study findings.

2. Study context

2.1 Emergence of Yemen's civil war

Yemen's current civil war emerged from the 2011-12 revolution against the government of President Ali Abdullah Saleh, who became the first president of a unified North and South Yemen in 1990. The onset of the Yemeni revolution shortly followed the Tunisian revolution that concluded with the ousting of longtime president Zine el-Abidine Ben Ali and the first mass protests in Egypt that marked the beginning of the Egyptian revolution leading to the overthrow of long-ruling president Hosni Mubarak. In Yemen, peaceful mass protests in early 2011 demanding democratic reforms and condemning official corruption and poor economic conditions escalated into violence. Uprisings quickly spread from the capital Sanaa to other cities across the country and fueled three prolonged, regional conflicts. First, civil unrest in Yemen's northern governorates became more frequent after the killing of Hussein Badreddin al-Houthi during the rebellion of the Houthi clan against the Yemeni military in 2004. The Houthi insurgency heated up in 2009 but quieted the following year after a ceasefire was signed (Figure 1). Second, in the south, protests against the political and economic marginalization of former South Yemen and resistance of southern separatists against the northern-dominated pro-union government and its security apparatus intensified after 2007 and gave birth to the Southern Movement. The government also struggled to control a range of lawless tribes, bandits, and jihadist groups in parts of the rural south. Third, since its formation in 2009, Al-Qaeda in the Arabian Peninsula (AQAP)—later rebranded as Ansar al-Sharia—launched terrorist attacks and gained influence among parts of the population and (temporary) territorial control in several areas across Yemen.

Figure 1. Armed conflict intensity in Yemen



Source: Authors' representation based on UCDP and GDELT data.

The Yemeni revolution ended with a power transfer from Saleh to his vice president Abdrabbuh Mansur Hadi in early 2012. In exchange for immunity from prosecution, Saleh signed the power transition agreement—brokered by the Gulf Cooperation Council—in Riyadh, Saudi Arabia, in November 2011. In February 2012, Hadi was officially elected president in a single-candidate election that was boycotted by the Houthis. The new government struggled to unite Yemen's fractious political landscape and to fend off threats both from Houthi militants and Ansar al-Sharia. 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 tribal militia groups and with government security forces flared across the country in the second half of 2013.

In mid-2014, the Houthis launched a rebellion and eventually managed to expand their territorial control southward from their stronghold in the mountainous far north toward Yemen's capital, located in the central highlands. After a few battles with military forces, Houthi rebels seized Sanaa and swiftly expanded their control southward toward the city of Taizz and westward toward the city of Hodeidah—the gateway to Yemen's main seaports on the Red Sea. The Houthis refrained from an immediate coup d'état but forced President Hadi to negotiate a "unity government" with other political factions. The following power play prompted the resignation of the president along with his ministers in February 2015. The Houthi political leadership declared themselves in control of the government, dissolved Parliament, and installed the interim Supreme Revolutionary Committee. Hadi first escaped to the southern port city of Aden before fleeing to Riyadh. 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, full-scale civil war erupted between loyalists of the Hadi government (which is the government officially recognized by Saudi Arabia and allied countries) and the Houthis, as well as military troops and tribal forces that refused to recognize Hadi's authority. A coalition of Arab countries led by Saudi Arabia began military operations against Houthi fighters. The Southern Transitional Council (STC)—a secessionist organization formed by a faction of the Southern Movement—initially backed the Hadi government against the Houthis, but in January 2018 tensions erupted into battles between SCT and pro-Hadi forces for control over Aden.

In April 2018, the United Nations (UN) declared the Yemeni civil war as the world's worst humanitarian crisis at present and warned of looming famine (UN, 2018b). Exacerbating surging malnutrition, a severe cholera epidemic began in September 2016—the largest documented cholera epidemic of modern times. Between September 2016 and March 2018, there were over 1.1 million suspected cholera cases and 2,300 deaths due to the disease (Camacho et al., 2018).

In December 2018, Houthi rebels and the Hadi government agreed to a UN-backed ceasefire for the highly contested port city of Hodeidah, which is the gateway for the bulk of humanitarian aid coming into the country, and the establishment of humanitarian corridors inland. The ceasefire has remained fragile, despite the deployment of foreign troops from Saudi Arabia and its coalition partners. The UN-led peace process has not achieved a breakthrough in the negotiations with Yemen's main warring parties up to now.

2.2 The SWF cash transfer program

The most important social protection program of the government of Yemen was an unconditional cash transfer program that was implemented nationwide by the Social Welfare Fund (SWF) with technical and financial support from the World Bank. The program handed out cash transfers to citizens who were temporarily or permanently unable to sustain themselves and whose families were not able to financially support them. The SWF was created in 1996 as a compensation mechanism to mitigate the negative impact of the removal of food subsidies on poor people's livelihoods. It underwent a series of reforms between 2008 and 2011.

A 2008 law and the SWF operations manual formally defined program eligibility criteria for two basic categories of households that were considered socially or economically disadvantaged (IPC-IG et al., 2014a). In the social category, a household was eligible for assistance if a household member was permanently or temporarily disabled; an orphaned minor or student aged 25 or younger; or an elderly person older than 55 years for women and 60 years for men. In the economic category, a household was eligible if a household member was a single woman older than 18 years who had been widowed or divorced or was a woman aged 18 years or younger who was the mother of at least one child; or was a man aged 18-60 years who was unemployed or had an income below the level of the SWF cash assistance.

In addition to these individual-based eligibility criteria, household eligibility was assessed based on legal conditions for assistance and household chronic poverty status. The legal conditions were that the individual or any other family member had (a) currently no other source of income that could compensate for not receiving SWF assistance and (b) no relatives who were legally obliged to provide financial support. Lack of data and a clear method to approximate household poverty status initially prevented enforcement of the household poverty criterion. After the completion of a survey-based poverty assessment and the official approval of a proxy means test formula, the criterion was formally applied in 2011. Household chronic poverty status was determined based on household assets, and households were classified into poor and non-poor. For beneficiary targeting purposes, the group of poor households was further divided into extremely poor, moderately poor, and vulnerable.

The payment amount per eligible household member was 6,000 Yemeni rial (YER) quarterly. It was topped up with YER 1,200 for each dependent household member up to a maximum of five persons. The maximum amount per beneficiary household was YER 12,000 per quarter, which was equivalent to about US$56 (in 2011–2015). While the cash amount is small, focus group discussions revealed that beneficiaries especially 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 (including food), helping to maintain creditworthiness (IPC-IG et al., 2014a).

The poverty assessment also served to identify new beneficiaries to be enrolled into the program. Gradual expansion of the program coverage started in 2011. By mid-2013, around one-third of the Yemeni population lived in a household with at least one program beneficiary (IPC-IG et al., 2014a). However, in the wake of the 2011-12 revolution, payments were partly suspended but resumed in the second half of 2012 and the first half of 2013, together with the incorporation of the remaining new beneficiaries identified. With the Houthis' increasing territorial gains and control over governments, the SWF downscaled and finally stopped payments in late 2014 due to a lack of funding.

During normal operations, transfer payments were made quarterly. Almost all payments were disbursed through the national postal service system and only a tiny proportion (less than 2%) through the national banking system, which required beneficiaries to hold a personal bank account. Most beneficiaries (or their proxies) received their payments directly from the local post office, while some beneficiaries living in very remote villages were visited by local post office cashiers to deliver the cash. The payments were supposed to be delivered to beneficiaries during the last week of the quarterly cycle, but were usually received within the following month due to delays in administrative procedures. The Yemen Ministry of Finance approved the SWF budget and requested the Central Bank of Yemen to deposit the approved program funds to the SWF account; the SWF wrote checks to the local post offices for the total amounts of the beneficiary payments to be made; and the post offices submitted the checks to the Central Bank, which transferred the beneficiaries' allocations from the SWF account to the accounts of the post offices. Once the funds were released from the Central Bank, the SWF communicated with beneficiaries through SMS and used social workers in the field to spread the word on the dates to visit the post offices and claim the payments. Under normal circumstances, the post offices could get cash as needed to disburse the payments to the beneficiaries. These normal processes were interrupted by armed conflict, causing delayed receipt of the payments. Most notably, insecurity along the road from the Central Bank in Sanaa to local post offices in the countryside caused considerable delays in moving the checks and cash. Insecurity also restricted the movement of local post office cashiers to remote villages and beneficiaries' visits to the local post offices.

3. Data and descriptive analysis

3.1 Survey data

The household panel data used in this study are taken from the Yemen National Social Protection Monitoring Survey (NSPMS) (IPC-IG, 2014a). The survey was conducted from October 2012 to September 2013 and hence captures the situation during the transfer of presidential power after the Yemeni revolution and before the Houthi rebellion and the following outbreak of the civil war (Figure 1). The main objectives of the NSPMS are to provide up-to-date information on the living conditions of poor households in Yemen after the 2011-12 revolution and to assess the targeting of the SWF cash transfer program after the 2008-11 SWF reforms and the program's impact on a variety of development indicators. The sampled households were interviewed in four rounds within one year, following the normal payment cycle of the SWF program.

Sample population

The household sample of the NSPMS was selected using a two-stage stratified sampling procedure.[4] In the first stage, enumeration areas were geographically stratified by governorate and selected using a probability proportional to size sampling design. In the second stage, a household listing exercise was conducted in each selected enumeration area to identify households' SWF beneficiary status. A stratified simple random sampling design was used to select households into treatment and control groups by enumeration area. The treatment group was comprised of SWF

[4] The sample size of the NSPMS was initially set to 7,560 households from all 21 governorates in Yemen. A detailed description of the sample design and survey methodology can be found in IPC-IG et al. (2014b). Because of major security concerns, Saada Governorate—the main Houthi stronghold (located in the far north)—was excluded before survey implementation. Of the 7,152 households selected for the sample, 6,943 were interviewed in the first round and kept for analysis, yielding a response rate of 97.1%. The final sample includes 6,397 households that were interviewed in all four rounds, yielding an overall attrition rate of 9.2%. Al-Jawf Governorate—largely controlled by the Houthis (and neighboring Saada Governorate)—suffered complete attrition in the fourth round due to security threats during survey implementation. This led to a loss of 432 households from the Round 1 sample. Thus, the attrition rate across the 19 governorates remaining in the sample was only 6.2%. Comparisons of the nutritional status of children and the characteristics of their households identifying SWF program eligibility as reported at baseline (Round 1) between the initial and final samples including observations from dropped households—with and without households in Al-Jawf Governorate—indicate no statistically significant differences at the sample means. See Tables A1 ad A2 in the Appendix.

beneficiary households that were defined as households that had at least one member who had ever received a SWF cash transfer payment. An equal number of households with at least one member either already selected or registered for the SWF program but without any beneficiary at the time of the survey was allocated to the control group. The control group was expanded by up to 40% by incorporating households without any members registered for the program. The treatment group includes "old beneficiary" and "new beneficiary" households. Old beneficiary households were defined as those with a member that received payments already before the 2008-11 SWF reforms. New beneficiary households were enrolled into the program after the completion of the reforms (earliest in 2011) and were selected based on the revised program eligibility criteria.[5]

Because the focus of our analysis is on acute child malnutrition, we restrict the sample to households with children aged 0-59 months who have biologically plausible WHZ values in all four survey rounds, yielding a child panel dataset. Our sample has 2,312 households, equivalent to 36.1% of the total sample of households that were interviewed in all survey rounds. It is nearly balanced between treatment group (50.3%) and control group (49.7%). The sample covers 218 districts (out of 331 districts in mainland Yemen, excluding Socotra Island) across 19 governorates.

SWF beneficiaries and payment regularity

Table 1 shows summary statistics for our household sample by beneficiary group and test results of mean differences between groups for the SWF program eligibility criteria. The results reveal that, on average, households already enrolled in the program tend to be more socially and economically disadvantaged than non-beneficiary households. This suggests that the program is to some degree targeted to the neediest ones. The finding also holds for the groups of old and new beneficiaries separately. Compared to non-beneficiary households, both old and new beneficiary households are more likely to have disabled, elderly, and widowed or divorced female household members; to have less income from non-SWF sources; and to be poor and, notably, extremely poor. The result that old beneficiary households are more likely to have elderly and widowed (or divorced) women than new beneficiary households can be explained by differences in the household age and sex structure and related eligibility for program enrollment. The head of old beneficiary households is on average 3.4 years older than the head of new beneficiary households (48.9 years compared to 45.5 years). Women are the beneficiaries in almost half all households (47.8%), while the proportion of households with female beneficiaries is larger among old beneficiary households than new beneficiary households (53.9% compared to 40.0%).

In contrast, new beneficiary households are more likely to be chronically poor. This result is likely due to the enforcement of the eligibility criterion for household poverty based on the proxy means tests formula in 2011 and thereafter. The finding that 11.9% of non-beneficiary households are extremely poor and 28.7% are moderately poor, while 27.7% of all beneficiary households are

[5] The beneficiary status could not be clearly identified for 7.4% of the beneficiary households (in the final sample).

non-poor, points to targeting issues related to economic eligibility. Most beneficiary households have only one beneficiary (86.7%), while old beneficiary households are more likely to have multiple beneficiaries than are new beneficiary households (17.6% compared to 8.9%). Beneficiaries from the same household typically receive their payments at the same time.

Table 1. Summary statistics and mean difference tests for program eligibility criteria by beneficiary household group

	All beneficiaries		Old beneficiaries		New beneficiaries		Non-beneficiaries		Significance of mean difference			
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	all vs. non	old vs. non	new vs. non	old vs. new
Households with …												
Disabled person	0.244	0.430	0.264	0.441	0.237	0.425	0.138	0.345	***	***	***	
Orphan	0.041	0.199	0.047	0.212	0.038	0.191	0.035	0.183				
Elderly	0.470	0.499	0.547	0.498	0.386	0.487	0.226	0.419	***	***	***	***
Widowed or divorced woman	0.347	0.476	0.407	0.492	0.281	0.450	0.132	0.338	***	***	***	***
Unemployed man	0.080	0.271	0.077	0.267	0.087	0.282	0.057	0.233	**		**	
Level of per capita household income (from non-SWF sources):												
Quintile 1	0.232	0.422	0.237	0.426	0.228	0.420	0.180	0.385	***	***	**	
Quintile 2	0.219	0.414	0.215	0.411	0.223	0.417	0.182	0.386	**	*	*	
Quintile 3	0.204	0.403	0.200	0.400	0.205	0.404	0.194	0.396				
Quintile 4	0.191	0.393	0.203	0.402	0.185	0.389	0.211	0.408				
Quintile 5	0.155	0.362	0.145	0.352	0.158	0.366	0.233	0.423	***	***	***	
Households chronic poverty status:												
Poor	0.723	0.448	0.714	0.452	0.768	0.423	0.585	0.493	***	***	***	**
Extremely poor	0.240	0.427	0.247	0.432	0.239	0.427	0.119	0.324	***	***	***	
Moderately poor	0.322	0.468	0.321	0.467	0.346	0.476	0.287	0.452	*		**	
Vulnerable	0.162	0.368	0.146	0.354	0.183	0.387	0.179	0.384		*		
Households	1,164		636		448		1,148					

Note: All variables are binary and coded as 1 if true and 0 otherwise. The statistics are reported for the first survey round.

***, **, * Per a two-sided *t*-test for data with possibly unequal variances, the mean difference is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively.

Our data examination confirms that beneficiaries received the SWF cash transfer payments irregularly during the observation period of the analysis.[6] The analysis period begins in July 2012, three months prior to the start of the NSPMS, and ends with completion of the survey in late September 2013. The first recall period corresponds to the time from the beginning of July 2012 to the household interview date in the first survey round; and the remaining three recall periods correspond to the time between interview dates of the respective survey rounds. Less than one-third of all beneficiary households in our sample population received payments during all four periods. The proportion of households with fewer regular payments is larger among new beneficiary households because of the gradual resumption of payments after the suspension of the SWF program in the wake of the 2011-12 revolution.

Child nutrition

The outcome variables of our analysis are two standard anthropometric indicators that measure the short-term nutritional status of children younger than five years and are commonly used to detect child "wasting," indicating acute malnutrition. Wasting describes a recent and severe process that has led to rapid weight loss, usually as a consequence of acute starvation and/or severe disease (WHO, 1995). The first indicator is the weight-for-height z-score. The second is the mid-upper arm circumference z-score. Measurements of mid-upper arm circumference provide an alternative means for nutritional screening of young children of at least half a year old and are particularly useful in rapid assessments when weight and height measurements cannot be done, but are less accurate in determining children's nutritional status (WHO, 2000). Both indicators are strong predictors of mortality among severely malnourished children (Briend et al., 1987; Berkley et al., 2005; Pelletier, 1994). The proportion of wasted children is used as one of the basic indicators for assessing the level of nutritional emergency in humanitarian crises (WHO, 2000).

A unique feature of the NSPMS is that it allows tracking of the nutritional status of the same child over a one-year period with quarterly observations. All survey rounds include an anthropometry module that records body height and weight measurements of all children who permanently lived in the sampled households and were between 0 and 59 months old at the time of each survey round. The NSPMS also collects measurements of mid-upper arm circumference for these children if they were 6 months or older. We use the height and weight measurements in combination with information on child sex, age, edema signs, and positioning for height measurement to compute WHZ by applying a routine developed by Leroy (2011) for the Stata software package. We drop children from our sample if their height in any survey round is lower than in any previous round (as shrinking in children is biologically impossible), if they have missing WHZ values in any survey round, or if their WHZ in any round is outside a biologically plausible range. We use the MUACZ as available in the released NSPMS dataset. We do not consider the MUACZ of children if they have missing MUACZ values in any survey round or if their MUACZ in any round is

[6] See Table A3 in the Appendix.

outside a biologically plausible range.[7] Thus, our dataset has WHZ for children that stayed in the age range of 0–59 months throughout the survey and with biologically plausible values in all four rounds, and MUACZ for the same children if they were at least six months old in the first round and have biologically plausible values in all rounds.

Table 2 shows summary statistics for WHZ and MUACZ of the cohort of children in our sample population and the respective wasting rates by survey round. Children are classified as wasted if their WHZ or MUACZ is below –2. Over the course of the analysis period, the body weight of the average child in our sample population is 0.61 standard deviations (SD) lower than it should be (i.e., equal to 0), and the mid-upper arm circumference of the average child is 1.04 SD shorter than the healthy mean. Consistent with the idea of these indicators being short-term in nature, acute child malnutrition substantially declined between the first and second survey rounds but then increased between the third and fourth survey rounds. The decline in acute child malnutrition during the last quarter of 2012 follows the attenuation of armed conflict after the Yemeni revolution (Figure 1). According to the World Health Organization's severity index for malnutrition in emergencies (WHO, 2000), the WHZ-based wasting rates classify the severity of malnutrition in our sample population as "serious" (i.e., 10.0–14.9%) during the first round and "poor" (i.e., 5.0–9.9%) during the following rounds. The standard deviations 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 (Mei and Grummer-Strawn, 2007).

Table 2. Summary statistics for the child nutrition indicators by survey round

Survey round	Weight-for-height z-score (WHZ)		Mid-upper arm circumference z-score (MUACZ)		Wasting rate (%)	
	Mean	SD	Mean	SD	WHZ<-2	MUACZ<-2
1	-0.69	1.24	-1.19	1.01	12.7	19.5
2	-0.54	0.95	-1.02	0.91	6.6	13.1
3	-0.55	0.93	-0.96	0.91	6.6	12.7
4	-0.65	0.98	-1.00	0.94	8.6	14.5
N (children)	3,281		2,780			

Note: The cohort of children has a mean age (and an age range) of 24.8 months (0–51 months) for WHZ and 27.7 months (6–51 months) for MUACZ in the first round; 27.8 months (3–54 months) for WHZ and 30.7 months (9–54 months) for MUACZ in the second round; 30.8 months (6–57 months) for WHZ and 33.7 months (12–57 months) for MUACZ in the third round; and 33.6 months (8–59 months) for WHZ and 36.5 months (14–59 months) for MUACZ in the fourth round.

[7] We defined the range of biologically plausible values for both indicators as between –5 and +5, using the cutoffs recommended by the World Health Organization (Mei and Grummer-Strawn, 2007).

3.2 Conflict data

To capture direct and indirect effects of Yemen's armed conflict, we construct two sets of conflict intensity variables, each from a different georeferenced conflict event dataset, and link them to the NSPMS panel data at the level of administrative districts. The two datasets are the Uppsala Conflict Data Program (UCDP) dataset (Sundberg and Melander, 2013) and the Global Database of Events, Language, and Tone (GDELT) Project dataset (Leetaru and Schrodt, 2013). The (main) sources of both datasets are reports of international newswires. The UCDP dataset is manually curated and compiled (with automated computer assistance); and the GDELT dataset is compiled and updated daily by an automated computer program using the Conflict and Mediation Event Observations (CAMEO) coding system.

UCDP defines an armed conflict "event" as "an incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least one direct death at a specific location and a specific date" (Högblath, 2019). We extract daily event observations from the UCDP dataset where the location of the actual event is exactly known, the event location is within a radius of less than 25 km around a known point, or at least the administrative district where the event happened is known. Our first conflict variable set is derived from the reported number of civilians killed in these events, which arguably provides the best available measure of violence against civilians.

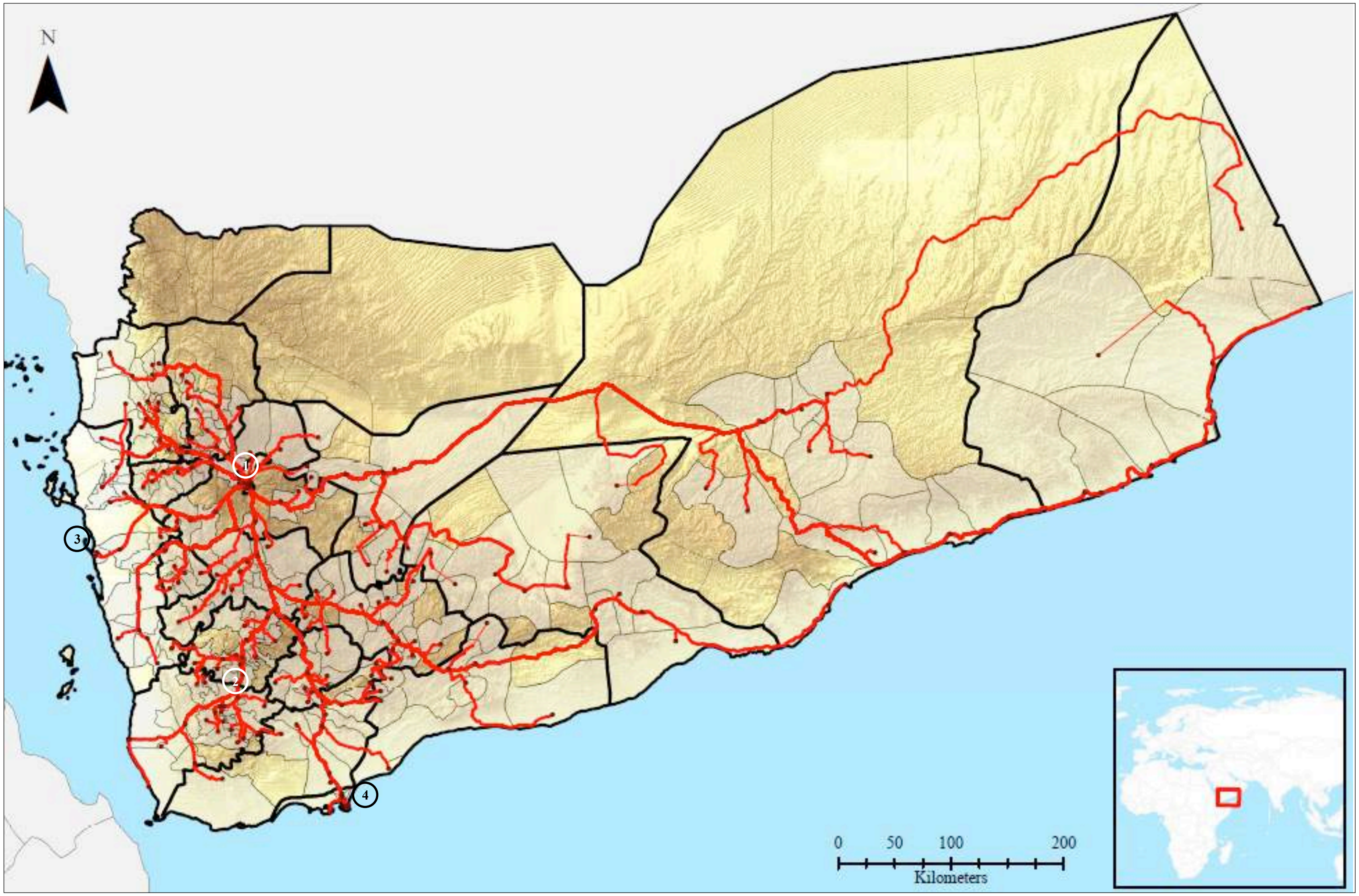
The CAMEO system is designed to code events relevant to the mediation of violent conflict and is organized under four primary classifications: *verbal cooperation, material cooperation*, *verbal conflict,* and *material conflict* (Schrodt, 2012; GDELT, 2015). We extract daily events classified as *material conflict* from the GDELT dataset. We limit the events to *important* events, which is proxied by the reference to an event in the lead paragraph of a document. We keep only event observations where the event location is precise, at least to the district level. The number of these events underly our alternative conflict variable set.

We use the Esri ArcGIS geospatial software to overlay the coordinates of the UCDP and GDELT events with an administrative boundary map and aggregate, respectively, the number of civilian casualties and the number conflict events to the district level. We match all conflict variables to the household observations in the NSPMS panel dataset by survey round and for each household individually, based on the survey round recall periods (the time periods between the interview dates of consecutive survey rounds and, for the first round, between the start date of the analysis period and the first interview date). We thus assume that households from the same district were equally affected by a conflict event in that district on a given day, but allow for variation across households and survey rounds subject to the household-specific time window of each survey round recall period.

The first conflict variable in the UCDP (and GDELT) variable set measures a household's direct exposure to armed conflict of varying intensity. It is the sum of civilian casualties (or conflict events) in a household's home district over the recall period. Figure 2 is a map of Yemen delineating the home districts of the sample households. Additional conflict variables included in our analysis capture indirect effects of armed conflict during the recall period. A household's livelihood and its children's nutrition may have been adversely affected by delayed payments of the SWF cash transfer program due to conflict along the road from the Central Bank (and the SWF headquarters) in the city of Sanaa to the post office in the home district. To implement an instrumental variable (IV) approach, we construct a variable that captures this disruption in normal payment disbursement. This variable counts the civilian casualties (or conflict events) in districts located along the shortest road from the Central Bank to the district post office, shown in Figure 2.[8] We include the count in the start district of the path (where the Central Bank is located), exclude the counts in the path destination district (where the district post office is located) and in its neighboring districts, and weight the total by the length of the road through the included districts. Additionally, we create a variable that controls for spillover effects of armed conflict in neighboring districts into a household's home district. This variable is constructed as the sum of civilian casualties (or conflict events) in the districts sharing a border with the home district.

[8] Because the exact locations of the main district post offices (as well as the locations of the district capitals) are unavailable, we use the locations of the districts' main health facilities as proxy landmarks, assuming that the post offices are nearby. We use data from the Yemen 2004-05 Health Facilities Survey (HFS) to select the main public health facility per district and extract its coordinates. We select the main facility based on size—in terms of both number of staff and number of rooms—and facility type. The selected facilities in our district sample are mostly hospitals (54.1%). We use a georeferenced road network dataset obtained from the OpenStreetMap database (OSM, 2019) and ArcGIS to identify the shortest road distance from the Central Bank in Sanaa to the selected health facility in a district. We consider only roads classified as "primary roads" in the database. If a health facility is not located within a corridor of one kilometer around the primary road, we calculate the length of the direct line from the facility to the nearest point on the road and add this off-road distance to the on-road distance of the path.

Figure 2. Map of sample districts and shortest on-road and off-road distances from the Central Bank of Yemen to proxy locations of district post offices



Note: The shaded districts are the sample districts of our analysis, and the black dots indicate the proxy location of the district post offices. The red thick lines are primary roads, and the thin red lines represent the shortest distance to the primary road network. The locations of Yemen's main cities are indicated as follows: (1) Sanaa, (2) Taizz, (3) Hodeidah, (4) Aden.

4. Empirical strategy

The empirical strategy of our econometric analysis includes two main steps. First, we establish that armed conflict has a strong negative impact on children's nutritional status, increasing the risk of acute child malnutrition in Yemen. Second, we show that the SWF cash transfer program mitigates the adverse nutritional impact and therefore offer different strategies to deal with the non-random targeting of program beneficiaries. We complement our analysis with a series of robustness checks for the main estimation results.

4.1 Estimation of the impact of armed conflict on child nutrition

We begin by estimating a panel ordinary least squares (OLS) regression model that relates the nutritional status of children to their households' direct exposure to armed conflict of varying intensity and controls for district and time fixed effects (FE). Implementing district FE helps to minimize potential estimation biases from unobserved factors at the district level that are time-constant over the analysis period and are correlated with child nutrition and conflict intensity. For instance, differences in sociocultural environments or poor economic and infrastructural conditions may explain differences in both outcomes across districts. Controlling for time FE helps to account for time-varying factors that affect all sample households similarly, such as seasonality or external food price shocks. The district-time FE model hence allows us to exploit variations in armed conflict intensity within districts.

Yet households' exposure to armed conflict may not be randomly distributed within districts. Violence could be targeted toward households with specific characteristics, such as the wealthier ones or those with certain family demographics (Blattman and Miguel, 2010; Dagnelie et al., 2018; Verpoorten, 2009). In models that do not control for such confounding factors, the resulting bias is likely to push the estimated conflict response in the outcome variable toward zero. We address such endogeneity concerns first by augmenting the basic district FE model specification with variables that control for observed individual and household characteristics. We then turn to a household FE model to account for potential unobserved household characteristics that are correlated with both child nutrition and conflict intensity. This model will help us to assess the importance of household selection by controlling for unobserved household heterogeneity such as differences in households' perception of conflict-related insecurity and coping mechanisms.

The district and household FE-OLS models have the following form:

$$y_{ihdr} = \alpha_{h|d} + \beta_1 x^D_{hdr} \ [+Z_{ihdr}{}'\gamma_1 + V_{hd}{}'\gamma_2 + W_{hdr}{}'\gamma_3] + \omega_r + \varepsilon_{ihdr} \ , \qquad (1)$$

where i refers to the individual child, h refers to the child's household, d refers to the household's home district, and r refers to the survey round. The dependent variable y_{ihdr} is the child's nutritional status, measured by WHZ or MUACZ at the time of the survey round. The independent variable x^D_{hdr} is the household's exposure to armed conflict in its home district over the household-specific recall period of the survey round, r. In our main model specifications, we focus on violence against civilians as proxied by the number of civilians killed in armed conflict events (from the UCDP dataset), because this variable provides the best measure of civil conflict intensity. Yet we assess the sensitivity of our main estimation results to the definition of armed conflict intensity. For ease of interpretation, we standardize the values of the conflict variable (and all other conflict variables used throughout our analysis) to yield a mean equal to zero and a standard deviation equal to one. A negative estimate of the coefficient β_1 indicates an adverse impact of armed conflict on child nutrition. District or household FE enter the model through the intercept, $\alpha_{h|d}$, and ω_r accounts for time FE by survey round. In all district FE model and household FE model estimations, standard errors (SE) are clustered at the district level. Additionally, we report SE that correct for spatial correlation following the approach proposed by Conley (1999) and resorting to the procedure introduced by Hsiang (2010). The reported Conley SE assume that spatial dependency matters up to a mean distance between the centroids of any pair of neighboring districts in our sample (equivalent to 93 kilometers).[9]

We proceed in a stepwise fashion to assess the stability of our coefficient estimates of interest. First, we augment the basic estimation equation by the vector Z_{ihdr}, which controls for individual child characteristics. It includes the child's sex and her/his age (in months) at the time of the survey round as linear and squared terms. Next, we add the vector V_{hd} for household characteristics—namely, a household asset-based wealth index; household size (measured by the number of household members who permanently live in the household); and the sex, age (in years), and literacy status of the household head—all as reported in the first survey round.[10] Then, we incorporate the vector W_{hdr} that controls for extreme weather, which has been found to generally aggravate armed conflict (Hsiang et al., 2013; Mach et al., 2019; Maystadt and Ecker, 2014). This vector includes two variables that capture district-level temperature and precipitation anomalies, respectively, occurring over a three-month period, with the last month being the interview month of the household, h, in the survey round, r.[11] Finally, we introduce household FE into the model,

[9] Our estimation results are largely similar if we choose a cutoff point of double the mean distance between the centroids of neighboring districts.

[10] To construct the household wealth index, we apply principal component analysis to the full household sample and a large set of household asset variables, following the procedure proposed by IPC-IG et al. (2014c).

[11] We construct the temperature anomaly variable using monthly georeferenced land surface temperature data from the Moderate Resolution Imaging Spectroradiometer (MODIS) database of the US National Aeronautics and Space Administration (NASA) (Wan et al., 2015) and the precipitation anomaly variable using monthly 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 et al., 2015). To convert these spatial raster data into a dataset with one observation per district (set at the district centroid), we perform a series of geoprocessing procedures. Most notably, we use the Spline spatial interpolation method (Mitas and Mitasova, 1988) to impute missing observations at the raster level, and the Zonal Statistics function in the ArcGIS software package to calculate district-level averages from the raster data. Temperature or precipitation anomaly per month is calculated as the deviation of the temperature or precipitation in the current month from the long-term monthly mean, divided by the monthly long-term standard deviation. Our reference period for determining the long-term mean and standard deviation spans 15 years, from 2001 to 2015. The final temperature and precipitation anomaly variables are calculated as running three-month averages of the anomalies per month.

which causes the vector of time-constant household characteristics, V_{hd}, to drop out because of perfect collinearity.

4.2 Estimation of the mitigation effect of the SWF cash transfer program

To examine whether the SWF cash transfer program mitigates the hypothesized, adverse impact of armed conflict on child nutrition, we augment the fully specified district and household FE models by first introducing a treatment variable (which drops out from the household FE model because of perfect collinearity) and then interacting the conflict variable with the treatment variable. The hypothesized mitigation effect is captured by the interaction term. The augmented district and household FE-OLS models have the following form:

$$\begin{aligned} y_{ihdr} = {} & \alpha_{h|d} + \beta_1 x_{hdr}^D + \beta_2 t_{hd} \, [+\beta_3 x_{hdr}^D * t_{hd}] \\ & + Z_{ihdr}{}'\gamma_1 + V_{hd}{}'\gamma_2 + W_{hdr}{}'\gamma_3 + \omega_r + \varepsilon_{ihdr} \ . \end{aligned} \quad (2)$$

The binary treatment variable, t_{hd}, indicates the program beneficiary status of the household and is time-constant over the analysis period. The estimate of the treatment variable's coefficient, β_2, indicates differences in the nutritional status of children from beneficiary and non-beneficiary households. A positive coefficient estimate of the interaction term, β_3, confirms the existence of the hypothesized mitigation effect of the SWF cash transfer program that counteracts the negative impact of armed conflict on child nutrition.

The estimated mitigation effect may be influenced by the program's beneficiary targeting. Our descriptive statistics suggest that households in greater need of support were more likely to be selected for the program than households in less need. Conceivably, children from households selected as program beneficiaries were more likely to be malnourished than children from non-selected households (before the start of the cash transfer payments). In this case, our estimations probably yield lower-bound estimates of the mitigation effect. To check this conjecture, we modify the specification of the district and household FE models and the household sample underlying the estimations in different ways.

First, considering the 2008-11 SWF reforms and particularly the introduction of a proxy means test formula for beneficiary selection, new beneficiary households are likely to be better targeted in terms of their economic neediness than the rest of the beneficiary households. Conversely, poor program targeting is likely to be more common among the group of old beneficiaries. We therefore expect that, in the case of new beneficiaries, we face a stronger "negative selection" into the program (meaning that needier households are better targeted), and a weaker "negative selection" in the case of old beneficiaries. Restricting the group of beneficiary households to old beneficiaries and comparing them with non-beneficiaries should prompt our estimations to yield higher lower-bound estimates of the mitigation effect. Accordingly, replicating this exercise for new beneficiaries should produce lower lower-bound estimates.

Next, one way to reduce the expected downward bias in the estimated mitigation effect is to restrict the sample to (all) beneficiary households and explore the effect of irregularity of transfer payments. We therefore replace the time-constant binary treatment variable, t_{hd}, with a binary variable, t_{hdr}, that indicates whether the beneficiary household received a payment during the recall period of each survey round. Anecdotal evidence indeed suggests that a common complaint about the SWF cash transfer program was delayed payments. Beneficiaries acknowledged particularly the support that (timely) cash transfers provided for covering regular essential household expenses such as food, water, and electricity and repaying debts to local shop owners (Bagash et al., 2012). Furthermore, the restriction of the sample to beneficiary households and introducing a time-varying treatment variable allows us to exploit an institutional feature of the program: timely delivery of payments by the local post offices to beneficiaries is conditional on the timely receipt of the payments from the Central Bank, which plausibly depends on security along transportation routes from Sanaa. To do so, we instrument the treatment variable for a beneficiary's probability of receiving the payment during the recall period with the variable that captures conflict intensity along the road between the Central Bank and the district post office during that period (excluding conflict intensity in the path destination district and its neighboring districts). To further isolate the direct and indirect conflict effects, we also augment the district and household FE models with controls for spillover effects of armed conflict in neighboring districts.

The district and household fixed effects two-stage least squares (FE-2SLS) regression models have the form:

1st stage:
$$t_{hdr} = \alpha^1_{h|d} + \beta^1_1 x^D_{hdr} + \beta^1_2 x^R_{hdr} + \beta^1_3 x^N_{hdr} + Z_{ihdr}'\gamma^1_1 + V_{hd}'\gamma^1_2 + W_{hdr}'\gamma^1_3 + \omega_r + \varepsilon^1_{ihdr} \tag{3}$$

And

2nd stage:
$$y_{ihdr} = \alpha^2_{h|d} + \beta^2_1 x^D_{hdr} + \beta^2_2 \widehat{t_{hdr}} + \beta^2_3 x^D_{hdr} * \widehat{t_{hdr}} + \beta^2_4 x^R_{hdr} + \beta^2_5 x^N_{hdr} + Z_{ihdr}'\gamma^2_1 + V_{hd}'\gamma^2_2 + W_{hdr}'\gamma^2_3 + \omega_r + \varepsilon^2_{ihdr} \ , \tag{4}$$

where x^R_{hdr} captures the conflict intensity along the road from the Central Bank to the district post office (weighted by the road length), and x^N_{hdr} accounts for the conflict intensity in districts neighboring the household's home district. This IV approach rests on strong identifying assumptions that are discussed in Section 6 along with robustness checks for the main estimation results of the FE-2SLS models.

5. Estimation results

5.1 Impact of armed conflict on child nutrition

Our FE-OLS regression results confirm that armed conflict has a strong negative impact on (short-term) child nutrition, increasing the probability of child wasting in Yemen. Table 3 shows the coefficient estimates of conflict intensity as measured by civilian casualties from the district and household FE models. For both WHZ and MUACZ, the estimated coefficient is statistically significant at least at the 5% level and remarkably stable across all model specifications. Such stability gives us confidence that endogeneity problems are of no or very little relevance in our basic model specifications.

The estimates indicate that an increase in the conflict intensity by one standard deviation (SD) is associated with a decrease in child WHZ by about 0.06 SD and a decrease in child MUACZ by about 0.05 SD. Applying these point estimates evenly across our child sample population reduces the WHZ mean by 9.6% and the MUACZ mean by 4.4%. To put these estimation results into perspective, a 1 SD–increased conflict intensity is equivalent to an average 0.31 civilian casualties per sample district and per survey round recall period (of about a quarter) over the 15-month analysis period in 2012-13. Over a high-conflict-intensity period of 15 months starting in January 2015 (that comprises the onset of the civil war), the 19 governorates included in our analysis recorded an average of 0.86 civilian casualties per district and per quarter. According to our estimates and assuming an even distribution of the estimated nutritional impact across the child sample population, this conflict intensification translates into a reduction of child WHZ and MUACZ by 26.7% and 12.3%, respectively, at the sample mean. The conflict intensity over the following 15-month period (that is, after one year of civil war) was down to 0.30 civilian casualties per district and per quarter—nearly 1 SD above the average in our sample.

Table 3. Estimated impact of armed conflict on child nutrition

Model specification	1	2	3	4	5
Panel A: Weight-for-height z-score (WHZ; N=13,124)					
Civilian casualties (std)	-0.0567	-0.0571	-0.0557	-0.0560	-0.0566
Cluster SE	(0.0200)***	(0.0202)***	(0.0201)***	(0.0201)***	(0.0204)***
Conley SE	(0.0067)***	(0.0067)***	(0.0078)***	(0.0077)***	(0.0054)***
R-squared	0.1312	0.1373	0.1414	0.1415	0.5263
RMSE	0.973	0.970	0.967	0.967	0.785
Panel B: Mid-upper arm circumference z-score (MUACZ; N=11,120)					
Civilian casualties (std)	-0.0503	-0.0503	-0.0478	-0.0469	-0.0485
Cluster SE	(0.0234)**	(0.0234)**	(0.0235)**	(0.0226)**	(0.0227)**
Conley SE	(0.0116)***	(0.0116)***	(0.0102)***	(0.0098)***	(0.0144)***
R-squared	0.1411	0.1429	0.1504	0.1516	0.6004
RMSE	0.887	0.886	0.882	0.882	0.664
Controls					
Individual characteristics	no	yes	yes	yes	yes
Household characteristics	no	no	yes	yes	n.a.
Extreme weather	no	no	no	yes	yes
Fixed effects					
District	yes	yes	yes	yes	no
Household	no	no	no	no	yes

Note: All model specifications control for time fixed effects.

***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level. Standard errors calculated based on the Conley (1999) approach correct for spatial correlation up to 93 kilometers.
N = number of observations; std = standardized; n.a. = not applicable.
The R-squared (overall) and Root Mean Square Error (RMSE) are reported for the model specifications using the cluster SE estimator.
Tables A4 and A5 in the Appendix show the complete estimation results.

The estimated impact of armed conflict on child nutrition is sizeable. Yet, the comparability of our estimates with estimates from previous studies is limited because of the use of different indicators for child nutrition and conflict exposure and often considerably different study designs. Most studies investigate the impact on children's long-term nutritional status, using height-for-age z-scores (HAZ)—the anthropometric indicator commonly used to detect child growth retardation and "stunting." Examples include studies by Akresh et al. (2012) on the 1998–2000 Eritrean-Ethiopian war, Bundervoet et al. (2009) on the Burundian civil war during the late 1990s, Alderman et al. (2006) on the Zimbabwean civil war during the late 1970s, and Minoiu and Shemyakina (2012) on the 2002–2007 Ivorian civil war. However, within a short timeframe, HAZ can be expected to be less responsive to shocks than WAZ (WHO, 1995). The definition of children's exposure to armed conflict and a set of regressions in the study by Akresh et al. (2012) that uses the number of internally displaced persons (IDPs) per administrative region as measure of war intensity comes closest to our specifications. The authors find that a one-percentage-point increase in the per capita number of IDPs in a region reduces child HAZ by 0.017–0.019 SD (with and without controlling for parent characteristics). The estimation results from another regression set that has a binary variable of residing in a war region or not but is identically specified otherwise suggest that war exposure reduces child HAZ by around 0.45 SD. One of the few studies that provides estimates of the impact on child WHZ is authored by Dunn (2018), but its study design is substantially different from ours. Using cross-sectional data and a difference-in-differences regression, the author finds for the Boko Haram insurgency in Northeastern Nigeria between 2008 and 2013 that children's mean WHZ would be 0.49 SD higher than it is, if there were no conflict. Compared to Dunn (2018), we find a much more modest impact: Our estimates imply that a reduction in conflict intensity to virtually zero across Yemen would increase child WHZ by about 0.17 SD on average.[12]

Regarding the controls in our regressions, we find that the coefficient estimates of several individual and household characteristics variables are statistically significant.[13] The estimates suggest for our sample that girls tend to be better nourished than boys and that very young children and children approaching five years of age are more likely to have low WHZ than two- to three-year-old children. Household wealth is positively associated with child WHZ and MUACZ, as

[12] A reduction in conflict intensity by 3 SD from the mean is equivalent to virtually no conflict. In our UCDP dataset, 99.7% of all civilian casualty observations lie within 3 SD around the mean, assuming a normal distribution. Table 3 shows that a change in civilian casualties by 1 SD results in a mean change of child WHZ by around -0.056 SD.
[13] See Tables A4 and A5 in the Appendix

expected. A possible explanation of the negative association between female-headed households and child nutrition, particularly MUACZ, is a lack of childcare resources. Female household heads are rare in Yemen's traditional society. They represent 5.1% of all households in our sample. Female-headed households mainly result from the absence of an adult male family member because of death, working abroad or in distant places, or living with another family in the case of polygamous marriages. Hence, the workload of a mother in a female-headed household is plausibly larger than a mother in a male-headed household and does not permit her to devote sufficient feeding and caring time to her young children. For the extreme weather variables, we find only a statistically significant, negative association between temperature anomaly and MUACZ, pointing to detrimental implications of heat spells for child nutrition.

5.2 Mitigation effects of cash transfers

Table 4 shows the FE-OLS regression results for the models that examine if the SWF cash transfer program mitigates the negative impact of armed conflict on child nutrition across all beneficiary households. We do find a statistically significant and positive mitigation effect for WHZ in the district and household FE model, confirming the hypothesized program benefit. For MUACZ, the coefficient estimate of the interaction term has the expected positive sign in both models, but it is not significant at any standard level of confidence. However, the coefficient estimates of the treatment variable suggest that children in beneficiary households have significantly higher MUACZ than their peers in non-beneficiary households according to the Conley SE (whereas there is virtually no difference in children's WHZ). The household (district) FE model estimates suggest that the program reduces the adverse impact of armed conflict on child nutrition by 35.8% (46.8%) for WHZ and 20.4% (40.6%) for MUACZ, on average.

The FE-OLS regression results in Table 5 indicate that these findings also hold for children in old beneficiary households and children in new beneficiary households, compared to children in non-beneficiary households. The positive mitigation effect of the SWF cash transfer program is stronger among children in old beneficiary households than children in new beneficiary households, particularly when using WHZ as the child nutrition indicator. This result provides supportive evidence that the estimates of the mitigation effect for the old and new beneficiaries denote upper-bound and lower-bound estimates, respectively. The estimated mitigation effect of the SWF cash transfer program found across all beneficiaries (Table 4) is therefore likely to be closer to a lower-bound estimate of the true mitigating effect.

Estimated by FE-2SLS regressions, the mitigation effect of the program's transfer payment regularity on child nutrition among all beneficiaries is shown in Table 6. The coefficient estimate of the interaction term is statistically significant at least at the 5% level and positive for WHZ and MUACZ in the district FE model and WHZ in the household FE model according to the Conley SE. These second-stage estimation results provide additional evidence for the likely downward bias in our estimates of the mitigation effect of the SWF cash transfer program. They also suggest that, going beyond the program's average mitigation effect, the regularity of transfer payments matters for the size of the mitigation effect. Furthermore, the first-stage estimation results confirm that increasing conflict intensity along the road from the Central Bank in Sanaa to the local post offices significantly diminishes the regularity of transfer payments to the beneficiary households.[14]

Table 4. Estimated mitigation effect of the SWF cash transfer program

Model specification	1	2	3
Panel A: Weight-for-height z-score (WHZ; N=13,124)			
Civilian casualties (std)	-0.0560	-0.0767	-0.0715
Cluster SE	(0.0201)***	(0.0169)***	(0.0153)***
Conley SE	(0.0078)***	(0.0089)***	(0.0105)***
Treatment (0=no, 1=yes)	-0.0099	-0.0094	n.a.
Cluster SE	(0.0321)	(0.0320)	
Conley SE	(0.0195)	(0.0195)	
Civilian casualties * treatment		0.0359	0.0256
Cluster SE		(0.0140)**	(0.0151)*
Conley SE		(0.0179)**	(0.0108)**
R-squared	0.1415	0.1418	0.5264
RMSE	0.967	0.967	0.785
Panel B: Mid-upper arm circumference z-score (MUACZ; N=11,120)			
Civilian casualties (std)	-0.0468	-0.0595	-0.0543
Cluster SE	(0.0226)**	(0.0202)***	(0.0097)***
Conley SE	(0.0098)***	(0.0121)***	(0.0121)***
Treatment (0=no, 1=yes)	0.0353	0.0358	n.a.
Cluster SE	(0.0375)	(0.0374)	
Conley SE	(0.0168)**	(0.0166)**	
Civilian casualties * treatment		0.0242	0.0111
Cluster SE		(0.0194)	(0.0292)
Conley SE		(0.0236)	(0.0208)
R-squared	0.1518	0.1519	0.6004
RMSE	0.882	0.882	0.664
Fixed effects			
District	yes	yes	no
Household	no	no	yes

Note: All model specifications control for individual and household characteristics, extreme weather, and time fixed effects.
***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level. Standard errors calculated based on the Conley (1999) approach correct for spatial correlation up to 93 kilometers.
N = number of observations; std = standardized; n.a. = not applicable.
The R-squared (overall) and Root Mean Square Error (RMSE) are reported for the model specifications using the cluster SE estimator.

[14] See Table A6 in the Appendix.

Table 5. Estimated mitigation effect of the SWF cash transfer program for old and new beneficiaries

	Old beneficiaries			New beneficiaries		
Model specification	1	2	3	4	5	6
Panel A: Weight-for-height z-score (WHZ)						
Civilian casualties (std)	-0.0525	-0.0785	-0.0715	-0.0687	-0.0739	-0.0729
Cluster SE	(0.0180)***	(0.0173)***	(0.0152)***	(0.0169)***	(0.0164)***	(0.0155)***
Conley SE	(0.0055)***	(0.0080)***	(0.0104)***	(0.0088)***	(0.0124)***	(0.0106)***
Treatment (0=no, 1=yes)	-0.0142	-0.0138	n.a.	-0.0072	-0.0069	n.a.
Cluster SE	(0.0407)	(0.0404)		(0.0406)	(0.0406)	
Conley SE	(0.0240)	(0.0234)		(0.0157)	(0.0157)	
Civilian casualties * treatment		0.0575	0.0404		0.0199	0.0178
Cluster SE		(0.0154)***	(0.0161)**		(0.0122)	(0.0107)*
Conley SE		(0.0116)***	(0.0112)***		(0.0278)	(0.0178)
R-squared	0.1572	0.1579	0.5254	0.1572	0.1572	0.5185
RMSE	0.973	0.973	0.795	0.951	0.951	0.782
N		*10,196*			*9,116*	
Panel B: Mid-upper arm circumference z-score (MUACZ)						
Civilian casualties (std)	-0.0488	-0.0566	-0.0545	-0.0606	-0.0656	-0.0542
Cluster SE	(0.0153)***	(0.0153)***	(0.0098)***	(0.0183)***	(0.0177)***	(0.0098)***
Conley SE	(0.0094)***	(0.0113)***	(0.0122)***	(0.0116)***	(0.0119)***	(0.0122)***
Treatment (0=no, 1=yes)	0.0299	0.0302	n.a.	0.0474	0.0480	n.a.
Cluster SE	(0.0477)	(0.0477)		(0.0504)	(0.0501)	
Conley SE	(0.0314)	(0.0313)		(0.0228)**	(0.0228)**	
Civilian casualties * treatment		0.0192	0.0115		0.0237	-0.0260
Cluster SE		(0.0194)	(0.0200)		(0.0221)	(0.0478)
Conley SE		(0.0263)	(0.0257)		(0.0328)	(0.0371)
R-squared	0.1691	0.1691	0.6059	0.1854	0.1854	0.6151
RMSE	0.865	0.865	0.651	0.857	0.857	0.644
N		*8,632*			*7,696*	
Fixed effects						
District	yes	yes	no	yes	yes	no
Household	no	no	yes	no	no	yes

Note: All model specifications control for individual and household characteristics, extreme weather, and time fixed effects.
***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively.
Cluster standard errors are clustered at the district level. Standard errors calculated based on the Conley (1999) approach correct for spatial correlation up to 93 kilometers.
N = number of observations; std = standardized; n.a. = not applicable.
The R-squared (overall) and Root Mean Square Error (RMSE) are reported for the model specifications using the cluster SE estimator.

Table 6. Estimated mitigation effect of the regularity of SWF cash transfer payments

	2SLS - 2nd stage	
Model specification	1	2
Panel A: Weight-for-height z-score (WHZ; N=6,516)		
Civilian casualties (std)	-1.4246	-1.3032
Cluster SE	(1.9380)	(1.3381)
Conley SE	(0.0991)***	(0.0840)***
Payment (0=no, 1=yes)	0.7658	1.0603
Cluster SE	(1.2768)	(1.2956)
Conley SE	(0.4763)	(0.5283)**
Civilian casualties * payment	2.2293	2.0393
Cluster SE	(3.2035)	(2.2600)
Conley SE	(0.1440)***	(0.1373)***
Civilian casualties in neighboring districts (std)	-0.0377	-0.0472
Cluster SE	(0.0383)	(0.0361)
Conley SE	(0.0332)	(0.0275)*
RMSE	1.479	1.191
KP rk Wald F	2.780	1.918
Panel B: Mid-upper arm circumference z-score (MUACZ; N=5,540)		
Civilian casualties (std)	-0.5117	-0.2994
Cluster SE	(0.7826)	(0.5127)
Conley SE	(0.2298)**	(0.2105)
Payment (0=no, 1=yes)	1.0615	1.4937
Cluster SE	(0.9914)	(1.1745)
Conley SE	(1.3217)	(1.3758)
Civilian casualties * payment	0.6935	0.3834
Cluster SE	(1.1395)	(0.7454)
Conley SE	(0.3301)**	(0.2968)
Civilian casualties in neighboring districts (std)	-0.0499	-0.0563
Cluster SE	(0.0311)	(0.0286)**
Conley SE	(0.0414)	(0.0411)
RMSE	1.012	0.811
KP rk Wald F	2.076	1.698
Fixed effects		
District	yes	no
Household	no	yes

Note: All model specifications control for individual and household characteristics, extreme weather, and time fixed effects.

***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level. Standard errors calculated based on Conley (1999)'s approach correct for spatial correlation up to 93 kilometers.

N = number of observations; std = standardized.

The Root Mean Square Error (RMSE) and Kleibergen-Paap rank Wald F-statistic (KP rk Wald F) (Baum et al., 2007; Kleibergen and Paap, 2006) are reported for the model specifications using the cluster SE estimator.

Table A6 in the Appendix shows the first-stage estimation results.

6. Robustness checks and validity tests

Our main estimation results may be sensitive to the definition of armed conflict intensity. To assess this conjecture, we estimate the impact of armed conflict on child nutrition and the mitigation effect of the SWF cash transfer program using the number of armed conflict events reported in the GDELT dataset as conflict variable. The estimations of the basic district and household FE-OLS models provide strong evidence for the robustness of our main estimation results to an alternative definition of armed conflict intensity. The coefficient estimates of the alternative conflict variable are statistically significant at the 1% level according to the cluster SE and Conley SE in all model specifications.[15] Moreover, as with the preferred model specifications, the coefficient estimates are remarkably stable across the alternative model specifications and vary within a reasonable range around the coefficient estimates of the preferred conflict variable.

In the models that examine the mitigation effect of the SWF cash transfer program using the GDELT conflict events variable, the coefficient estimates of the interaction term confirm the positive mitigation effect found in the estimations of the preferred model specifications, although the significance levels of the estimates differ.[16] The alternative district and household FE-OLS model specifications yield stronger results for the mitigation effect on child MUACZ than the respective preferred model specifications. For child WHZ, the coefficient estimates of the alternative and preferred model specifications are similar, which further increases our confidence in the robustness of our main estimation results for this child nutrition indicator.

There is also the possibility that unobserved district-specific shocks (other than weather-related shocks) may act as confounding factors, compromising our identification strategy. While we cannot formally exclude this possibility, we rate the probability that the main coefficient estimates of interest are notably biased due to the absorption of unobserved district-time varying changes as low. Introducing paired district-time FE into the fully specified district and household FE models shows that the main estimation results are robust to this augmentation.[17] Note that these model specifications are only possible, because the variables that measure conflict exposure are constructed based on the time periods between survey round interview dates which vary across households. However, it also means that the identification in these models may be driven by minor differences in the household-specific recall periods—and, hence, potentially by "noise" in the definition of conflict exposure (given the infrequent nature of conflict events). In the light of such a potential threat to identification, it is reinsuring that our estimation results are qualitatively unchanged, although the magnitudes of the main coefficient estimates decrease when adding district-time FE in our preferred model specifications.

Other potential threats relate to the validity of the IV approach that underlies our estimations of the mitigation effect of transfer payment regularity (Table 6). The validity of the IV approach rests on strong identifying assumptions, including the relevance of the instrumental variable and the

[15] See Table A7 in the Appendix.
[16] See Table A8 in the Appendix.
[17] See Table A9 in the Appendix.

exclusion restriction. Regarding the former threat, our first-stage estimation results indicate that armed conflict along the road from the Central Bank to the district post offices indeed disrupts the regularity of SWF cash transfer payments.[18] The Kleibergen-Paap Wald F-statistics in Table 6 are rather low, but we report a just-identified IV specification, known to be median unbiased and therefore unlikely to be subject to weak instrumentation (Angrist and Pischke, 2008).

We are much more concerned about the violation of the exclusion restriction. It is indeed difficult to exclude a priori the possibility that conflict-caused insecurity along the road from the Central Bank to the district post offices affects child nutrition through another channel rather than the SWF cash transfer payments. To minimize the potential threat to the validity of this identifying assumption of our FE-2SLS models, we control for possible spillover effects of armed conflict in neighboring districts on child nutrition observed in a sample district in all model specifications. Further, we explore the existence of other channels that could compromise our identification strategy. An obvious driver of acute child malnutrition is the unavailability or unaffordability of staple foods. Conflict-caused insecurity along the supply routes is likely to affect food volumes and prices in local markets (Tandon and Vishwanath, 2020).[19] Yemenis' food consumption has been highly dependent on imports, especially for the main staple foods (Breisinger and Ecker, 2014; Ianchovichina et al., 2014). Almost all grains are imported through three seaports—Hodeidah and Saleef on the Red Sea and Aden on the Gulf of Aden—that are far from Sanaa (World Bank, 2017a). We construct variables of armed conflict intensity for the shortest primary road distance from each of these seaports to the district post offices, using the same method as for the calculation of armed conflict intensity along the road from the Central Bank in Sanaa. The overlap of the roads from the seaports and the road from the Central Bank tends to be small, especially for peripheral districts. We include these variables in the district and household FE-2SLS models to check the stability of the coefficient estimate of the interaction term. The estimation results confirm that the found mitigation effect of transfer payment regularity is robust when accounting for food supply disruptions.[20]

Conflict-caused insecurity along the road from the Central Bank in Sanaa to the district post offices may affect child nutrition through interruptions of private and other public cash transfers, as their delivery mainly relies on the national postal service system—like the SWF cash transfer payments. Indeed, 36.6% of the beneficiary households in our sample receive remittances, and 31.5% of the beneficiary households receive pensions or other government transfers from non-SWF sources. Our FE-2SLS model estimation results are largely unaltered when controlling for receiving remittances by survey round recall period or the remittance amount per recall period and adding

[18] See Table A6 in the Appendix.
[19] District-level data on food market volumes and food prices are unavailable for Yemen, which limits our options for testing this potential threat to the validity of the exclusion restriction.
[20] See Table A10 in the Appendix.

the respective interaction term.[21,22] Estimating the same model specifications with pensions and other non-SWF government transfers instead of remittances yields the same finding.[23] Due to the introduction of these additional variables into the FE-2SLS models, the efficiency of our estimations is weakened, and we caution against interpreting the coefficient estimates of the added variables since they are clearly endogenous.

Finally, we check the validity of the exclusion restriction by replacing the endogenous variable in our preferred FE-2SLS model specifications with an alternative one. The alternative variable is the reported transfer amount that beneficiary households received as the last payment of the SWF cash transfer program per survey round recall period.[24] Table 7 shows that the estimation results for these alternative model specifications are highly consistent with those of our preferred model specifications, confirming the plausibility of the hypothesized mechanism underlying the mitigation effect of the SWF cash transfer program.

Because of data limitations, we cannot completely rule out the possibility that unobserved confounding factors violate our empirical strategy. However, the performed robustness checks and validity tests provide suggestive evidence that the existence of such factors does not jeopardize the findings of our analysis.

[21] All variables having monetary values (including remittances, pensions, other non-SWF government transfers, and SWF cash transfers) enter the FE-2SLS models in logarithms, using the $ln(1+x)$ transformation.
[22] See Table A11 in the Appendix.
[23] See Table A12 in the Appendix.
[24] We acknowledge that the SWF cash transfer amount variable may suffer from measurement errors due to misreporting and recording inaccuracies during the interviews (IPC-IG et al., 2014a).

Table 7. Estimated mitigation effect of the amount of SWF cash transfer payments

	2SLS - 2nd stage	
Model specification	1	2
Panel A: Weight-for-height z-score (WHZ; N=6,516)		
Civilian casualties (std)	-1.3126	-1.1869
Cluster SE	(1.6066)	(1.0910)
Conley SE	(0.0891)***	(0.0803)***
Transfer amount (log)	0.0788	0.1083
Cluster SE	(0.1216)	(0.1246)
Conley SE	(0.0482)	(0.0535)**
Civilian casualties * transfer amount	0.2191	0.1981
Cluster SE	(0.2845)	(0.1980)
Conley SE	(0.0137)***	(0.0141)***
Civilian casualties in neighboring districts (std)	-0.0321	-0.0415
Cluster SE	(0.0385)	(0.0349)
Conley SE	(0.0337)	(0.0278)
RMSE	1.412	1.128
KP rk Wald F	2.611	1.775
Panel B: Mid-upper arm circumference z-score (MUACZ; N=5,540)		
Civilian casualties (std)	-0.4665	0.1500
Cluster SE	(0.6564)	(0.1191)
Conley SE	(0.2116)**	(0.2078)
Transfer amount (log)	0.1070	0.1500
Cluster SE	(0.0980)	(0.1191)
Conley SE	(0.1331)	(0.1380)
Civilian casualties * transfer amount	0.0673	0.0354
Cluster SE	(0.1022)	(0.0688)
Conley SE	(0.0325)**	(0.0312)
Civilian casualties in neighboring districts (std)	-0.0485	-0.0548
Cluster SE	(0.0302)	(0.0282)*
Conley SE	(0.0377)	(0.0415)
RMSE	0.999	0.796
KP rk Wald F	2.014	1.584
Fixed effects		
District	yes	no
Household	no	yes

Note: All model specifications control for individual and household characteristics, extreme weather, and time fixed effects.

***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level. Standard errors calculated based on the Conley (1999) approach correct for spatial correlation up to 93 kilometers.

N = number of observations; std = standardized; log = logarithmic.

The Root Mean Square Error (RMSE) and Kleibergen-Paap rank Wald F-statistic (KP rk Wald F) (Baum et al., 2007; Kleibergen and Paap, 2006)) are reported for the model specifications using the cluster SE estimator.

Table A13 in the Appendix shows the first-stage estimation results.

7. Conclusions

Our study demonstrates the detrimental impact of armed conflict on child nutrition in Yemen. Our estimation results show that increasing conflict intensity significantly reduces WHZ and MUACZ of children younger than five years and, hence, increases the risk of acute child malnutrition. We find that a one-standard-deviation increase in conflict intensity, measured by the number of civilian casualties, reduces child WHZ by about 0.06 and child MUACZ by about 0.05—equivalent to respective decreases of 9.6% and 4.4% at the sample mean. The estimated effect sizes are relatively small, given the period of low-intensity violence that is covered by the survey data used in our analysis. However, our estimates are plausibly lower-bound estimates of the true impact of armed conflict on child nutrition, because they capture only the direct effects from armed conflict events occurring in the children's home districts, and do not consider cumulative effects of prolonged exposure to civil conflict. Moreover, our estimation results provide some evidence that violence is targeted at the poor, so that the nutritional impact of armed conflict is likely to be disproportionally larger among children who are already malnourished or are at high risk of becoming malnourished than among well-nourished children, who are usually living in better-off households. Nonetheless, extrapolation of our estimation results suggests that an intensification of armed conflict to the average level experienced in Yemen for more than the first year of the current civil war translates into a reduction of child WHZ and MUACZ by 26.7% and 12.3%, respectively, at the sample mean.

Finding a political resolution of Yemen's current civil war is an absolute priority to tackle what has been recognized as the world's worst humanitarian crisis in recent history. There have been several ceasefire agreements in recent years, primarily to safeguard imports and transport of food aid and humanitarian supplies from the Red Sea ports inland to the main cities in the highlands and to establish humanitarian corridors. However, these ceasefires have had only mixed success, and the road to a sustainable peace agreement appears to be still long and bumpy. Building resilience to civil conflict and violence-sparking shocks in fragile states is challenging (Breisinger et al., 2014), but recent political developments could open a new window of opportunity for targeted interventions to support Yemen's recovery. Such a window of opportunity makes findings from the second step of our econometric analysis particularly relevant to the present situation.

The escalation of armed conflict in March 2015 and a subsequent fiscal crisis resulted in full suspension of the national cash transfer program due to lack of public funding for the SWF and suspension of donor funds to government organizations. After more than two years of civil war, with devastating consequences for the civilian population, the World Bank stepped in with an initial US$200 million grant to resume unconditional cash transfers under the Yemen Emergency Crisis Response Project (ECRP), implemented by UNICEF (World Bank, 2017b). This project component uses the existing beneficiary list from the SWF cash transfer program to target extremely vulnerable households. It follows the program's quarterly payment schedule and delivered the first round of transfer payments in October 2017 (World Bank, 2018). Given that key implementation modalities of the ECRP component are similar to those of the SWF cash transfer program, our findings are likely to be transferable to a large extent.

Our analysis confirms that unconditional cash transfers can be an effective tool in complex emergencies and provides scientific evidence on Yemen that complements learning from the practical experiences of program implementers in several fragile countries and civil conflict zones (e.g., HPN, 2012; ODI and CGD, 2015). Precisely, we show that unconditional cash transfers can mitigate the adverse impact of armed conflict on child nutrition in Yemen. We estimate the mitigation effect of the SWF cash transfer program before the current civil war at more than one-third of the size of the estimated impact on children's nutritional status when measured by WHZ—the more accurate anthropometric indicator for detecting acute malnutrition in populations. Thus, even with suboptimal implementation of the program (IPC-IG et al., 2014a), the estimated mitigation effect is sizeable. The SWF cash transfer program was able to reach vulnerable households. Beneficiary households were more socially and economically disadvantaged than non-beneficiary households. A critical operational challenge that persisted at least throughout the analysis period of our study was the irregularity of cash transfer payments. Our estimation results indicate that the regularity of transfer payments matters for the size of the mitigation effect (independent of the cash amount). Hence, the effectiveness of the ECRP component in mitigating the nutritional impact of armed conflict is also likely to depend on timely delivery of transfer payments on (at least) a quarterly basis.

Finally, we call for a cautious interpretation of the estimated effect sizes. Given the study design, our estimates should be understood as local average treatment effects rather than average treatment effects. There is a possibility that we may overestimate the detrimental impact of armed conflict and the mitigation effect of the SWF cash transfer program across the Yemeni population. The estimates are obtained from a sample of households who tend to be particularly vulnerable to shocks, so that the response heterogeneity in the sample may facilitates finding sizeable effects. On the other hand, the sample does not include observations from Saada and Al-Jawf Governorates, where conflict-caused insecurity was extremely high at the time of the survey and years prior to it. Thus, the sample may also not take account of the households that have been most exposed to prolonged armed conflict.

More broadly, our analysis provides additional evidence for the beneficial role of cash transfer programs in civil conflict settings found in other contexts—for example, to promote the use of maternal and child health services in Afghanistan (Edmond et al., 2019), to support demobilization of combatants in Colombia (Pena et al., 2017), and to influence local insurgents in the Philippines (Crost et al, 2016). Our study also complements recent work by Tranchant et al. (2019), who find that food assistance has a protective effect among food-insecure populations experiencing civil conflict in Mali. Assessing the relative efficiency of unconditional cash transfers and general food distribution in complex emergencies and fragile countries is an important area of future research that can help humanitarian and development aid agencies in strategizing and further improving their efforts to protect vulnerable populations from hunger and malnutrition.

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Appendix

Table A1. Attrition check: Summary statistics and mean difference tests for child nutrition indicators and household characteristics at baseline, with Al-Jawf Governorate

	All households					All beneficiaries					Non-beneficiaries				
	Initial sample		Final sample		t-test	Initial sample		Final sample		t-test	Initial sample		Final sample		t-test
	Mean	SD	Mean	SD	Pr(|T|>|t|)	Mean	SD	Mean	SD	Pr(|T|>|t|)	Mean	SD	Mean	SD	Pr(|T|>|t|)
Child nutrition															
WHZ	-0.630	1.200	-0.644	1.178	0.630	-0.626	1.215	-0.639	1.194	0.738	-0.634	1.187	-0.648	1.163	0.724
N (children)	*3,593*		*3,281*			*1,725*		*1,629*			*1,868*		*1,652*		
MUACZ	-1.167	0.986	-1.184	0.972	0.488	-1.190	1.001	-1.200	0.992	0.785	-1.147	0.972	-1.170	0.953	0.502
N (children)	*3,244*		*2,949*			*1,538*		*1,449*			*1,706*		*1,500*		
Households with …															
Disabled person	0.185	0.389	0.191	0.393	0.592	0.241	0.428	0.244	0.430	0.860	0.132	0.339	0.138	0.345	0.681
Orphan	0.039	0.193	0.038	0.191	0.910	0.040	0.197	0.041	0.199	0.920	0.037	0.189	0.035	0.183	0.772
Elderly	0.334	0.472	0.349	0.477	0.257	0.459	0.499	0.470	0.499	0.598	0.214	0.410	0.226	0.419	0.448
Widowed or divorced woman	0.230	0.421	0.240	0.427	0.399	0.340	0.474	0.347	0.476	0.697	0.125	0.331	0.132	0.338	0.630
Unemployed man	0.071	0.257	0.069	0.253	0.755	0.082	0.275	0.080	0.271	0.819	0.060	0.238	0.057	0.233	0.778
Level of per capita household income (from non-SWF sources):															
Quintile 1	0.207	0.405	0.206	0.405	0.962	0.224	0.417	0.232	0.422	0.639	0.191	0.393	0.180	0.385	0.515
Quintile 2	0.201	0.400	0.201	0.401	0.990	0.226	0.418	0.219	0.414	0.703	0.177	0.382	0.182	0.386	0.730
Quintile 3	0.199	0.399	0.199	0.399	0.973	0.208	0.406	0.204	0.403	0.801	0.190	0.392	0.194	0.396	0.781
Quintile 4	0.201	0.401	0.201	0.401	0.982	0.184	0.387	0.191	0.393	0.651	0.218	0.413	0.211	0.408	0.683
Quintile 5	0.193	0.395	0.193	0.395	0.980	0.159	0.366	0.155	0.362	0.756	0.225	0.418	0.233	0.423	0.669
Households chronic poverty status:															
Poor	0.661	0.474	0.655	0.476	0.659	0.730	0.444	0.723	0.448	0.716	0.595	0.491	0.585	0.493	0.632
Extremely poor	0.174	0.379	0.180	0.384	0.595	0.239	0.427	0.240	0.427	0.982	0.112	0.315	0.119	0.324	0.565
Moderately poor	0.313	0.464	0.304	0.460	0.500	0.329	0.470	0.322	0.468	0.720	0.299	0.458	0.287	0.452	0.515
Vulnerable	0.173	0.379	0.170	0.376	0.790	0.162	0.368	0.162	0.368	0.991	0.184	0.388	0.179	0.384	0.751
N (households)	*2,533*		*2,312*			*1,237*		*1,164*			*1,296*		*1,148*		

Note: All household characteristics variables are binary and coded as 1 if true and 0 otherwise.

Table A2. Attrition check: Summary statistics and mean difference tests for child nutrition indicators and household characteristics at baseline, without Al-Jawf Governorate

	All households					All beneficiaries					Non-beneficiaries				
	Initial sample		Final sample		t-test	Initial sample		Final sample		t-test	Initial sample		Final sample		t-test
	Mean	SD	Mean	SD	Pr(|T|>|t|)	Mean	SD	Mean	SD	Pr(|T|>|t|)	Mean	SD	Mean	SD	Pr(|T|>|t|)
Child nutrition															
WHZ	-0.629	1.181	-0.644	1.178	0.613	-0.628	1.202	-0.639	1.194	0.786	-0.630	1.160	-0.648	1.163	0.655
N (children)	*3,430*		*3,281*			*1,669*		*1,629*			*1,761*		*1,652*		
MUACZ	-1.172	0.975	-1.184	0.972	0.628	-1.190	0.994	-1.200	0.992	0.791	-1.156	0.957	-1.170	0.953	0.687
N (children)	*3,085*		*2,949*			*1,486*		*1,449*			*1,599*		*1,500*		
Households with …															
Disabled person	0.190	0.392	0.191	0.393	0.917	0.244	0.430	0.244	0.430	0.997	0.137	0.344	0.138	0.345	0.985
Orphan	0.039	0.194	0.038	0.191	0.823	0.042	0.200	0.041	0.199	0.935	0.037	0.188	0.035	0.183	0.798
Elderly	0.342	0.475	0.349	0.477	0.626	0.468	0.499	0.470	0.499	0.915	0.220	0.414	0.226	0.419	0.703
Widowed or divorced woman	0.236	0.424	0.240	0.427	0.714	0.344	0.475	0.347	0.476	0.862	0.130	0.336	0.132	0.338	0.912
Unemployed man	0.068	0.252	0.069	0.253	0.948	0.080	0.271	0.080	0.271	0.981	0.057	0.232	0.057	0.233	0.979
Level of per capita household income (from non-SWF sources):															
Quintile 1	0.207	0.405	0.206	0.405	0.957	0.222	0.416	0.232	0.422	0.569	0.192	0.394	0.180	0.385	0.460
Quintile 2	0.200	0.400	0.201	0.401	0.975	0.225	0.418	0.219	0.414	0.745	0.177	0.381	0.182	0.386	0.730
Quintile 3	0.199	0.399	0.199	0.399	0.980	0.211	0.408	0.204	0.403	0.648	0.186	0.390	0.194	0.396	0.628
Quintile 4	0.201	0.401	0.201	0.401	0.996	0.185	0.389	0.191	0.393	0.734	0.216	0.412	0.211	0.408	0.764
Quintile 5	0.193	0.395	0.193	0.395	0.997	0.157	0.364	0.155	0.362	0.888	0.229	0.420	0.233	0.423	0.834
Households chronic poverty status:															
Poor	0.650	0.477	0.655	0.476	0.718	0.723	0.448	0.723	0.448	0.965	0.579	0.494	0.585	0.493	0.750
Extremely poor	0.175	0.380	0.180	0.384	0.690	0.238	0.426	0.240	0.427	0.926	0.114	0.319	0.119	0.324	0.713
Moderately poor	0.303	0.460	0.304	0.460	0.910	0.321	0.467	0.322	0.468	0.953	0.285	0.452	0.287	0.452	0.948
Vulnerable	0.171	0.377	0.170	0.376	0.931	0.163	0.370	0.162	0.368	0.898	0.179	0.384	0.179	0.384	0.981
N (households)	*2,416*		*2,312*			*1,193*		*1,164*			*1,223*		*1,148*		

Note: All household characteristics variables are binary and coded as 1 if true and 0 otherwise.

Table A3. Regularity of SWF cash transfer payments by household beneficiary group and survey round

Recall period	Round 1	Round 2	Round 3	Round 4
All beneficiaries (N=1,164)				
0	45.0	11.3	4.0	1.5
1	55.0	41.4	23.7	7.5
2		47.3	39.0	19.7
3			33.3	38.7
4				32.6
Old beneficiaries (N=636)				
0	36.0	6.9	1.1	0.0
1	64.0	36.2	17.9	1.9
2		56.9	39.6	17.5
3			41.4	40.3
4				40.4
New beneficiaries (N=448)				
0	55.1	14.5	4.9	0.2
1	44.9	44.6	24.1	4.9
2		40.8	43.3	24.3
3			27.7	43.3
4				27.2

Table A4. Complete estimation results for the impact of armed conflict on child WHZ

	Weight-for-height z-score (WHZ; N=13,124)				
Model specification	1	2	3	4	5
Civilian casualties (std)	-0.0567	-0.0571	-0.0557	-0.0560	-0.0566
Cluster SE	(0.0200)***	(0.0202)***	(0.0201)***	(0.0201)***	(0.0204)***
Conley SE	(0.0067)***	(0.0067)***	(0.0078)***	(0.0077)***	(0.0054)***
Individual characteristics					
Child sex (0=male, 1=female)		0.0857	0.0881	0.0881	0.0525
Cluster SE		(0.0277)***	(0.0274)***	(0.0274)***	(0.0379)
Conley SE		(0.0193)***	(0.0191)***	(0.0191)***	(0.0163)***
Child age (months)		0.0205	0.0211	0.0211	0.0274
Cluster SE		(0.0039)***	(0.0039)***	(0.0039)***	(0.0045)***
Conley SE		(0.0021)***	(0.0021)***	(0.0021)***	(0.0028)***
Child age squared		-0.0003	-0.0003	-0.0003	-0.0004
Cluster SE		(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***
Conley SE		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Household characteristics					
Household wealth index			0.1043	0.1044	
Cluster SE			(0.0240)***	(0.0240)***	
Conley SE			(0.0156)***	(0.0156)***	
Household size (headcount)			0.0011	0.0011	
Cluster SE			(0.0043)	(0.0043)	
Conley SE			(0.0025)	(0.0025)	
Sex of household head (0=male, 1=female)			-0.0601	-0.0600	
Cluster SE			(0.0732)	(0.0732)	
Conley SE			(0.0349)*	(0.0349)*	
Age of household head (years)			0.0005	0.0005	
Cluster SE			(0.0012)	(0.0012)	
Conley SE			(0.0007)	(0.0007)	
Literacy of household head (0=illiterate, 1=literate)			-0.0587	-0.0586	
Cluster SE			(0.0370)	(0.0369)	
Conley SE			(0.0279)**	(0.0278)**	
Extreme weather					
Precipitation anomaly				0.0075	0.0053
Cluster SE				(0.0095)	(0.0094)
Conley SE				(0.0142)	(0.0140)
Temperature anomaly				-0.0116	0.0034
Cluster SE				(0.0284)	(0.0286)
Conley SE				(0.0308)	(0.0332)
Fixed effects					
District	yes	yes	yes	yes	no
Household	no	no	no	no	yes
R-squared	0.1312	0.1373	0.1414	0.1415	0.5263
RMSE	0.973	0.970	0.967	0.967	0.785

Note: All model specifications control for time fixed effects.

***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level. Standard errors calculated based on the Conley (1999) approach correct for spatial correlation up to 93 kilometers.

N = number of observations; std = standardized.

The R-squared (overall) and Root Mean Square Error (RMSE) are reported for the model specifications using the cluster SE estimator.

Table A5. Complete estimation results for the impact of armed conflict on child MUACZ

	Mid-upper arm circumference z-score (MUACZ; N=11,120)				
Model specification	1	2	3	4	5
Civilian casualties (std)	-0.0503	-0.0503	-0.0478	-0.0469	-0.0485
Cluster SE	(0.0234)**	(0.0234)**	(0.0235)**	(0.0226)**	(0.0227)**
Conley SE	(0.0116)***	(0.0116)***	(0.0102)***	(0.0098)***	(0.0144)***
Individual characteristics					
Child sex (0=male, 1=female)		0.0506	0.0516	0.0517	0.1070
Cluster SE		(0.0298)*	(0.0297)*	(0.0296)*	(0.0432)**
Conley SE		(0.0092)***	(0.0102)***	(0.0101)***	(0.0208)***
Child age (months)		-0.0015	-0.0010	-0.0011	0.0027
Cluster SE		(0.0053)	(0.0053)	(0.0053)	(0.0054)
Conley SE		(0.0041)	(0.0041)	(0.0041)	(0.0056)
Child age squared		-0.0000	-0.0000	-0.0000	-0.0000
Cluster SE		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Conley SE		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Household characteristics					
Household wealth index			0.1383	0.1379	
Cluster SE			(0.0246)***	(0.0246)***	
Conley SE			(0.0228)***	(0.0230)***	
Household size (headcount)			-0.0031	-0.0030	
Cluster SE			(0.0043)	(0.0043)	
Conley SE			(0.0025)	(0.0026)	
Sex of household head (0=male, 1=female)			-0.1683	-0.1686	
Cluster SE			(0.0704)**	(0.0705)**	
Conley SE			(0.0236)***	(0.0239)***	
Age of household head (years)			-0.0006	-0.0006	
Cluster SE			(0.0011)	(0.0011)	
Conley SE			(0.0010)	(0.0010)	
Literacy of household head (0=illiterate, 1=literate)			-0.0515	-0.0517	
Cluster SE			(0.0394)	(0.0394)	
Conley SE			(0.0370)	(0.0369)	
Extreme weather					
Precipitation anomaly				-0.0085	-0.0099
Cluster SE				(0.0097)	(0.0096)
Conley SE				(0.0121)	(0.0105)
Temperature anomaly				-0.0937	-0.0839
Cluster SE				(0.0384)**	(0.0375)**
Conley SE				(0.0430)**	(0.0431)*
Fixed effects					
District	yes	yes	yes	yes	no
Household	no	no	no	no	yes
R-squared	0.1411	0.1429	0.1504	0.1516	0.6004
RMSE	0.887	0.886	0.882	0.882	0.664

Note: All model specifications control for time fixed effects.

***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level. Standard errors calculated based on the Conley (1999) approach correct for spatial correlation up to 93 kilometers.

N = number of observations; std = standardized.

The R-squared (overall) and Root Mean Square Error (RMSE) are reported for the model specifications using the cluster SE estimator.

Table A6. First-stage estimation results of the 2SLS regressions for transfer payment regularity

	Payment (0=no, 1=yes)	
Model specification	1	2
Panel A: Weight-for-height z-score (WHZ; N=6,516)		
Civilian casualties along the road from the Central Bank (std)	-0.0196	-0.0161
Cluster SE	(0.0078)**	(0.0077)**
Conley SE	(0.0038)***	(0.0036)***
Civilian casualties (std)	-0.0018	-0.0011
Cluster SE	(0.0052)	(0.0051)
Conley SE	(0.0066)	(0.0058)
Civilian casualties in neighboring districts (std)	-0.0069	-0.0058
Cluster SE	(0.0095)	(0.0095)
Conley SE	(0.0061)	(0.0081)
R-squared	0.2048	0.4095
F-test	2.679	3.544
Panel B: Mid-upper arm circumference z-score (MUACZ; N=5,540)		
Civilian casualties along the road from the Central Bank (std)	-0.0173	-0.0152
Cluster SE	(0.0077)**	(0.0081)*
Conley SE	(0.0059)***	(0.0049)***
Civilian casualties (std)	0.0026	0.0030
Cluster SE	(0.0041)	(0.0043)
Conley SE	(0.0043)	(0.0057)
Civilian casualties in neighboring districts (std)	-0.0104	-0.0092
Cluster SE	(0.0090)	(0.0090)
Conley SE	(0.0060)*	(0.0079)
R-squared	0.2045	0.4109
F-test	2.416	3.458
Fixed effects		
District	yes	no
Household	no	yes

Note: All model specifications control for individual and household characteristics, extreme weather, and time fixed effects.

***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level. Standard errors calculated based on the Conley (1999) approach correct for spatial correlation up to 93 kilometers.

N = number of observations; std = standardized.

The R-squared (overall) and F-test statistic are reported for the model specifications using the cluster SE estimator.

Table A7. Estimated impact of armed conflict on child nutrition for GDELT conflict events

Model specification	1	2	3	4	5
Panel A: Weight-for-height z-score (WHZ; N=13,124)					
Conflict events (std)	-0.0500	-0.0512	-0.0486	-0.0488	-0.0464
Cluster SE	(0.0076)***	(0.0076)***	(0.0072)***	(0.0074)***	(0.0087)***
Conley SE	(0.0124)***	(0.0122)***	(0.0126)***	(0.0128)***	(0.0098)***
R-squared	0.1299	0.1360	0.1402	0.1402	0.5249
RMSE	0.974	0.970	0.968	0.968	0.786
Panel B: Mid-upper arm circumference z-score (MUACZ; N=11,120)					
Conflict events (std)	-0.0603	-0.0603	-0.0564	-0.0537	-0.0557
Cluster SE	(0.0064)***	(0.0065)***	(0.0064)***	(0.0065)***	(0.0065)***
Conley SE	(0.0100)***	(0.0100)***	(0.0099)***	(0.0101)***	(0.0101)***
R-squared	0.1404	0.1423	0.1498	0.1509	0.5997
RMSE	0.887	0.886	0.882	0.882	0.664
Controls					
Individual characteristics	no	yes	yes	yes	yes
Household characteristics	no	no	yes	yes	n.a.
Extreme weather	no	no	no	yes	yes
Fixed effects					
District	yes	yes	yes	yes	no
Household	no	no	no	no	yes

Note: All model specifications control for time fixed effects.

***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level. Standard errors calculated based on the Conley (1999) approach correct for spatial correlation up to 93 kilometers.

N = number of observations; std = standardized; n.a. = not applicable.

The R-squared (overall) and Root Mean Square Error (RMSE) are reported for the model specifications using the cluster SE estimator.

Table A8. Estimated mitigation effect of the SWF cash transfer program for GDELT conflict events

Model specification	1	2	3
Panel A: Weight-for-height z-score (WHZ; N=13,1240)			
Conflict events (std)	-0.0488	-0.0688	-0.0611
Cluster SE	(0.0074)***	(0.0111)***	(0.0224)***
Conley SE	(0.0128)***	(0.0108)***	(0.0136)***
Treatment (0=no, 1=yes)	-0.0100	-0.0096	n.a.
Cluster SE	(0.0321)	(0.0318)	
Conley SE	(0.0194)	(0.0192)	
Conflict events * treatment		0.0364	0.0261
Cluster SE		(0.0129)***	(0.0257)
Conley SE		(0.0104)***	(0.0218)
R-squared	0.1402	0.1405	0.5249
RMSE	0.968	0.968	0.786
Panel B: Mid-upper arm circumference z-score (MUACZ; N=11,120)			
Conflict events (std)	-0.0536	-0.0725	-0.0877
Cluster SE	(0.0065)***	(0.0114)***	(0.0122)***
Conley SE	(0.0101)***	(0.0136)***	(0.0158)***
Treatment (0=no, 1=yes)	0.0352	0.0362	n.a.
Cluster SE	(0.0375)	(0.0375)	
Conley SE	(0.0167)**	(0.0162)**	
Conflict events * treatment		0.0384	0.0626
Cluster SE		(0.0253)	(0.0158)***
Conley SE		(0.0177)**	(0.0179)***
R-squared	0.1512	0.1515	0.5999
RMSE	0.882	0.882	0.664
Fixed effects			
District	yes	yes	no
Household	no	no	yes

Note: All model specifications control for individual and household characteristics, extreme weather, and time fixed effects.

***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level. Standard errors calculated based on the Conley (1999) approach correct for spatial correlation up to 93 kilometers.

N = number of observations; std = standardized; n.a. = not applicable.

The R-squared (overall) and Root Mean Square Error (RMSE) are reported for the model specifications using the cluster SE estimator.

Table A9. Robustness of the estimated impact of armed conflict and the estimated mitigation effect of the SWF cash transfer program to the introduction of district-time FE in the fully specified district and household FE models

	Impact of armed conflict among all households		Mitigation effect of cash transfers for …					
			All beneficiaries		Old beneficiaries		New beneficiaries	
Model specification	1	2	3	4	5	6	7	8
Panel A: Weight-for-height z-score (WHZ)								
Civilian casualties (std)	-0.0325	-0.0301	-0.0624	-0.0584	-0.0549	-0.0488	-0.0759	-0.0763
	(0.0074)***	(0.0073)***	(0.0038)***	(0.0056)***	(0.0038)***	(0.0075)***	(0.0033)***	(0.0044)***
Treatment (0=no, 1=yes)			-0.0103	n.a.	-0.0144	n.a.	-0.0081	n.a.
			(0.0321)		(0.0404)		(0.0407)	
Civilian casualties * treatment			0.0488	0.0454	0.0713	0.0612	0.0344	0.0381
			(0.0123)***	(0.0065)***	(0.0175)***	(0.0085)***	(0.0090)***	(0.0186)**
N	*13,108*		*13,108*		*10,156*		*9,056*	
R-squared	0.2051	0.5917	0.2059	0.5922	0.2242	0.5940	0.2264	0.5918
RMSE	0.963	0.759	0.963	0.759	0.974	0.774	0.953	0.761
Panel B: Mid-upper arm circumference z-score (MUACZ)								
Civilian casualties (std)	-0.0033	-0.0009	-0.0244	-0.0184	-0.0210	-0.0170	-0.0114	0.0038
	(0.0015)**	(0.0020)	(0.0143)*	(0.0056)***	(0.0114)*	(0.0063)***	(0.0079)	(0.0040)
Treatment (0=no, 1=yes)			0.0373	n.a.	0.0309	n.a.	0.0506	n.a.
			(0.0374)		(0.0476)		(0.0498)	
Civilian casualties * treatment			0.0414	0.0345	0.0320	0.0286	0.0474	0.0039
			(0.0225)*	(0.0071)***	(0.0237)	(0.0111)**	(0.0278)*	(0.0165)
N	*11,080*		*11,080*		*8,584*		*7,636*	
R-squared	0.2293	0.6791	0.2309	0.6799	0.2512	0.6894	0.2750	0.7060
RMSE	0.874	0.624	0.873	0.624	0.863	0.615	0.854	0.601
Fixed effects								
District	yes	no	yes	no	yes	no	yes	no
Household	no	yes	no	yes	no	yes	no	yes
District × survey round	yes	yes	yes	yes	yes	yes	yes	yes

Note: All model specifications control for individual and household characteristics and time fixed effects. The (district-time varying) extreme weather variables are dropped because of the addition of district-time FE. Due to the introduction of district-time FE, singleton observations drop out from the samples (accounting for less than 1% of all observations in any sample).

***, **, * Per the reported cluster standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level.

N = number of observations; std = standardized; n.a. = not applicable.

Table A10. Robustness of the estimated mitigation effect of transfer payment regularity to food supply disruptions

	2SLS - 2nd stage	
Model specification	1	2
Panel A: Weight-for-height z-score (WHZ; N=6,516)		
Civilian casualties (std)	-1.3151	-1.4803
Cluster SE	(1.3361)	(1.1523)
Conley SE	(0.0579)***	(0.0728)***
Payment per period (0=no, 1=yes)	-2.1446	-2.3303
Cluster SE	(1.8349)	(1.6477)
Conley SE	(1.2797)*	(1.0031)**
Civilian casualties * payment	2.0463	2.3195
Cluster SE	(2.2536)	(2.0099)
Conley SE	(0.0722)***	(0.1171)***
Civilian casualties in neighboring districts (std)	-0.0589	-0.0666
Cluster SE	(0.0355)*	(0.0374)*
Conley SE	(0.0271)**	(0.0243)***
Civilian casualties along the road from the Port of Hodeidah (std)	-0.4708	-0.7411
Cluster SE	(0.9944)	(0.9244)
Conley SE	(0.3788)	(0.2617)***
Civilian casualties along the road from the Port of Saleef (std)	0.4091	0.6871
Cluster SE	(1.0127)	(0.9304)
Conley SE	(0.4049)	(0.2727)**
Civilian casualties along the road from the Port of Aden (std)	0.0176	0.0160
Cluster SE	(0.0254)	(0.0243)
Conley SE	(0.0169)	(0.0142)
RMSE	1.602	1.436
KP rk Wald F	1.546	4.135
Panel B: Mid-upper arm circumference z-score (MUACZ; N=5,540)		
Civilian casualties (std)	-0.4616	-0.3613
Cluster SE	(0.5462)	(0.3653)
Conley SE	(0.2409)*	(0.1617)**
Payment per period (0=no, 1=yes)	-0.3738	-0.6869
Cluster SE	(1.2307)	(1.1194)
Conley SE	(0.8519)	(0.7422)
Civilian casualties * payment	0.6238	0.4793
Cluster SE	(0.8006)	(0.5387)
Conley SE	(0.3471)*	(0.2326)**
Civilian casualties in neighboring districts (std)	-0.0677	-0.0772
Cluster SE	(0.0269)**	(0.0230)***
Conley SE	(0.0441)	(0.0425)*
Civilian casualties along the road from the Port of Hodeidah (std)	0.3051	0.4930
Cluster SE	(0.3999)	(0.3313)
Conley SE	(0.4969)	(0.3795)
Civilian casualties along the road from the Port of Saleef (std)	-0.3304	-0.5292
Cluster SE	(0.4172)	(0.3396)
Conley SE	(0.5010)	(0.3777)
Civilian casualties along the road from the Port of Aden (std)	-0.0353	-0.0330
Cluster SE	(0.0221)	(0.0189)*
Conley SE	(0.0114)***	(0.0096)***

RMSE	0.940	0.700
KP rk Wald F	2.086	3.234
Fixed effects		
District	yes	no
Household	no	yes

Note: All model specifications control for individual and household characteristics, extreme weather, and time fixed effects.

***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level. Standard errors calculated based on the Conley (1999) approach correct for spatial correlation up to 93 kilometers.

N = number of observations; std = standardized.

The Root Mean Square Error (RMSE) and Kleibergen-Paap rank Wald F-statistic (KP rk Wald F) (Baum et al., 2007; Kleibergen and Paap, 2006) are reported for the model specifications using the cluster SE estimator.

Table A11. Robustness of the estimated mitigation effect of the regularity of SWF cash transfer payments to remittances

	2SLS - 2nd stage			
Model specification	1	2	3	4
Panel A: Weight-for-height z-score (WHZ; N=6,516)				
Civilian casualties (std)	-1.3423	-1.2310	-1.3638	-1.2479
Cluster SE	(1.5957)	(1.0886)	(1.6575)	(1.1273)
Conley SE	(0.0914)***	(0.0810)***	(0.0934)***	(0.0821)***
Payment (0=no, 1=yes)	0.7302	1.0527	0.7391	1.0655
Cluster SE	(1.1009)	(1.1909)	(1.1320)	(1.2278)
Conley SE	(0.4481)	(0.5074)**	(0.4499)	(0.5102)**
Civilian casualties * payment	1.9687	1.8020	2.0143	1.8400
Cluster SE	(2.4640)	(1.7069)	(2.5770)	(1.7799)
Conley SE	(0.1230)***	(0.1289)***	(0.1268)***	(0.1310)***
Civilian casualties in neighboring districts (std)	-0.0330	-0.0428	-0.0333	-0.0431
Cluster SE	(0.0367)	(0.0336)	(0.0372)	(0.0340)
Conley SE	(0.0338)	(0.0281)	(0.0337)	(0.0280)
Remittances (0=no, 1=yes)	-0.0120	-0.0341		
Cluster SE	(0.0553)	(0.0737)		
Conley SE	(0.0450)	(0.0474)		
Civilian casualties * remittances	0.3056	0.2800		
Cluster SE	(0.5025)	(0.4028)		
Conley SE	(0.0303)***	(0.0173)***		
Remittance amount (log)			-0.0005	-0.0028
Cluster SE			(0.0054)	(0.0074)
Conley SE			(0.0042)	(0.0046)
Civilian casualties * remittance amount			0.0279	0.0255
Cluster SE			(0.0480)	(0.0384)
Conley SE			(0.0029)***	(0.0016)***
RMSE	1.377	1.110	1.395	1.124
KP rk Wald F	2.794	1.868	2.786	1.839
Panel B: Mid-upper arm circumference z-score (MUACZ; N=5,540)				
Civilian casualties (std)	-0.4155	-0.2402	-0.4305	-0.2478
Cluster SE	(0.4832)	(0.3502)	(0.5115)	(0.3623)
Conley SE	(0.1969)**	(0.1864)	(0.2038)**	(0.1905)
Payment (0=no, 1=yes)	1.0068	1.4223	1.0297	1.4431
Cluster SE	(0.8679)	(1.0994)	(0.8818)	(1.1158)
Conley SE	(1.2695)	(1.3601)	(1.2728)	(1.3695)
Civilian casualties * payment	0.4403	0.2154	0.4627	0.2262
Cluster SE	(0.5772)	(0.4191)	(0.6179)	(0.4382)
Conley SE	(0.2444)*	(0.2280)	(0.2558)*	(0.2355)
Civilian casualties in neighboring districts (std)	-0.0488	-0.0553	-0.0483	-0.0550
Cluster SE	(0.0268)*	(0.0264)**	(0.0274)*	(0.0267)**
Conley SE	(0.0413)	(0.0409)	(0.0415)	(0.0409)
Remittances (0=no, 1=yes)	0.0001	0.0126		
Cluster SE	(0.0507)	(0.0572)		
Conley SE	(0.0346)	(0.0180)		
Civilian casualties * remittances	0.2409	0.1690		
Cluster SE	(0.2622)	(0.1837)		
Conley SE	(0.0941)**	(0.0783)**		

Remittance amount (log)			-0.0004	0.0007
Cluster SE			(0.0049)	(0.0055)
Conley SE			(0.0032)	(0.0013)
Civilian casualties * remittance amount			0.0238	0.0169
Cluster SE			(0.0265)	(0.0181)
Conley SE			(0.0092)***	(0.0076)**
RMSE	0.974	0.786	0.979	0.790
KP rk Wald F	2.190	1.659	2.175	1.633
Fixed effects				
District	yes	no	yes	no
Household	no	yes	no	yes

Note: All model specifications control for individual and household characteristics, extreme weather, and time fixed effects.

***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level. Standard errors calculated based on the Conley (1999) approach correct for spatial correlation up to 93 kilometers.

N = number of observations; std = standardized; log = logarithmic.

The Root Mean Square Error (RMSE) and Kleibergen-Paap rank Wald F-statistic (KP rk Wald F) (Baum et al., 2007; Kleibergen and Paap, 2006) are reported for the model specifications using the cluster SE estimator.

Table A12. Robustness of the estimated mitigation effect of the regularity of SWF cash transfer payments to pensions (including other non-SWF government transfers)

	2SLS - 2nd stage			
Model specification	1	2	3	4
Panel A: Weight-for-height z-score (WHZ; N=6,516)				
Civilian casualties (std)	-0.8179	-0.8429	-0.8448	-0.8645
Cluster SE	(0.8533)	(0.7104)	(0.8922)	(0.7355)
Conley SE	(0.0836)***	(0.0525)***	(0.0824)***	(0.0536)***
Payment (0=no, 1=yes)	0.5179	0.8315	0.5348	0.8458
Cluster SE	(0.8779)	(1.0104)	(0.8962)	(1.0234)
Conley SE	(0.4820)	(0.5397)	(0.4813)	(0.5383)
Civilian casualties * payment	1.4226	1.4543	1.4756	1.4970
Cluster SE	(1.5547)	(1.2927)	(1.6348)	(1.3475)
Conley SE	(0.1162)***	(0.0921)***	(0.1155)***	(0.0952)***
Civilian casualties in neighboring districts (std)	-0.0468	-0.0550	-0.0467	-0.0549
Cluster SE	(0.0263)*	(0.0284)*	(0.0268)*	(0.0289)*
Conley SE	(0.0341)	(0.0279)**	(0.0341)	(0.0278)**
Pension (0=no, 1=yes)	-0.1245	-0.0739		
Cluster SE	(0.0661)*	(0.0880)		
Conley SE	(0.0335)***	(0.0502)		
Civilian casualties * pension	-0.3848	-0.3588		
Cluster SE	(0.4282)	(0.3450)		
Conley SE	(0.0295)***	(0.0320)***		
Pension amount (log)			-0.0123	-0.0075
Cluster SE			(0.0069)*	(0.0100)
Conley SE			(0.0035)***	(0.0051)
Civilian casualties * pension amount			-0.0392	-0.0363
Cluster SE			(0.0446)	(0.0355)
Conley SE			(0.0030)***	(0.0032)***
RMSE	1.179	0.980	1.195	0.992
KP rk Wald F	2.716	1.794	2.719	1.796
Panel B: Mid-upper arm circumference z-score (MUACZ; N=5,540)				
Civilian casualties (std)	-0.3899	-0.2645	-0.3932	-0.2623
Cluster SE	(0.5876)	(0.4492)	(0.5936)	(0.4488)
Conley SE	(0.1862)**	(0.1883)	(0.1870)**	(0.1896)
Payment (0=no, 1=yes)	1.0012	1.4934	1.0028	1.4929
Cluster SE	(0.9407)	(1.2167)	(0.9427)	(1.2162)
Conley SE	(1.3114)	(1.4009)	(1.3102)	(1.3997)
Civilian casualties * payment	0.5664	0.3525	0.5737	0.3508
Cluster SE	(0.9000)	(0.6829)	(0.9135)	(0.6862)
Conley SE	(0.2823)**	(0.2760)	(0.2848)**	(0.2787)
Civilian casualties in neighboring districts (std)	-0.0542	-0.0566	-0.0542	-0.0565
Cluster SE	(0.0265)**	(0.0273)**	(0.0266)**	(0.0273)**
Conley SE	(0.0399)	(0.0398)	(0.0399)	(0.0398)
Pension (0=no, 1=yes)	0.0037	0.0873		
Cluster SE	(0.0548)	(0.0731)		
Conley SE	(0.0460)	(0.0568)		
Civilian casualties * pension	-0.0967	-0.0366		
Cluster SE	(0.1340)	(0.0908)		
Conley SE	(0.0347)***	(0.0257)		

Pension amount (log)			-0.0003	0.0088
Cluster SE			(0.0057)	(0.0080)
Conley SE			(0.0049)	(0.0060)
Civilian casualties * pension amount			-0.0099	-0.0038
Cluster SE			(0.0136)	(0.0093)
Conley SE			(0.0036)***	(0.0026)
RMSE	0.988	0.808	0.989	0.808
KP rk Wald F	2.070	1.555	2.073	1.554
Fixed effects				
District	yes	no	yes	no
Household	no	yes	no	yes

Note: All model specifications control for individual and household characteristics, extreme weather, and time fixed effects.

***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level. Standard errors calculated based on the Conley (1999) approach correct for spatial correlation up to 93 kilometers.

N = number of observations; std = standardized; log = logarithmic.

The Root Mean Square Error (RMSE) and Kleibergen-Paap rank Wald F-statistic (KP rk Wald F) (Baum et al., 2007; Kleibergen and Paap, 2006) are reported for the model specifications using the cluster SE estimator.

Table A13. First-stage estimation results of the 2SLS regressions for the amount of SWF cash transfer payments

	Transfer amount (log)	
Model specification	1	2
Panel A: Weight-for-height z-score (WHZ; N=6,516)		
Civilian casualties along the road from the Central Bank (std)	-0.1941	-0.1593
Cluster SE	(0.0832)**	(0.0802)**
Conley SE	(0.0318)***	(0.0287)***
Civilian casualties (std)	-0.0200	-0.0139
Cluster SE	(0.0450)	(0.0452)
Conley SE	(0.0594)	(0.0528)
Civilian casualties in neighboring districts (std)	-0.0799	-0.0707
Cluster SE	(0.0938)	(0.0910)
Conley SE	(0.0646)	(0.0842)
R-squared	0.2090	0.4209
F-test	2.522	2.931
Panel B: Mid-upper arm circumference z-score (MUACZ; N=5,540)		
Civilian casualties along the road from the Central Bank (std)	-0.1726	-0.1529
Cluster SE	(0.0838)**	(0.0856)*
Conley SE	(0.0544)***	(0.0408)***
Civilian casualties (std)	0.0223	0.0251
Cluster SE	(0.0399)	(0.0418)
Conley SE	(0.0395)	(0.0547)
Civilian casualties in neighboring districts (std)	-0.1117	-0.1020
Cluster SE	(0.0894)	(0.0872)
Conley SE	(0.0612)*	(0.0812)
R-squared	0.2106	0.4224
F-test	2.244	2.464
Fixed effects		
District	yes	no
Household	no	yes

Note: All model specifications control for individual and household characteristics, extreme weather, and time fixed effects.

***, **, * Per the reported standard error (SE), coefficient is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level. Standard errors calculated based on the Conley (1999) approach correct for spatial correlation up to 93 kilometers.

N = number of observations; std = standardized; log = logarithmic.

The Root Mean Square Error (RMSE) and Kleibergen-Paap rank Wald F-statistic (KP rk Wald F) (Baum et al., 2007; Kleibergen and Paap, 2006) are reported for the model specifications using the cluster SE estimator.