Civil Conflict, Cash Transfers, and Child Nutrition in Yemen

Olivier Ecker[a,*], Afnan Al-Malk[b], and Jean-François Maystadt[c,d,e]

[a] Foresight and Policy Modeling Unit, International Food Policy Research Institute, Washington, DC, United States.

[b] Department of Finance and Economics, Qatar University, Doha, Qatar.

[c] Department of Economics, Institute of Economic and Social Research / Louvain Institute of Data Analysis and Modeling in Economics and Statistics, UCLouvain, Ottignies-Louvain-la-Neuve, Belgium.

[d] Fonds de la Recherche Scientifique, Belgium.

[e] Department of Economics, Lancaster University Management School, Lancaster, United Kingdom.

* Corresponding author: Olivier Ecker, IFPRI; 1201 I Street, NW; Washington, DC 20005; Tel: +1 202-862-5632; Fax: +1 202-862-5606; Email: o.ecker@cgiar.org.

Short title: Conflict, cash & child nutrition

Acknowledgements

We thank Yemen's Ministry of Planning and International Cooperation (MOPIC), the United Nations Children's Fund (UNICEF), the International Policy Centre for Inclusive Growth (IPC-IG), and Interaction In Development for providing data from the Yemen National Social Protection Monitoring Survey, 2012-13. In particular, we would like to thank Abdulmajeed Al-Batuly from MOPIC; Buthaina Al-Iryani, Agostino Munyiri, and Tammy Smith from UNICEF; Fabio Vagas from IPC-IG; and Khalid Al-Dubai from Interaction In Development. We thank Hagar El-Didi, Mekamu Kedir Jemal, and Zhe Guo from the International Food Policy Research Institute for their assistance in preparing the data for analysis. We are grateful to Afrah Alawi Al-Ahmadi, Hani Abdulrahman Zaid Enan, and Khalid Ahmed Ali Moheyddeen from the World Bank for their valuable insights into Yemen's national cash transfer program of the Social Welfare Fund. We thank Cevat Aksoy, Tracy Brown, Kalle Hirvonen, and Bilal Malaeb for their useful comments on earlier versions of this article. We appreciate the helpful feedback from participants of the 15th Annual Households in Conflict Network Workshop at the Paris School of Economics and the Economic Research Forum webinar on the Foundations for Post-Conflict Growth Agenda in the Middle East and North Africa Region. We would like to thank the Associate Editor and two anonymous reviewers of our article manuscript for their valuable comments and suggestions. This work was undertaken as part of the CGIAR Research Program on Policies, Institutions, and Markets (PIM) led by the International Food Policy Research Institute (IFPRI). Funding support for this study was provided by the German Federal Ministry of Economic Cooperation and Development / Gesellschaft fuer Internationale Zusammenarbeit (BMZ/GIZ), PIM, and the CGIAR Research Initiative on Fragility, Conflict, and Migration

(FCM). The opinions expressed here belong to the authors, and do not necessarily reflect those of IFPRI, CGIAR PIM and FCM, BMZ/GIZ, Lancaster University, or UC Louvain.

Abstract

The most dramatic outcomes of protracted civil conflict include increased malnutrition among children and the resulting consequences for lifelong health and prosperity. Little is known about how to mitigate the nutritional impact of conflict. Understanding the potential of social protection measures is particularly important when the risk of intense armed conflict is high. We use quarterly panel data from Yemen to estimate the impact of civil conflict on child nutrition and the effect of unconditional cash transfers in mitigating the adverse nutritional impact. The results show that a one-standard-deviation increase in armed conflict intensity reduces children's weight-for-height z-scores by 9.6%, on average. We also find that the studied cash transfer program mitigates the estimated nutritional impact by 42.4%. Our analysis suggests that unconditional cash transfers can be an effective development policy tool to curb rising acute child malnutrition in Yemen.

Keywords: Civil conflict, child nutrition, social protection, cash transfers, Yemen

JEL: D74, I15, O15

I. Introduction

Hunger and acute child malnutrition are increasingly concentrated in fragile countries and conflict zones (von Grebmer et al. 2015; FAO et al. 2017). About 1.35 billion children and adolescents younger than 18 years lived in a conflict-ridden country in 2016, and almost 357 million of them lived within a distance of 50 km from where the actual fighting occurred (Bahgat et al. 2017). The number of children affected by armed conflict has likely further increased in more recent years due to a significant rise in wars and other violent conflict events globally (ACLED 2022). 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). 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. 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.

A key concern of international development assistance is about effective interventions to mitigate the impact of armed conflict on child nutrition and hence to prevent child deaths and long-term health consequences. Understanding the relationship between child malnutrition and conflict intensity and the mitigation potential of social protection measures is particularly important in countries experiencing civil conflict and for post-war reconstruction when the risk of intense violence resurgence is high. Yet, the development literature provides little systematic evidence in this regard. This study contributes to fill this knowledge gap using data from Yemen.

Yemen’s current civil war is one of the world’s worst humanitarian crises in recent history (OCHA 2022). Since the outbreak of civil war in 2015, more than 150,000 people were killed in direct violence as of mid-2022, including more than 15,000 civilian casualties (ACLED

2022). Many more civilians died from indirect causes of the conflict (OCHA 2022). According to the United Nations, more than 2,600 children were killed only between April 2015 and December 2018 (UNICEF 2019), and Save the Children estimates that about 85,000 children younger than five years died from acute malnutrition during the same time period, as a result of the conflict (Save the Children 2018). Children's nutritional status drastically deteriorated more recently. More than 2.25 million children younger than five years were expected to suffer from acute malnutrition in 2021, of which about 400,000 children were at risk of death from starvation (IPC 2021).

In this article, we first quantify the adverse impact of civil conflict on child nutrition in Yemen. We use household and child panel data from the time before the outbreak of the current civil war, when survey data collection was still possible. We exploit quarterly variation in armed conflict intensity at the district level to estimate the local impact on child weight-for-age z-scores (WHZ)—the standard anthropometric indicator for measuring acute child malnutrition in populations. The results show that an increase by one standard deviation in conflict intensity reduces child WHZ by at least 0.06 in our sample. For a child at the mean of the WHZ distribution, the estimated impact translates into a deterioration of nutritional status by about 9.6%. By estimating the impact of civil 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., Bundervoet, Verwimp, and Akresh 2009; Akresh, Verwimp, and Bundervoet 2011; Akresh, Lucchetti, and Thirumurthy 2012; Minoiu and Shemyakina 2012; Domingues and Barre 2013).

In the second step of our econometric investigation, we examine whether unconditional cash transfers can mitigate the adverse impact of civil conflict on child nutrition in Yemen and estimate the size of this mitigating effect. Particularly, we explore the national cash transfer program of the Social Welfare Fund (SWF). To deal with a potential selection bias associated with households' enrollment into the program, we follow the approach proposed by Hirano, Imbens, and Ridder (2003) and use inverse probability weighting in our fixed effects (FE) model estimations. The estimation results of various model specifications provide robust evidence for the hypothesized mitigating effect of the unconditional cash transfers. Estimates from our individual FE model suggest that the cash transfer program mitigates the estimated impact of civil conflict on child WHZ by 42.4%, on average. This finding expands the existing evidence on the effectiveness of cash transfers in civil conflict settings and humanitarian crises (e.g., HPN 2012; ODI and CGD 2015; Doocy and Tappis 2017; Ghorpade 2020). Specifically, while the development literature has made considerable progress in understanding how cash transfer programs can be used to reduce the risk of conflict outbreak and intensification (e.g., Willibald 2006; Crost, Felter, and Johnston 2016; Pena, Urrego, and Villa 2017), there is little quantitative evidence on the effectiveness of cash transfers in mitigating the impact of civil conflict on food security and nutrition outcomes. A study that is closest to ours is an evaluation of the impact of food assistance provided by the World Food Programme in a conflict-affected region in Mali (Tranchant et al. 2019). The authors find a protective effect of general food distribution on household calorie and micronutrient consumption. However, the transferability of findings from 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.[1]

The rest of the paper proceeds as follows. Section 2 provides the context of our study and a brief overview of social protection in Yemen. Section 3 presents the data of our empirical analysis and descriptive statistics of the main variables. Section 4 explains the empirical strategy of our econometric investigation. Section 5 presents the estimation results, and Section 6 provides robustness checks of the main results. Section 7 draws conclusions from the study's findings.

II. Study Context and Social Protection

Our empirical analysis focuses on the time after the 2011–2012 Yemeni revolution and before the launch of the Houthi rebellion in 2014 and the subsequent outbreak of the current civil war in 2015 (Figure 1). The analysis covers the period of power transfer from the government of the ousted, long-time president Ali Abdullah Saleh to a government led by his hitherto vice president Abdrabbuh Mansur Hadi—a period of relatively low armed conflict intensity in Yemen's recent history. A priority of the national Transitional Plan for Development and Stabilization was social protection, especially to mitigate further deterioration of the poor's living conditions from the aftermaths of the 2011–2012 revolution (IPC-IG, UNDP, and UNICEF 2014a).

The cash transfer program of the Social Welfare Fund was the government's main social protection program. The SWF was established in 1996 as a compensation mechanism to mitigate the negative impact of the removal of food subsidies on poor people's living conditions. The main responsibility of the SWF was the implementation of the unconditional cash transfer program nationwide, which was supported by the World Bank. The SWF paid out cash transfers on a quarterly basis to citizens who were temporarily or permanently unable to sustain themselves and whose families were not able to financially support them.[2] The SWF underwent a series of reforms between 2008 and 2011 to improve its effectiveness. 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 groups. For beneficiary targeting purposes, the group of poor households was further divided into extremely poor, moderately poor, and vulnerable.

The quarterly transfer amount per eligible household member was 6,000 Yemeni rial (YER). 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). The average transfer amount among beneficiary households in our sample accounts for 4.1% of their total reported income (with a standard deviation of 5.9%). While the transfer 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). Anecdotal evidence suggests that the cash transfers allowed the average six-person beneficiary household to afford one additional bread per person per day (Bagash, Pereznieto, and Dubai 2012).

The conducted 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 2011–2012 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 local and national government institutions, the SWF downscaled its operation and finally discontinued the cash transfer program after the outbreak of the civil war in late 2014, due to a lack of funding.

III. Data and Descriptive Statistics

A. Survey Data

The household and child panel data used in the empirical analysis are taken from the Yemen National Social Protection Monitoring Survey (NSPMS). The survey was conducted in the context of the national Transitional Plan for Development and Stabilization and implemented from October 2012 to September 2013 (IPC-IG 2014a). The main objectives of the NSPMS were to produce up-to-date information on the living conditions of poor households after the 2011–2012 revolution and to provide data for assessment of the cash transfer program targeting after the 2008–2011 SWF reforms. The sampled households were interviewed in four rounds within one year, following the normal payment cycle of the cash transfer program.

Sample Population

The NSPMS used a two-stage stratified sampling design to randomly select households into treatment and comparison groups (IPC-IG et al. 2014a). In the first sampling stage, enumeration areas were geographically stratified by governorate and selected using a probability-proportional-to-size sampling scheme. In the second stage, a household listing was conducted in each selected enumeration area to identify all households and classify them by cash transfer program beneficiary status. A stratified simple random sampling design was used to select households by enumeration area into treatment and comparison groups. A detailed description of the sampling design can be found in the NSPMS sample and survey methodology document (IPC-IG, UNDP, and UNICEF 2014b).

The treatment group consists of beneficiary households, defined as households with at least one person who had ever received a cash transfer payment. The comparison group is comprised of non-beneficiary households that had never received a payment (including throughout the survey's observation period). The treatment group has "old beneficiary" and "new beneficiary" households. Old beneficiary households are those whose members were selected into the cash transfer program and received payments already before the 2008–2011

SWF reforms, as well as during the survey's observation period. New beneficiary households were enrolled into the program after the completion of the reforms (earliest in 2011) and were selected by applying the formal program eligibility criteria, outlined above.[3]

The sample size of the NSPMS was initially set to 7,560 households from all 21 governorates in Yemen. 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 bordering Saada Governorate)—suffered complete attrition in the fourth round due to serious security threats during survey implementation. This led to a loss of 432 households from the Round 1 sample. The attrition rate across the 19 governorates remaining in the sample was only 6.2%. Our comparisons of the nutritional status of children and the characteristics of their households identifying cash transfer 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.[4] Thus, we do not expect our estimation results to be biased because of survey attrition.

Because the focus of our study 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 the child panel dataset of our empirical analysis. Our main sample includes children from 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 beneficiary households

(50.3%) and non-beneficiary households (49.7%). The sample covers 218 districts (out of 331 districts in mainland Yemen) across 19 governorates.[5]

Program Beneficiaries

Table 1 shows summary statistics for household eligibility criteria of the cash transfer program. The statistics are presented for all, old, and new beneficiary households and non-beneficiary households. Comparisons reveal that, on average, beneficiaries are more socially and economically disadvantaged than non-beneficiaries. This means 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 of 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 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.

Child Nutrition

The main outcome variable of our empirical analysis is child weight-for-height z-scores. WHZ is a standard anthropometric indicator that measures the short-term nutritional status of children under five years of age and is commonly used to detect child "wasting," indicating acute child malnutrition. Wasting describes a recent and severe process that has led to rapid weight loss, usually as a consequence of acute starvation (WHO 1995). Weight-for-height measurements are the preferred index for assessing and monitoring children's nutritional status in emergencies (WHO 2000). For robustness checks of the estimated relationship between child nutrition and civil conflict, we use mid-upper arm circumference-for-age z-scores (MUACZ)—another anthropometric indicator for measuring children's short-term nutritional status and detecting acute child malnutrition. We also test the relationship for the incidence of wasting according to both indicators.[6]

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. 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 they have missing WHZ observations in any survey round, or if their WHZ in any round is outside a biologically plausible range (which is the case for only 38 children, or 1.1% of children, with WHZ observations in all four rounds).[7] Our main sample includes 3,281 children that stayed in the age range of 0–59 months throughout the survey and have biologically plausible WHZ values in all four rounds.[8]

Table 2 shows summary statistics of WHZ and the prevalence rate of wasting for the cohort of children in our sample population by survey round. Children are classified as wasted if their WHZ is below –2 standard deviations (SD) of the mean of an international reference population (WHO 2006). Across all survey rounds, the body weight of the average child in our sample population is 0.61 SD lower than the reference mean. Consistent with the conception of this indicator 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 civil conflict after the Yemeni revolution (Figure 1). According to the World Health Organization's severity index for malnutrition in emergencies (WHO 2000), the wasting rates identify the severity of acute 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 SD of WHZ in all rounds are near or even below one, which gives us confidence in the quality of the anthropometric measurements (Mei and Grummer-Strawn 2007). Moreover, there is no statistically significant difference between children from cash transfer program beneficiary households and non-beneficiary households at baseline (Round 1).[9]

B. Conflict Data

The conflict variables in our main analysis measure the intensity of armed conflict events that took place in a household's home district during the recall period per survey round (which somewhat vary across households because of different interview dates).[10] We use two different georeferenced conflict event datasets and the same method to construct the variables. These 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 preferred conflict variable in our estimations is based on the UCDP data. 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" (Högbladh 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. To construct the UCDP-data-based variables for our main analysis, we focus on events of violence against civilians, which arguably provides the best available proxy of civil conflict. Conflict intensity is determined by the reported number of civilians killed in these events.

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 yield an alternative variable of conflict intensity that is used in robustness checks of our main estimation results.

The next step of the conflict variable construction is the spatial matching of the conflict event locations with the home districts of the households in our sample. 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 the conflict variables to the household observations in the NSPMS dataset by survey round and for each household individually, based on the survey round recall periods. The recall periods of the NSPMS span the time 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.

A visual inspection of the association of child WHZ and our preferred conflict variable over survey rounds, shown in Figure 2, suggests a negative relationship between the (short-term) nutritional status of young children and the intensity of armed conflict. The observed correlation motivates the first step of our econometric investigation.

IV. Empirical Strategy

The empirical strategy of our econometric investigation includes two main steps. First, we establish that civil conflict has a strong negative impact on children's short-term 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. To deal with the non-random targeting of program beneficiaries, we follow Hirano et al. (2003) in adjusting the FE model estimations with an inverse probability weighting. We demonstrate the stability of the estimated nutritional impact of civil conflict and the estimated mitigating effect of the cash transfer program and perform a series of robustness checks that confirm our main estimation results.

A. Estimating the Impact of Civil Conflict on Child Nutrition

We begin by estimating a set of panel data models using ordinary least squares regressions. Our basic model relates the nutritional status of children to their households' direct exposure to armed conflict of varying intensity and controls for child characteristics known to influence child nutrition outcomes, weather-related shocks, and district and time fixed effects. 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 effects or external food price shocks. This basic district FE model allows us to explore variations in armed conflict intensity within districts.

However, households' exposure to armed conflict may not be randomly distributed within districts. In the absence of a baseline survey prior to the emergence of armed violence in Yemen, we cannot determine pre-conflict differences between households. Violence could be targeted toward households with specific characteristics, such as the wealthier ones or those with certain family demographics (Verpoorten 2009; Blattman and Miguel 2010; Dagnelie, De Luca, and Maystadt 2018). 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 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 armed 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. We finally estimate an individual FE model to control for unobserved heterogeneity between children living in the same household, such as inequalities in intra-household resource allocation.

The district, household, and individual FE models have the following form:

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

where i refers to an 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} in our preferred model specifications is a child's nutritional status, measured by WHZ at the time of the survey round. The independent variable x^D_{hdr} is a household's exposure to armed conflict in its home district over the household-specific recall period of the survey round, r. In our preferred specifications, we focus on violence against civilians as proxied by the number of civilians killed in armed conflict events (from the UCDP dataset). For ease of interpretation, we standardize the values of this conflict variable (and all other conflict variables used in our study) 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 civil conflict on child nutrition.

All model specifications control for standard child characteristics known to influence child nutrition measurements, as well as extreme weather events that tend to aggravate armed conflict (Hsiang, Burke, and Miguel 2013; Maystadt and Ecker 2014; Mach et al. 2019). The vector Z_{ihdr} includes a child's sex and her/his age (in months) at the time of the interview of her/his household, h, in the survey round, r, as linear and squared terms. The vector W_{hdr} captures district-level temperature and precipitation anomalies, respectively, occurring over a three-month period, with the last month being the household interview month of the survey round.[11] District, household, or individual FE enter the model through the intercept, $\alpha_{i|h|d}$, and ω_r denotes time FE (i.e., survey round identifiers). In all 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).[12]

To assess the stability of estimated impact of civil conflict on child nutrition—displayed by the coefficient β_1, we refine our preferred FE model specifications in a stepwise fashion and observe changes in the coefficient estimates. We first modify the basic district FE model by adding a vector of time-constant household characteristics, V_{hd}. The vector includes 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.[13] Then, we introduce household FE into the model, which causes the vector of household characteristics to drop out because of perfect collinearity. Finally, we introduce individual FE that causes the child sex variable to drop out. We perform robustness checks for our main estimation results to various modifications of all these model specifications, as discussed in a later section.

B. Estimating the Mitigating Effect of Cash Transfers

To examine whether the cash transfer program mitigates the adverse impact of civil conflict on child nutrition, we augment the fully specified district, household, and individual FE models by introducing a treatment variable (which drops out from the household and individual FE models because of perfect collinearity) and interacting the conflict variable with the treatment variable. The augmented FE models have the following form:

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

The binary treatment variable, t_{hd}, indicates the program beneficiary status of the household and is time-constant over the analysis period. A household is defined as a beneficiary household if at least one household member was selected into the cash transfer program and has ever received a transfer payment (prior to data collection). 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 estimate of the interaction term coefficient, β_3, confirms the hypothesized mitigating effect of the cash transfer program, which counteract the negative impact of civil conflict on child nutrition (given a negative estimate for β_1). As for the first step of our empirical strategy, we check the robustness of the main estimation results to various modifications of the different FE model specifications, after presenting the main results.

The estimated mitigating effect may be influenced by the non-random targeting of program beneficiaries. Our descriptive statistics suggest that households in greater need of support were more likely to be selected into the program than households in less need. Conceivably, children from households selected as potential program beneficiaries were more likely to be malnourished than children from non-selected households (before the start of the cash transfer payments). To correct for the non-random selection of households into treatment and comparison groups, we estimate Equation 2 by using an inverse probability weighting estimator that weights the observations by the reciprocal of the probability of households' selection into the program (Angrist and Pischke 2009). This approach—proposed by Hirano et al. (2003)—assigns greater weights to observations in the comparison group to improve its comparability with the treatment group (Acemoglu et al. 2019) and therewith yields efficient estimates of the treatment effect.[14]

To further examine the potential selection bias, we exploit changes in the program eligibility criteria resulting from the 2008–2011 SWF reforms. Because of 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 hence 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 for the mitigating effect. Accordingly, replicating this exercise for new beneficiaries should produce lower lower-bound estimates.[15]

V. Estimation Results

A. Impact of Civil Conflict on Child Nutrition

Our estimations results confirm that civil conflict has a strong negative impact on short-term child nutrition, increasing the probability of acute child malnutrition in Yemen. Table 3 shows the coefficient estimates for armed conflict intensity as measured by civilian casualties in the district, household, and individual FE models that have WHZ as dependent variables.[16] The estimated coefficient is statistically significant at the 1% level and remarkably stable across all model specifications. Such stability gives us confidence that omitted variable concerns are unlikely to influence the main estimation results.

The estimates indicate that an increase in the conflict intensity by one standard deviation is associated with a decrease in child WHZ by about 0.06 SD. Applying this point estimate evenly across our child sample population reduces the WHZ mean by 9.6%. To put the 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 2012–2013. Over a high-conflict-intensity period of 15 months starting in January 2015 (that comprises the outbreak 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 estimate and assuming an even distribution of the estimated nutritional impact across the child sample population, this conflict intensification translates into a reduction of mean WHZ by 26.7%. 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.

The estimated impact of civil conflict on child nutrition is sizeable. However, 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 examine the impact on children's long-term nutritional status, using height-for-age z-scores (HAZ)—the anthropometric indicator used to detect linear growth retardation among children. Examples include studies by Akresh et al. (2011) on the 1990–1994 Rwandan civil war, Akresh et al. (2012) on the 1998–2000 Eritrean-Ethiopian war, Bundervoet et al. (2009) on the Burundian civil war during the late 1990s, and Minoiu and Shemyakina (2012) on the 2002–2007 Ivorian civil war. However, within a short timeframe—such as in the case of our study, HAZ can be expected to be less responsive or even unresponsive to current shocks than WHZ (WHO 1995). HAZ to a large extent reflect children's nutritional and health status in the past—especially in the womb and during the first two life years (Shrimpton et al. 2001; Victora et al. 2010), which is partially or completely unobserved for the children in our sample, because it was present before the first survey round. Beyond that, 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 displaced persons 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 displaced persons 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.[17]

B. Mitigating Effect of Cash Transfers

Table 4 shows the estimation results of the district, household, and individual FE models augmented to examine whether the SWF cash transfer program mitigates the negative impact of civil conflict on child nutrition. We do find a statistically significant and positive mitigating effect for all three model specifications, confirming the hypothesized protective role of the program across the beneficiaries, and very similar estimated effect sizes for the household and individual FE models. The coefficient estimates of the conflict variable and the term for its interaction with the treatment variable suggest that the program reduces the nutritional impact of civil conflict, on average, by 43.2% as per the household FE model and 42.4% as per the individual FE model.

The estimation results in Table 5 indicate that these findings also hold separately for children from old beneficiary households and children from new beneficiary households, compared to children from non-beneficiary households. The mitigating effect is larger among children of old beneficiaries (amounting to 61.6% as per the household FE model and 61.1% as per the individual FE model, on average) than children of new beneficiaries (amounting to 32.8% and 33.1%, respectively). Two-sided *t*-test statistics confirm that the differences between the coefficient estimates of the interaction terms in the models for old beneficiaries and the models for new beneficiaries are statistically significant at least at the 95% level of confidence across all specifications. These results provide supportive evidence that the mitigating effect estimates for the old and new beneficiaries mark a range in which the true average mitigating effect of the program is likely to be found.

VI. Robustness Checks

The estimation results obtained from our preferred model specifications may be sensitive to the indicator choice for measuring children's short-term nutritional status and detecting acute child malnutrition. To assess this conjecture, we replace child WHZ in the district, household, and individual FE models for estimating the impact of civil conflict and the mitigating effect of the SWF cash transfer program first with child MUACZ—another anthropometric indicator, which does not rely on body weight and height measurements, and then with a short-term child nutrition index.[18] The index is a composite of children's WHZ and MUACZ and is constructed by applying the weighting procedure proposed by Anderson (2008). We also examine the validity of the relationships for two binary outcome indicators of the probability of child wasting, as identified based on WHZ (i.e., WHZ<–2) and MUACZ (i.e., MUACZ<–2), respectively. The estimation results of these alternative model specifications show that, first, the found impact of civil conflict and mitigating effect of the cash transfer program are robust to the choice of the short-term child nutrition indicator. Second, the risk of acute child malnutrition increases with armed conflict intensity, which is significantly lower among children from program beneficiary households than children from non-beneficiary households (at least for WHZ-based child wasting). Hence, the estimated changes in average WHZ in the preferred model specification results are no artifact that is driven by changes in the nutritional status of children with steady adequate nutrition or even at risk of overweight (or obesity), who form the child subpopulation on the right-hand side of the WHZ distribution. Third, the estimated relationships are somewhat weaker for MUACZ-based indicators than for WHZ-based indicators. Possible reasons are that MUACZ is a less precise anthropometric measure of children's short-term nutritional status and arm circumference measurements were only taken from children age 6 months and older, yielding a smaller sample size (with about 15% fewer observations).[19] Fourth, the statistical significance of the estimated impact of conflict (and mitigating effect of the program) on child nutrition outcomes is consistently higher for the indicators of nutritional status (i.e., WHZ, MUACZ) than the corresponding indicators of the probability of malnutrition (i.e., wasting). A plausible explanation is that an incremental change in armed conflict intensity pushes (lifts) only a small proportion of children below (above) the malnutrition threshold, whereas that change also affects the nutritional status of many other children further away from the threshold, including severely malnourished children. Based on these findings, we proceed with our robustness checks limiting modifications of our preferred model specifications to estimations with child WHZ as dependent variable.

Next, we check the robustness of our main estimation results for the nutritional impact of civil conflict and the mitigating effect of the cash transfer program to alternative definitions of armed conflict intensity.[20] We first modify our preferred UCDP-data-based conflict variable by harmonizing the household-specific length of the conflict exposure period to the number of fatalities per day. For a second robustness check, we change the preferred conflict variable by expressing civilian casualties per capita instead of per total district population. Lastly, we estimate the FE models with the number of armed conflict events per district reported in the GDELT dataset instead of the preferred civilian casualty count from the UCDP dataset. The estimation results using the modified UCDP-data-based conflict variables show that neither variations in the timing of survey round implementation nor differences in district population size considerably alter the adverse impact on child nutrition found in the preferred model specifications, although the sizes of the estimated impact are somewhat smaller, and the statistical significance levels of the coefficient estimates are lower, especially when conflict intensity is measured on a per-capita basis. The estimated relationship between child nutrition and civil conflict is also robust to another definition of armed conflict intensity used in a substantially different (and noisier) dataset: The coefficient estimates of the GDELT-data-based conflict variable are statistically significant at the 1% level according to the cluster SE and Conley SE in all model specifications. As with the preferred model specifications, the estimates are also remarkably stable across the district, household, and individual FE models and vary within a reasonable range around the coefficient estimates of the preferred conflict variable. The estimation results of the alternative model specifications confirm the robustness of the mitigating effect of the cash transfer program to varying length of the conflict exposure period, while the two latter robustness checks do not yield statistically significant estimates.

In our preferred model specifications, we do not use survey sampling weights so as to obtain precise estimates for the survey sample subpopulation that is of most interest to our analysis, namely young children from SWF beneficiary households. Instead, we check the robustness of our main estimation results to the inclusion of survey sampling weights, as suggested by Solon, Haider, and Wooldridge (2015).[21] In these alternative model specifications, the coefficient estimates of the main variables of interest are statistically significant at least at the 5% level in all models for the nutritional impact of civil conflict, as well as all models for the mitigating effect of the cash transfer program where they are even higher than in the preferred specifications. The results also show that applying survey sampling weights yields consistently smaller estimates for the nutritional impact and larger estimates for the mitigating effect. This confirms that the estimations of our preferred model specifications give more weight to cash transfer beneficiaries than non-beneficiaries.

Finally, there may be concerns about the sensitivity of our results to alternative specifications of the functional form of the estimating equations. For instance, one may expect non-uniformity in the relationship between child nutrition and civil conflict exposure, and the nutritional response to cash transfers, that is dependent on child age. To test for this possibility, we first estimate our district, household, and individual FE models with child age FE by month instead of continuous variables controlling for child age. The estimation results are very similar to those for our preferred model specifications, indicating the robustness of our main estimation results to potential child-age-dependent peculiarities.[22] We then check the sensitivity of our main results to specific child development periods by estimating our preferred model specifications for a younger and an older cohort of children separately.[23] We use the typical child age cutoff of 24 months (at the time of the first survey round) that splits our sample of children into two subsamples with roughly similar size. The estimation results based on the subsamples are qualitatively similar to those based on the full sample, although the reduction in the number of observations considerably reduces the efficiency of our model estimations. These robustness checks provide no supportive evidence for child-growth-differential nutritional impacts of civil conflict within our sample of children under five years of age, although the mitigating effect of the cash transfer program seems to be stronger at a younger age.

Another set of robustness checks shows that estimations of model specifications having the functional form in first differences yield results that are consistent with but weaker than our main estimation results.[24] There is also the possibility that unobserved household-location-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 coefficient estimates of interest are notably biased due to the absorption of unobserved location-time-varying changes as low. Introducing paired district-survey-round FE into the preferred model specifications shows that the main estimation results are robust to this augmentation.[25] Estimations of 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 armed conflict intensity. In light of such a potential threat to identification, it is reinsuring that our estimation results are qualitatively unchanged, although the magnitude of the coefficient estimates of interest decreases when adding district-survey-round FE in our preferred model specifications.

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

VII. Conclusions

Our study demonstrates the detrimental impact of civil conflict on child nutrition in Yemen. The estimation results show that increasing armed conflict intensity significantly reduces WHZ of children under five years of age 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 0.065—equivalent to respective decreases of 9.6% at the sample mean. The size of the estimated impact is 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 civil conflict on child nutrition because they capture only the direct outcome of armed conflict events occurring in the children's home districts. They do not consider cumulative nutrition deterioration from prolonged exposure to civil conflict and indirect impacts due to conflict events in more distant places such as from destruction of basic infrastructure and disfunction of essential institutions. 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 by 26.7%, on average.

Finding a lasting political resolution of Yemen's ongoing civil war is an absolute priority to tackle what has been recognized as one of the world's worst humanitarian crises in recent history and to bring the country back onto a sustained development path. 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 withdrawal of donor funds to government organizations. After more than two years of civil war, with devastating consequences for the civilian population, the World Bank and UNICEF stepped in with a first grant to resume portions of the cash transfer program in response to the growing humanitarian emergency (World Bank 2017; UNICEF 2022). This intervention used the beneficiary list from the cash transfer program that we studied here to target extremely vulnerable households and follows the program's quarterly payment schedule (World Bank 2018). Given that key implementation modalities of the intervention were similar to those of the studied program, our findings were likely to be transferable to a large extent.

Our empirical analysis confirms that unconditional cash transfers can be an effective policy tool to protect households affected by civil conflict and provides scientific evidence on Yemen that complements learning from the practical experiences of program implementers made in several fragile countries and conflict zones (e.g., HPN 2012; ODI and CGD 2015). Precisely, we show that unconditional cash transfers can mitigate the adverse impact of civil conflict on child nutrition in Yemen. We estimate the mitigating effect of the SWF cash transfer program before the current civil war at more than 40% of the size of the estimated impact on child WHZ. Thus, even with suboptimal implementation of the program (IPC-IG et al. 2014a), the estimated mitigating effect is sizeable.

Yet, we acknowledge that there are important limits for the generalization of our estimation results to the broader context. Given the study design, our estimate of the mitigating effect should be understood as an intention-to-treat effect since less than one-third of the program beneficiaries received timely cash transfer payments over the four quarters under study. We may therefore underestimate the true mitigating effect across the Yemeni population. Furthermore, 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. The analysis may thus not take account of the households that have been most exposed to prolonged armed violence. The lack of precise geo-referenced data for the survey respondents' location (at greater granularity than the district level) may also lead to an underestimation of the detrimental consequences of armed conflict (Tapsoba 2023).

More broadly, our study expands the evidence base on the protective role of cash transfers in civil conflict settings by demonstrating their potential to mitigate the nutritional impact of armed violence. It adds to recent studies that, in other conflict contexts, show the contribution of cash transfer programs to achieve different objectives—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 reduce local insurgent influence in the Philippines (Crost et al. 2016). Our study also complements work by Tranchant et al. (2019), who find that food assistance has protective effects among food-insecure populations experiencing civil conflict in Mali. Assessing the relative efficiency of unconditional cash transfers and general food distribution under high-intensity conflict conditions and in fragile countries is an important area of future research that can help humanitarian and development assistance agencies in strategizing and further improving their efforts to protect vulnerable populations from hunger and malnutrition.

References

Acemoglu, Daron, Suresh Naidu, Pascual Restrepo, and James A. Robinson. 2019. "Democracy Does Cause Growth." *Journal of Political Economy* 127, no. 1: 47-100.

ACLED (Armed Conflict Location and Event Data Project). 2022. "10 Conflicts to Worry About in 2022: Yemen Mid-year Update." https://acleddata.com/10-conflicts-to-worry-about-in-2022/yemen/mid-year-update (accessed 11 January 2023).

———. 2023. "Data Dashboard." https://acleddata.com/dashboard/#/dashboard (accessed 11 January 2023).

Akresh, Richard, Philip Verwimp, and Tom Bundervoet. 2011. "Civil War, Crop Failure, and Child Stunting in Rwanda." *Economic Development and Cultural Change* 59, no. 4: 777-810.

Akresh, Richard, Leonardo Lucchetti, and Harsha Thirumurthy. 2012. "Wars and Child Health: Evidence from the Eritrean–Ethiopian Conflict." *Journal of Development Economics* 99, no. 2: 330-40.

Anderson, Michael L. 2008. "Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American Statistical Association* 103, no. 484: 1481-95.

Angrist, Joshua D., and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Bagash, Thabet, Paola Pereznieto, and Khalid Dubai. 2013. *Transforming Cash Transfers: Beneficiary and Community Perspectives on the Social Welfare Fund in Yemen*. London: Overseas Development Institute.

Bahgat, Karim, Kendra Dupuy, Gudrun Østby, Siri Aas Rustad, Håvard Strand, and Tore Wig. 2018. *Children and Armed Conflict: What Existing Data Can Tell Us*. Oslo: Peace Research Institute Oslo.

Balhara, Kamna S., David M. Silvestri, W. Tyler Winders, Anand Selvam, Sean M. Kivlehan, Torben K. Becker, Adam C. Levine, and Global Emergency Medicine Literature Review Group. 2017. "Impact of Nutrition Interventions on Pediatric Mortality and Nutrition Outcomes in Humanitarian Emergencies: A Systematic Review." *Tropical Medicine & International Health* 22, no. 12: 1464-92.

Blattman, Christopher, and Edward Miguel. 2010. "Civil War." *Journal of Economic Literature* 48, no. 1: 3-57.

Bundervoet, Tom, Philip Verwimp, and Richard Akresh. 2009. "Health and Civil War in Rural Burundi." *Journal of Human Resources* 44, no. 2: 536-63.

Conley, Timothy G. "GMM Estimation with Cross Sectional Dependence." *Journal of Econometrics* 92, no. 1: 1-45.

Crost, Benjamin, Joseph H. Felter, and Patrick B. Johnston. 2016. "Conditional Cash Transfers, Civil Conflict and Insurgent Influence: Experimental Evidence from the Philippines." *Journal of Development Economics* 118: 171-82.

Custodio, Estefania, Rocio Martin-Cañavate, Federica Di Marcantonio, Daniel Molla, Yusuf Abukar, and Francois Kayitakire. 2018. "MUAC-for-age More Useful than Absolute MUAC for Nutritional Surveillance in Somalia: Results from Nineteen Cross-sectional Surveys (2007–2016)." *BMC Nutrition* 4: 1-10.

Dagnelie, Olivier, Giacomo Davide De Luca, and Jean-François Maystadt. 2018. "Violence, Selection and Infant Mortality in Congo." *Journal of Health Economics* 59: 153-77.

Domingues, Patrick, and Thomas Barre. 2013. "The Health Consequences of the Mozambican Civil War: An Anthropometric Approach." *Economic Development and Cultural Change* 61, no. 4: 755-88.

Doocy, Shannon, Martin Busingye, Emily Lyles, Elizabeth Colantouni, Bridget Aidam, George Ebulu, and Kevin Savage. 2020. "Cash and Voucher Assistance and Children's Nutrition Status in Somalia." *Maternal & Child Nutrition* 16, no. 3: e12966.

Doocy, Shannon, and Hannah Tappis. 2017. "Cash- based Approaches in Humanitarian Emergencies: A Systematic Review." *Campbell Systematic Reviews* 13, no. 1: 1-200.

Dunn, Gillian. 2018. "The Impact of the Boko Haram Insurgency in Northeast Nigeria on Childhood Wasting: A Double-difference Study." *Conflict and Health* 12, no. 1: 1-12.

FAO (Food and Agriculture Organization of the United Nations), IFAD (International Fund for Agricultural Development), UNICEF (United Nations Children's Fund, WFP (World Food Programme), and WHO (World Health Organization). 2017. *The State of Food Security and Nutrition in the World 2017: Building Resilience for Peace and Food Security*. Rome: FAO.

Frongillo, Edward A., Jef L. Leroy, and Karin Lapping. 2019. "Appropriate Use of Linear Growth Measures to Assess Impact of Interventions on Child Development and Catch-up Growth." *Advances in Nutrition* 10, no. 3: 372-9.

Funk, Chris, Pete Peterson, Martin Landsfeld, Diego Pedreros, James Verdin, Shraddhanand Shukla, Gregory Husak, et al. 2015. "The Climate Hazards Infrared Precipitation with Stations—a New Environmental Record for Monitoring Extremes." *Scientific Data* 2, no. 1: 1-21.

GDELT (The GDELT Project). 2015. "The GDELT Event Database: Data Format Codebook V2.0." http://data.gdeltproject.org/documentation/GDELT-Event_Codebook-V2.0.pdf (accessed 1 April 2020).

Ghorpade, Yashodhan. 2020. "Calamity, Conflict, and Cash Transfers: How Violence Affects Access to Aid in Pakistan." *Economic Development and Cultural Change* 68, no. 4: 1131-84.

Grijalva-Eternod, Carlos S., Mohamed Jelle, Hassan Haghparast-Bidgoli, Tim Colbourn, Kate Golden, Sarah King, Cassy L. Cox, et al. 2018. "A Cash-based Intervention and the Risk of Acute Malnutrition in Children Aged 6–59 Months Living in Internally Displaced Persons Camps in Mogadishu, Somalia: A Non-randomised Cluster Trial." *PLoS Medicine* 15, no. 10: e1002684.

Hirano, Keisuke, Guido W. Imbens, and Geert Ridder. 2003. "Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score." *Econometrica* 71, no. 4: 1161-89.

HPN (Humanitarian Practice Network). 2012. "New Learning in Cash Transfer Programming." Humanitarian Exchange Magazine no. 54, Overseas Development Institute, London.

Hsiang, Solomon M. 2010. "Temperatures and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America." *Proceedings of the National Academy of Sciences* 107, no. 35: 15367-72.

Hsiang, Solomon M., Marshall Burke, and Edward Miguel. 2013. "Quantifying the Influence of Climate on Human Conflict." *Science* 341, no. 6151: 1235367.

IPC (Integrated Food Security Phase Classification). 2021. "Yemen: IPC Acute Malnutrition Analysis, January 2020 – March 2021." http://www.ipcinfo.org/ipcinfo-website/alerts-archive/issue-34/en (accessed 9 March 2021).

IPC-IG (International Policy Centre for Inclusive Growth), UNDP (United Nations Development Programme), UNICEF (United Nations Children's Fund). 2014a. *Yemen National Social Protection Monitoring Survey (NSPMS): 2012-2013, Final Report.* Brasilia: IPC-IG.

———. 2014b. *Yemen National Social Protection Monitoring Survey (NSPMS): 2012-2013, Technical Note 1: Sample and Survey Methodology*. Brasilia: IPC-IG.

———, 2014c. *Yemen National Social Protection Monitoring Survey (NSPMS): 2012-2013, Technical Note 5: Note on the Wealth Index*. Brasilia: IPC-IG.

Leetaru, Kalev, and Philip A. Schrodt. 2013. "GDELT: Global Data on Events, Location, and Tone, 1979–2012." http://data.gdeltproject.org/documentation/ISA.2013.GDELT.pdf (accessed 1 April 2020).

Leroy, Jef L. 2011. "zscore06: Stata Command for the Calculation of Anthropometric Z-scores Using the 2006 WHO Child Growth Standards." http://fmwww.bc.edu/repec/bocode/z/zscore06.html (accessed 1 April 2020).

Leroy, Jef L., Edward A. Frongillo, Pragya Dewan, Maureen M. Black, and Robert A. Waterland. 2020. "Can Children Catch Up from the Consequences of Undernourishment? Evidence from Child Linear Growth, Developmental Epigenetics, and Brain and Neurocognitive Development." *Advances in Nutrition* 11, no. 4: 1032-41.

Mach, Katharine J., Caroline M. Kraan, W. Neil Adger, Halvard Buhaug, Marshall Burke, James D. Fearon, Christopher B. Field, et al. 2019. "Climate as a Risk Factor for Armed Conflict." *Nature* 571, no. 7764: 193-7.

Maystadt, Jean-François, and Olivier Ecker. 2014. "Extreme Weather and Civil War: Does Drought Fuel Conflict in Somalia Through Livestock Price Shocks?" *American Journal of Agricultural Economics* 96, no. 4: 1157-82.

Mei, Zuguo, and Laurence M. Grummer-Strawn. 2007. "Standard Deviation of Anthropometric Z-scores as a Data Quality Assessment Tool Using the 2006 WHO Growth Standards: A Cross Country Analysis." *Bulletin of the World Health Organization* 85: 441-8.

Minoiu, Camelia, and Olga Shemyakina. 2012. "Child Health and Conflict in Côte d'Ivoire." *American Economic Review* 102, no. 3: 294-9.

Mitáš, L., and H. Mitášová. 1988. "General Variational Approach to the Interpolation Problem." *Computers & Mathematics with Applications* 16, no. 12: 983-92.

OCHA (United Nations Office for the Coordination of Humanitarian Affairs). 2022. *Global Humanitarian Overview 2023*. Geneva: OCHA.

ODI (Overseas Development Institute), CGD (Center for Global Development). 2015. *Doing Cash Differently: How Cash Transfers Can Transform Humanitarian Aid, Report of the High Level Panel on Humanitarian Cash Transfers*. London: ODI.

Pena, Paola, Joaquin Urrego, and Juan M. Villa. 2017. "Civil Conflict and Conditional Cash Transfers: Effects on Demobilization." *World Development* 99: 431-40.

Save the Children. 2018. "Yemen: 85,000 Children May Have Died from Starvation Since Start of War." Press release, 20 November 2018. https://www.savethechildren.org/us/about-us/media-and-news/2018-press-releases/yemen-85000-children-may-have-died-from-starvation (accessed 1 April 2020).

Schrodt, Philip A. 2012. "CAMEO, Conflict and Mediation Event Observations: Event and Actor Codebook." http://data.gdeltproject.org/documentation/CAMEO.Manual.1.1b3.pdf (accessed 1 April 2020).

Shrimpton, Roger, Cesar G. Victora, Mercedes de Onis, Rosangela Costa Lima, Monika Blossner, and Graeme Clugston. 2001. "Worldwide Timing of Growth Faltering: Implications for Nutritional Interventions." *Pediatrics* 107, no. 5: e75.

Solon, Gary, Steven J. Haider, and Jeffrey M. Wooldridge. 2015. "What Are We Weighting For?" *Journal of Human Resources* 50, no. 2: 301-16.

Sundberg, Ralph, and Erik Melander. 2013. "Introducing the UCDP Georeferenced Event Dataset." *Journal of Peace Research* 50, no. 4: 523-32.

Tapsoba, Augustin. 2023. "The Cost of Fear: Impact of Violence Risk on Child Health During Conflict." *Journal of Development Economics* 160: 102975.

Tranchant, Jean-Pierre, Aulo Gelli, Lilia Bliznashka, Amadou Sekou Diallo, Moussa Sacko, Amidou Assima, Emily H. Siegel, Elisabetta Aurino, and Edoardo Masset. 2019. "The Impact of Food Assistance on Food Insecure Populations During Conflict: Evidence from a Quasi-experiment in Mali." *World Development* 119: 185-202.

UNICEF. 2019. *Fast facts: Yemen Crisis, February 2019*. Amman: UNICEF Middle East and North Africa Regional Office.

———. 2022. "Emergency Cash Transfer Project." https://www.unicef.org/yemen/emergency-cash-transfer-project (accessed 3 March 2022).

Verpoorten, Marijke. 2009. "Household Coping in War- and Peacetime: Cattle Sales in Rwanda, 1991–2001." *Journal of Development Economics* 88, no. 1: 67-86.

Victora, Cesar Gomes, Mercedes De Onis, Pedro Curi Hallal, Monika Blössner, and Roger Shrimpton. 2010. "Worldwide Timing of Growth Faltering: Revisiting Implications for Interventions." *Pediatrics* 125, no. 3: e473-80.

Von Grebmer, Klaus, Jill Bernstein, Alex de Waal, Nilam Prasai, Sandra Yin, and Yisehac Yohannes. 2015. *2015 Global Hunger Index: Armed Conflict and the Challenge of Hunger*. Washington, DC: International Food Policy Research Institute.

Wagner, Zachary, Sam Heft-Neal, Zulfiqar A. Bhutta, Robert E. Black, Marshall Burke, and Eran Bendavid. 2018. "Armed Conflict and Child Mortality in Africa: A Geospatial Analysis." *The Lancet* 392, no. 10150: 857-65.

Wan, Zhengming, Simon Hook, and Glynn Hulle. 2015. "MOD11A2 MODIS/Terra Land Surface Temperature and the Emissivity 8-Day L3 Global 1km SIN Grid. NASA LP DAAC." http://doi.org/10.5067/MODIS/MOD11A2.006 (accessed 1 April 2020).

Willibald, Sigrid. 2006. "Does Money Work? Cash Transfers to Ex- combatants in Disarmament, Demobilisation and Reintegration Processes." *Disasters* 30, no. 3: 316-39.

WHO (World Health Organization). 1995. *Physical Status: The Use of and Interpretation of Anthropometry*. *Report of a WHO Expert Committee*. Geneva: WHO.

———. 2000. *The Management of Nutrition in Major Emergencies*. Geneva: WHO.

———. 2006. *WHO Child Growth Standards: Length/Height-for-age, Weight-for-age, Weight-for-length, Weight-for-height and Body Mass Index-for-age: Methods and Development*. Geneva: WHO.

World Bank. 2017. *Yemen Emergency Crisis Response Project: Second Additional Financing*. Washington, DC: World Bank.

———. 2018. “Building Resilience and Protecting Vulnerable Yemenis Through Cash Transfers.” https://www.worldbank.org/en/news/feature/2018/03/21/building-resilience-and-protecting-vulnerable-yemenis-through-cash-transfers (accessed 1 April 2020).

Endnotes

[1] The public health literature also offers little conclusive evidence on the effects of cash transfers on child nutrition in conflict-affected areas. In a systematic review by Balhara et al. (2017) on the impact of nutritional interventions (including food assistance and cash transfer programs) on pediatric mortality and nutrition outcomes in humanitarian emergencies, only seven out of the 31 selected studies took place in a conflict setting. None of them explored the role of food assistance or cash transfers for children's nutritional status. More recent studies provide mixed evidence on the effectiveness of cash-based assistance in reducing acute child malnutrition in conflict settings. For example, in a non-randomized cluster trial in internally displaced person camps in Somalia, Grijalva-Eternod and colleagues did not find an association between unconditional cash transfers and reduced risk of acute child malnutrition among beneficiary households (Grijalva-Eternod et al. 2018). In another study of two humanitarian assistance programs in Somalia, Doocy and colleagues used a non-randomized prospective cohort design to assess the preventive effect of cash transfers and food vouchers on acute child malnutrition in the context of rising food shortages (Doocy et al. 2020). The authors found reduced risk of acute child malnutrition for the program that delivered mixed transfers (combining unrestricted cash and in-kind food transfers and food vouchers) but increased malnutrition risk for the program that delivered food vouchers only, after adjusting the estimation models for baseline imbalances between the intervention groups.

[2] For more information on the disbursement of SWF cash transfer payments, see Supplementary Appendix B.

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

[4] See Tables A1 ad A2 in Supplementary Appendix A.

[5] The districts included in our sample are home to about 76% of Yemen's mainland population and 81% of the population outside of Saada and Al-Jawf Governorates. Figure B1 in the Supplementary Appendix B shows a map that indicates the sample districts.

[6] Measurements of mid-upper arm circumference (MUAC) provide a simple method for nutritional screening of children of at least half a year old, which is particularly useful in rapid assessments when weight and height measurements cannot be done. However, arm circumference measurements are generally less precise than weight- and height-based measurements in determining children's nutritional status (WHO 2000). We use age- and sex-standardized MUAC instead of absolute MUAC, because a recent study in a similar setting found greater convergence of prevalence rates measured by MUACZ with WHZ-based prevalence rates (Custodio et al. 2018). The standard anthropometric indicator to measure young children's long-term nutritional status is height-for-age z-scores (HAZ). HAZ is used to detect child "stunting," indicating chronic child malnutrition. Stunting reflects a (cumulative) process of failure to reach linear growth potential as a result of suboptimal nutritional and/or health conditions in the past (WHO 1995). The low responsiveness of HAZ to recent shocks makes this indicator less suitable than WHZ for use in our econometric analysis that explores quarterly variations in child nutrition over a short period of only one year. Moreover, growth faltering mostly manifests during pregnancy and the first two life years, while achieving catch-up in linear growth is difficult especially in our study's context (Frongillo, Leroy, and Lapping 2019; Leroy et al. 2020). Observed HAZ of children conceived or born before the first survey round therefore likely reflect their nutritional and health conditions prior to our analysis period to a considerable extent, which interferes with our identification strategy for the hypothesized mitigating effect of the SWF cash transfer program.

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

[8] For the robustness checks, we use the MUACZ observations as they are available from the released NSPMS dataset. The NSPMS anthropometry module provide measurements of mid-upper arm circumference only for children who were between 6 and 59 months old at the time of the survey round. We do not consider the MUACZ of children if they have missing MUACZ observations in any survey round or if their MUACZ in any round is outside a biologically plausible range, using the same rule of defining outliers as for WHZ. The sample for this set of robustness checks includes 2,780 children that have valid WHZ and MUACZ observations and were at least six months old in the first survey round. Children are classified as wasted based on MUACZ if their MUACZ is below –2 SD of the mean of an international reference population (WHO 2006). Table A3 in Supplementary Appendix A shows summary statistics of MUACZ and the prevalence rate of wasting for our cohort of children by survey round.

[9] See Table A4 in Supplementary Appendix A.

[10] The additional analysis presented in Supplementary Appendix B uses additional conflict variables that are derived from the main conflict variables described here.

[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, Hook, and Hulley 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.

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

[13] To construct the household wealth index, we apply principal component analysis to the full, balanced household sample (including households with and without children under five years of age that were interviewed in all four survey rounds) and a large set of household asset variables, following the procedure proposed by IPC-IG, UNDP, and UNICEF (2014c).

[14] The inverse probability weighting (IPW) estimator is derived from an estimated propensity score of SWF cash transfer program participation. In the propensity score estimation, we use the household eligibility criteria of the program, shown in Table 1. Additionally, we include a binary variable that indicates whether a household is a beneficiary of a non-SWF social safety net program, because being registered and a recipient of other social welfare benefits may help for enrollment and continued participation in the SWF cash transfer program. All robustness checks

for the mitigating effect of the cash transfer program use the IPW estimator. The results of the estimations are qualitatively similar to those without the IPW estimator.

[15] In Supplementary Appendix B, we present an additional analysis of the hypothesized mitigating effect of the SWF cash transfer program. We restrict the sample to beneficiary households and use an instrumental variable approach to examine the regularity of cash transfer payments. The estimation results confirm the findings of our main analysis and provide additional evidence for the expected downward bias of the estimated mitigating effect.

[16] Table A5 in Supplementary Appendix A demonstrates that, according to *t*-test statistics, there are no statistically significant mean differences between the dependent, main independent, and control variables of our estimation models after partialling out household or individual fixed effects.

[17] 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.

[18] See Tables A7 and A8 in Supplementary Appendix A.

[19] See Footnote 8.

[20] See Tables A9 and A10 in in Supplementary Appendix A.

[21] See Tables A11 and A12 in Supplementary Appendix A. We refrain from providing Conley SE for the estimation models for the nutritional impact of civil conflict, because the correct implementation of Conley SE with accounting for the survey's longitudinal sampling design is complex and beyond the scope of this study.

[22] See Tables A13 and A14 in Supplementary Appendix A.

[23] See Tables A15 and A16 in Supplementary Appendix A.

[24] See Tables A17 and A18 in Supplementary Appendix A.

[25] See Tables A19 and A20 in Supplementary Appendix A.

Tables

Table 1. Household eligibility criteria of the SWF cash transfer program by beneficiary group

	All beneficiaries			Old beneficiaries			New beneficiaries			Non-beneficiaries		
	Mean	[95% CI]		Mean	[95% CI]		Mean	[95% CI]		Mean	[95% CI]	
Households with …												
Disabled person	0.244	0.219	0.269	0.264	0.230	0.299	0.237	0.197	0.276	0.138	0.118	0.158
Orphan	0.041	0.030	0.053	0.047	0.031	0.064	0.038	0.020	0.056	0.035	0.024	0.045
Elderly	0.470	0.441	0.499	0.547	0.508	0.586	0.386	0.341	0.431	0.226	0.202	0.251
Widowed or divorced woman	0.347	0.320	0.374	0.407	0.369	0.446	0.281	0.239	0.323	0.132	0.112	0.151
Unemployed man	0.080	0.064	0.095	0.077	0.056	0.098	0.087	0.061	0.113	0.057	0.044	0.071
Level of per capita household income (from non-SWF sources):												
Quintile 1	0.232	0.208	0.256	0.237	0.204	0.271	0.228	0.189	0.267	0.180	0.158	0.203
Quintile 2	0.219	0.195	0.243	0.215	0.183	0.247	0.223	0.185	0.262	0.182	0.160	0.204
Quintile 3	0.204	0.180	0.227	0.200	0.169	0.231	0.205	0.168	0.243	0.194	0.171	0.217
Quintile 4	0.191	0.168	0.213	0.203	0.171	0.234	0.185	0.149	0.221	0.211	0.187	0.234
Quintile 5	0.155	0.134	0.175	0.145	0.117	0.172	0.158	0.125	0.192	0.233	0.208	0.257
Household chronic poverty status:												
Poor	0.723	0.698	0.749	0.714	0.679	0.749	0.768	0.729	0.807	0.585	0.557	0.614
Extremely poor	0.240	0.215	0.264	0.247	0.213	0.280	0.239	0.199	0.278	0.119	0.101	0.138
Moderately poor	0.322	0.295	0.349	0.321	0.284	0.357	0.346	0.302	0.390	0.287	0.260	0.313
Vulnerable	0.162	0.140	0.183	0.146	0.119	0.174	0.183	0.147	0.219	0.179	0.157	0.202
N (households)		*1,164*			*636*			*448*			*1,148*	

Note: All variables are binary, with yes = 1 and no = 0.
SWF = Social Welfare Fund; CI = confidence interval; *N* = number of observations.

Table 2. Summary statistics for children's WHZ and the prevalence of child wasting by survey round

Survey round	Weight-for-height z-score (WHZ)		Wasting rate (%)
	Mean	SD	WHZ<-2
1	-0.694	1.241	12.7
2	-0.545	0.951	6.6
3	-0.552	0.932	6.6
4	-0.646	0.977	8.6
N (children)		*3,281*	

Note: The cohort of all sample children has a mean age (and an age range) of 24.8 months (0–51 months) in the first round; 27.8 months (3–54 months) in the second round; 30.8 months (6–57 months) in the third round; and 33.6 months (8–59 months) in the fourth round. Table A3 in the Appendix shows summary statistics for child MUACZ—another short-term child nutrition indicator—and the corresponding wasting rate.
N = number of observations.

Table 3. Estimated impact of civil conflict on child WHZ

Model specification	1	2	3	4
Civilian casualties (std)	-0.0574	-0.0560	-0.0566	-0.0561
Cluster SE	(0.0202)***	(0.0201)***	(0.0204)***	(0.0203)***
Conley SE	(0.0066)***	(0.0077)***	(0.0054)***	(0.0052)***
Household controls	no	yes	n.a.	n.a.
Fixed effects				
District	yes	yes	no	no
Household	no	no	yes	no
Individual	no	no	no	yes
R-squared	0.1374	0.1415	0.5263	0.6459
RMSE	0.970	0.967	0.785	0.711

Note: The sample includes 13,124 child – survey round observations.
Household controls include household wealth status, household size, and sex, age, and literacy of the household head. All model specifications control for child sex and age, extreme weather events, and time fixed effects. Because of perfect collinearity, the household controls drop out from the household and individual fixed effects estimations (Models 3 and 4), and the child controls drop out from the individual fixed effects estimation (Model 4). Table A6 in Supplementary Appendix A shows the complete estimation results.
***, **, * Per the reported standard error (SE), the coefficient estimate 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.
WHZ = weight-for-height z-score; std = standardized; n.a. = not applicable.
The R-squared (overall) and root mean square error (RMSE) are reported for the estimations using the cluster SE estimator.

Table 4. Estimated mitigating effect of the SWF cash transfer program on child WHZ

Model specification	1	2	3	4
Civilian casualties (std)	-0.0545	-0.0822	-0.0801	-0.0787
Cluster SE	(0.0241)**	(0.0243)***	(0.0238)***	(0.0236)***
Treatment (0=no, 1=yes)	-0.0263	-0.0256	n.a.	n.a.
Cluster SE	(0.0353)	(0.0352)		
Civilian casualties * treatment		0.0430	0.0346	0.0334
Cluster SE		(0.0119)***	(0.0095)***	(0.0089)***
Fixed effects				
District	yes	yes	no	no
Household	no	no	yes	no
Individual	no	no	no	yes
R-squared	0.1541	0.1544	0.5295	0.6556
RMSE	0.963	0.963	0.785	0.703

Note: The sample includes 13,124 child – survey round observations.
All model specifications control for household and child characteristics, extreme weather events, and time fixed effects. All estimations use an inverse probability weighting estimator to correct for non-random household selection into the program.
***, **, * Per the reported standard error (SE), the coefficient estimate is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level.
SWF = Social Welfare Fund; WHZ = weight-for-height z-score; std = standardized; n.a. = not applicable; RMSE = root mean square error.

Table 5. Estimated mitigating effect of the SWF cash transfer program on child WHZ among old and new beneficiary households

	Old beneficiaries				New beneficiaries			
Model specification	1	2	3	4	5	6	7	8
Civilian casualties (std)	-0.0502	-0.0845	-0.0802	-0.0786	-0.0681	-0.0773	-0.0813	-0.0801
Cluster SE	(0.0235)**	(0.0256)***	(0.0235)***	(0.0234)***	(0.0226)***	(0.0236)***	(0.0239)***	(0.0238)***
Treatment (0=no, 1=yes)	-0.0380	-0.0377	n.a.	n.a.	-0.0162	-0.0159	n.a.	n.a.
Cluster SE	(0.0417)	(0.0414)			(0.0452)	(0.0452)		
Civilian casualties * treatment		0.0652	0.0494	0.0480		0.0283	0.0267	0.0265
Cluster SE		(0.0162)***	(0.0117)***	(0.0109)***		(0.0104)***	(0.0115)**	(0.0114)**
Fixed effects								
District	yes	yes	no	no	yes	yes	no	no
Household	no	no	yes	no	no	no	yes	no
Individual	no	no	no	yes	no	no	no	yes
R-squared	0.1746	0.1752	0.5294	0.6609	0.1781	0.1782	0.5236	0.6588
RMSE	0.966	0.965	0.794	0.707	0.943	0.943	0.781	0.693
N	*10,196*				*9,116*			

Note: All model specifications control for household and child characteristics, extreme weather events, and time fixed effects. All estimations use an inverse probability weighting estimator to correct for non-random household selection into the program.

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

SWF = Social Welfare Fund; WHZ = weight-for-height z-score; std = standardized; n.a. = not applicable; RMSE = root mean square error; *N* = number of child – survey round observations.

Figures

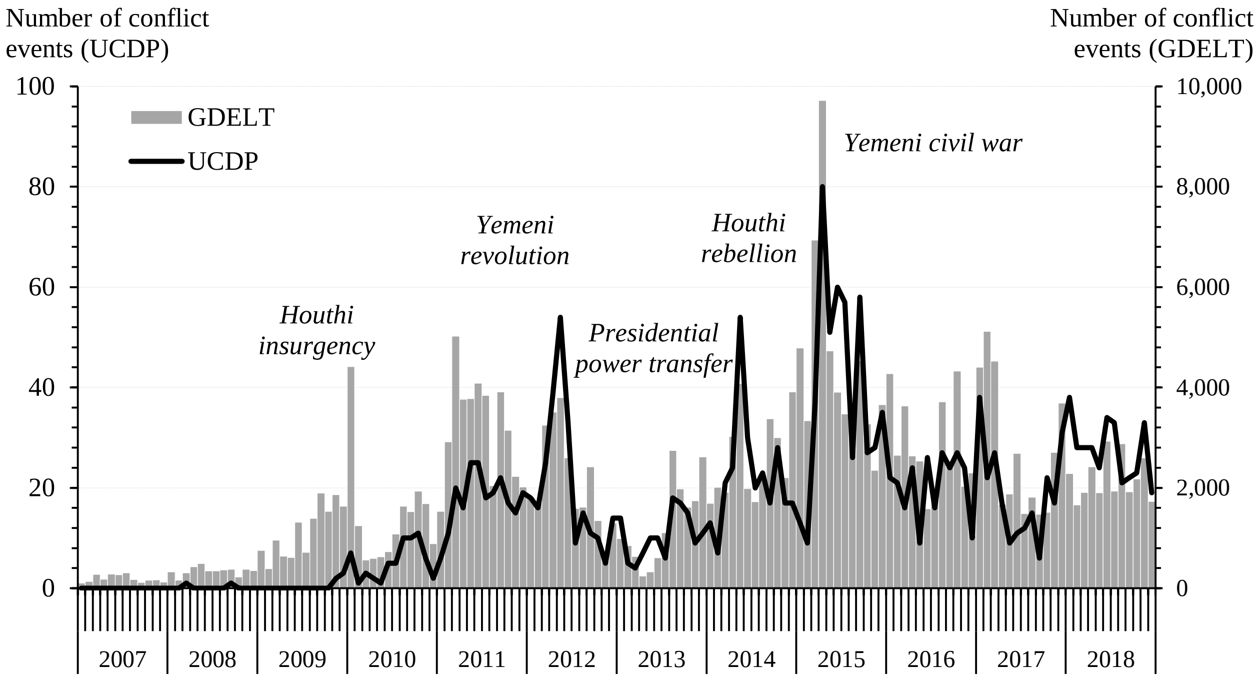


Figure 1. Armed conflict intensity in Yemen

Note: The data were obtained from the Uppsala Conflict Data Program (UCDP) and the Global Database of Events, Language, and Tone (GDELT) databases (Leetaru and Schrodt 2013; Sundberg and Melander 2013).

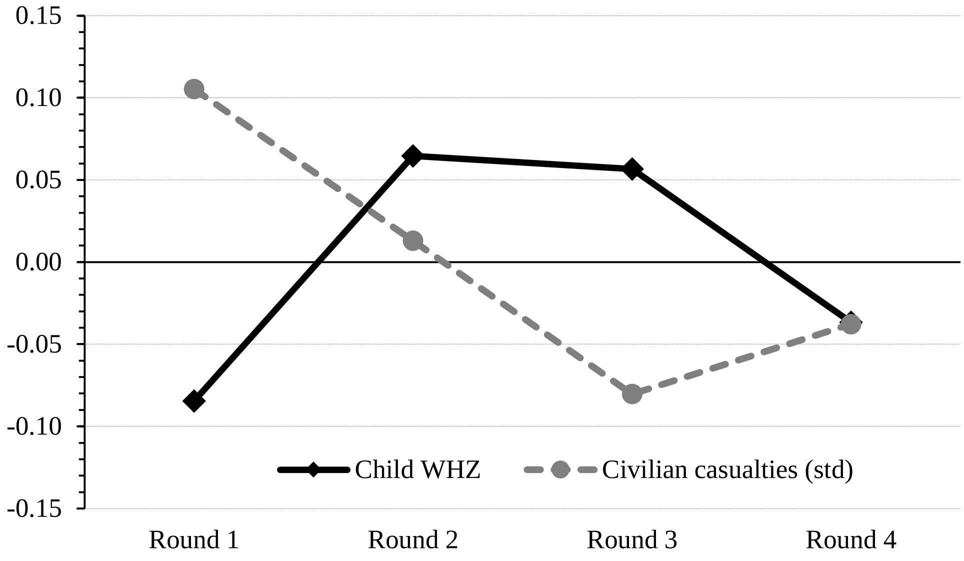


Figure 2. Association of children's short-term nutritional status and armed conflict intensity over survey rounds at sample means

Note: The data points are obtained by partialling out district fixed effects.
WHZ = weight-for-height z-score; std = standardized.

Supplementary Appendix:

Civil Conflict, Cash Transfers, and Child Nutrition in Yemen

Olivier Ecker*, Afnan Al-Malk, and Jean-François Maystadt

[ADD ARTICLE REFERENCE HERE.]

* Corresponding author: Olivier Ecker; 1201 I Street, NW; Washington, DC 20005; Tel: +1 202-862-5632; Fax: +1 202-862-5606; Email: o.ecker@cgiar.org.

Appendix A: Complementary Statistics and Estimation Results

Table A1. Attrition check: Children's short-term nutritional status (at baseline) and household eligibility criteria of the SWF cash transfer program by beneficiary group, with Al-Jawf Governorate

	All households					
	Initial sample			Final sample		
	Mean	[95% CI]		Mean	[95% CI]	
Child WHZ	-0.630	-0.669	-0.590	-0.644	-0.684	-0.603
N (children)		*3,593*			*3,281*	
Households with …						
Disabled person	0.185	0.170	0.200	0.191	0.175	0.207
Orphan	0.039	0.031	0.046	0.038	0.030	0.046
Elderly	0.334	0.315	0.352	0.349	0.330	0.368
Widowed or divorced woman	0.230	0.213	0.246	0.240	0.223	0.257
Unemployed man	0.071	0.061	0.081	0.069	0.058	0.079
Level of per capita household income (from non-SWF sources):						
Quintile 1	0.207	0.191	0.223	0.206	0.190	0.223
Quintile 2	0.201	0.185	0.216	0.201	0.184	0.217
Quintile 3	0.199	0.183	0.214	0.199	0.183	0.215
Quintile 4	0.201	0.185	0.217	0.201	0.184	0.217
Quintile 5	0.193	0.178	0.208	0.193	0.177	0.209
Household chronic poverty status:						
Poor	0.661	0.642	0.679	0.655	0.635	0.674
Extremely poor	0.174	0.159	0.189	0.180	0.164	0.196
Moderately poor	0.313	0.295	0.332	0.304	0.286	0.323
Vulnerable	0.173	0.159	0.188	0.170	0.155	0.186
N (households)		*2,533*			*2,312*	

Note: All household-level variables are binary with values, with yes = 1 and no = 0.
SWF = Social Welfare Fund; WHZ = weight-for-height z-score; CI = confidence interval; *N* = number of observations.

Table A1—continued.

	All beneficiaries						Non-beneficiaries					
	Initial sample			Final sample			Initial sample			Final sample		
	Mean	[95% CI]		Mean	[95% CI]		Mean	[95% CI]		Mean	[95% CI]	
Child WHZ	-0.626	-0.683	-0.568	-0.639	-0.697	-0.581	-0.634	-0.687	-0.580	-0.648	-0.704	-0.591
N (children)		*1,725*			*1,629*			*1,868*			*1,652*	
Households with …												
Disabled person	0.241	0.217	0.265	0.244	0.219	0.269	0.132	0.113	0.150	0.138	0.118	0.158
Orphan	0.040	0.029	0.051	0.041	0.030	0.053	0.037	0.027	0.047	0.035	0.024	0.045
Elderly	0.459	0.431	0.487	0.470	0.441	0.499	0.214	0.191	0.236	0.226	0.202	0.251
Widowed or divorced woman	0.340	0.313	0.366	0.347	0.320	0.374	0.125	0.107	0.143	0.132	0.112	0.151
Unemployed man	0.082	0.067	0.098	0.080	0.064	0.095	0.060	0.047	0.073	0.057	0.044	0.071
Level of per capita household income (from non-SWF sources):												
Quintile 1	0.224	0.201	0.247	0.232	0.208	0.256	0.191	0.169	0.212	0.180	0.158	0.203
Quintile 2	0.226	0.202	0.249	0.219	0.195	0.243	0.177	0.156	0.197	0.182	0.160	0.204
Quintile 3	0.208	0.185	0.230	0.204	0.180	0.227	0.190	0.168	0.211	0.194	0.171	0.217
Quintile 4	0.184	0.162	0.205	0.191	0.168	0.213	0.218	0.195	0.240	0.211	0.187	0.234
Quintile 5	0.159	0.139	0.180	0.155	0.134	0.175	0.225	0.203	0.248	0.233	0.208	0.257
Household chronic poverty status:												
Poor	0.730	0.705	0.755	0.723	0.698	0.749	0.595	0.568	0.622	0.585	0.557	0.614
Extremely poor	0.239	0.215	0.263	0.240	0.215	0.264	0.112	0.095	0.129	0.119	0.101	0.138
Moderately poor	0.329	0.303	0.355	0.322	0.295	0.349	0.299	0.274	0.324	0.287	0.260	0.313
Vulnerable	0.162	0.141	0.182	0.162	0.140	0.183	0.184	0.163	0.206	0.179	0.157	0.202
N (households)		*1,237*			*1,164*			*1,296*			*1,148*	

Table A2. Attrition check: Children's short-term nutritional status (at baseline) and household eligibility criteria of the SWF cash transfer program by beneficiary group, without Al-Jawf Governorate

	All households					
	Initial sample			Final sample		
	Mean	[95% CI]		Mean	[95% CI]	
Child WHZ	-0.629	-0.668	-0.589	-0.644	-0.684	-0.603
N (children)		*3,430*			*3,281*	
Households with …						
Disabled person	0.190	0.174	0.206	0.191	0.175	0.207
Orphan	0.039	0.032	0.047	0.038	0.030	0.046
Elderly	0.342	0.323	0.361	0.349	0.330	0.368
Widowed or divorced woman	0.236	0.219	0.252	0.240	0.223	0.257
Unemployed man	0.068	0.058	0.078	0.069	0.058	0.079
Level of per capita household income (from non-SWF sources):						
Quintile 1	0.207	0.191	0.223	0.206	0.190	0.223
Quintile 2	0.200	0.184	0.216	0.201	0.184	0.217
Quintile 3	0.199	0.183	0.214	0.199	0.183	0.215
Quintile 4	0.201	0.185	0.217	0.201	0.184	0.217
Quintile 5	0.193	0.178	0.209	0.193	0.177	0.209
Household chronic poverty status:						
Poor	0.650	0.631	0.669	0.655	0.635	0.674
Extremely poor	0.175	0.160	0.191	0.180	0.164	0.196
Moderately poor	0.303	0.285	0.321	0.304	0.286	0.323
Vulnerable	0.171	0.156	0.186	0.170	0.155	0.186
N (households)		*2,416*			*2,312*	

Note: All household-level variables are binary with values, with yes = 1 and no = 0.
SWF = Social Welfare Fund; WHZ = weight-for-height z-score; CI = confidence interval; *N* = number of observations.

Table A2—continued.

	All beneficiaries						Non-beneficiaries					
	Initial sample			Final sample			Initial sample			Final sample		
	Mean	[95% CI]		Mean	[95% CI]		Mean	[95% CI]		Mean	[95% CI]	
Child WHZ	-0.628	-0.686	-0.570	-0.639	-0.697	-0.581	-0.630	-0.684	-0.576	-0.648	-0.704	-0.591
N (children)		*1,669*			*1,629*			*1,761*			*1,652*	
Households with …												
Disabled person	0.244	0.220	0.268	0.244	0.219	0.269	0.137	0.118	0.157	0.138	0.118	0.158
Orphan	0.042	0.031	0.053	0.041	0.030	0.053	0.037	0.026	0.047	0.035	0.024	0.045
Elderly	0.468	0.439	0.496	0.470	0.441	0.499	0.220	0.197	0.243	0.226	0.202	0.251
Widowed or divorced woman	0.344	0.317	0.371	0.347	0.320	0.374	0.130	0.111	0.149	0.132	0.112	0.151
Unemployed man	0.080	0.064	0.095	0.080	0.064	0.095	0.057	0.044	0.070	0.057	0.044	0.071
Level of per capita household income (from non-SWF sources):												
Quintile 1	0.222	0.199	0.246	0.232	0.208	0.256	0.192	0.170	0.214	0.180	0.158	0.203
Quintile 2	0.225	0.201	0.248	0.219	0.195	0.243	0.177	0.155	0.198	0.182	0.160	0.204
Quintile 3	0.211	0.188	0.234	0.204	0.180	0.227	0.186	0.165	0.208	0.194	0.171	0.217
Quintile 4	0.185	0.163	0.207	0.191	0.168	0.213	0.216	0.193	0.239	0.211	0.187	0.234
Quintile 5	0.157	0.136	0.177	0.155	0.134	0.175	0.229	0.205	0.253	0.233	0.208	0.257
Household chronic poverty status:												
Poor	0.723	0.697	0.748	0.723	0.698	0.749	0.579	0.551	0.607	0.585	0.557	0.614
Extremely poor	0.238	0.214	0.262	0.240	0.215	0.264	0.114	0.097	0.132	0.119	0.101	0.138
Moderately poor	0.321	0.295	0.348	0.322	0.295	0.349	0.285	0.260	0.311	0.287	0.260	0.313
Vulnerable	0.163	0.142	0.184	0.162	0.140	0.183	0.179	0.158	0.201	0.179	0.157	0.202
N (households)		*1,193*			*1,164*			*1,223*			*1,148*	

Table A3. Summary statistics for children's MUACZ and corresponding prevalence of child wasting by survey round

Survey round	Mid-upper arm circumference z-score (MUACZ)		Wasting rate (%)
	Mean	SD	MUACZ<-2
1	-1.191	1.006	19.5
2	-1.020	0.909	13.1
3	-0.958	0.910	12.7
4	-0.999	0.943	14.5
N (children)		*2,780*	

Note: MUACZ is only available for children aged 6 months and older.
N = number of observations.

Table A4. Children's mean short-term nutritional status and the probability of child wasting among SWF cash transfer program beneficiaries and non-beneficiaries at baseline

	All beneficiaries			Non-beneficiaries		
	Mean	[95% CI]		Mean	[95% CI]	
Child weight-for-height z-score (WHZ)	-0.676	-0.737	-0.615	-0.711	-0.771	-0.652
Child wasting (WHZ<-2)	0.129	0.113	0.145	0.126	0.110	0.142
N (children)		*1,629*			*1,652*	
Child mid-upper arm circumference z-score (MUACZ)	-1.190	-1.245	-1.136	-1.192	-1.244	-1.141
Child wasting (MUACZ<-2)	0.207	0.186	0.229	0.184	0.163	0.204
N (children)		*1,385*			*1,395*	

Note: The statistics are based on observations from the first survey round (baseline).
SWF = Social Welfare Fund; CI = confidence interval; *N* = number of observations.

Table A5. Summary statistics for estimation variables as observed and after partialling out of district, household, and individual fixed effects

	Observed					District FE partialled out				
	Beneficiaries		Non-beneficiaries		Mean	Beneficiaries		Non-beneficiaries		Mean
	Mean	SD	Mean	SD	difference	Mean	SD	Mean	SD	difference
Short-term child nutrition indicators										
Weight-for-height z-score (WHZ)	-0.584	1.039	-0.634	1.031	-0.050 **	-0.001	0.974	0.001	0.962	0.003
Wasting (WHZ<-2; 0=no, 1=yes)	0.085	0.279	0.088	0.283	-0.009	0.003	0.267	-0.003	0.273	-0.005
Mid-upper arm circumference z-score (MUACZ)	-1.038	0.981	-1.047	0.912	0.003	0.009	0.925	-0.009	0.839	-0.017
Wasting (MUACZ<-2; 0=no, 1=yes)	0.160	0.367	0.139	0.346	-0.019 **	0.007	0.354	-0.007	0.334	-0.015 *
Conflict										
Civilian casualties (std)	0.003	1.015	-0.018	0.862	-0.021	0.000	0.870	0.000	0.736	0.001
Child characteristics										
Sex (0=male, 1=female)	0.493	0.500	0.488	0.500	-0.004	0.000	0.481	0.000	0.477	0.001
Age (months)	29.23	14.82	29.29	14.74	0.06	-0.26	14.43	0.25	14.26	0.51 *
Household characteristics										
Wealth index	-0.017	0.969	-0.072	1.034	-0.056 **	-0.019	0.574	0.019	0.576	0.038 ***
Household size (persons)	10.44	4.51	8.53	4.18	-1.91 ***	0.71	3.87	-0.70	3.69	-1.40 ***
Sex of household head (0=male, 1=female)	0.060	0.237	0.037	0.189	-0.023 ***	0.011	0.218	-0.010	0.185	-0.021 ***
Age of household head (years)	47.51	15.09	41.94	14.15	-5.57 ***	2.08	14.10	-2.05	12.48	-4.13 ***
Literacy status of household head (0=none, 1=literate)	0.506	0.500	0.660	0.474	0.154 ***	-0.067	0.469	0.066	0.436	0.133 ***
Household eligibility criteria of the SWF cash transfer program										
Disabled person (0=no, 1=yes)	0.137	0.344	0.063	0.243	-0.074 ***	0.032	0.325	-0.032	0.237	-0.064 ***
Orphan (0=no, 1=yes)	0.033	0.180	0.030	0.172	-0.003	0.001	0.173	-0.001	0.166	-0.002
Elderly (0=no, 1=yes)	0.510	0.500	0.242	0.428	-0.268 ***	0.108	0.462	-0.107	0.382	-0.215 ***
Widowed or divorced woman (0=no, 1=yes)	0.383	0.486	0.148	0.355	-0.235 ***	0.104	0.456	-0.103	0.333	-0.207 ***
Unemployed man (0=no, 1=yes)	0.161	0.367	0.109	0.312	-0.052 ***	0.024	0.347	-0.023	0.295	-0.047 ***
Chronically poor (0=no, 1=yes)	0.750	0.433	0.608	0.488	-0.142 ***	0.056	0.381	-0.055	0.416	-0.111 ***
Social welfare benefits from non-SWF sources (0=no, 1=yes)	0.075	0.263	0.048	0.213	-0.027 ***	0.001	0.232	-0.001	0.189	-0.003
Extreme weather events										
Precipitation anomaly	-0.753	1.250	-0.830	1.213	-0.077 ***	0.000	1.038	0.000	1.027	0.000
Temperature anomaly	0.023	0.640	0.066	0.614	0.043 ***	0.001	0.605	-0.001	0.576	-0.003

Note: The sample includes 6,516 and 6,608 child – survey round observations for beneficiary and non-beneficiary households, respectively. The MUAC-based variables have 5,580 and 5,540 child – survey round observations, respectively.
SWF = Social Welfare Fund; FE = fixed effects; SD = standard deviation.

Table A5—continued.

	Household FE partialled out					Individual FE partialled out				
	Beneficiaries		Non-beneficiaries		Mean difference	Beneficiaries		Non-beneficiaries		Mean difference
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Short-term child nutrition indicators										
Weight-for-height z-score (WHZ)	0.000	0.713	0.000	0.728	0.000	0.000	0.622	0.000	0.620	0.000
Wasting (WHZ<-2; 0=no, 1=yes)	0.000	0.219	0.000	0.224	0.000	0.000	0.198	0.000	0.199	0.000
Mid-upper arm circumference z-score (MUACZ)	0.000	0.647	0.000	0.567	0.000	0.000	0.559	0.000	0.499	0.000
Wasting (MUACZ<-2; 0=no, 1=yes)	0.000	0.269	0.000	0.250	0.000	0.000	0.242	0.000	0.224	0.000
Conflict										
Civilian casualties (std)	0.000	0.869	0.000	0.735	0.000	0.000	0.869	0.000	0.735	0.000
Child characteristics										
Sex (0=male, 1=female)	0.000	0.271	0.000	0.266	0.000	0.000	0.000	0.000	0.000	0.000
Age (months)	0.00	9.55	0.00	9.87	0.00	0.00	3.31	0.00	3.30	0.00
Household characteristics										
Wealth index	0.000	0.234	0.000	0.227	0.000	0.000	0.234	0.000	0.227	0.000
Household size (persons)			n.a.					n.a.		
Sex of household head (0=male, 1=female)			n.a.					n.a.		
Age of household head (years)			n.a.					n.a.		
Literacy status of household head (0=none, 1=literate)			n.a.					n.a.		
Household eligibility criteria of the SWF cash transfer program										
Disabled person (0=no, 1=yes)	0.000	0.251	0.000	0.177	0.000	0.000	0.251	0.000	0.177	0.000
Orphan (0=no, 1=yes)	0.000	0.111	0.000	0.096	0.000	0.000	0.111	0.000	0.096	0.000
Elderly (0=no, 1=yes)	0.000	0.079	0.000	0.047	0.000	0.000	0.079	0.000	0.047	0.000
Widowed or divorced woman (0=no, 1=yes)	0.000	0.090	0.000	0.075	0.000	0.000	0.090	0.000	0.075	0.000
Unemployed man (0=no, 1=yes)	0.000	0.268	0.000	0.227	0.000	0.000	0.268	0.000	0.227	0.000
Chronically poor (0=no, 1=yes)	0.000	0.223	0.000	0.228	0.000	0.000	0.223	0.000	0.228	0.000
Social welfare benefits from non-SWF sources (0=no, 1=yes)	0.000	0.148	0.000	0.124	0.000	0.000	0.148	0.000	0.124	0.000
Extreme weather events										
Precipitation anomaly	0.000	1.028	0.000	1.017	0.000	0.000	1.028	0.000	1.017	0.000
Temperature anomaly	0.000	0.602	0.000	0.573	0.000	0.000	0.602	0.000	0.573	0.000

***, **, * According to a two-sided t-test, the mean difference is statistically significant at the 1%, 5%, and 10% level, respectively.
n.a. = not applicable. All household characteristics, except for households' wealth index, were measured in the first survey round and therefore do not vary across survey rounds. There is no variation between children in these variables after partialling out household or individual fixed effects.

Table A6. Complete estimation results for the impact of civil conflict on child WHZ

Model specification	1	2	3	4
Civilian casualties (std)	-0.0574	-0.0560	-0.0566	-0.0561
Cluster SE	(0.0202)***	(0.0201)***	(0.0204)***	(0.0203)***
Conley SE	(0.0066)***	(0.0077)***	(0.0054)***	(0.0052)***
Child characteristics				
Child sex (0=male, 1=female)	0.0857	0.0881	0.0525	n.a.
Cluster SE	(0.0277)***	(0.0274)***	(0.0379)	
Conley SE	(0.0193)***	(0.0191)***	(0.0163)***	
Child age (months)	0.0205	0.0211	0.0274	n.a.
Cluster SE	(0.0039)***	(0.0039)***	(0.0045)***	
Conley SE	(0.0021)***	(0.0021)***	(0.0028)***	
Child age squared	-0.0003	-0.0003	-0.0004	n.a.
Cluster SE	(0.0001)***	(0.0001)***	(0.0001)***	
Conley SE	(0.0000)***	(0.0000)***	(0.0000)***	
Household characteristics				
Household wealth index		0.1044	n.a.	n.a.
Cluster SE		(0.0240)***		
Conley SE		(0.0156)***		
Household size (headcount)		0.0011	n.a.	n.a.
Cluster SE		(0.0043)		
Conley SE		(0.0025)		
Sex of household head (0=male, 1=female)		-0.0600	n.a.	n.a.
Cluster SE		(0.0732)		
Conley SE		(0.0349)*		
Age of household head (years)		0.0005	n.a.	n.a.
Cluster SE		(0.0012)		
Conley SE		(0.0007)		
Literacy of household head (0=illiterate, 1=literate)		-0.0586	n.a.	n.a.
Cluster SE		(0.0369)		
Conley SE		(0.0278)**		
Extreme weather events				
Precipitation anomaly	0.0067	0.0075	0.0053	0.0052
Cluster SE	(0.0096)	(0.0095)	(0.0094)	(0.0096)
Conley SE	(0.0141)	(0.0142)	(0.0140)	(0.0142)
Temperature anomaly	-0.0124	-0.0116	0.0034	0.0041
Cluster SE	(0.0285)	(0.0284)	(0.0286)	(0.0285)
Conley SE	(0.0323)	(0.0308)	(0.0332)	(0.0329)
Fixed effects				
District	yes	yes	no	no
Household	no	no	yes	no
Individual	no	no	no	yes
R-squared	0.1374	0.1415	0.5263	0.6459
RMSE	0.970	0.967	0.785	0.711

Note: The sample includes 13,124 child – survey round observations.
***, **, * Per the reported standard error (SE), the coefficient estimate 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.
WHZ = weight-for-height z-score; std = standardized.
n.a. = not applicable. Because of perfect collinearity, the household characteristics drop out from the household and individual fixed effects estimations (Models 3 and 4), and the child characteristics drop out from the individual fixed effects estimation (Model 4).
The R-squared (overall) and root mean square error (RMSE) are reported for the estimations using the cluster SE estimator.

Table A7. Estimated impact of civil conflict on alternative indicators of short-term child nutrition and acute child malnutrition

Model specification	1	2	3	4
Panel A: Mid-upper arm circumference z-score (MUACZ)				
Civilian casualties (std)	-0.0493	-0.0469	-0.0485	-0.0485
Cluster SE	(0.0225)**	(0.0226)**	(0.0227)**	(0.0228)**
Conley SE	(0.0110)***	(0.0098)***	(0.0144)***	(0.0144)***
R-squared	0.1441	0.1516	0.6004	0.6985
RMSE	0.885	0.882	0.664	0.601
Panel B: Short-term child nutrition index, based on WHZ and MUACZ				
Civilian casualties (std)	-0.0632	-0.0608	-0.0630	-0.0630
Cluster SE	(0.0242)***	(0.0242)**	(0.0243)**	(0.0245)**
Conley SE	(0.0122)***	(0.0105)***	(0.0130)***	(0.0128)***
R-squared	0.1560	0.1627	0.6333	0.7406
RMSE	0.928	0.925	0.671	0.588
Panel C: Probability of child wasting, based on WHZ				
Civilian casualties (std)	0.0090	0.0088	0.0087	0.0086
Cluster SE	(0.0020)***	(0.0020)***	(0.0020)***	(0.0020)***
Conley SE	(0.0031)***	(0.0033)***	(0.0019)***	(0.0018)***
R-squared	0.0959	0.0970	0.3946	0.5095
RMSE	0.269	0.269	0.241	0.227
Panel D: Probability of child wasting, based on MUACZ				
Civilian casualties (std)	0.0074	0.0066	0.0071	0.0072
Cluster SE	(0.0062)	(0.0063)	(0.0063)	(0.0063)
Conley SE	(0.0013)***	(0.0018)***	(0.0012)***	(0.0012)***
R-squared	0.0785	0.0836	0.4781	0.5783
RMSE	0.346	0.345	0.286	0.267
Household controls	no	yes	n.a.	n.a.
Fixed effects				
District	yes	yes	no	no
Household	no	no	yes	no
Individual	no	no	no	yes

Note: Children are classified as wasted if, respectively, their WHZ or MUACZ is below -2. The WHZ-based sample and MUACZ-based sample have 13,124 and 11,120 child – survey round observations, respectively.
The short-term child nutrition index is a composite index of children's WHZ and MUACZ and is constructed by applying the weighting procedure proposed by Anderson (2008) and the STATA command developed by Schwab et al. (2020).
All model specifications control for child characteristics, extreme weather events, and time fixed effects.
***, **, * Per the reported standard error (SE), the coefficient estimate 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.
std = standardized; n.a. = not applicable.
The R-squared (overall) and root mean square error (RMSE) are reported for the estimations using the cluster SE estimator.

Table A8. Estimated mitigating effect of the SWF cash transfer program on alternative indicators of short-term child nutrition and acute child malnutrition

Model specification	1	2	3	4
Panel A: Mid-upper arm circumference z-score (MUACZ)				
Civilian casualties (std)	-0.0578	-0.0798	-0.0760	-0.0761
Cluster SE	(0.0277)**	(0.0298)***	(0.0184)***	(0.0185)***
Treatment (0=no, 1=yes)	0.0382	0.0390	n.a.	n.a.
Cluster SE	(0.0458)	(0.0457)		
Civilian casualties * treatment		0.0372	0.0316	0.0318
Cluster SE		(0.0204)*	(0.0206)	(0.0205)
R-squared	0.1691	0.1693	0.6034	0.7062
RMSE	0.884	0.884	0.670	0.601
Panel B: Short-term child nutrition index, based on WHZ and MUACZ				
Civilian casualties (std)	-0.0682	-0.0959	-0.0917	-0.0913
Cluster SE	(0.0310)**	(0.0293)***	(0.0229)***	(0.0232)***
Treatment (0=no, 1=yes)	0.0062	0.0072		
Cluster SE	(0.0440)	(0.0439)		
Civilian casualties * treatment		0.0470	0.0342	0.0336
Cluster SE		(0.0186)**	(0.0215)	(0.0208)
R-squared	0.1875	0.1879	0.6346	0.7495
RMSE	0.917	0.917	0.675	0.582
Panel C: Probability of child wasting, based on WHZ				
Civilian casualties (std)	0.0083	0.0021	0.0030	0.0026
Cluster SE	(0.0020)***	(0.0019)	(0.0019)	(0.0021)
Treatment (0=no, 1=yes)	0.0037	0.0039	n.a.	n.a.
Cluster SE	(0.0080)	(0.0080)		
Civilian casualties * treatment		0.0096	0.0084	0.0087
Cluster SE		(0.0026)***	(0.0040)**	(0.0043)**
R-squared	0.1091	0.1093	0.3897	0.5091
RMSE	0.269	0.269	0.243	0.229
Panel D: Probability of child wasting, based on MUACZ				
Civilian casualties (std)	0.0056	0.0060	0.0022	0.0021
Cluster SE	(0.0064)	(0.0049)	(0.0040)	(0.0041)
Treatment (0=no, 1=yes)	0.0062	0.0062	n.a.	n.a.
Cluster SE	(0.0132)	(0.0132)		
Civilian casualties * treatment		-0.0007	0.0073	0.0074
Cluster SE		(0.0032)	(0.0055)	(0.0054)
R-squared	0.0967	0.0967	0.4732	0.5828
RMSE	0.348	0.348	0.292	0.270
Fixed effects				
District	yes	yes	no	no
Household	no	no	yes	no
Individual	no	no	no	yes

Note: Children are classified as wasted if, respectively, their WHZ or MUACZ is below -2. The WHZ-based sample and MUACZ-based sample have 13,124 and 11,120 child – survey round observations, respectively.
The short-term child nutrition index is a composite index of children's WHZ and MUACZ and is constructed by applying the weighting procedure proposed by Anderson (2008) and the STATA command developed by Schwab et al. (2020).
All model specifications control for household and child characteristics, extreme weather events, and time fixed effects.
***, **, * Per the reported standard error (SE), the coefficient estimate is statistically significant at the 1%, 5%, and 10% level, respectively.
SWF = Social Welfare Fund; std = standardized; n.a. = not applicable; RMSE = root mean square error.

Table A9. Estimated impact of civil conflict on child WHZ, for alternative definitions of armed conflict intensity

Model specification	1	2	3	4
Panel A: UCDP data				
Civilian casualties per day (std)	-0.0530	-0.0516	-0.0527	-0.0523
Cluster SE	(0.0191)***	(0.0191)***	(0.0193)***	(0.0192)***
Conley SE	(0.0073)***	(0.0083)***	(0.0059)***	(0.0056)***
R-squared	0.1373	0.1414	0.5262	0.6459
RMSE	0.970	0.968	0.785	0.711
Panel B: UCDP data				
Civilian casualties per capita (std)	-0.0408	-0.0402	-0.0402	-0.0399
Cluster SE	(0.0209)*	(0.0202)**	(0.0208)*	(0.0205)*
Conley SE	(0.0156)***	(0.0150)***	(0.0161)**	(0.0159)**
R-squared	0.1365	0.1407	0.5255	0.6452
RMSE	0.970	0.968	0.786	0.712
Panel C: GDELT data				
Conflict events (std)	-0.0475	-0.0452	-0.0429	-0.0412
Cluster SE	(0.0073)***	(0.0069)***	(0.0081)***	(0.0081)***
Conley SE	(0.0114)***	(0.0119)***	(0.0091)***	(0.0090)***
R-squared	0.1361	0.1402	0.5249	0.6446
RMSE	0.970	0.968	0.786	0.713
Household controls	no	yes	n.a.	n.a.
Fixed effects				
District	yes	yes	no	no
Household	no	no	yes	no
Individual	no	no	no	yes

Note: The sample includes 13,124 child – survey round observations.
All model specifications control for child characteristics, extreme weather events, and time fixed effects.
***, **, * Per the reported standard error (SE), the coefficient estimate 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.
WHZ = weight-for-height z-score; UCDP = Uppsala Conflict Data Program; GDELT = Global Database of Events, Language, and Tone; std = standardized; n.a. = not applicable.
The R-squared (overall) and root mean square error (RMSE) are reported for the estimations using the cluster SE estimator.

Table A10. Estimated mitigating effect of the SWF cash transfer program on child WHZ, for alternative definitions of armed conflict intensity

Model specification	1	2	3	4
Panel A: UCDP data				
Civilian casualties per day (std)	-0.0499	-0.0728	-0.0721	-0.0710
Cluster SE	(0.0225)**	(0.0229)***	(0.0227)***	(0.0225)***
Treatment (0=no, 1=yes)	-0.0263	-0.0258	n.a.	n.a.
Cluster SE	(0.0353)	(0.0352)		
Civilian casualties * treatment		0.0382	0.0308	0.0298
Cluster SE		(0.0122)***	(0.0114)***	(0.0106)***
R-squared	0.1541	0.1543	0.5295	0.6555
RMSE	0.963	0.963	0.785	0.704
Panel B: UCDP data				
Civilian casualties per capita (std)	-0.0449	-0.044	-0.0396	-0.0392
Cluster SE	(0.0213)**	(0.0237)*	(0.0227)*	(0.0222)*
Treatment (0=no, 1=yes)	-0.0265	-0.0265	n.a.	n.a.
Cluster SE	(0.0353)	(0.0353)		
Civilian casualties * treatment		-0.002	-0.0162	-0.0163
Cluster SE		(0.0224)	(0.0251)	(0.0245)
R-squared	0.1536	0.1536	0.5288	0.6549
RMSE	0.963	0.963	0.785	0.704
Panel C: GDELT data				
Conflict events (std)	-0.0406	-0.0304	-0.0218	-0.0196
Cluster SE	(0.0063)***	(0.0167)*	(0.0210)	(0.0205)
Treatment (0=no, 1=yes)	-0.0268	-0.0270	n.a.	n.a.
Cluster SE	(0.0353)	(0.0354)		
Conflict events * treatment		-0.0196	-0.0360	-0.0367
Cluster SE		(0.0287)	(0.0346)	(0.0338)
R-squared	0.1530	0.1531	0.5284	0.6544
RMSE	0.964	0.964	0.785	0.705
Fixed effects				
District	yes	yes	no	no
Household	no	no	yes	no
Individual	no	no	no	yes

Note: The sample includes 13,124 child – survey round observations.
All model specifications control for household and child characteristics, extreme weather events, and time fixed effects.
***, **, * Per the reported standard error (SE), the coefficient estimate is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level.
SWF = Social Welfare Fund; WHZ = weight-for-height z-score; UCDP = Uppsala Conflict Data Program; GDELT = Global Database of Events, Language, and Tone; std = standardized; n.a. = not applicable; RMSE = root mean square error.

Table A11. Estimated impact of civil conflict on child WHZ, accounting for survey sampling weights

Model specification	1	2	3	4
Civilian casualties (std)	-0.0246	-0.0237	-0.0243	-0.0238
Cluster SE	(0.0091)***	(0.0093)**	(0.0090)***	(0.0091)***
Household controls	no	yes	n.a.	n.a.
Fixed effects				
District	yes	yes	no	no
Household	no	no	yes	no
Individual	no	no	no	yes
R-squared	0.2603	0.2634	0.5692	0.6834
RMSE	0.921	0.919	0.768	0.690

Note: The sample includes 13,124 child – survey round observations.
All model specifications control for child characteristics, extreme weather events, and time fixed effects.
***, **, * Per the reported standard error (SE), the coefficient estimate is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level.
WHZ = weight-for-height z-score; std = standardized; n.a. = not applicable; RMSE = root mean square error.

Table A12. Estimated mitigating effect of the SWF cash transfer program on child WHZ, accounting for survey sampling weights

Model specification	1	2	3	4
Civilian casualties (std)	0.0014	-0.0741	-0.0585	-0.0576
Cluster SE	(0.0085)	(0.0170)***	(0.0129)***	(0.0138)***
Treatment (0=no, 1=yes)	0.0339	0.0383	n.a.	n.a.
Cluster SE	(0.0717)	(0.0714)		
Civilian casualties * treatment		0.0923	0.0694	0.0682
Cluster SE		(0.0144)***	(0.0081)***	(0.0093)***
Fixed effects				
District	yes	yes	no	no
Household	no	no	yes	no
Individual	no	no	no	yes
R-squared	0.2504	0.2513	0.5753	0.6829
RMSE	0.933	0.932	0.767	0.694

Note: The sample includes 13,124 child – survey round observations.

All model specifications control for household and child characteristics, extreme weather events, and time fixed effects.

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

SWF = Social Welfare Fund; WHZ = weight-for-height z-score; std = standardized; n.a. = not applicable; RMSE = root mean square error.

Table A13. Estimated impact of civil conflict on child WHZ, controlling for child age fixed effects

Model specification	1	2	3	4
Civilian casualties (std)	-0.0578	-0.0563	-0.0570	-0.0579
Cluster SE	(0.0191)***	(0.0190)***	(0.0197)***	(0.0198)***
Conley SE	(0.0070)***	(0.0082)***	(0.0056)***	(0.0053)***
Household controls	no	yes	n.a.	n.a.
Fixed effects				
District	yes	yes	no	no
Household	no	no	yes	no
Individual	no	no	no	yes
R-squared	0.1438	0.1478	0.5307	0.6509
RMSE	0.968	0.966	0.783	0.708

Note: The sample includes 13,124 child – survey round observations.
All model specifications control for child sex, extreme weather events, and time fixed effects.
***, **, * Per the reported standard error (SE), the coefficient estimate 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.
WHZ = weight-for-height z-score; std = standardized; n.a. = not applicable.
The R-squared (overall) and root mean square error (RMSE) are reported for the estimations using the cluster SE estimator.

Table A14. Estimated mitigating effect of the SWF cash transfer program on child WHZ, controlling for child age fixed effects

Model specification	1	2	3	4
Civilian casualties (std)	-0.0555	-0.0809	-0.0785	-0.0824
Cluster SE	(0.0229)**	(0.0239)***	(0.0236)***	(0.0237)***
Treatment (0=no, 1=yes)	-0.0262	-0.0256	n.a.	n.a.
Cluster SE	(0.0352)	(0.0351)		
Civilian casualties * treatment		0.0394	0.0316	0.0351
Cluster SE		(0.0125)***	(0.0094)***	(0.0089)***
Fixed effects				
District	yes	yes	no	no
Household	no	no	yes	no
Individual	no	no	no	yes
R-squared	0.1598	0.1600	0.5337	0.6614
RMSE	0.962	0.962	0.783	0.700

Note: The sample includes 13,124 child – survey round observations.
All model specifications control for household characteristics, child sex, extreme weather events, and time fixed effects.
***, **, * Per the reported standard error (SE), the coefficient estimate is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level.
SWF = Social Welfare Fund; WHZ = weight-for-height z-score; std = standardized; n.a. = not applicable; RMSE = root mean square error.

Table A15. Estimated impact of civil conflict on child WHZ, by age cohort

Model specification	1	2	3	4
Cohort A: Children age 0 – 23 months in Round 1				
Civilian casualties per capita (std)	-0.0227	-0.0204	-0.0224	-0.0224
Cluster SE	(0.0508)	(0.0509)	(0.0512)	(0.0511)
Conley SE	(0.0083)***	(0.0076)***	(0.0087)**	(0.0087)**
R-squared	0.1786	0.1858	0.5732	0.6142
RMSE	1.035	1.031	0.832	0.805
Cohort B: Children age 24 – 51 months in Round 1				
Civilian casualties per day (std)	-0.0744	-0.0733	-0.0736	-0.0736
Cluster SE	(0.0111)***	(0.0108)***	(0.0112)***	(0.0112)***
Conley SE	(0.0092)***	(0.0098)***	(0.0080)***	(0.0080)***
R-squared	0.1631	0.1662	0.6322	0.6877
RMSE	0.884	0.883	0.654	0.614
Household controls	no	yes	n.a.	n.a.
Fixed effects				
District	yes	yes	no	no
Household	no	no	yes	no
Individual	no	no	no	yes

Note: The samples of children aged 0 – 23 months and 24 – 51 months at the time of the first survey round include 6,144 and 6,980 child – survey round observations, respectively.

All model specifications control for child sex, extreme weather events, and time fixed effects. The estimation results are little altered when controlling for child age (in months) in addition.

***, **, * Per the reported standard error (SE), the coefficient estimate 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.

WHZ = weight-for-height z-score; std = standardized; n.a. = not applicable.

The R-squared (overall) and root mean square error (RMSE) are reported for the estimations using the cluster SE estimator.

Table A16. Estimated mitigating effect of the SWF cash transfer program on child WHZ, by age cohort

Model specification	1	2	3	4
Cohort A: Children age 0 – 23 months in Round 1				
Civilian casualties (std)	-0.0211	-0.0905	-0.0830	-0.0830
Cluster SE	(0.0547)	(0.0614)	(0.0615)	(0.0615)
Treatment (0=no, 1=yes)	-0.0746	-0.0702	n.a.	n.a.
Cluster SE	(0.0522)	(0.0521)		
Civilian casualties * treatment		0.0972	0.0801	0.0801
Cluster SE		(0.0354)***	(0.0287)***	(0.0287)***
R-squared	0.2027	0.2034	0.5762	0.6216
RMSE	1.031	1.031	0.838	0.806
Cohort B: Children age 24 – 51 months in Round 1				
Civilian casualties (std)	-0.0715	-0.0791	-0.0800	-0.0800
Cluster SE	(0.0131)***	(0.0119)***	(0.0109)***	(0.0109)***
Treatment (0=no, 1=yes)	0.0090	0.0088	n.a.	n.a.
Cluster SE	(0.0440)	(0.0441)		
Civilian casualties * treatment		0.0124	0.0091	0.0091
Cluster SE		(0.0066)*	(0.0072)	(0.0072)
R-squared	0.2010	0.2010	0.6427	0.7047
RMSE	0.859	0.859	0.640	0.593
Fixed effects				
District	yes	yes	no	no
Household	no	no	yes	no
Individual	no	no	no	yes

Note: The samples of children aged 0 – 23 months and 24 – 51 months at the time of the first survey round include 6,144 and 6,980 child – survey round observations, respectively.

All model specifications control for child sex, extreme weather events, and time fixed effects. The estimation results are little altered when controlling for child age (in months) in addition.

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

SWF = Social Welfare Fund; WHZ = weight-for-height z-score; std = standardized; n.a. = not applicable; RMSE = root mean square error.

Table A17. Estimated impact of civil conflict on child WHZ, based on estimations in first differences

Model specification	1	2	3
Civilian casualties (std)	-0.0446	-0.0446	-0.0469
Cluster SE	(0.0100)***	(0.0100)***	(0.0105)***
Conley SE	(0.0072)***	(0.0072)***	(0.0061)***
Household controls	no	yes	n.a.
Fixed effects			
District	yes	yes	no
Household	no	no	yes
R-squared	0.0681	0.0681	0.1929
RMSE	0.867	0.867	0.912

Note: The sample includes 9,843 child – survey round observations.
All model specifications control for child characteristics, extreme weather events, and time fixed effects.
***, **, * Per the reported standard error (SE), the coefficient estimate 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.
WHZ = weight-for-height z-score; std = standardized; n.a. = not applicable.
The R-squared (overall) and root mean square error (RMSE) are reported for the estimations using the cluster SE estimator.

Table A18. Estimated mitigating effect of the SWF cash transfer program on child WHZ, based on estimations in first differences

Model specification	1	2	3
Civilian casualties (std)	-0.0471	-0.0499	-0.0506
Cluster SE	(0.0125)***	(0.0166)***	(0.0179)***
Treatment (0=no, 1=yes)	0.0194	0.0203	n.a.
Cluster SE	(0.0162)	(0.0169)	
Civilian casualties * treatment		0.0141	0.0069
Cluster SE		(0.0256)	(0.0346)
Household controls	no	yes	n.a.
Fixed effects			
District	yes	yes	no
Household	no	no	yes
R-squared	0.0673	0.0674	0.1884
RMSE	0.860	0.860	0.907

Note: The sample includes 9,843 child – survey round observations.
All model specifications control for child characteristics, extreme weather events, and time fixed effects.
***, **, * Per the reported standard error (SE), the coefficient estimate is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level.
SWF = Social Welfare Fund; WHZ = weight-for-height z-score; std = standardized; n.a. = not applicable; RMSE = root mean square error.

Table A19. Estimated impact of civil conflict on child WHZ, controlling for location-time fixed effects

Model specification	1	2	3
Civilian casualties (std)	-0.0331	-0.0310	-0.0315
Cluster SE	(0.0071)***	(0.0073)***	(0.0073)***
Fixed effects			
District	yes	no	no
Household	no	yes	no
Individual	no	no	yes
R-squared	0.2054	0.5917	0.7116
RMSE	0.963	0.759	0.672

Note: The sample includes 13,108 child–survey round observations.
All model specifications control for household and characteristics, extreme weather events, and time fixed effects.
***, **, * Per the reported standard error (SE), the coefficient estimate is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level.
WHZ = weight-for-height z-score; std = standardized; RMSE = root mean square error.

Table A20. Estimated mitigating effect of the SWF cash transfer program on child WHZ, controlling for location-time fixed effects

Model specification	1	2	3
Civilian casualties (std)	-0.0619	-0.0560	-0.0554
Cluster SE	(0.0039)***	(0.0052)***	(0.0048)***
Treatment (0=no, 1=yes)	-0.0260	n.a.	n.a.
Cluster SE	(0.0350)		
Civilian casualties * treatment	0.0501	0.0437	0.0419
Cluster SE	(0.0119)***	(0.0061)***	(0.0066)***
Fixed effects			
District	yes	no	no
Household	no	yes	no
Individual	no	no	yes
R-squared	0.2171	0.5916	0.7178
RMSE	0.959	0.762	0.666

Note: The sample includes 13,108 child–survey round observations.
All model specifications control for household and characteristics, extreme weather events, and time fixed effects.
***, **, * Per the reported standard error (SE), the coefficient estimate is statistically significant at the 1%, 5%, and 10% level, respectively. Cluster standard errors are clustered at the district level.
SWF = Social Welfare Fund; WHZ = weight-for-height z-score; std = standardized; n.a. = not applicable; RMSE = root mean square error.

Appendix B: Additional Analysis of the Conflict Impact Mitigating Effect of Cash Transfers

This additional analysis employs an instrumental variable (IV) approach to estimate the effect of the cash transfer program of the Social Welfare Fund (SWF) in mitigating the adverse impact of civil conflict on child nutrition. The estimations use spatial information on program implementation and exploit variations in the panel survey data that plausibly are due to disruptions of regular payment disbursement caused by armed conflict events. Anecdotal evidence indeed suggests that a common complaint about the cash transfer program was delayed payments. However, beneficiaries highly appreciated 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, Pereznieto, and Dubai 2012).

I. Cash Transfer Disbursement

Normally, cash transfers of the SWF program were paid out quarterly. Almost all transfers were disbursed through the national postal service system and only a negligible proportion (less than 2%) through the national banking system. Most beneficiaries (or their proxies) received their transfers 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. Cash transfers usually were received within the following month of the payment quarter.

Disbursement of cash transfer payments proceeded as follows. 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 events, 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 appeared to have 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.

Table B1 shows that beneficiaries received the cash transfer payments irregularly during the observation period of our analysis that ran from July 2012 to September 2013 and comprised the four recall periods of the Yemen National Social Protection Monitoring Survey (NSPMS). The first recall period corresponds to the time from the beginning of July 2012 to the household interview date in the first round; and the remaining three recall periods correspond to the time between interview dates of the respective quarterly 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 cash transfers after the suspension of the SWF program in the wake of the 2011-12 revolution.

Table B1. Household proportions reported to have received payments from the SWF cash transfer program during the analysis period by beneficiary group and survey round

Number of payments	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

Note: N = number of household observations.

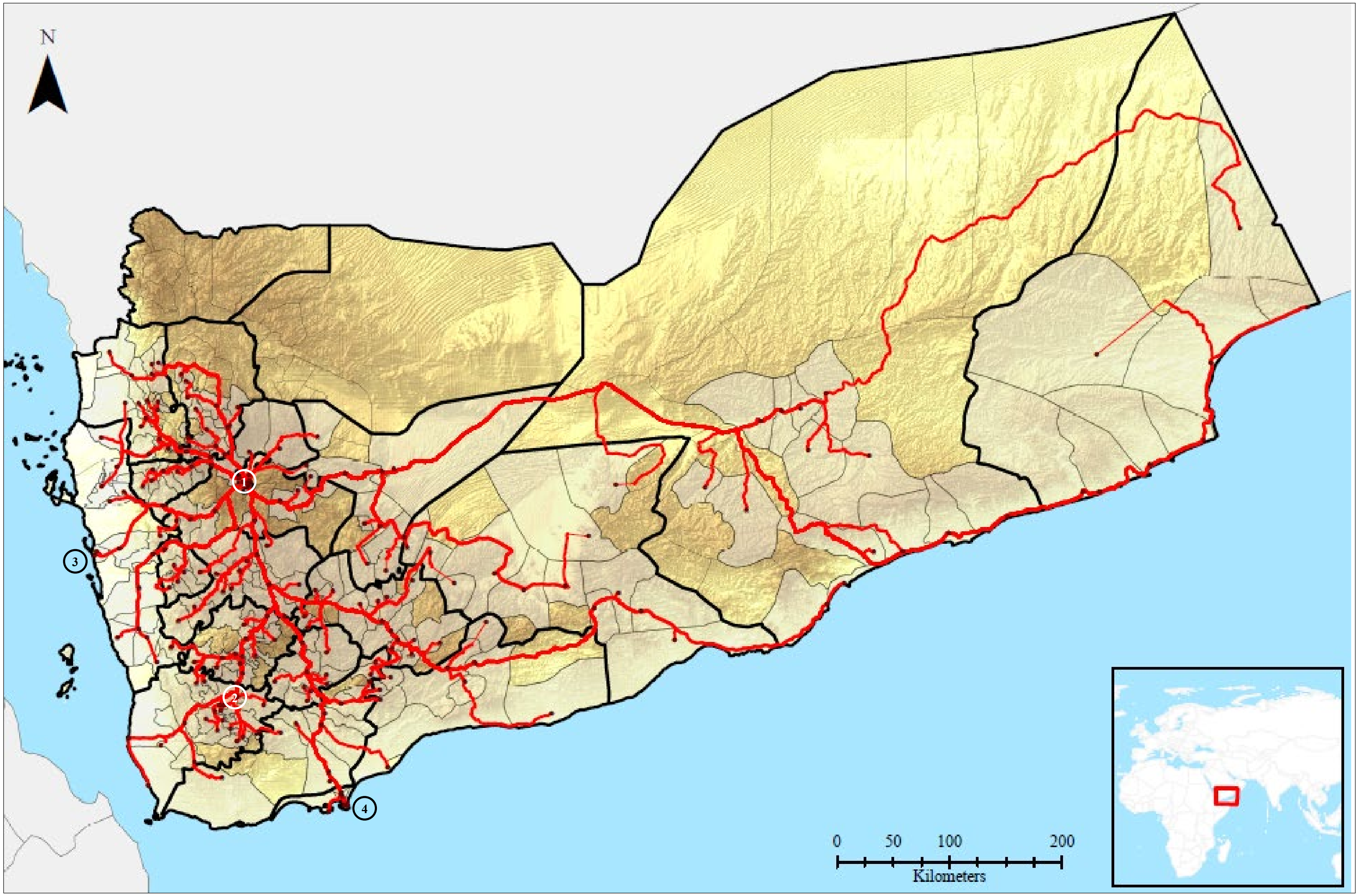
II. Spatial Conflict Data

In this additional analysis, we expand on the impact channels of civil conflict. The conflict variable used in our main analysis, as well as in this analysis, measures a household's direct exposure to civil conflict. It is constructed as the sum of civilian casualties in a household's home district during the recall period per survey round (which somewhat vary across households because of different interview dates). Figure B1 shows a map of Yemen delineating the home districts of the sample households. The data for this and other conflict variables used here are taken from the Uppsala Conflict Data Program dataset (Sundberg and Melander 2013).

We construct additional conflict variables that serve to capture an indirect impact of armed conflict. A household's livelihood and its children's nutritional status may have been adversely affected by delayed payments of the 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. The first additional variable measures the disruption in normal payment disbursement. This variable counts the civilian casualties in districts located along the shortest road from the Central Bank to the district post office, shown in Figure B1. We include the casualty count in the start district of the path (where the Central Bank is located), exclude the casualty 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.

Because the coordinates for the locations of the main district post offices (as well as for the locations of the district capitals) are unavailable, we use the coordinates for the locations of the districts' main health facilities as proxy landmarks, assuming that the post offices are nearby. We employ data from the Yemen Health Facilities Survey 2004-05 to select the main public health facility per district and extract its coordinates from the survey dataset. 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%). To identify the shortest road distance from the Central Bank in Sanaa to the selected health facility in a district, we use a georeferenced road network dataset obtained from the OpenStreetMap database (OSM 2019) and ArcGIS. 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 (see Figure B1).

Figure B1. 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.

The second additional conflict variable 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 in the districts sharing a border with the home district.

III. Identification Strategy

To implement our IV approach for estimating the mitigating effect of the cash transfer program, we start off from the district and household FE models used in our main analysis. Specifically, we examine the effect of (ir)regularity of cash transfer payments, restricting the sample to children from beneficiary households (by dropping out children from non-beneficiary households). Based on this setup, we expect to obtain additional evidence for the likely downward bias of the estimated mitigating effect found in our main analysis. The likely bias originates from the (non-random) targeting of the cash transfer program to socially and economically disadvantaged households.

In the preferred specifications of the district and household FE models (Eq. 2 in the article), we replace the time-constant binary treatment variable, t_{hd}, with a binary variable, t_{hdr}, that indicates whether a beneficiary household received a payment during the recall period of each survey round. The restriction of the sample to beneficiary households and introducing a time-varying treatment variable allow us to examine the cash transfer payment (ir)regularity by tracing the delays in disbursement. 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. Accordingly, we instrument the treatment variable for a beneficiary's probability of receiving the payment during the survey round recall period with the first additional conflict 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 impacts, we include the second additional conflict variable in the district and household FE models, which controls for spillover effects from neighboring districts.

The district and household FE models using two-stage least squares (2SLS) regressions have the form:

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

and

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

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 that share a border with the household's home district.

IV. Estimation Results

Table B2 shows the estimation results of the district and household FE-2SLS models for children from beneficiary households of the cash transfer program. The second-stage estimates are highly consistent with the estimation results of our main analysis and confirm the program's positive effect mitigating the adverse impact of civil conflict on child nutrition. The coefficient estimates for the conflict impact and the mitigating effect are statistically significant at the 1% level according to the Conley SE (but are not statistically significant according to the cluster SE). Furthermore, the coefficient estimates of the interaction term suggest that, going beyond the program's average mitigating effect, the regularity of cash transfer payments matters for the size of the mitigating outcome. Because irregular payments are more common among new beneficiaries than old beneficiaries, and new beneficiaries tend to be poorer than old beneficiaries, the finding of the mitigating effect size being influenced by timely cash transfer disbursement also confirms our conjecture of the downward bias in our estimates of the program's average mitigating effect in our main analysis.

The first-stage estimation results show 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. The coefficient estimates of the respective conflict variable is statistically significant at least at the 5% level according to both cluster SE and Conley SE. Overall, there is no strong evidence for (additional) spillover effects of civil conflict in neighboring districts on child nutrition observed in a sample district.

Table B2. Estimated mitigating effect of the regularity of SWF cash transfer payments on child WHZ, based on two-stage least squares estimations

Model specification	1	2
1st stage: Payment (0=no, 1=yes)		
Civilian casualties along the road from the Central Bank (std)	-0.0196	-0.0161
Cluster SE	(0.0078)**	(0.0077)**
Conley SE	(0.0042)***	(0.0032)***
Civilian casualties (std)	-0.0018	-0.0011
Cluster SE	(0.0052)	(0.0051)
Conley SE	(0.0063)	(0.0057)
Civilian casualties in neighboring districts (std)	-0.0069	-0.0058
Cluster SE	(0.0095)	(0.0095)
Conley SE	(0.0060)	(0.0083)
R-squared	0.2048	0.4095
F-test	2.679	3.544
2nd stage: Weight-for-height z-score (WHZ)		
Civilian casualties (std)	-1.4246	-1.3032
Cluster SE	(1.9397)	(1.3419)
Conley SE	(0.0991)***	(0.0840)***
Payment (0=no, 1=yes)	0.7658	1.0603
Cluster SE	(1.2882)	(1.2953)
Conley SE	(0.4763)	(0.5283)**
Civilian casualties * payment	2.2293	2.0393
Cluster SE	(3.2060)	(2.2659)
Conley SE	(0.1440)***	(0.1373)***
Civilian casualties in neighboring districts (std)	-0.0377	-0.0472
Cluster SE	(0.0383)	(0.0360)
Conley SE	(0.0332)	(0.0275)*
RMSE	1.479	1.191
KP rk Wald F	2.730	1.875
Fixed effects		
District	yes	no
Household	no	yes

Note: The sample includes 6,515 child – survey round observations.

All model specifications control for household and child characteristics, extreme weather events, and time fixed effects.

***, **, * Per the reported standard error (SE), the coefficient estimate 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.

SWF = Social Welfare Fund; WHZ = weight-for-age z-score; std = standardized.

The R-squared (overall), F-test, root mean square error (RMSE), and Kleibergen-Paap rank Wald F-statistic (KP rk Wald F) (Kleibergen and Paap 2006; Baum, Schaffer, and Stillman 2007) are reported for the estimations using the cluster SE estimator.

V. Validity Tests

The validity of our IV approach rests on strong identifying assumptions. These include the relevance of the instrumental variable and the exclusion restriction. Regarding the former, the coefficient estimates of the instrument are statistically significant and confirm our hypothesis that armed conflict events along the road from the Central Bank to the district post offices disrupts the regularity of SWF cash transfer payments. The Kleibergen-Paap Wald F-statistics in Table B2 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 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 than the cash transfer payments. To minimize the potential threat to the validity of this identifying assumption, we control for possible spillover effects of civil conflict in neighboring districts on child nutrition in our FE-2SLS models.

Moreover, we explore the existence of other channels that could compromise our identification strategy. An obvious cause 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).[1] Household food consumption in Yemen has been highly dependent on imports, especially for the main staple foods (Breisinger and Ecker 2014; Ianchovichina, Loening, and Wood 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 2017). We construct variables of armed conflict intensity for the shortest primary road distance from each of these seaports to the locations of the districts' main health facilities (i.e., our proxy landmarks for the districts' main post offices) that are usually located in the district capital, where the main food markets are located as well. For this variable construction, we use 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

[1] 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.

variables in the district and household FE-2SLS models to check the stability of the coefficient estimate of the interaction term. The estimation results in Table B3 suggest that the mitigating effect of transfer payment regularity is robust when accounting for food supply disruptions.

Finally, 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 transfers. The NSPMS data suggest that about 37% of the beneficiary households in our sample receive remittances, and 32% of the beneficiary households receive other government transfers (such as pensions) from non-SWF sources. Table B4 shows that the coefficient estimates of the mitigating effect are largely unaltered when controlling for receiving remittances by survey round recall period and adding the respective interaction term. This also holds when estimating the same model specifications with a variable for receipt of other non-SWF government transfers instead of remittances. Due to the introduction of these other cash 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.

Our options for comprehensive tests of the validity of our IV approach are clearly limited by the available data. Yet, most notably, the estimation results of all FE-2SLS model specifications are highly consistent with those of the FE model specifications using ordinary least squares regressions in the main analysis.

Table B3. Estimated mitigating effect of the regularity of SWF cash transfer payments on child WHZ, based on two-stage least squares estimations controlling for food supply disruptions

Model specification	1	2
1st stage: Payment (0=no, 1=yes)		
Civilian casualties along the road from the Central Bank (std)	0.0407	0.0429
Cluster SE	(0.0164)**	(0.0165)**
Conley SE	(0.0022)	(0.0044)
Civilian casualties (std)	-0.0021	-0.0013
Cluster SE	(0.0047)	(0.0047)
Conley SE	(0.0062)	(0.0055)
Civilian casualties along the road from the Port of Hodeidah (std)	-0.1146	-0.1986
Cluster SE	(0.2396)	(0.2432)
Conley SE	(0.2295)	(0.2470)
Civilian casualties along the road from the Port of Saleef (std)	0.0479	0.1338
Cluster SE	(0.2327)	(0.2371)
Conley SE	(0.2235)	(0.2429)
Civilian casualties along the road from the Port of Aden (std)	0.0063	0.0058
Cluster SE	(0.0083)	(0.0083)
Conley SE	(0.0072)	(0.0064)
Civilian casualties in neighboring districts (std)	-0.0081	-0.0071
Cluster SE	(0.0095)	(0.0094)
Conley SE	(0.0060)	(0.0082)
R-squared	0.2082	0.4123
F-test	3.139	3.695
2nd stage: Weight-for-height z-score (WHZ)		
Civilian casualties (std)	-1.3151	-1.4803
Cluster SE	(1.3386)	(1.1563)
Conley SE	(0.0579)***	(0.0728)***
Payment (0=no, 1=yes)	-2.1446	-2.3303
Cluster SE	(1.8352)	(1.6511)
Conley SE	(1.2796)*	(1.0031)**
Civilian casualties * payment	2.0463	2.3195
Cluster SE	(2.2573)	(2.0158)
Conley SE	(0.0722)***	(0.1171)***
Civilian casualties along the road from the Port of Hodeidah (std)	-0.4708	-0.7411
Cluster SE	(1.0026)	(0.9322)
Conley SE	(0.3788)	(0.2617)***
Civilian casualties along the road from the Port of Saleef (std)	0.4091	0.6871
Cluster SE	(1.0209)	(0.9385)
Conley SE	(0.4049)	(0.2727)**
Civilian casualties along the road from the Port of Aden (std)	0.0176	0.0160
Cluster SE	(0.0253)	(0.0243)
Conley SE	(0.0169)	(0.0142)
Civilian casualties in neighboring districts (std)	-0.0589	-0.0666
Cluster SE	(0.0351)*	(0.0371)*
Conley SE	(0.0271)**	(0.0243)***
RMSE	1.602	1.436
KP rk Wald F	1.573	4.180
Fixed effects		
District	yes	no
Household	no	yes

Note: The sample includes 6,515 child – survey round observations.

All model specifications control for household and child characteristics, extreme weather events, and time fixed effects.

***, **, * Per the reported standard error (SE), the coefficient estimate 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.

SWF = Social Welfare Fund; std = standardized.

The R-squared (overall), F-test, root mean square error (RMSE), and Kleibergen-Paap rank Wald F-statistic (KP rk Wald F) (Kleibergen and Paap 2006; Baum, Schaffer, and Stillman 2007) are reported for the estimations using the cluster SE estimator.

Table B4. Estimated mitigating effect of the regularity of SWF cash transfer payments on child WHZ, based on two-stage least squares estimations controlling for other income transfers

Model specification	1	2	3	4
1st stage: Payment (0=no, 1=yes)				
Civilian casualties along the road from the Central Bank (std)	-0.0199	-0.0162	-0.0198	-0.0161
Cluster SE	(0.0079)**	(0.0077)**	(0.0078)**	(0.0078)**
Conley SE	(0.0040)***	(0.0034)***	(0.0042)***	(0.0033)***
Civilian casualties (std)	-0.0011	0.0009	-0.0042	-0.0026
Cluster SE	(0.0061)	(0.0063)	(0.0072)	(0.0074)
Conley SE	(0.0076)	(0.0064)	(0.0078)	(0.0067)
Remittances (0=no, 1=yes)	-0.0131	-0.0047		
Cluster SE	(0.0220)	(0.0308)		
Conley SE	(0.0168)	(0.0179)		
Civilian casualties * remittances	-0.0030	-0.0074		
Cluster SE	(0.0048)	(0.0058)		
Conley SE	(0.0048)	(0.0089)		
Other social transfers (0=no, 1=yes)			0.0188	-0.0187
Cluster SE			(0.0244)	(0.0309)
Conley SE			(0.0215)	(0.0312)
Civilian casualties * other government transfers			0.0095	0.0050
Cluster SE			(0.0092)	(0.0117)
Conley SE			(0.0059)	(0.0085)
Civilian casualties in neighboring districts (std)	-0.0071	-0.0060	-0.0067	-0.0059
Cluster SE	(0.0095)	(0.0095)	(0.0096)	(0.0094)
Conley SE	(0.0060)	(0.0083)	(0.0060)	(0.0083)
R-squared	0.2049	0.4096	0.2050	0.4096
F-test	3.219	3.717	2.542	2.948

Table B4—continued.

Model specification	1	2	3	4
2nd stage: Weight-for-height z-score (WHZ)				
Civilian casualties (std)	-1.3423	-1.2310	-0.8179	-0.8429
Cluster SE	(1.5971)	(1.0961)	(0.8711)	(0.7342)
Conley SE	(0.0914)***	(0.0810)***	(0.0836)***	(0.0525)***
Payment (0=no, 1=yes)	0.7302	1.0527	0.5179	0.8315
Cluster SE	(1.1130)	(1.1910)	(0.8956)	(1.0343)
Conley SE	(0.4481)	(0.5074)**	(0.4820)	(0.5397)
Civilian casualties * payment	1.9687	1.8020	1.4226	1.4543
Cluster SE	(2.4656)	(1.7139)	(1.5857)	(1.3338)
Conley SE	(0.1230)***	(0.1289)***	(0.1162)***	(0.0921)***
Remittances (0=no, 1=yes)	-0.0120	-0.0341		
Cluster SE	(0.0550)	(0.0734)		
Conley SE	(0.0450)	(0.0474)		
Civilian casualties * remittances	0.3056	0.2800		
Cluster SE	(0.5027)	(0.4043)		
Conley SE	(0.0303)***	(0.0173)***		
Other social transfers (0=no, 1=yes)			-0.1245	-0.0739
Cluster SE			(0.0672)*	(0.0902)
Conley SE			(0.0335)***	(0.0502)
Civilian casualties * other government transfers			-0.3848	-0.3588
Cluster SE			(0.4365)	(0.3541)
Conley SE			(0.0295)***	(0.0320)***
Civilian casualties in neighboring districts (std)	-0.0330	-0.0428	-0.0468	-0.0550
Cluster SE	(0.0367)	(0.0334)	(0.0262)*	(0.0285)*
Conley SE	(0.0338)	(0.0281)	(0.0341)	(0.0279)**
RMSE	1.377	1.110	1.179	0.980
KP rk Wald F	2.790	1.861	2.715	1.793
Fixed effects				
District	yes	no	yes	no
Household	no	yes	no	yes

Note: The sample includes 6,515 child – survey round observations.

All model specifications control for household and child characteristics, extreme weather events, and time fixed effects.

***, **, * Per the reported standard error (SE), the coefficient estimate 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.

SWF = Social Welfare Fund; std = standardized.

The R-squared (overall), F-test, root mean square error (RMSE), and Kleibergen-Paap rank Wald F-statistic (KP rk Wald F) (Kleibergen and Paap 2006; Baum, Schaffer, and Stillman 2007) are reported for the estimations using the cluster SE estimator.

References

Anderson, M.L., 2008. Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American Statistical Association, 103*(484), 1481–1495. https://doi.org/10.1198/016214508000000841

Angrist, J.D., Pischke, J.S., 2008. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, Princeton, NJ, and Oxford, United Kingdom.

Bagash, T., Pereznieto, P., Dubai, K., 2012. *Transforming Cash Transfers: Beneficiary and Community Perspectives on the Social Welfare Fund in Yemen*. Overseas Development Institute, London, United Kingdom.

Baum, C.F., Schaffer, M.E., Stillman, S., 2007. Enhanced routines for instrumental variables/generalized method of moments estimation and testing. *The Stata Journal*, *7*(4), 465–506. https://doi.org/10.1177/1536867X0800700402

Breisinger, C., Ecker, O., 2014. Simulating economic growth effects on food and nutrition security in Yemen: A new macro-micro modeling approach. *Economic Modelling*, *43*, 100–113. https://doi.org/10.1016/j.econmod.2014.07.029

Conley, T.G., 1999. GMM estimation with cross sectional dependence. *Journal of Econometrics*, *92*(1), 1–45. https://doi.org/10.1016/S0304-4076(98)00084-0

Ianchovichina, E.I., Loening, J.L., Wood, C.A., 2014. How vulnerable are Arab countries to global food price shocks? *Journal of Development Studies*, *50*(9), 1302–1319. https://doi.org/10.1080/00220388.2014.928698

Kleibergen, F., Paap, R., 2006. Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics*, *133*(1), 97–126. https://doi.org/10.1016/j.jeconom.2005.02.011

OSM (OpenStreetMap contributors), 2015. Planet dump. Data file from 20 May 2019 OpenStreetMap database. Retrieved from https://planet.openstreetmap.org.

Schwab, B., Janzen, S., Magnan, N.P., Thompson, W.M., 2020. Constructing a summary index using the standardized inverse-covariance weighted average of indicators. *The Stata Journal, 20*(4), 952–964. https://doi.org/10.1177/1536867X20976325

Sundberg, R., Melander, E., 2013. Introducing the UCDP georeferenced event dataset. *Journal of Peace Research*, 50(4), 523–532. https://doi.org/10.1177%2F0022343313484347

Tandon, S., Vishwanath, T., 2020. The evolution of poor food access over the course of the conflict in Yemen. *World Development*, *130*, 104922. https://doi.org/10.1016/j.worlddev.2020.104922

World Bank, 2017. *Securing Imports of Essential Food Commodities to Yemen: An Assessment of Constraints and Options for Intervention*. World Bank, Washington, DC.