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Children of War: Conflict and Child Welfare in Iraq

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CHILDREN OF WAR: CONFLICT AND CHILD WELFARE IN IRAQ

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Abstract

What are the impacts of violent conflict on child health and nutrition? In this paper, we examine conflict events from 2013 to 2018 in Iraq. We match household microdata from the 2018 Multiple Indicator Cluster Survey with conflict event data derived from the Global Database of Events, Language, and Tone (GDLET) to estimate the number of conflicts a child age 0-4 in the MICS data was exposed to during her lifetime. To account for endogenous conflict event locations, we use a two-stage least squares estimation approach in which governorate distance to the Syrian border serves as our instrument. Our results suggest that a 1% increase in conflict frequency results in a significant reduction in height-for-age z-scores of -0.15. We repeat our estimates using alternative conflict data as a robustness check, and the sign and significance of the result holds, though these alternative estimates are smaller in magnitude. Our mechanism analysis suggests that more exposed children were statistically less likely to have been breastfed.

Keywords: Iraq, conflict, child health.
JEL Classifications: I12, J13, O12.

1. Introduction

There have been 240 active armed conflicts in 152 countries since the end of World War II (Harbom and Wallensteen 2009). Conflicts lead to not only deaths, but the consequences could be a source of stress on household decisions related to capital accumulation and child labor (Rodríguez and Sánchez 2012) and lead to food shortages and health crises (Gates et al. 2012; Justino 2011, 2010). It is crucial to understand how conflict impacts children to determine the social costs that armed conflicts entail, particularly for those exposed during early childhood, since such exposure can have lasting effects on health and education outcomes that are difficult to reverse.

In this paper, we estimate the effects of exposure to conflict on child's nutritional and health outcomes using data for Iraq that reflects the 2013-2018 period. In a sense, this constitutes a case study of the impacts of Islamic State (ISIS) activity in Iraq, since during this time, the militant group occupied considerable territory in Iraq by force, seizing natural resources and carrying out tremendous violence against minority groups and opposition figures.

The topic of conflict and child health and nutrition has received attention before, and the novelty of the paper over the existing literature is twofold. First, similar to Akresh, Lucchetti, and Thirumurthy (2012), we take endogenous migration into account. Because households exposed to conflict are often induced (or forced) to relocate, we use data on guardians' retrospective migration history to build our conflict measures based on where the household resided at a particular time (not just to time of the survey). By contrast, some previous literature (Minoiu and Shemyakina 2014) has focused on households who stay in the same region or assumes no endogenous migration. This yields important estimates about how the regions are changing on average, but we cannot determine the degree to which these changes reflect selective migration versus the direct impacts of conflict exposure. Second, to address the bias from endogenous event locations, our identification strategy relies on an instrumental variables (IV) approach that aims at addressing bias due to unobservables. By doing so, we can test the validity of the findings of past studies that relied on difference-in-differences or fixed effects to account for endogenous unobserved variables (Akresh, Lucchetti, and Thirumurthy 2012).

Our work fits into the globally-focused literature that examines the possible effects of armed conflicts on an array of development outcomes, including schooling (Akresh and de Walque 2008; Barrera and Ibañez 2004; Buvinic, Gupta, and Shemyakina 2013; Chamarbagwala and Moran 2011), health (Akresh, Lucchetti, and Thirumurthy 2012; Minoiu and Shemyakina 2014), child labor (Rodríguez and Sánchez 2012), psychological behavior and cognitive skills, productivity, and marital outcomes (Duque 2013; Islam et al. 2016). Our work also complements recent efforts to better understand how Iraq's recent wars have negatively impacted Iraqi children (Diwakar 2015; Naufal, Malcolm, and Diwakar 2019).

The literature on child nutrition and health tends to converge on a particular finding: children more exposed to armed conflict tend to have lower height-for-age (HAZ), meaning that they are stunted. In their work on the Ethiopian-Eritrean War, Akresh, Lucchetti, and Thirumurthy (2012) use a difference-in-difference model where they exploit variation in conflict exposure based on geographic location and child cohort. They find that children in high-conflict areas alive during the war experience a reduction in HAZ by 0.45 standard deviations. Minoiu and Shemyakina (2014) use a similar difference-in-differences approach in their study of Cote d'Ivoire during the 2002-2007 Ivoirian Conflict. They find that HAZ falls by 0.11-0.15 standard deviations for each 15-month increase in war exposure. To understand why child health declines in response to civil war, Akresh, Verwimp, and Bundervoet (2011) examine the impact of conflict in Rwanda and also use a difference-in-difference exploiting cohort age and regional conflict variation. They estimate a 0.82 standard deviation reduction in HAZ for exposed children and do not find evidence that the impact is worse for girls than boys. We build on this literature by using a different identification strategy and a new case study. And unlike Minoiu and Shemyakina (2014), our estimation approach accounts for endogenous household migration.

We use Unicef's Multiple Indicator Cluster Survey (MICS) to examine several outcomes of interest. For children age 0-4, we consider height-for-age z-scores, weight-for-age z-scores and weight-for-height z-scores as well as binary health variables indicating whether the child had a cough, fever, or diarrheal illness in the two weeks prior to the survey. For our primary estimation strategy, we produce counts of child lifetime conflict exposure using the Global Database of Events, Language, and Tone (GDELT) 2013-2018. As a robustness check, we repeat our estimates using two other conflict datasets, namely the Armed Conflict Event Location Dataset (ACLED) and the Iraq Body Count (IBC) database.

Building on a simple OLS strategy, we identify a two-stage least squares approach in which we use the Euclidean distance between a governorate centroid and the Syrian border as our instrument. We account for a potential violation of the exclusion restriction by controlling for the governorate's mean lights index. Our findings suggest that conflict exposure due to border proximity significantly drives down child height-for-age z-scores. This result is consistent when using the GDELT, ACLED, or IBC data, though the magnitude of this local average treatment effect (LATE) estimate varies across the dataset.

The remainder of the paper is organized as follows. Section 2 discusses the data used, which includes the Global Database of Events, Language, and Tone (GDELT) data for Iraq 2000-2018 as well as the MICS 2018 data. We will discuss why these were our preferred data and also describe how we used these data to construct our exposure variables. In Section 3 we introduce our OLS specification and 2SLS identification strategy. We present our preliminary results in Section 4, and as a robustness check, we also repeat our estimates using two different conflict data sources in Section 5. We examine mechanisms in Section 6, including whether the child was ever breastfed and the child's recent food consumption. In Section 7, we share our concluding remarks.

2. Data

Household microdata for our analysis comes from Unicef's Multiple Indicator Cluster Survey (MICS). We focus on the 2018 MICS wave, which contains the greatest breadth of variables of interest, including some important internal migration information. The MICS is a nationally representative cross-section with a particular focus on children's health, nutrition, and educational outcomes. The survey has a two-stage sampling design, with stratified random sampling of enumeration areas in the first stage and stratification by governorate and urban vs. rural residence (Unicef 2019). The MICS 2018 team decided to collect data for the same number of households in each governorate (1,080), with the exception of Baghdad, where they sampled 2,160 households. Due to insecurity, the MICS 2018 team could not sample several northern districts, including Ba-aj, al-Hader, Telafer, Sinjar, and Makhmoor (Unicef 2019). These districts saw high conflict intensity 2013-2018, meaning that the MICS 2018 may not capture the households that have been the most severely affected. Overall, the 2018 MICS includes 20,521 households and 16,379 observations of children aged 0-4 (Unicef 2019).

Our conflict exposure variables come from the Global Database of Events, Language, and Tone (GDELT) Version 2.0. The GDELT is a geo-referenced dataset that identifies (among other events) the incidence of inter-group conflict around the world, as well as information on the different actors involved. To gather observations, the GDELT team uses machine learning approaches, scraping news media outlets in various languages to identify the date and location of an event type. This means that the GDELT is not subject to the level of review for individual observations as a conflict dataset such as the Armed Conflict Location and Event Data (ACLED). But the main advantage of using the GDELT over ACLED is the GDELT's temporal scope: with ACLED we have no event observations for Iraq prior to 2016, while the GDELT database has events going back to 2000 and even earlier. For the purpose of this analysis, we focus exclusively on several event types falling into the broad category of "fight" over the 2000-2018 period in Iraq.[3]

GDELT 2.0 produces new observations based on data scraping in 15-minute intervals of time. This means that a single observation tells us which event type is taking place at a particular landmark in the world based on sources that became available during a given 15-minute period. While this incredible pace of updating allows researchers to track the spread of information over time, it may for our purposes lead to over-counts of the same event. For example, if event type j took place at landmark g at time t, then we may see news reports of this event appearing at time $t, t+m, t+2m$, etc., where m represents the 15-minute interval. Although the GDELT would count $n > 1$

[3] The different event sub-categories under the "Fight" event type include: "use conventional military force, not specified", "impose blockade, restrict movement", "occupy territory", "fight with small arms and light weapons", "fight with artillery and tanks", "employ aerial weapons", and "violate ceasefire".

observations of event type j happening at landmark g, the actual event count is only one. To ameliorate the corresponding measurement error, we collapse GDELT events by geography (in this case, by sub-district) and day. By doing so, we count 1 event when we observe n observations of event type j happening in a sub-district on a given day.[4]

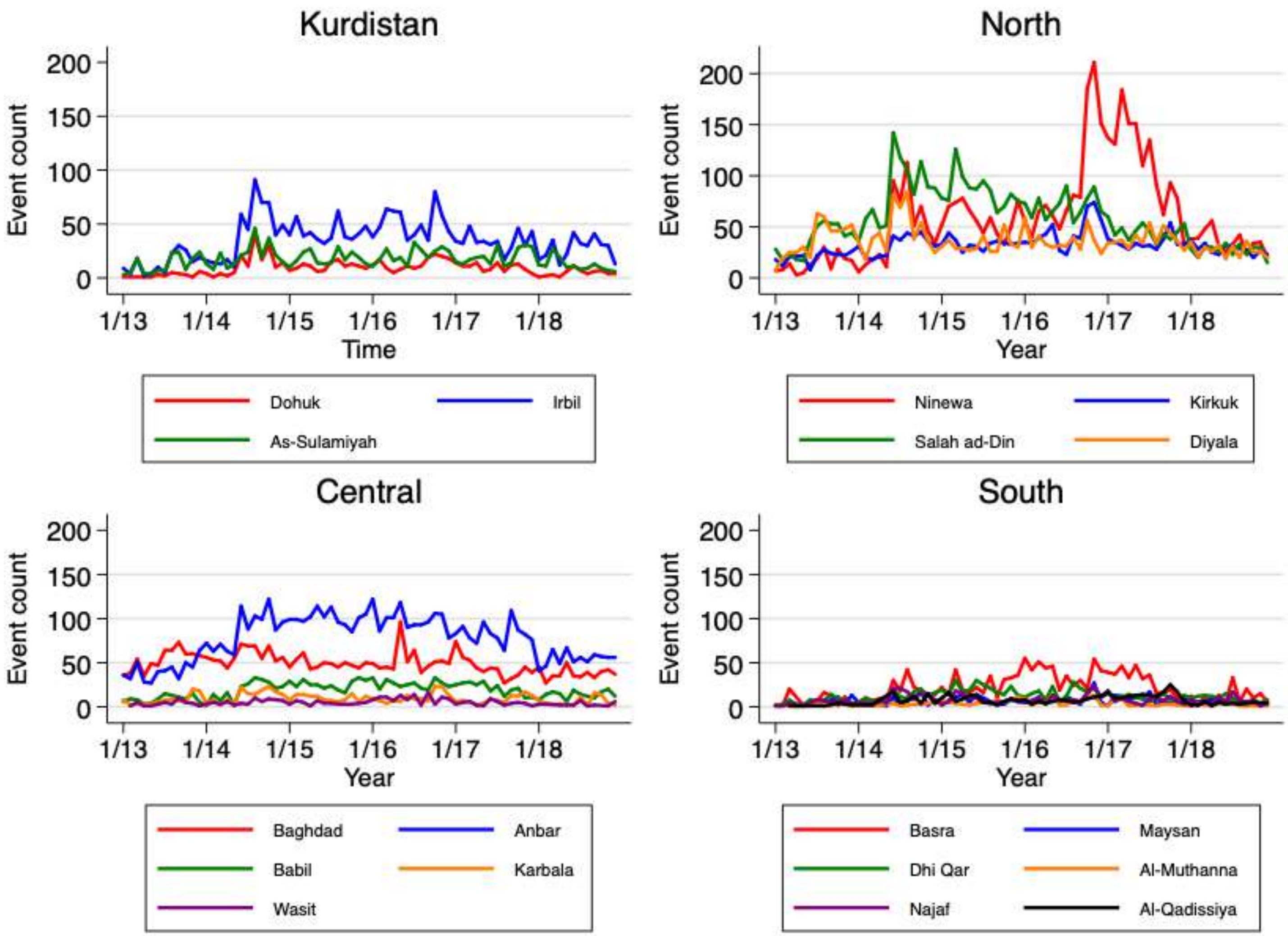
We impose additional criteria on our event data to remove erroneous entries. The machine learning approach central to GDELT results in some incorrect observations where an event that happened outside of a country, but involving people with some relationship to that country, is incorrectly identified as having happened in that country.[5] As an additional precaution, we limit our observations to only events in which, among all the associated actors, at least one is geographically present in Iraq according to our data.

Figure 1 displays the time series of monthly GDELT events by governorate and region. We find the greatest conflict intensity over this period in the northern governorates outside of Iraqi Kurdistan, particularly Salah ad-Din, and Ninewa. In both of these governorates, the Islamic State occupied cities (Tikrit in Salah ad-Din and Mosul in Ninewa). In central Iraq, we see high conflict intensity in the Anbar province over the 2013-2016 period, where ISIS occupied the city of Ramadi. Relatively speaking, the South experienced far less conflict than the other regions over this time. And while the governorates of Iraqi Kurdistan experienced less conflict than other regions, we still see frequent conflict in Irbil, where, for several months, the number of events exceeded 50.

[4] This approach, however, will not eliminate measurement error arising from an event being referenced on the day it takes place but also discussed in news outlets on the following day. In this case, we will inadvertently count 2 events instead of 1.

[5] For example, we found one observation drawn from a newspaper report on the murder of an Iraqi-British businessman in the Alps. When scraped, GDELT identified the event location as Baghdad, even though Baghdad was only referenced in the article when discussing the city of birth of the deceased man. The URL for this entry is here: https://www.sknvibes.com/news/newsdetails.cfm/80426. Although the country listed in GDELT for the observation was Iraq, the country of the actors involved were listed as the United Kingdom and France. By only permitting only observations in which at least one of these associated actor countries is listed as Iraq, we can mitigate the presence of these false positive observations.

Figure 1: Count of monthly conflict events by year, governorate, and region, GDELT Iraq 2013-2018



Source: authors' calculations using GDELT data for Iraq 2013-2018. A GDELT monthly count adds up the number of days of conflict for each of the governorate's subdistricts.

To identify child conflict exposure, we build a retrospective panel in which we identify the months every child surveyed in the 2018 MICS was alive between January 2013 and March 2018, the last month the data was collected. We match this data with information on the child's guardian's migration history – in almost all cases (99.5%), the guardian is the child's mother.

As we will later show, households exposed to higher conflict frequency are more likely to migrate at some point over the 2013-2018 period. This means that we cannot assume that the child's guardian's governorate of residence in the 2018 data represents the guardian's governorate of residence from 2013 to 2018. We account for adverse selection in conflict-induced migration as much as the MICS data allows via the following strategy. First, we assume that the guardian never lived separately from her children between 2013 and 2018. If a guardian moved at some point between 2013 and 2018, we then identify the years in which the guardian was living in a different governorate and which governorate that was. For the child, we use the guardian's information to identify the years in which we believe the child was living in this previous governorate (if relevant).[6] The primary shortcoming of this method is that we cannot accurately identify the case in which a household moves more than once over the study period (2013-2018) using the MICS.

We match the monthly child panel (which includes the predicted governorate, based on guardian migration history) with the governorate-month level event counts from GDELT. We then aggregate to produce a sum of lifetime exposure for each child. The result is a longitudinal dataset at the child level. Finally, we match these child observations with additional information on the child's mother (age, educational attainment, language of interview, etc.), household (number of members, urban or rural area in 2018, gender of household head) and the child (age, gender, anthropometrics, educational attainment, etc.).

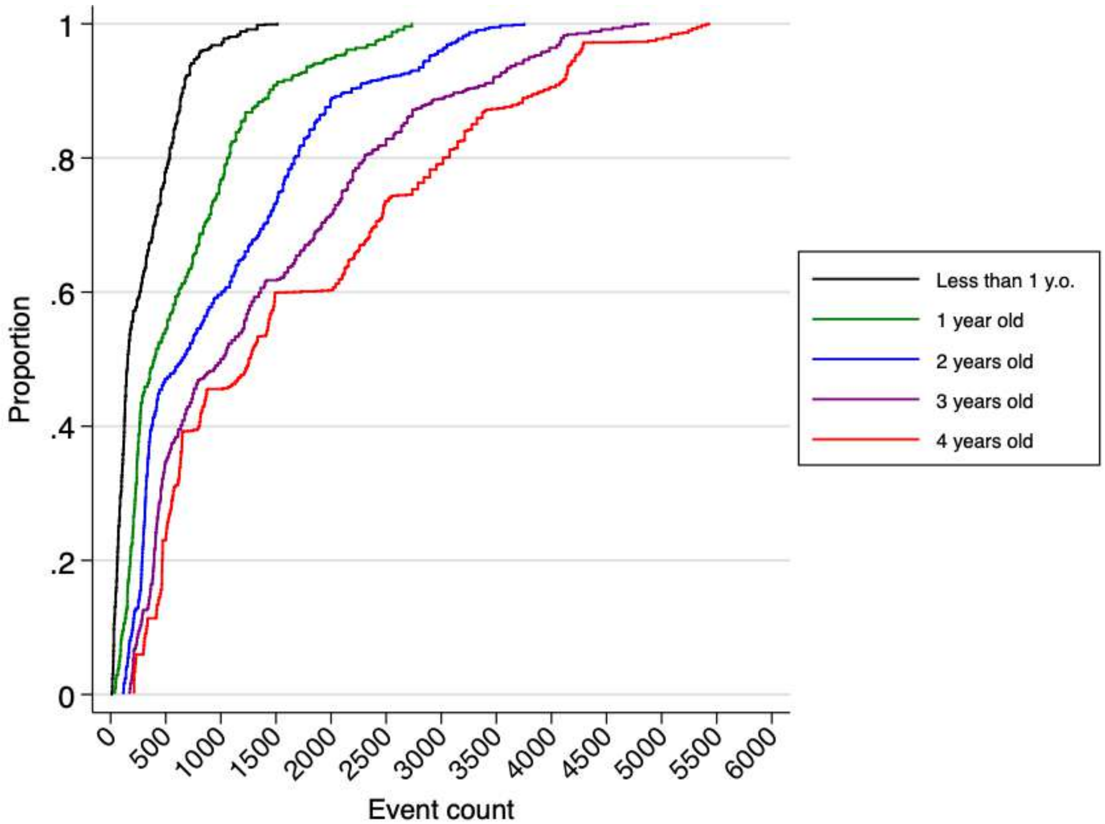
The publicly accessible MICS data identifies the respondent's governorate of residence (ADM1) at the time of the survey, as well as the previous governorate of residence of a guardian. But MICS does not identify a respondent's geographic location at the district (ADM2) or subdistrict (ADM3) level. And by counting child exposure based on the child's governorate of residence over time and her age, we are likely over-stating exposure for many children. In a geographically large governorate, a child may reside in an area quite far from the (sub)district where most events are taking place. If we assume that the impact of conflict decays over space, we likely will end up with an over-estimate of their exposure. For the purpose of our OLS estimation, the measurement error will be correlated

[6] The MICS asks mothers how long they have been living in their current governorate in years. For mothers who have been living in their current governorate for 17 years or less we then identify the year they moved. For this year and all preceding years, if a child was alive, we assume the child was living in the previous governorate with the mother for the entirety of that year. For example, if a mother reports she has been living in Anbar governorate at the time of the interview for 10 years but lived in Karbala before, then we assume that from 2000 to 2007, any of the mother's children who were alive at the time were living in Karbala.

with the "true" unobserved variable. In this situation, measurement error in our explanatory variable will increase the error variance, but it will not bias our coefficient estimates.[7]

Figure 2 shows the cumulative density of child exposure by child age. As expected, exposure is increasing in age. The distributions also demonstrate how high the conflict exposure counts are when using GDELT and governorate-level conflict event counts. For example, around 40% of children aged four were exposed to 1,500 GDELT events or more, and around 20% of children aged three were exposed to 2,000 GDELT events or more. These high counts are likely attributable, to some extent, to the aforementioned measurement error that arises when counting conflict events at the governorate level.

Figure 2: Cumulative density of child conflict exposure counts by age, GDELT Iraq 2013-2020 and MICS 2018



Source: authors' calculations using GDELT data for Iraq 2000-2018 and MICS 2018. A GDELT monthly count adds up the number of days of conflict for each of the governorate's subdistricts. We use these GDELT monthly governorate

[7] Suppose $e = x - x^*$, where e is the measurement error, x is the observed exposure count, and x^* is the "true", unobserved exposure count. For two children with identical birthdays residing in the same governorate, x will be the same for the two children, but x^* will vary based on how close or far the child actually resides from within-governorate areas of higher conflict. Hence $Cov(e, x) = 0$ and $Cov(e, x^*) \neq 0$. In this case of measurement error in the explanatory variable, the measurement error will increase the error variance but will not violate OLS assumptions (Wooldridge 2010).

event counts to estimate the exposure of MICS 2018 children based on the child's governorate during the survey, the child guardian's migration history, and the months the child was alive.

Table 1 provides descriptive statistics for the entire child sample and by conflict exposure quintiles (based on the child's 2018 governorate). The sample children are on average about 30 months of age, with a close to even split between boys and girls. Across the exposure quintiles, children have below average weight for age and weight for height, as shown by their negative average z-scores. Height-for-age, by contrast, is higher than the mean in the HAZ distribution. Overall, sample children have non-negligible rates of recent illness: 13% had a cough, 18% had a fever, and 18% had a diarrheal illness in the two weeks prior to the survey. It does not appear that any mean child health or nutritional statistics worsen as the conflict quintiles rise.

Children tend to come from households that are slightly more likely to be urban (63%), and almost all of the children have male household heads (94%). Household sizes are large on average, about 8-9 persons. About half (54%) of the children's guardians (in almost all cases, their mothers) completed schooling beyond the primary level. While most of these guardians were Arabic-speakers, 12% spoke in Kurdish for their MICS interview.

Nearly half (46%) of the children living in high-conflict governorates in 2018 had a guardian who moved during the 2013-2018 period: for other exposure quintiles, the rate is much lower, 7-9%. For the high-conflict governorate children, a much larger share (21%) had a guardian who moved to a different governorate between 2013 and 2018 as compared to the other exposure quintiles (1-2%). These results highlight the tremendous importance of carefully accounting for migration when estimating conflict exposure retrospectively.

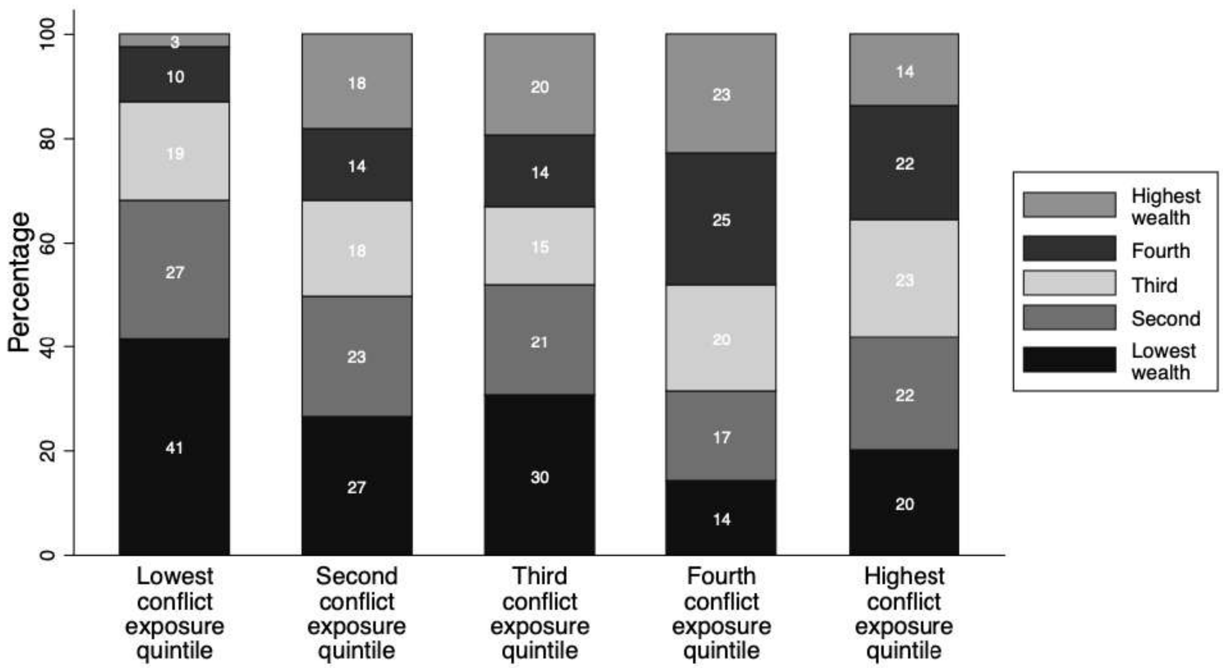
Table 1: Descriptive statistics for children age 0-4 by conflict exposure quintile, MICS 20118 and GDELT 2013-2018

	Total	Lowest exposure quintile	Second exposure quintile	Third exposure quintile	Fourth exposure quintile	Highest exposure quintile
Age (months)	30.11	29.41	30.31	30.32	30.18	30.81
Female	48.88%	49.76%	48.20%	47.91%	49.63%	48.58%
WAZ	-0.25	-0.36	-0.21	-0.18	-0.20	-0.28
HAZ	-0.34	-0.46	-0.25	-0.15	-0.37	-0.45
WHZ	0.12	0.05	0.13	0.10	0.20	0.16
Diarrhea last 2 wks.	12.81%	14.67%	11.23%	12.27%	14.18%	10.60%
Cough last 2 wks.	18.25%	17.31%	16.84%	18.55%	21.53%	17.56%
Fever last 2 wks.	17.61%	17.76%	16.54%	17.55%	20.21%	15.17%
HH resides in urban area	62.54%	55.09%	63.17%	68.43%	68.52%	60.88%
HH head is male	94.05%	94.41%	94.68%	94.39%	92.91%	93.81%
Number of HH members	8.53	9.23	8.54	7.92	8.07	8.57
Guardian's age	29.51	29.47	29.65	29.56	29.68	29.09
Guardian attended school past primary	55.59%	60.22%	57.82%	57.96%	53.65%	44.98%
Guardian's primary language is Arabic	86.34%	99.68%	78.28%	80.03%	78.89%	94.34%
Guardian's primary language is Kurdish	12.16%	0.29%	20.97%	19.85%	18.68%	0.65%
Guardian migrated between '13-'18	13.57%	7.11%	6.89%	9.17%	9.13%	45.47%
Guardian migrated to new gov. '13-'18	4.04%	0.61%	0.84%	1.01%	1.93%	20.63%
N	16,527	3,756	3,687	2,388	3,780	2,472

Source: authors calculations based on MICS 2018 and GDELT 2013-2018. Conflict exposure quintiles are based on the sum of conflict events that took place 2013-2018 in a governorate. A child's exposure quintile reflects the exposure quintile of the governorate that child lived in at the time of the MICS 2018 survey.

Figure 3 provides a household-level depiction of wealth and conflict exposure. We see no evidence of a linear relationship between the 2013-2018 conflict intensity in a household's governorate and that household's wealth level. In fact, the lowest conflict exposure governorates have the smallest share of the wealthiest households in our sample (3%) and the largest share of the poorest households (41%). These outcomes likely reflect the persistent poverty in southern Iraq, a region that we have shown (Figure 1) had lower conflict event frequencies over the 2013-2018 period.

Figure 3: household wealth quintiles by household's governorates' conflict intensity, MICS 2018 and GDELT 2013-2018



Source: authors' calculations based on MICS 2018 and GDELT 2013-2018. Estimates are based on the household, not child, level, focusing exclusively on households that our sample children reside in. Conflict exposure quintiles are based on the sum of conflict events that took place 2013-2018. A child's exposure quintile reflects the exposure quintile of the governorate that child lived in at the time of the MICS 2018 survey.

3. Method

We begin with simple OLS regressions that examine how conflict exposure impacts child outcomes. Consider the following specification for child i from household h living with guardian (mother) m in governorate g.

$$y_{ighm} = \alpha + \alpha_1 \ln{(event_{ig})} + X'_{ighm}\gamma_{ighm} + \varepsilon_{ic} \quad (1)$$

We use a natural log transformation of the child's total lifetime event exposure to facilitate interpretation of our coefficients. For children age 0-4, outcome variables y_i include child height-for-age z-scores, weight-for-age z-scores, weight-for-height z-scores, and the binary indicators of whether the child had a cough, fever, or diarrheal illness in the two weeks prior to the survey.

We include several covariates X_{ighm}, including the child's age and gender. We also include several mother characteristics, including mother's age, mother's primary language (Arabic, Kurdish, or "other"), and whether the mother had attended school beyond the primary level. At the household level, we control for the gender of household head, the household size, whether the household was in a rural or urban area in 2018, and the household's wealth quintile. We additionally include the 2013 mean night lights index for the child's 2018 governorate, which is a proxy for the economic productivity of a governorate.[8] Given the possibility that measurement error may be tied to the MICS two-stage sampling (Abadie et al. 2017), we cluster our standard errors by household sampling cluster.

The OLS estimates will be biased in the event that conflict exposure is endogenous to other factors. Conflict events do not happen randomly, and certain characteristics (proximity to borders, proximity to natural resources, local incomes and price shocks, etc.) may make conflict events more or less likely. To address the bias from endogenous event locations, we take an instrumental variables (IV) approach in which the minimum distance from the child's governorate's centroid and the Syrian border serves as our instrument.[9]

Our rationale for this instrument comes from the evolution of ISIS and its territorial expansion patterns in Iraq and Syria. An offshoot of al-Qaeda in Iraq (AQI), ISIS became one of several militias active in the Syrian Civil War in 2013, seizing territory and moving military assets into the areas under their control (Weiss and Hassan 2015). This initial foothold in Syria provided ISIS with an advantageous launchpad as its campaign turned towards Iraq. By the end of 2013, ISIS had occupied the city of Fallujah and areas of the city of Ramadi. And in mid-2014, ISIS also seized Mosul, Tikrit, the border town of Qa'im, and the Kurdish towns of Sinjar and Zumair (The Wilson Center 2019).

Based on patterns in ISIS occupation, we suspect that ISIS activities were, to some extent, constrained by border proximity. If the group is exploiting its holdings in Syria and control over the border to reallocate soldiers, weapons, and goods, then travel costs accumulate as they move resources further and further away from Syria and deeper into Iraq. Border control also means that

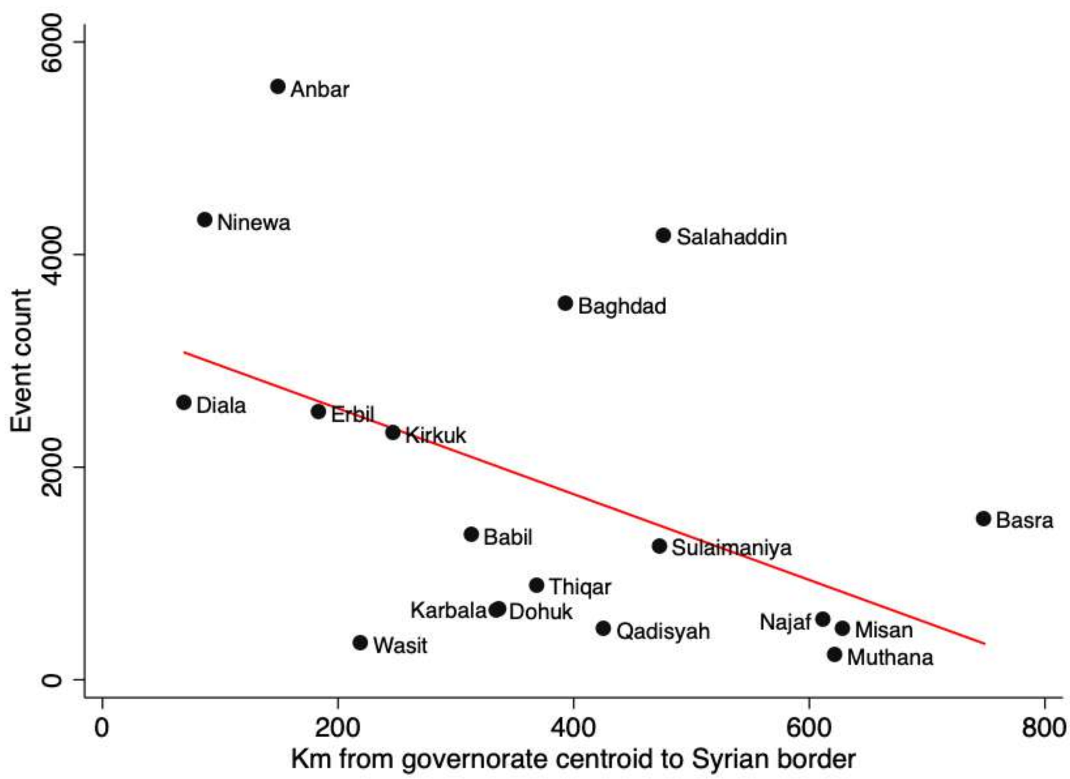
[8] The most recent year that night lights data are available is 2013. We focus on this year because it is the first year of our period of interest, and because we expect the 2013 data to reflect the changes in economic production stimulated by war in Syria and the disrupted trade that followed.

[9] We considered and ruled out two other instruments: rainfall and distance to nearest oilfield. The oilfield instrument will violate monotonicity, given the fact that oil fields are mainly concentrated in the northern and southern governorates. Since the southern governorates experienced the least conflict over this period, an observation close to an oilfield in one of these governorates will be less exposed to conflict, not the other way around. Rainfall is indeed related to conflict, but this relationship is mediated by rainfall shocks to incomes and prices. However, rainfall does not stimulate variation in conflict on its own. Rainfall will therefore be a weak instrument in a 2SLS approach. A 3SLS approach, in which rainfall is used to predict incomes, predicted incomes are used to predict conflict, and then predicted conflict is used to estimate impacts on child welfare, may be feasible, but will require localized income data, which we currently do not have.

ISIS soldiers can retreat to ISIS's territorial holdings in Syria if need be. Additional distance from the border can therefore increase the risk of soldiers being killed or captured.

Figure 4 shows the relationship between a governorate centroid's nearest linear distance from the Syrian border and the number of conflict events in that governorate over the 2013-2018 period. Indeed, we find that the governorates furthest from the Syrian border exhibited the lowest event frequencies, while nearby governorates like Ninewa exhibited high frequencies. The measure has its limitations: for example, Anbar appears rather close to the Syrian border, though there are subdistricts of this very large governorate that are twice as far from Syria as the centroid. Measures at the subdistrict (instead of the governorate) level may reveal that those areas of Anbar closer to the border indeed experienced more conflict than those further away.

Figure 4: governorate centroid nearest distance to Syrian border by conflict event count 2013-2018, GDELT



Source: authors' calculations based on GDELT. We obtain the minimum distance of the governorate centroid to the Syrian border using Google Earth Engine's Javascript API and governorate shapefiles for Iraq.. Event counts are the sum of all conflict events in the governorate 2013-2018.

The graph above supports the satisfaction of the relevance and monotonicity assumptions required for an IV. But in order to satisfy the exclusion restriction, we must account for the fact that border proximity can influence child outcomes outside of the conflict channel. If border areas are more dependent on trade with Syria, then the trade disruptions brought by the Syrian Civil War could mean that poverty is rising in these areas, resulting in worse child nutritional and health outcomes. To address this violation of the exclusion restriction, we control for the governorate's mean night lights index based on 2013 data.[10] Our rationale is that this proxy of economic productivity will account for the market-based channel through which border proximity can influence child health. Our first stage for the IV regression is:

$$\ln\left(event_{ig}\right) = \alpha_0 + \alpha_1 distanceToBorder_g + X'_{ighm}\lambda + u_{ic} \quad (2)$$

The second stage mirrors Equation 1, except we replace $\ln(event_i)$ with the predicted natural log of the event count, $\ln\left(\widehat{event_{ig}}\right)$.

4. Results

Table 2 displays all of the coefficient estimates of interest for the OLS and IV regressions using conflict exposure from GDELT (see Appendix for full results). The OLS estimates show negative (1% level) correlations between aggregate conflict exposure over the child's lifetime and the child's 2018 anthropometrics. This applies to all three measures - weight-for-age, height-for-age, and weight-for-height. The OLS results also provide weakly significant, positive estimates of the coefficient of interest in the regressions where health in the past two weeks was the outcome variable, though these coefficients are rather small in magnitude.

Table 2: coefficient estimates of interest from OLS and IV regressions using GDELT conflict exposure data

			OLS results			
	Diarrhea	**Cough**	**Fever**	**WAZ**	**HAZ**	**WHZ**
Log event count	0.007*	0.026***	0.010**	-0.042**	-0.087***	0.003
	(0.003)	(0.004)	(0.004)	(0.014)	(0.017)	(0.017)
Observations	16464	16463	16468	16470	16470	16470
R squared	0.026	0.013	0.013	0.025	0.032	0.008
			IV results (distance to Syrian border)			
	Diarrhea	**Cough**	**Fever**	**WAZ**	**HAZ**	**WHZ**
Predicted log event count	-0.019*	0.003	-0.001	-0.041	-0.147***	0.030
	(0.008)	(0.010)	(0.010)	(0.029)	(0.035)	(0.035)
Observations	16464	16463	16468	16470	16470	16470
R squared	0.020	0.009	0.012	0.025	0.031	0.007
F statistic	507.913	507.726	508.013	507.922	507.922	507.922

[10] The year 2013 is the most recent year in which global night lights rasters are publicly available. Using the 2013 data, we are assuming that the economic spillovers from the Syrian Civil War had already stimulated changes in child health endogenous to border proximity.

Source: authors' calculations based on MICS 2018 and GDELT 2013-2018 data for Iraq. Child conflict event exposure is the sum of conflict events in the child's governorate for all months that child was alive. For the IV approach, the instrument is the minimum linear distance between the child's governorate's centroid and the Syrian border. . Standard errors are clustered at the MICS sample cluster level. Standard errors in parentheses. ***p<0.01, **p<0.5, *p<0.1

The IV estimations all produced first-stage F-statistics that are high ($F > 500$), which suggests that our instrument is not weak. The IV approach yields insignificant coefficient estimates for most of the coefficients of interest with the important exception with height-for-age z-scores (HAZ), where the coefficient is significant (1% level) and negative. The estimate suggests that *ceteris paribus,* a 1% increase in conflict frequency due to border proximity results in a decline in child HAZ of about -0.15. Interestingly, the coefficient of interest from the IV regression with a binary outcome of whether the child had diarrhea in the past two weeks is significant and negative, suggesting that more exposed children were *less* likely to have recently had a diarrheal illness. But this coefficient is very small in magnitude, meaning it may not be economically significant.

The results of our IV suggest that past conflict exposure does not significantly reduce WAZ, or WHZ. It seems possible that because ISIS was in retreat in 2018 and Iraq was seeing reduced conflict relative to earlier years, communities in conflict-affected areas may have started to show signs of market and institutional recovery. By the time the MICS surveyors arrived to these households, perhaps children were no longer facing acute hunger (which WAZ reflects). But perhaps the long years of conflict, and the resulting disruptions, resulted in long periods of food insecurity, leading some of the exposed children to be stunted (which HAZ reflects). And if stunted children and their households found greater food security as conflict abated, then the numerator in the weight-for-age measure would increase, resulting in no significant difference in WHZ when comparing exposed and unexposed children.

Likewise, if the communities previously exposed to high levels of conflict had entered a period of recovery by the time of the MICS 2018 survey, then the public health environment may have improved by this time such that higher lifetime exposure did not manifest in recent child health outcomes.

5. Robustness checks

Because of its data collection strategy, GDELT can yield false positives and may miss events that did not receive media attention. As a robustness check, we repeat our OLS and IV regressions using child exposure counts from the Armed Conflict Location and Event Data (2016-2018) and the Iraq Body Count (2013-2017) data. ACLED is global dataset that tracks and geo-locates conflict event occurrences over time. Unlike GDELT, the ACLED team verifies observations, which reduces the previously discussed overcounts and false positives. Because of its geographic and temporal scope as well as the aforementioned verification, ACLED has been the data of choice for numerous empirical studies of conflict. While ACLED data goes back to 1997 for many countries on the African continent, its temporal scope is limited for Iraq, as the earliest events available for the country occurred in 2016. Using ACLED, we count exposure based on the sum of violent conflict events (battles, bombings and remote violence, and violence against civilians) in the child's governorate over their lifetime.

The IBC data is an open-source platform based on citizen reporting of war casualties. It may serve as a proxy for conflict events under the assumption that the majority of observations represent casualties of violent conflict (and not arrests and torture) and that the reporting of other casualties (the mismeasurement) is not endogenous to our specification.[11] The latest event data in the IBC is for early 2017, meaning that like ACLED, the IBC also does not cover the entire study period we focus on in this paper. But since it provides a conflict event proxy for Iraq, the IBC has been used by numerous studies of conflict in the country. In our analysis, exposure based on the IBC is the sum of all bodies identified by the IBC for the child's governorate during their lifetime.

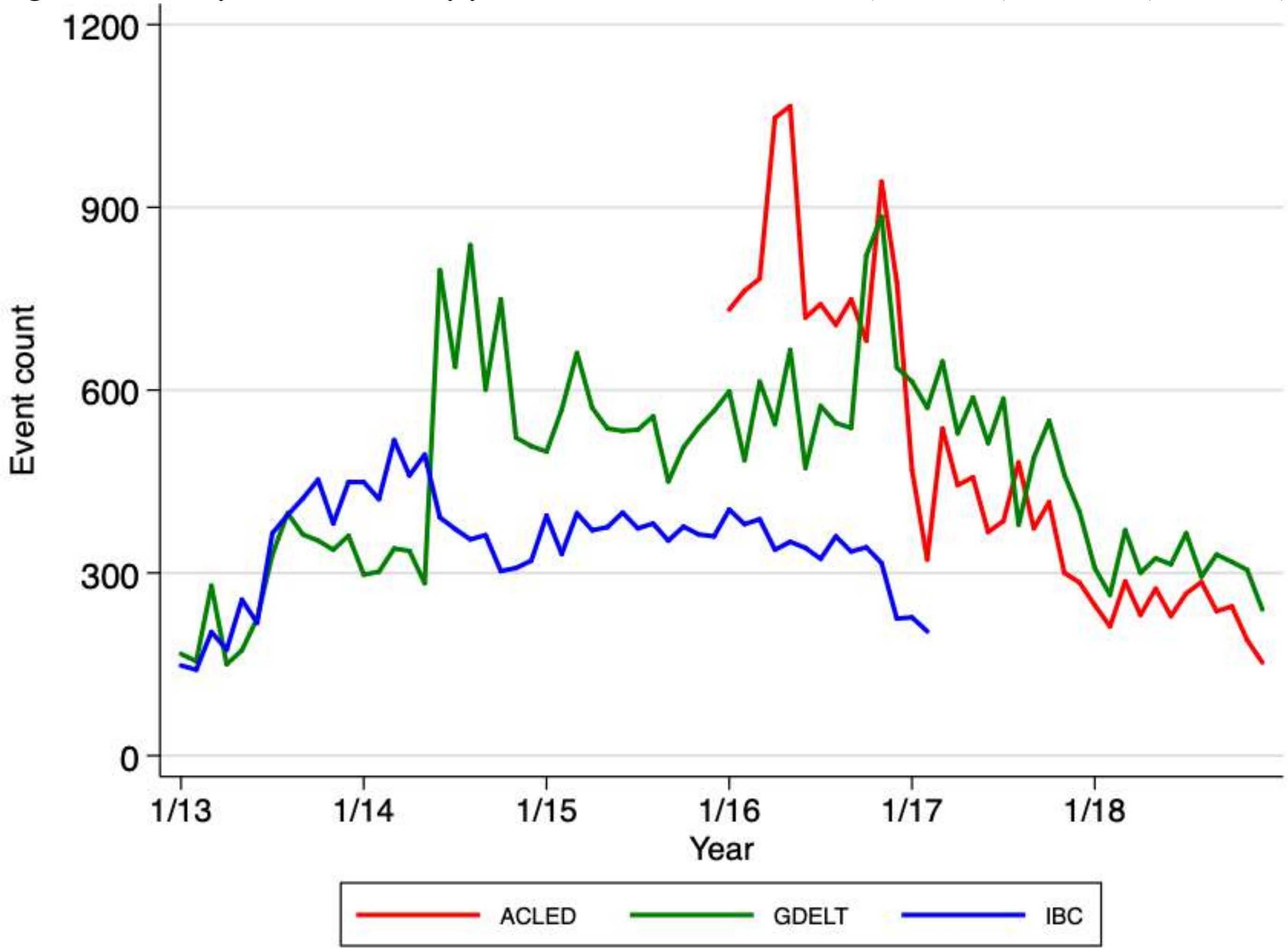
How does the GDELT data compare to ACLED and the IBC data? Figure 5 plots Iraq's monthly conflict trends according to GDELT and compares this to trends in violent conflict events[12] based on the Armed Conflict Location and Event Database (ACLED) as well as the Iraq Body Count (IBC) data. Neither the IBC nor ACLED provide temporal coverage throughout the 2013-2018 period, but we can look at areas of temporal overlap. The ACLED and GDELT data show some correspondence for national trends. Both include a spike in late 2016, followed by a gradual decline in national monthly event counts. As Figure 5 shows, the IBC trends are quite different from ACLED and GDELT. We'd expect the level to be different due to the differences in the unit of measurement (bodies vs. events), but the IBC does not seem to capture any of the 2016 national spikes in event frequency.

When we compare GDELT, ACLED, and the IBC by region and time (Figure 6), we find considerable differences across the three datasets. There are moments where two seem to exhibit very similar trends. ACLED and the IBC both show monthly counts in the Southern governorates close to zero, whereas the GDELT shows monthly counts across the region closer to 50 for much of 2014-2017. By contrast, in the Northern governorates (excluding Kurdistan), GDELT and ACLED exhibit similar trends and levels, while the IBC trend is rather flat and does not pick up on a spike shown by GDELT and ACLED in late 2016. In Kurdistan, the three trend lines share little in common, and they all deviate considerably for the Central governorates as well. Observing these trends, it is not apparent which data source is the most representative of reality.

[11] Unfortunately, the "observations" (bodies) that constitute the IBC cannot always be confirmed as direct casualties of a conflict episode. For example, a person may have been arrested and executed by ISIS for defiance, but this event is quite different than a battle or a bombing. Prisoners of war may also be executed, and their bodies found, in a place different from the conflict event during which they were initially taken into custody. There can also be a time lag between arrest and the discovery of their body.

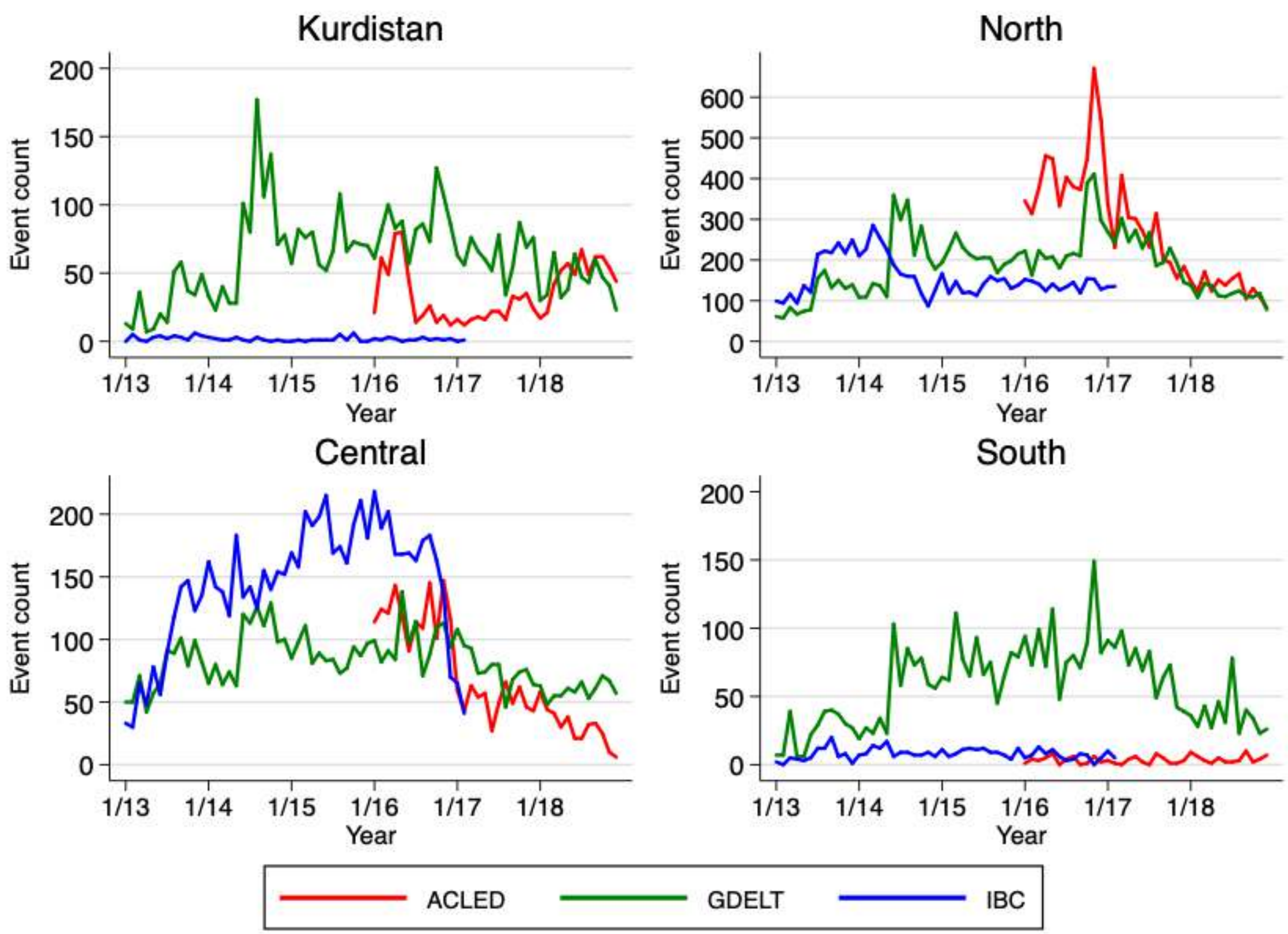
[12] When using ACLED, we restrict our counts to the following categories: battles, explosions and remote violence, and violence against civilians.

Figure 5: monthly conflict events by year and data source, GDELT (2013-2018), ACLED (2016-2018), IBC (2013-2017)



Source: authors' calculations using GDELT 2013-2018, the Iraq Body Count data 2013-2017, and the Armed Conflict Location and Event Database (ACLED) 2016-2018. ACLED events are restricted to only violent conflict events: battles, bombings and remote violence, and violence against civilians.

Figure 6: monthly conflict events by year, region, and data source, GDELT (2013-2018), ACLED (2016-2018), IBC (2013-2017)



Source: authors' calculations using GDELT 2013-2018, the Iraq Body Count data 2013-2017, and the Armed Conflict Location and Event Database (ACLED) 2016-2018. ACLED events are restricted to only violent conflict events: battles, bombings and remote violence, and violence against civilians.

Using the ACLED data, all sample children are coded as being exposed to at least one event, hence we can perform the logarithmic transformation on the event count variable. But some children have zero “exposure” in the IBC data, so we cannot use a natural logarithmic transformation for this vector. Instead, we use the inverse hyperbolic sine (IHS) transformation, which approximates the natural logarithm of that variable while retaining observations of zero (Bellemare, Barrett, and Just 2013).

The results (Table 3) largely confirm the findings of the GDELT-based estimation, especially with the IV specification (see Appendix for full results). The OLS estimation using ACLED yields a positive, significant coefficient on the probability of a cough in the past two weeks and negative, a weakly significant and negative coefficient when WAZ is the outcome variable, and a significant, negative coefficient when HAZ is the outcome variable. As in the GDELT-based estimations, the IV using ACLED shows high first-stage F-tests (F > 1,200). When estimating the impact on HAZ, the IV approach yields a negative coefficient significant at the 1% level. But the magnitude is smaller than with the GDELT estimates: the results suggest that a 1% increase in conflict exposure due to border proximity results in a reduction in HAZ of 0.04. This is one-third of the magnitude of the coefficient derived from the GDELT-based IV estimation.

Table 3: Estimates on coefficient of interest for OLS and IV specifications, MICS 2018, ACLED 2016-2018, IBC 2013-2017

Exposure based on ACLED

OLS results

	Diarrhea	**Cough**	**Fever**	**WAZ**	**HAZ**	**WHZ**
Log event count	0.001	0.008***	0.002	-0.014*	-0.044***	0.009
	(0.001)	(0.002)	(0.002)	(0.006)	(0.008)	(0.008)
Observations	16464	16463	16468	16470	16470	16470
R squared	0.025	0.011	0.012	0.024	0.032	0.008

IV results (distance to Syrian border)

	Diarrhea	**Cough**	**Fever**	**WAZ**	**HAZ**	**WHZ**
Predicted log event count	-0.007*	0.001	-0.001	-0.014	-0.051***	0.010
	(0.003)	(0.003)	(0.003)	(0.010)	(0.012)	(0.012)
Observations	16464	16463	16468	16470	16470	16470
R squared	0.023	0.009	0.012	0.024	0.032	0.008
F statistic	1242.311	1242.153	1242.194	1241.594	1241.594	1241.594

Exposure based on IBC

OLS results

	Diarrhea	**Cough**	**Fever**	**WAZ**	**HAZ**	**WHZ**
Log event count	0.001	0.006***	0.001	-0.019**	-0.041***	0.001
	(0.001)	(0.002)	(0.002)	(0.006)	(0.008)	(0.007)
Observations	16464	16463	16468	16470	16470	16470
R squared	0.025	0.010	0.012	0.025	0.032	0.008

IV results (distance to Syrian border)

	Diarrhea	**Cough**	**Fever**	**WAZ**	**HAZ**	**WHZ**
Predicted IHS event count	-0.011*	0.002	-0.001	-0.025	-0.090***	0.018
	(0.005)	(0.006)	(0.006)	(0.018)	(0.021)	(0.021)
Observations	16464	16463	16468	16470	16470	16470
R squared	0.019	0.009	0.012	0.024	0.028	0.007
F statistic	687.412	686.780	687.493	687.260	687.260	687.260

Source: authors' calculations based on MICS 2018, ACLED 2016-2018, and the IBC 2013-2017. The instrument is the minimum distance between the child's governorate's centroid and the Syrian border. Standard errors are clustered at the MICS sample cluster level. Standard errors in parentheses. ***p<0.01, **p<0.5, *p<0.1

The IBC-based OLS estimations yield positive coefficient estimates with the probability of a cough in the past two weeks as the outcome variable, though the magnitude is very small. The coefficient is again significant and negative for the OLS regression estimating HAZ. The IV estimations based on the predicted IHS of event counts (from the IBC data) have high first-stage F-statistics (F > 680).

The results again estimate a negative, significant (1% level) impact on HAZ. All else equal, a 1% increase in the governorate body count during a child's lifetime results in a reduction in child HAZ of 0.09. This magnitude is smaller than the GDELT-based IV result (0.15) and greater than the ACLED-based IV result (0.04).

6. Mechanism analysis

Our mechanism analysis so far is limited to what data we have available in the MICS 2018 survey. For this draft, we focus on food consumption indicators. While the MICS does collect some information on food consumption for children, the questionnaire prompts guardians to report consumption on the previous day of the survey. As mentioned, we suspect that the communities surveyed in 2018 may have already entered a period of market and institutional recovery, given the fact that the more exposed children were not more under-weight (WAZ) than less exposed children and exposed children were not more likely to have worse recent health outcomes. The only retrospective food consumption variable for the sample children was a binary indicator of whether or not the child was ever breastfed.

We estimate our IV specification using the binary data on child food consumption on the previous day as well as whether or not the child was breastfed using the GDELT-based exposure measure. We provide the coefficient results in Table 4 (see Appendix for OLS outcomes and full IV results). The results based on the child's consumption the day before do not suggest that children with higher lifetime exposure were less likely to obtain certain foods important for early development at the time of the DHS interview. In fact, these children were more likely to have recently consumed eggs, a protein-rich food positively linked to early child physical development (Filmer et al. 2018). They are also more likely to have recently eaten yogurt, but less likely to have recently eaten certain categories of vegetables. However, we do find that the more exposed children were less likely to have ever been breastfed. Our IV results that *ceteris paribus*, a 1% increase in conflict exposure due to border proximity results in a reduction in the probability a child was breastfed by 0.025, or 2.5 percentage points. The lower likelihood of breastfeeding for high exposure children may help explain their greater propensity towards stunting.

Table 4: Results of IV regression with nutritional outcomes as dependent variable, MICS 2018 and GDELT 2013-2018

	Ever breastfed	Yogurt	Fortified baby food	Grains	Squash/ carrots	Potatoes/ yams	Green vegetables	Mangoes/ papayas
Predicted ln event count	-0.025***	0.054***	-0.009	-0.014	-0.042***	-0.022	-0.019	-0.030**
	(0.007)	(0.013)	(0.008)	(0.010)	(0.011)	(0.012)	(0.011)	(0.010)
Observations	9542	6394	6393	6393	6394	6392	6393	6391
R squared	0.005	0.119	0.030	0.379	0.083	0.133	0.077	0.078
F statistic	496.049	478.122	477.585	478.234	478.829	478.892	479.265	480.433

	Other fruit/veg	Organ meat	Meat	Eggs	Fish	Beans/nuts	Cheese
Predicted ln event count	-0.042***	0.001	-0.021	0.048***	-0.071***	-0.060***	-0.030**
	(0.012)	(0.008)	(0.011)	(0.012)	(0.009)	(0.012)	(0.011)
Observations	6394	6390	6393	6389	6386	6388	6379
R squared	0.258	0.045	0.156	0.275	0.076	0.086	0.109
F statistic	478.822	477.013	478.656	478.776	478.177	477.472	478.767

Source: authors' calculations based on MICS 2018 and GDELT 2013-2018. The instrument is the minimum distance between the child's governorate's centroid and the Syrian border. Standard errors are clustered at the MICS sample cluster level. Standard errors in parentheses. ***p<0.01, **p<0.5, *p<0.1

7. Conclusion

The paper addresses the effects of armed conflict on children's nutritional and health outcomes in Iraq over the 2013-2018 period. Our primary analysis uses cleaned GDELT data for Iraq, and as a robustness check, we repeat our estimates using the ACLED and IBC datasets. Our preferred specification uses an instrumental variables (IV) approach in which the minimum distance between the child's 2018 governorate's centroid and the Syrian border is used to predict the natural log of child conflict exposure. To satisfy the exclusion restriction, we control for the child's governorate's level of economic activity using 2013 night lights remote sensing data.

The main results and robustness checks suggest that higher conflict exposure due to border proximity leads to lower height-for-age z-scores for children. Holding all else constant, our evidence suggests that a 1% increase in conflict exposure due to border proximity results in a reduction in child HAZ by $0.04 - 0.14$ units. Although the ACLED data would suggest the magnitude is rather small, the GDELT results are three times as large, meaning the magnitude of this outcome may not be economically insignificant.

We interpret these findings as indicative of some community recovery following periods of high conflict prior to 2018. As communities recover and markets are restored, health and nutritional outcomes will improve for children with high exposure in the past. But during high conflict periods, where markets are disrupted, households may have faced food insecurity at critical moments in a young child's early development. While a child may gain weight once conflict abides, prolonged periods of nutritional deficiency can manifest as stunting.

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Appendix Tables

Table A1: Full results of OLS regression using GDELT event counts, MICS 2018 and GDELT 2013-2018

	Diarrhea	Cough	Fever	WAZ	HAZ	WHZ
Log event count	0.007*	0.026***	0.010**	-0.042**	-0.087***	0.003
	(0.003)	(0.004)	(0.004)	(0.014)	(0.017)	(0.017)
Gender	-0.005	-0.010	-0.008	0.023	-0.027	0.099***
	(0.005)	(0.006)	(0.006)	(0.021)	(0.026)	(0.025)
Age in mos.	0.003***	0.001***	0.002***	0.004***	-0.002	0.006***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Mother's age	0.000	0.001	0.002***	0.002	0.004	0.001
	(0.000)	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)
Mother +primary school	-0.014	0.001	0.001	0.108***	0.211***	-0.017
	(0.008)	(0.009)	(0.009)	(0.030)	(0.037)	(0.036)
Mean gov. lights '13	0.003***	0.004***	0.005***	0.004	0.002	0.005
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
HH urban	0.009	0.017	0.011	-0.008	0.053	-0.052
	(0.008)	(0.010)	(0.010)	(0.031)	(0.038)	(0.037)
HH wealth index	0.018***	0.015***	-0.008*	0.098***	0.121***	0.057***
	(0.003)	(0.004)	(0.003)	(0.012)	(0.014)	(0.014)
No. HH members	-0.002**	-0.001	-0.002**	-0.005	-0.006	-0.003
	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)	(0.004)
HH head gender	-0.004	0.007	-0.017	0.069	0.048	0.096
	(0.012)	(0.014)	(0.015)	(0.051)	(0.059)	(0.058)
Mother speaks Arabic	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Mother speaks Kurdish	-0.017	0.027	-0.017	0.181***	0.359***	0.025
	(0.011)	(0.016)	(0.015)	(0.054)	(0.065)	(0.063)
Mother speaks other lang.	-0.024	-0.054*	-0.035	0.062	-0.077	0.172
	(0.022)	(0.024)	(0.027)	(0.104)	(0.141)	(0.118)
Observations	16464	16463	16468	16470	16470	16470
R squared	0.026	0.013	0.013	0.025	0.032	0.008

Source: authors' calculations based on MICS 2018 and GDELT 2013-2018. Results correspond to Table 2, which presents the results for the coefficient of interest (log event count). Standard errors are clustered at the MICS sample cluster level. Standard errors in parentheses. ***p<0.01, **p<0.5, *p<0.1

Table A2: Full results of IV regression using GDELT event counts, MICS 2018 and GDELT 2013-2018

	Diarrhea	Cough	Fever	WAZ	HAZ	WHZ
Predicted log event count	-0.019*	0.003	-0.001	-0.041	-0.147***	0.030
	(0.008)	(0.010)	(0.010)	(0.029)	(0.035)	(0.035)
Gender	-0.005	-0.009	-0.008	0.023	-0.026	0.099***
	(0.005)	(0.006)	(0.006)	(0.021)	(0.026)	(0.025)
Age in mos.	0.002***	-0.001	-0.001**	-0.004**	0.000	0.007***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)
Mother's age	-0.000	0.001	0.002***	0.002	0.003	0.001
	(0.000)	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)
Mother +primary school	-0.007	0.007	0.004	0.108***	0.228***	-0.025
	(0.008)	(0.009)	(0.009)	(0.031)	(0.038)	(0.037)
Mean gov. lights '13	0.004***	0.005***	0.005***	0.004	0.002	0.004
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
HH urban	0.007	0.015	0.010	-0.008	0.048	-0.050
	(0.008)	(0.010)	(0.010)	(0.031)	(0.038)	(0.037)
HH wealth index	-0.014***	-0.011**	-0.006	0.098***	0.131***	0.052***
	(0.003)	(0.004)	(0.003)	(0.012)	(0.015)	(0.015)
No. HH members	-0.002**	-0.001	-0.002**	-0.005	-0.007	-0.002
	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)	(0.004)
HH head gender	-0.006	0.006	-0.018	0.069	0.044	0.098
	(0.012)	(0.014)	(0.015)	(0.051)	(0.059)	(0.059)
Mother speaks Arabic	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Mother speaks Kurdish	-0.028*	0.017	-0.022	0.182**	0.334***	0.037
	(0.012)	(0.017)	(0.015)	(0.055)	(0.066)	(0.064)
Mother speaks other lang.	-0.010	-0.042	-0.028	0.061	-0.045	0.157
	(0.023)	(0.025)	(0.028)	(0.105)	(0.142)	(0.119)
Observations	16464	16463	16468	16470	16470	16470
R squared	0.020	0.009	0.012	0.025	0.031	0.007
F statistic	507.913	507.726	508.013	507.922	507.922	507.922

Source: authors' calculations based on MICS 2018 and GDELT 2013-2018. Results correspond to Table 2, which presents the results for the coefficient of interest (predicted log event count). The instrument is the minimum distance between the child's governorate's centroid and the Syrian border. Standard errors are clustered at the MICS sample cluster level. Standard errors in parentheses. ***p<0.01, **p<0.5, *p<0.1

Table A3: Full results of OLS regression using ACLED event counts, MICS 2018 and GDELT 2016-2018

	Diarrhea	Cough	Fever	WAZ	HAZ	WHZ
Log event count	0.001	0.008***	0.002	-0.014*	-0.044***	0.009
	(0.001)	(0.002)	(0.002)	(0.006)	(0.008)	(0.008)
Gender	-0.005	-0.010	-0.008	0.023	-0.027	0.099***
	(0.005)	(0.006)	(0.006)	(0.021)	(0.026)	(0.025)
Age in mos.	-0.003***	-0.001***	-0.001***	-0.006***	-0.004***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Mother's age	-0.000	0.001	0.002***	0.002	0.004	0.001
	(0.000)	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)
Mother +primary	-0.013	0.004	0.002	0.103***	0.208***	-0.021
	(0.008)	(0.009)	(0.009)	(0.030)	(0.037)	(0.036)
Mean gov. lights '13	0.003***	0.004***	0.005***	0.004	0.003	0.004
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
HH urban	0.009	0.019*	0.011	-0.012	0.036	-0.047
	(0.008)	(0.010)	(0.010)	(0.031)	(0.038)	(0.037)
HH wealth index	-0.018***	-0.015***	-0.007*	0.098***	0.129***	0.053***
	(0.003)	(0.004)	(0.003)	(0.012)	(0.014)	(0.014)
No. HH members	-0.002**	-0.001	-0.002**	-0.005	-0.006	-0.003
	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)	(0.004)
HH head gender	-0.004	0.007	-0.017	0.069	0.045	0.098
	(0.012)	(0.014)	(0.015)	(0.051)	(0.059)	(0.058)
Mother speaks Arabic	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Mother speaks Kurdish	-0.019	0.019	-0.021	0.194***	0.380***	0.028
	(0.011)	(0.016)	(0.015)	(0.054)	(0.064)	(0.063)
Mother speaks other lang.	-0.022	-0.055*	-0.033	0.064	-0.045	0.157
	(0.022)	(0.025)	(0.028)	(0.105)	(0.141)	(0.119)
Observations	16464	16463	16468	16470	16470	16470
R squred	0.025	0.011	0.012	0.024	0.032	0.008

Source: authors' calculations based on MICS 2018 and ACLED 2016-2018. Results correspond to Table 3, which presents the results for the coefficient of interest (log event count). Standard errors are clustered at the MICS sample cluster level. Standard errors in parentheses. ***p<0.01, **p<0.5, *p<0.1

Table A4: Full results of IV regression using ACLED event counts, MICS 2018 and ACLED 2016-2018

	Diarrhea	Cough	Fever	WAZ	HAZ	WHZ
Predicted log event count	-0.007*	0.001	-0.001	-0.014	-0.051***	0.010
	(0.003)	(0.003)	(0.003)	(0.010)	(0.012)	(0.012)
Gender	-0.005	-0.009	-0.008	0.023	-0.027	0.099***
	(0.005)	(0.006)	(0.006)	(0.021)	(0.026)	(0.025)
Age in mos.	-0.002***	-0.000*	-0.001***	-0.006***	-0.004***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Mother's age	-0.000	0.001	0.002***	0.002	0.004	0.001
	(0.000)	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)
Mother +primary	-0.009	0.008	0.004	0.103***	0.212***	-0.021
	(0.008)	(0.009)	(0.009)	(0.030)	(0.037)	(0.036)
Mean gov. lights '13	0.004***	0.005***	0.005***	0.004	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
HH urban	0.005	0.015	0.010	-0.012	0.032	-0.046
	(0.008)	(0.010)	(0.010)	(0.031)	(0.038)	(0.037)
HH wealth index	-0.013***	-0.011**	-0.006	0.098***	0.133***	0.052***
	(0.003)	(0.004)	(0.003)	(0.012)	(0.015)	(0.015)
No. HH members	-0.002**	-0.001	-0.002**	-0.005	-0.006	-0.003
	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)	(0.004)
HH head gender	-0.006	0.006	-0.018	0.069	0.043	0.098
	(0.012)	(0.014)	(0.015)	(0.051)	(0.059)	(0.058)
Mother speaks Arabic	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Mother speaks Kurdish	-0.022	0.017	-0.022	0.194***	0.378***	0.028
	(0.012)	(0.016)	(0.015)	(0.054)	(0.064)	(0.063)
Mother speaks other lang.	-0.008	-0.042	-0.028	0.064	-0.033	0.155
	(0.023)	(0.025)	(0.028)	(0.106)	(0.142)	(0.120)
Observations	16464	16463	16468	16470	16470	16470
R squared	0.023	0.009	0.012	0.024	0.032	0.008
F statistic	1242.311	1242.153	1242.194	1241.594	1241.594	1241.594

Source: authors' calculations based on MICS 2018 and ACLED 2016-2018. Results correspond to Table 3, which presents the results for the coefficient of interest (predicted log event count). The instrument is the minimum distance between the child's governorate's centroid and the Syrian border. Standard errors are clustered at the MICS sample cluster level. Standard errors in parentheses. ***p<0.01, **p<0.5, *p<0.1

Table A5: Full results of OLS regression using IBC event counts, MICS 2018 and IBC 2013-2017

	Diarrhea	Cough	Fever	WAZ	HAZ	WHZ
Log event count	0.001	0.006***	0.001	-0.019**	-0.041***	0.001
	(0.001)	(0.002)	(0.002)	(0.006)	(0.008)	(0.007)
Gender	-0.005	-0.009	-0.008	0.022	-0.028	0.099***
	(0.005)	(0.006)	(0.006)	(0.021)	(0.026)	(0.025)
Age in mos.	-0.003***	-0.001***	-0.001***	-0.004***	-0.001	-0.006***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Mother's age	-0.000	0.001	0.002***	0.002	0.004	0.001
	(0.000)	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)
Mother +primary	-0.012	0.006	0.003	0.103***	0.201***	-0.017
	(0.008)	(0.009)	(0.009)	(0.030)	(0.037)	(0.035)
Mean gov. lights '13	0.003***	0.005***	0.005***	0.004	0.002	0.005
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
HH urban	0.008	0.016	0.010	-0.009	0.050	-0.052
	(0.008)	(0.010)	(0.010)	(0.031)	(0.038)	(0.037)
HH wealth index	-0.017***	-0.013***	-0.007*	0.097***	0.118***	0.057***
	(0.003)	(0.004)	(0.003)	(0.012)	(0.014)	(0.014)
No. HH members	-0.002**	-0.001	-0.002**	-0.005	-0.006	-0.003
	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)	(0.004)
HH head gender	-0.005	0.007	-0.018	0.067	0.044	0.096
	(0.012)	(0.014)	(0.015)	(0.051)	(0.059)	(0.058)
Mother speaks Arabic	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Mother speaks Kurdish	-0.018	0.032	-0.019	0.150**	0.293***	0.027
	(0.012)	(0.017)	(0.015)	(0.055)	(0.066)	(0.065)
Mother speaks other lang.	-0.020	-0.042	-0.029	0.045	-0.111	0.173
	(0.022)	(0.024)	(0.027)	(0.104)	(0.140)	(0.118)
Observations	16464	16463	16468	16470	16470	16470
R squared	0.025	0.010	0.012	0.025	0.032	0.008

Source: authors' calculations based on MICS 2018 and ACLED 2016-2018. Results correspond to Table 3, which presents the results for the coefficient of interest (log event count). Because of zero values in IBC-based conflict exposure, we use the inverse hyperbolic sine transformation of the event count variable. Standard errors are clustered at the MICS sample cluster level. Standard errors in parentheses. ***p<0.01, **p<0.5, *p<0.1

Table A6: Full results of IV regression using IBC event counts, MICS 2018 and IBC 2013-2017

	Diarrhea	Cough	Fever	WAZ	HAZ	WHZ
Predicted log event count	-0.011*	0.002	-0.001	-0.025	-0.090***	0.018
	(0.005)	(0.006)	(0.006)	(0.018)	(0.021)	(0.021)
Gender	-0.005	-0.009	-0.008	0.022	-0.029	0.099***
	(0.005)	(0.006)	(0.006)	(0.021)	(0.026)	(0.025)
Age in mos.	-0.001*	-0.001	-0.001	-0.003	0.005	-0.008**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Mother's age	-0.000	0.001	0.002***	0.002	0.004	0.001
	(0.000)	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)
Mother +primary	-0.008	0.007	0.004	0.105***	0.219***	-0.023
	(0.008)	(0.009)	(0.009)	(0.031)	(0.037)	(0.036)
Mean gov. lights '13	0.004***	0.005***	0.005***	0.004	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
HH urban	0.005	0.015	0.010	-0.011	0.038	-0.048
	(0.008)	(0.010)	(0.010)	(0.031)	(0.038)	(0.037)
HH wealth index	-0.013***	-0.011**	-0.006	0.098***	0.132***	0.052***
	(0.003)	(0.004)	(0.003)	(0.012)	(0.015)	(0.015)
No. HH members	-0.002**	-0.001	-0.002**	-0.005	-0.007	-0.002
	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)	(0.004)
HH head gender	-0.008	0.006	-0.018	0.065	0.032	0.100
	(0.012)	(0.014)	(0.015)	(0.051)	(0.059)	(0.059)
Mother speaks Arabic	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Mother speaks Kurdish	-0.049**	0.020	-0.024	0.137*	0.172*	0.070
	(0.017)	(0.023)	(0.021)	(0.069)	(0.084)	(0.081)
Mother speaks other lang.	-0.016	-0.041	-0.029	0.047	-0.097	0.168
	(0.023)	(0.024)	(0.028)	(0.104)	(0.139)	(0.118)
Observations	16464	16463	16468	16470	16470	16470
R squared	0.019	0.009	0.012	0.024	0.028	0.007
F statistic	687.412	686.780	687.493	687.260	687.260	687.260

Source: authors' calculations based on MICS 2018 and the IBC 2013-2017. Results correspond to Table 3, which presents the results for the coefficient of interest (predicted log event count). The instrument is the minimum distance between the child's governorate's centroid and the Syrian border. Because of zero values in IBC-based conflict exposure, we use the inverse hyperbolic sine transformation of the event count variable. Standard errors are clustered at the MICS sample cluster level. Standard errors in parentheses. ***p<0.01, **p<0.5, *p<0.1

Table A7: Full results of OLS regression for mechanism analysis, MICS 2018 and GDELT 2013-2018

	Ever breastfed	Yogurt	Fortified baby food	Grains	Squash/ carrots	Potatoes/ yams	Green vegetables	Mangoes/ papayas
Predicted log event count	-0.008*	0.018**	0.001	0.021***	-0.013*	0.020***	-0.026***	-0.022***
	(0.004)	(0.006)	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
Gender	-0.004	0.000	-0.008	-0.001	-0.013	-0.010	-0.014	-0.004
	(0.006)	(0.010)	(0.007)	(0.010)	(0.009)	(0.010)	(0.009)	(0.008)
Age in mos.	-0.001**	0.020***	-0.001*	0.042***	0.014***	0.023***	0.015***	0.013***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mother's age	-0.001	0.000	0.000	-0.001	-0.001	-0.001	0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mother +primary	-0.008	-0.029*	0.005	0.008	-0.014	0.000	-0.003	-0.009
	(0.008)	(0.015)	(0.008)	(0.013)	(0.012)	(0.015)	(0.012)	(0.011)
Mean gov. lights '13	0.002**	0.000	0.002**	-0.000	-0.010***	-0.003**	-0.005***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HH urban	0.003	-0.037**	0.030***	0.024*	0.033**	0.011	0.010	0.022
	(0.008)	(0.014)	(0.008)	(0.012)	(0.011)	(0.014)	(0.012)	(0.011)
HH wealth index	-0.008*	0.007	0.024***	-0.004	0.012**	0.003	0.011*	0.004
	(0.003)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
No. HH members	-0.000	-0.001	-0.002*	-0.000	-0.001	0.002	0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HH head gender	-0.016	0.032	-0.025	-0.002	0.005	0.007	-0.018	0.028
	(0.012)	(0.021)	(0.017)	(0.019)	(0.020)	(0.023)	(0.021)	(0.016)
Mother speaks Arabic	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Mother speaks Kurdish	0.016	0.094***	-0.008	-0.014	0.095***	-0.109***	-0.041*	-0.030
	(0.012)	(0.024)	(0.018)	(0.020)	(0.020)	(0.022)	(0.016)	(0.015)
Mother speaks other lang.	0.035	0.112*	-0.007	-0.060	0.018	-0.091*	0.023	0.012
	(0.022)	(0.054)	(0.038)	(0.047)	(0.039)	(0.043)	(0.042)	(0.036)

Observations	9542	6394	6393	6393	6394	6392	6393	6391
R squared	0.008	0.125	0.032	0.384	0.089	0.141	0.078	0.078

Source: authors' calculations based on MICS 2018 and GDELT 2013-2018. Results not reported in paper. Table continues on following page. Standard errors are clustered at the MICS sample cluster level. Standard errors in parentheses. ***p<0.01, **p<0.5, *p<0.1

	Other fruit/veg	Organ meat	Meat	Eggs	Fish	Beans/nuts	Cheese
Predicted log event count	-0.024***	-0.019***	-0.002	0.031***	-0.033***	-0.010	-0.001
	(0.006)	(0.004)	(0.005)	(0.006)	(0.004)	(0.006)	(0.006)
Gender	-0.007	-0.008	-0.014	-0.014	0.008	-0.004	0.007
	(0.011)	(0.006)	(0.010)	(0.011)	(0.007)	(0.009)	(0.009)
Age in mos.	0.038***	0.009***	0.024***	0.034***	0.014***	0.018***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mother's age	-0.002*	0.000	-0.000	-0.001	0.000	-0.001	0.002*
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mother +primary	0.062***	-0.007	0.015	0.051***	0.004	0.002	-0.005
	(0.016)	(0.009)	(0.013)	(0.014)	(0.010)	(0.013)	(0.013)
Mean gov. lights '13	-0.000	-0.002**	-0.004***	-0.004***	-0.001*	-0.005***	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HH urban	0.029*	-0.018*	-0.003	0.000	0.026**	0.014	0.033**
	(0.014)	(0.008)	(0.013)	(0.014)	(0.010)	(0.013)	(0.013)
HH wealth index	0.023***	0.013***	0.021***	0.023***	-0.000	-0.001	0.014**
	(0.005)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
No. HH members	-0.002	0.001	-0.001	0.000	0.002	0.001	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HH head gender	0.061*	0.008	0.001	0.037	0.030*	0.017	-0.012
	(0.024)	(0.012)	(0.021)	(0.023)	(0.014)	(0.020)	(0.020)
Mother speaks Arabic	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Mother speaks Kurdish	-0.086***	0.024*	0.027	-0.092***	-0.077***	-0.044*	-0.100***
	(0.024)	(0.012)	(0.022)	(0.023)	(0.013)	(0.020)	(0.019)
Mother speaks other lang.	-0.018	0.043	0.069	0.002	-0.043*	-0.022	0.096
	(0.050)	(0.029)	(0.043)	(0.049)	(0.021)	(0.040)	(0.050)
Observations	6394	6390	6393	6389	6386	6388	6379

R squared	0.259	0.051	0.158	0.276	0.090	0.101	0.114

Source: authors' calculations based on MICS 2018 and GDELT 2013-2018. Results not reported in paper. This is an extension of the table on the previous page. Standard errors are clustered at the MICS sample cluster level. Standard errors in parentheses. ***p<0.01, **p<0.5, *p<0.1

Table A8: Full results of IV regression for mechanism analysis, MICS 2018 and GDELT 2013-2018

	Ever breastfed	Yogurt	Fortified baby food	Grains	Squash/ carrots	Potatoes/ yams	Green vegetables	Mangoes/ papayas
Predicted log event count	-0.025***	0.054***	-0.009	-0.014	-0.042***	-0.022	-0.019	-0.030**
	-0.007	-0.013	-0.008	-0.01	-0.011	-0.012	-0.011	-0.01
Gender	-0.004	0.000	-0.008	-0.001	-0.013	-0.010	-0.014	-0.004
	(0.006)	(0.010)	(0.007)	(0.010)	(0.009)	(0.010)	(0.009)	(0.008)
Age in mos.	-0.000	0.017***	-0.000	0.045***	0.016***	0.026***	0.014***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mother's age	-0.001*	0.000	0.000	-0.001	-0.001	-0.001	0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mother +primary	-0.003	-0.041**	0.008	0.019	-0.004	0.014	-0.006	-0.006
	(0.009)	(0.015)	(0.008)	(0.014)	(0.012)	(0.016)	(0.012)	(0.012)
Mean gov. lights '13	0.002***	-0.000	0.003**	0.001	-0.010***	-0.002	-0.005***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HH urban	0.001	-0.033*	0.029***	0.021	0.030**	0.007	0.011	0.021
	(0.008)	(0.014)	(0.008)	(0.012)	(0.011)	(0.014)	(0.012)	(0.011)
HH wealth index	-0.005	0.000	0.025***	0.003	0.018***	0.011	0.010*	0.006
	(0.004)	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
No. HH members	-0.000	-0.000	-0.003**	-0.001	-0.001	0.001	0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HH head gender	-0.017	0.035	-0.025	-0.004	0.003	0.005	-0.018	0.028
	(0.012)	(0.021)	(0.017)	(0.019)	(0.020)	(0.023)	(0.021)	(0.016)
Mother speaks Arabic	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Mother speaks Kurdish	0.007	0.113***	-0.013	-0.033	0.079***	-0.131***	-0.037*	-0.035*
	(0.013)	(0.024)	(0.019)	(0.021)	(0.019)	(0.023)	(0.017)	(0.016)
Mother speaks other lang.	0.045*	0.090	-0.001	-0.039	0.036	-0.065	0.019	0.017
	(0.022)	(0.054)	(0.039)	(0.047)	(0.040)	(0.045)	(0.042)	(0.037)

Observations	9542	6394	6393	6393	6394	6392	6393	6391
R squared	0.005	0.119	0.030	0.379	0.083	0.133	0.077	0.078
F statistic	496.049	478.122	477.585	478.234	478.829	478.892	479.265	480.433

Source: authors' calculations based on MICS 2018 and GDELT 2013-2018. Table continues on following page. Results correspond to Table 3, which presents the results for the coefficient of interest (predicted log event count). The instrument is the minimum distance between the child's governorate's centroid and the Syrian border. Standard errors are clustered at the MICS sample cluster level. Standard errors in parentheses. ***p<0.01, **p<0.5, *p<0.

	Other fruit/veg	Organ meat	Meat	Eggs	Fish	Beans/nuts	Cheese
Predicted log event count	-0.042***	0.001	-0.021	0.048***	-0.071***	-0.060***	-0.030**
	-0.012	-0.008	-0.011	-0.012	-0.009	-0.012	-0.011
Gender	-0.007	-0.008	-0.014	-0.014	0.008	-0.005	0.007
	(0.011)	(0.006)	(0.010)	(0.011)	(0.007)	(0.009)	(0.009)
Age in mos.	0.040***	0.007***	0.025***	0.033***	0.017***	0.022***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mother's age	-0.002*	0.000	-0.000	-0.001	0.000	-0.001	0.002*
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mother +primary	0.068***	-0.013	0.022	0.045**	0.017	0.018	0.004
	(0.016)	(0.009)	(0.013)	(0.015)	(0.010)	(0.014)	(0.013)
Mean gov. lights '13	0.000	-0.002***	-0.004***	-0.005***	-0.001	-0.004***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HH urban	0.027*	-0.016	-0.005	0.002	0.022*	0.009	0.030*
	(0.014)	(0.008)	(0.013)	(0.014)	(0.010)	(0.013)	(0.013)
HH wealth index	0.027***	0.009**	0.025***	0.020***	0.007	0.009	0.019***
	(0.006)	(0.003)	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)
No. HH members	-0.003*	0.002	-0.001	0.000	0.001	0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HH head gender	0.060*	0.009	0.000	0.038	0.027*	0.014	-0.014
	(0.024)	(0.013)	(0.021)	(0.023)	(0.014)	(0.021)	(0.020)
Mother speaks Arabic	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Mother speaks Kurdish	-0.095***	0.034**	0.017	-0.083***	-0.097***	-0.071***	-0.116***
	(0.024)	(0.013)	(0.022)	(0.024)	(0.014)	(0.020)	(0.020)
Mother speaks other lang.	-0.007	0.031	0.081	-0.008	-0.020	0.009	0.114*
	(0.051)	(0.030)	(0.043)	(0.049)	(0.023)	(0.042)	(0.051)
Observations	6394	6390	6393	6389	6386	6388	6379

R squared	0.258	0.045	0.156	0.275	0.076	0.086	0.109
F statistic	478.822	477.013	478.656	478.776	478.177	477.472	478.767

Source: authors' calculations based on MICS 2018 and GDELT 2013-2018. This is an extension of the table on the previous page.. Results correspond to Table 3, which presents the results for the coefficient of interest (predicted log event count). The instrument is the minimum distance between the child's governorate's centroid and the Syrian border. Standard errors are clustered at the MICS sample cluster level. Standard errors in parentheses. ***p<0.01, **p<0.5, *p<0.