Less is Too Much: Afghan Child Health and In Utero Exposure to Conflict

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The growing body of literature that supports Barker's (1990) fetal origins hypothesis by showing the negative effects of in utero shock exposure on child health and pregnancy and later life outcomes focuses on a wide range of shocks, from drought, weather, and natural disasters (Currie and Rossin-Slater, 2013; Kumar et al., 2016; Maccini and Yang, 2008; Molina and Saldarriaga, 2017; Torche and Kleinhaus, 2012), armed conflict (Akresh et al., 2014, 2012; Lee, 2014, 2017; Mansour and Rees, 2012; Minoiu and Shemyakina, 2012; Tsujimoto and Kijima, 2015; Valente, 2011), and mothers' stress factors (Camacho, 2008; Quintana-Domeque and Rodenas, 2014) - for an extensive review see Almond and Currie (2011).

In this study, I test this hypothesis using the Afghan National Nutrition Survey (NNS) 2013 provincial representative cross-sectional data. My analysis provides novel insights into how intrauterine exposure to protracted armed conflict[1] affects child health, an area that remains understudied. My work also differs substantially from that of Mansour and Rees (2012), a rare exception to this dearth, in that rather than estimating the effect of armed conflict on child health outcomes immediately after birth, I do so over a subsequent period using anthropometric measures taken at time of mother's interview by specialized personnel. A major advantage of this procedure is that such measures are generally more reliable than recalled pregnancy outcomes. I am also able to isolate persistent effects of in utero conflict exposure on child health, something that studies focused on birth outcomes cannot achieve.

One final strength is that the dynamics of the protracted Afghan conflict differ greatly from those in Palestine - as studies by Mansour and Rees (2012). In fact, protracted conflict are not characterized only by longevity but substantial contextual differences exists (ICRC, 2011). Over the course of the conflict in Afghanistan (from the 1979 start of the Afghan-Soviet war to today), both the local and international actors involved and the motives, modalities, and spatial distribution of the conflict have shifted radically, producing an accumulated disruption that has led not only to state fragility but to heavy degradation of infrastructure and general living conditions. Since the mid-2000s in particular, violence has gradually spread out to the north of the country, leaving virtually no Afghan province completely unaffected by conflict. On the one hand, this distribution poses serious methodological challenges for the researcher wanting to estimate the conflict's effects at a given point in time; on the other, it provides a valuable opportunity to calculate the short-term differential effects of conflict between households in areas of historically high violence intensity and those only affected in recent years.

Overall, in line with previous studies, I find a negative causal relation between in utero conflict exposure and child health. Additionally, by exploiting the different levels of long-term conflict among Afghan districts, I find heterogeneous effects of in utero conflict exposure between children born in districts of historically high and constant conflict intensity and those born in districts where violence is sudden and intermittent. That is, holding all other factors constant, those born in districts where conflict tends to be comparatively lower in the long-term are more likely to be negatively affected by increased violence while in utero. I attribute these heterogeneous effects to the fact that households living in environments of constant conflict have developed more effective coping strategies, whereas households in comparatively safer areas may be disadvantaged by their inexperience in mitigating the negative effects of the violence that has spread across the country in recent years. This assumption is supported by D'Souza and Jolliffe's (2013) finding, in their analysis of food price spikes' effect on Afghan household food security, of more muted negative effects for households in provinces with higher levels of conflict. They attribute these heterogeneous effects to the limited market integration in areas of higher conflict intensity. Although little is known about other mechanism driving these results, an emerging body of literature does isolate the relative positive effects of conflict, including the reinforcement of collective actions (Bellows and Miguel, 2009), solidarity links, and cooperative behaviors (Justino et al., 2013). My study contributes to the above-cited research stream by revealing the existence, at the subnational level, of heterogeneity in household abilities to cope with violent shocks according to the degree of their experience with the war-torn environment. I further explain these results by the fact that physical insecurity favors opium poppy cultivation and mitigates the overall negative conflict's impact on household wealth in district engaged in this illegal cultivation.

The remainder of my discussion unfolds as follows: Section 2 provides a brief contextual background, after which Section 3 describes the data and variable construction. Section 4 then outlines the methodology and explains its validity. Section 5 reports the results, and Section 6 concludes the paper. The Appendix presents full regressions' results and additional maps.

Background

Since the 1979 Soviet invasion until today, Afghanistan has suffered from almost uninterrupted conflict because even though the Afghan Islamic Republic was established a few years after Soviet withdrawal (1992), its very weak nature permitted the Taliban to impose its own regime beginning in 1996. As a reaction to the events of 9/11, the United States and NATO declared war on the Taliban and attacked Afghanistan in late 2001, leading to nationwide devastation, the loss of many civilian lives, and the displacement of many Afghans from their original communities (Barfield, 2010; Maley, 2009). As Figure 1 shows, the conflict has gradually grown in intensity, especially since 2004, two years after the fall of the Taliban and after the first phase of NATO withdrawal in 2012. Among the 10,582 events recorded between late 2001 and 2013, the Taliban were involved in 9,904. Most Taliban actions (9,445) have been against the official pro-government forces, although a relevant share (442) has also been directed at civilians. These events were spatially distributed in the south and south-east of the country, the area between the Syistan plateau and the Indus and Hindu Kush in Central and South Asia (Figure 2). Since 2004, however, violence by both the military and insurgents has spread across the country, with the presence of pro-government forces associated with a higher degree of violence but also with low-skilled job opportunities like construction, and the reception of aid from both official and private donors. One of the most noteworthy economic aspects is that following the first phase of NATO withdrawal in 2012, the GDP growth rate dropped from 14.4% in 2012 to 2% in 2013 (World Bank, 2015).

From a subnational perspective, however, the net effect of the conflict on Afghan households remains unclear, although households in historically safer areas may be disadvantaged not only by their inexperience with conflict but also by the lower amount of aid they receive. For example, Fishstein and Wilder (2012), in their qualitative study, report widespread dissatisfaction among such households that "violent places [have been] getting the bulk of the assistance, and that this funding imbalance [is] setting up perverse incentives" (p. 47). Hence, although various coping strategies are already in place among the Afghan population (Bove and Gavrilova, 2014), they may be more effective for households most used to cope with conflict (D'Souza and Jolliffe, 2013, p. 39). In particular, the households' involvement in the opium economy is often a matter of coping with the unfavorable environment. Previous work analyzing dynamics and effects produced by the opium economy on households' livelihoods have been able to isolate potential positive outcomes of this economy on both poor and rural households, as well as on the overall national economy (Buddenberg and Byrd, 2006; Goodhand et al., 2012; Thompson, 2006). However, opium economy related coping strategies should not to be seen as transitory or short-term, but they represent long-term responses to a war-torn environment which lacks of viable livelihood alternatives. It is estimated that in 2013, in face of the opium poppy net farm gate value of US$ 945 millions, the opiate economy was worth US$ 2.99 billions, roughly 15% of the national GDP (UNODC, 2013). What is undisputed is that Afghanistan is struggling to recover from the disruptive conflicts of recent decades of which the opium economy is both a cause and an outcome: over and beyond the enormous cost in human life, basic infrastructure has been bombed and destroyed, production systems are largely inefficient, and the country is characterized by a critical degree of political instability, physical insecurity, warlordism, and corruption (Giustozzi, 2007).

Data and Measures

This study employs a unique dataset that combines two primary sources: the National Nutrition Survey, 2013 (NNS), on child health information and the Uppsala Conflict Data Program Georeferenced Event Dataset 2.0 (UCDP GED 2.0) on district violence intensity. Once the number of fatalities was derived from the latter,

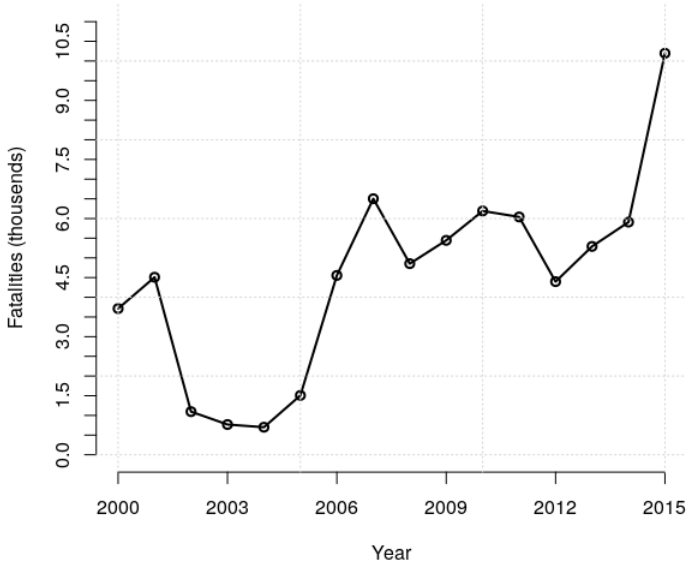

FIGURE 1 Total number of fatalities by year based on author computations using number of fatalities in thousands from UCDP GED 2.0.

they were assigned to each observation in the former by projecting each event's coordinates onto the AGCHO shapefile for the second administrative division (AGCHO, 2012). The study dataset itself was created by merging information for each child aged 0-59 months with that of the corresponding mother, household demographics, and socioeconomic variables. The control variables selected are those used in similar studies (e.g., Kumar et al., 2016 and Mansour and Rees, 2012) and those that best reflect the specific Afghan context. After deletion of implausible and missing values in both controls and the outcome variable, the final sample contains 16,962 children[2]. After these manipulations, the original proportions between urban and rural households, and among number of observations per province are preserved. The specific sources and collection methods for each of the two data types, as well as other relevant constructs, are described below.

Child health data Child health status, together with household socioeconomic information and mother characteristics, are taken from the Afghanistan National Nutrition Survey, 2013 (NNS), developed by Aga Khan University, Pakistan, in consultation with the Afghan Ministry of Public Health and UNICEF Afghanistan. The survey, which focused specifically on the Afghan population's nutritional situation and associated factors, was not seasonally representative but rather was administered between the second week of June 2013 and the end of October 2013, with collection activities suspended for 50 days to reflect changed eating behaviors during the month of Ramadan. A total of 17,339 households were interviewed with an average response rate of 94.44%, with security concerns given as the main reason for nonparticipation (Ministry of Public Health, Afghanistan, 2013). The study sample, which includes both urban and rural households and is representative of all 34

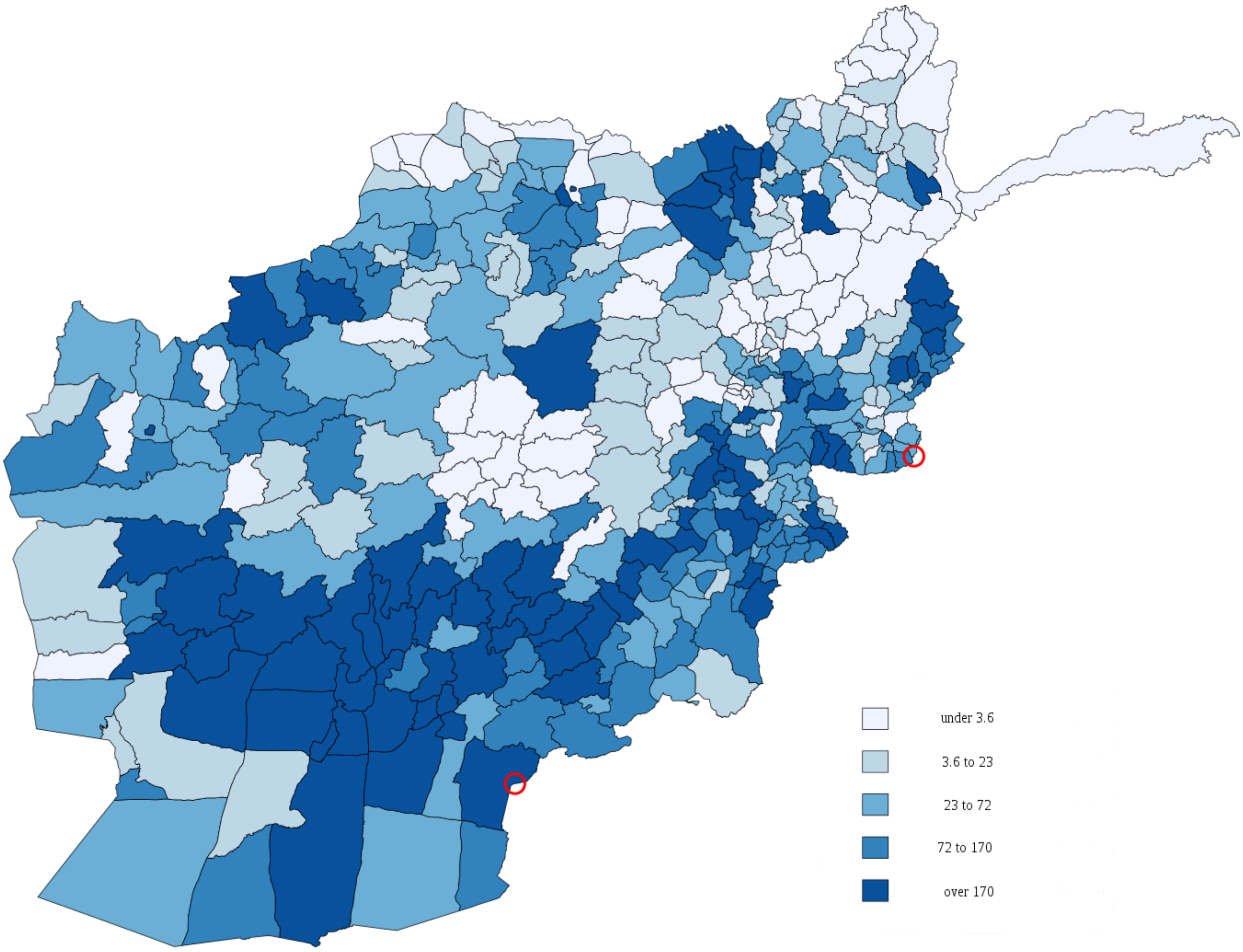

FIGURE 2 Fatalities by district (2001-2013) using quintile cuts, based on author computations using UCDP GED 2.0 data projected onto the AGCHO shapefile for second administrative division. The red circles in the south-west and south-east of the map, respectively, represent the Chaman (Kandahar) and Torkham (Nangahar) border crossings used in Section to compute the instrumental variable.

Afghan provinces, was obtained using a two-stage cluster sampling technique within the Afghan Central Statistics Organization sampling frame .

Among the health information, the NNS (2013) includes three anthropometric measures (height, weight and mid-upper arm circumference) collected for four target age groups: children aged 0-59 months, unmarried adolescent girls (10-19 years), women of reproductive age (15-49), and individuals over 50 years of age. To assure accuracy at the household level, anthropometric measures for a household's index mother (youngest woman of reproductive age) and index child (youngest child in the household) were validated through multiple measurements. The women's survey provides accurate information on reproductive history, including number of pregnancies, miscarriages, infant feeding practices, and health care access, but only as related to the latest born child.

Conflict data The data on violence intensity are drawn from the Uppsala Conflict Data Program Georeferenced Event Dataset 2.0 (UCDP GED 2.0), a human-coded dataset that lists events of organized violence disaggregated by type (state-based conflict, non-state conflict, and one-sided violence), temporally and spatially (Sundberg and Melander, 2013). The raw UCDP GED 2.0 contains events of fatal violence for both the African and the Asian continent for the period 1989-2014. For this study, I select only those referring to any type of organized violence within Afghan national borders in the time frame of September 2001 to December 2013. Each event is described by a set of characteristics, including the names of the actors involved and the number of related fatalities, as well as a measure of location identification precision. This last-mentioned characteristic specifies whether the coordinates refer to the exact event location; to a 25 km approximation from the actual event location; or to coordinates for the centroid of the second administrative division (district level), primary administrative division (province level), or country or international level. Only the events identifiable as occurring at least at the district level are retained in the final analysis, ruling out events aggregated at the country or province level or labeled as not clearly identifiable events. These data encompass 10,582 events with 47,349 fatalities of which 7,651 are reported to be civilians[3].

Outcome variable The outcome variable in this study is the weight-for-age z-score (WAZ) (underweight), which is widely used to assess the health status of young children under 5 years of age. This variable is constructed based on the WHO guidelines, and the final weight-for-age z-scores are computed using the R macro from the WHO Child Growth Standards (2011). The computations are based on WHO Multicentre Growth Reference Study data collected between 1997 and 2003 from a set of heterogeneous countries[4] to describe normal child growth in absence of disease and reared following healthy practices (WHO, 1999).

Variable of interest The main variable of interest, intrauterine violence intensity ($fat_{t=p_i}$), is approximated by the number of per capita[5] fatalities at the district level, measured for each child over the exact in utero period. As an additional control, I compute violence intensity right before the interview (fat_{t-1_i}) as the number of per capita fatalities in the 365 days before the interview. Finally, I also approximate long-term conflict intensity as the cumulative number of fatalities by district from late 2001 up until the interview date ($fat_{tot,d}$[6]). Figure 3 depicts the conflict intensity measures along a time line of relevant events.

Other relevant constructs In addition to computing a household wealth index by applying polychoric principal component analysis (PCA) to a set of 15 dummy and categorical variables describing ownership of assets and consumer durables[7], I also construct the Hunger Scale Index (HS) (cf. Ballard et al., 2011), and a dummy for whether the household was interviewed after the month of Ramadan. These above-mentioned variables capture the effects of recent food (un)availability and eventual weight loss from changed eating behaviors during Ramadan, respectively. Households that do not speak neither Dari or Pashto as their primary language are categorized as belonging to an ethnic minority. Additional controls are per capita

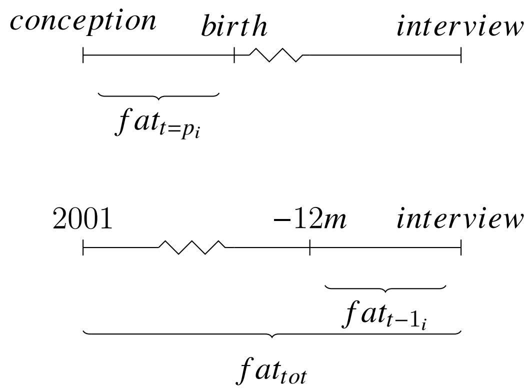

FIGURE 3 Time line of relevant events

aid by province, a proxy for economic activity, opium poppy cultivation and severity of natural disaster by district. The data on per capita provincial development assistance committed for 2013 is taken from the Development Assistance Database for Afghanistan, which is part of the National Budget and Aid Management System (DAD, Afghanistan, 2015). I proxy economic activity by district using NOAA (2013) data on stable night light intensity (cf. Henderson et al., 2012), recorded by the National Geophysical Data Center in 30 arc second grids with a value ranging from 0 (no light) to 63 (maximum light intensity). Keeping these data at their original scale, I merge them with the main dataset by projecting the information onto the AGCHO (2012) shapefile (see Figure A3). Information on per capita opium poppy cultivation by district are taken from the Afghanistan Opium Survey, 2013 (UNODC, 2013). Estimates of opium poppy cultivated area in hectares are obtained by employing remote sensing methodologies (for further details see UNODC, 2013, p.78). Finally, I draw information on natural disasters by district for 2013 from OCHA Afghanistan (2013) Natural Disaster Incidents Database (NDID), which provides information on type of incident, event location (district), precise date, number of injured and dead, and damaged or destroyed houses[8]. I compute the natural district intensity index by adding the number of damaged houses weighted by 0.5 with the number of houses destroyed[9]. Figure A2 in Appendix shows the spatial distribution of natural disasters among districts. Due to lack of information in the NNS (2013) on the household migration history I am not able to track the international and internal movements of each household. This limitations imply a potential for measurement error in the variable of interest and consequent biased estimates. I therefore exploit detailed information on household migration from the Afghanistan Living Condition Survey (2013/2014) (ALCS) (CSO Afghanistan, 2016) to compute for each Afghan province the probability that a random child aged 0-59 months in 2013 could had been born in a province different from that of residence at the time of interview (see table A3 in Appendix). Finally, I compute the overall incidence of maternal mortality for the period 2008-2013 using the Afghanistan Demographic Health Survey, 2015 (AfDHS) (CSO Afghanistan, 2015). This indicator is constructed as the count of each respondent's sisters died at age 15-49 in the period 2008-2013, excluding duplicates (i.e. respondents born to the same mother) and using survey sampling weights.

Descriptive statistics As shown in the Table 1, the average value of WAZ is -1.206 standard deviations, with 26.5% of the children classified as moderately underweight (WAZ <-2 s.d.) and 10% as severely underweight (WAZ <-3 s.d.). According to WHO standards, the presented prevalence of underweight (WAZ <-2 s.d.) among Afghan children in 2013 is classifiable as a public health concern of high severity (de Onis et al., 1997). The average fertility rate per woman in the sample is 5.289 pregnancies, and only 14.3% of the mothers are literate. On average each child was exposed to 14.8 fatalities during the gestation period, and to 11.9 in the 365 days before the interview, with both variables showing large variability (s.d. = 30.4 and 24.6 respectively).

The Empirical Model

The identification strategy of this study aims at estimating the effect of violent conflict experienced while in utero on later children's health outcomes (WAZ) using cross-sectional child-level data. Simple OLS inference that accounts for violence intensity at pregnancy without controlling for violent shocks experienced before the interview and right after birth could lead to biased results. When estimating the causal impact of in utero conflict exposure on child health for countries in protracted conflict is always challenging, it is crucial that any identification strategy be able to isolate the effect during pregnancy from that experienced in other periods. When conflict can be considered of exogenous nature and researchers are able to observe similar cohorts before and after the shock, they frequently achieve such isolation by using a difference in difference method (see Akresh et al., 2012; Camacho, 2008 and Valente, 2011). In the case of Afghanistan, however, this option is not viable because of both the protracted conflict in the country and its possible endogenous nature. In fact, as widely stressed in the literature, estimating the relation between health and nutrition outcomes and level of conflict risks the possibility of joint determination (see, e.g., Pinstrup-Andersen and Shimokawa, 2008 and Wischnath and Buhaug, 2014): on the one hand, conflict affects child health; on the other, household food insecurity which is correlated with child health may fuel conflict. Another possible source of bias is represented by the omission of food prices for which no data is available at the district or lower level[10]. In fact, I expect the multivariate OLS results to show strong evidence of bias in the coefficients of interest because when short-term conflict (fat_{t-1_i}) is excluded, the probable effect of recent conflict on current child health (Figure 4, top) is likely to cause biased estimates. This bias could not be corrected by including fat_{t-1_i} as an additional regressor, however, because of possible reverse causality between it and the outcome variable weight-for-age z-score (WAZ) and/or the omission of food prices (P_d) with which (fat_{t-1_i}) is likely to be correlated (Figure 4, bottom).

Given the above considerations, I estimate the proposed causal relation using 2SLS regressions with an instrumental variable capable of denoting conflict during pregnancy while simultaneously remaining independent of other potential confounding factors, allowing me to jointly solve for an omitted variables bias and reverse causality. The first and second stages of this IV estimation are expressed by equations 1 and 2, respectively:

TABLE 1 Characteristics of the main sample

Variable	Mean	St. Dev.
WAZ	−1.206	1.384
WAZ <-2	0.265	0.441
WAZ <-3	0.100	0.300
child age (months)	26.925	16.305
child sex (male)	0.490	0.500
$\mathrm{fat}_{\mathrm{t=p}}$	14.779	30.400
$\mathrm{fat}_{\mathrm{t\text{-}1}}$	11.870	24.564
born in 1st quarter (Spring)	0.301	0.459
born in 2nd quarter	0.305	0.461
born in 3rd quarter	0.177	0.382
born in 4th quarter	0.217	0.412
interview taken after Ramadan	0.318	0.466
mother age at pregnancy (years)	27.296	6.848
mother BMI	22.995	4.078
mother is literate	0.143	0.350
number of pregnancies	5.289	2.883
mortality	0.177	0.202
urban	0.129	0.335
wealth index (PCA)	0.007	1.118
dependency ratio	134.499	85.747
ethnic minority	0.244	0.430
HS (no-hunger)	0.897	0.304
HS (mild-huger)	0.097	0.296
HS (severe-hunger)	0.005	0.075
head sex (male)	0.936	0.244
head is literate	0.410	0.492
head is married	0.912	0.284
stable night $\mathrm{light}_{\mathrm{d}}$	7.254	9.035
disaster $\mathrm{index}_{\mathrm{d}}$	3.964	12.716
poppy $\mathrm{(ha)}_{\mathrm{d}}$	542.9	2516.439
$\text{non-poppy-free}_{\mathrm{d}}$	0.357	0.479
committed $\mathrm{aid}_{\mathrm{p}}$ (1,000 USD)	30,900	27,533.9
number of districts	290	

Notes: The sample includes 16,962 children aged 0-59 months and 11,335 households. No values are missing for any covariates. The number of fatalities relative to the in utero period ($\mathrm{fat}_{\mathrm{t=p}}$) and the 365 days before interview ($\mathrm{fat}_{\mathrm{t\text{-}1}}$) are reported in absolute values. The subscripts $_{\mathrm{p}}$ and $_{\mathrm{d}}$ refer to variables computed at the province and district level, respectively. All tables had been created using the stargazer package for R (Hlavac, 2015)

$$fat_{t=p_i} = \alpha_1 + \alpha_2 Z_i + \delta_{\mathrm{c}}\mathrm{CC_i} + \delta_{\mathrm{h}}\mathrm{HC_i} + \delta_{\mathrm{m}}\mathrm{MC_i} + \delta_{\mathrm{p}}\mathrm{PD} + \eta_i \tag{1}$$

$$WAZ_i = \beta_1 + \beta_2 \widehat{fat_{t=p,i}} + \gamma_{\mathrm{c}}\mathrm{CC_i} + \gamma_{\mathrm{h}}\mathrm{HC_i} + \gamma_{\mathrm{m}}\mathrm{MC_i} + \gamma_{\mathrm{p}}\mathrm{PD} + \epsilon_i \tag{2}$$

where $fat_{t=p_i}$ and $\widehat{fat_{t=p_i}}$ are a measure of conflict intensity for child i at in utero

$$WAZ_i = \alpha + \beta_1\ fat_{t=p_i} + \sum_{k=2}^{N} \boldsymbol{\beta}_k \mathrm{X_i} + \epsilon_i$$

$$fat_{t-1_i}$$

$$WAZ_i = \alpha + \beta_1\ fat_{t=p_i} + \beta_2\ fat_{t-1_i} + \sum_{k=3}^{N} \boldsymbol{\beta}_k \mathrm{X_i} + \epsilon_i$$

$$P_d$$

FIGURE 4 Bias from the omission of short-term conflict and price levels. Full stretch and dashed two-ways arrow represent correlation and reverse causality, respectively.

time $t = p_i$ in district d and the corresponding predicted values from the first stage in equation 1, respectively. Z_i is the instrumental variable (described below), and CC is a vector of child characteristics including age, sex, birth season, and a dummy for interviewed after Ramadan. Similarly, HC is a vector of household characteristics including dummies for married head of household, literate head of household, urban household, and belonging to an ethno-linguistic minority, as well as dependency ratio, wealth index, and hunger scale index. MC contains mother BMI, a dummy for mother's literacy, mother's age at time of pregnancy, number of pregnancies, and mortality rate[11]. PD denotes a set of provincial and district characteristics in the year of interview; namely, provincial aid, district economic activity, district opium poppy cultivated area, and district natural disasters severity. Lastly, η_i and ϵ_i are an idiosyncratic individual error terms from the first and second stage respectively. For all models, survey sampling weights are used, and robust standard errors clustered at the district level are computed. First stage F-statistics are computed adjusting the standard errors for the clustered structure of the data.

Instrumental variable The levels of physical insecurity in the Afghan conflict are highest close to the Afghan-Pakistani border, also called the Durand Line, where approximately 1,100 kilometers of the total 1,700 kilometer border area are uncontrolled and thus ideal for weapon and drug smuggling. This openness leads to frequent clashes between insurgents and Afghan, Pakistani, or NATO officials, especially along the Torkham and Chaman crossings, which connect Jalalbad to Peshawar and Kandahar to Quetta, respectively (circled in red in Figure 2). Hence, in constructing my instrument, I assume that conflict at the country level varies according to both the actual violence intensity in a specific period at the two crossing points and the proximity to these latter[12]. After first computing the minimum true distance[13] between each district center of mass and the selected border crossings on the Durand Line, I then count the number of fatalities during each child's specific in utero period for the districts in which Chaman and Torkham are located; namely, Spin Boldak (Kandahar) and Momand Dara (Nangahar). One major advantage of this procedure is that the two districts selected show high variability in the number of fatalities during different years and seasons. The final instrument takes the following form:

$$Z_i = \frac{Min\ dist_d}{fat\ crossings_{t=p_i}} \tag{3}$$

where $Min\ dist$ is the distance from each district d to the closest border crossing, and *fat crossings* is the number of fatalities in the districts to which the crossing points belong administratively during the period when each child i was in utero ($t = p_i$). Higher values of Z indicate lower conflict intensity in a particular district during a specific period, either because of its greater distance from the conflict's hotspots or the relative general low intensity of fighting during that time, as measured by $fat\ crossings$, or both jointly. It must be noted that this instrument is able to capture variability both in space and time, reducing the possibility of being correlated with conflict in periods different than the one in utero. In fact, this instrument correlates to the measure of conflict at pregnancy (the Pearson's correlation coefficient statistically significant at $\alpha = 5\%$ equals -0.12), however, Z is valid only if it also satisfies the exclusion restriction (i.e., it must affect child health only through conflict during pregnancy). As stated above, the instrument must not capture conflict variation in periods other than the pregnancy. In fact, the Pearson correlation coefficients for conflict in the year before interview (fat_{t-1_i}) and the instrument Z equals 0.03. Moreover, I argue that the instrument has no effects on child health via transmission channels different than conflict. The districts of Spin Boldak and Momand Dara play no important role on child health except for the fact that are the major entry points for both Taliban's and NATO's insurgent/soldiers and weapons' trafficking. Taking the line distances among points eliminates any concern about picking up the effects of road infrastructure. This supposition also holds for the natural environment in that altitude, climate and occurence of natural disasters are exogenous to the distance from the selected border crossings (see Figures A4 and A2 in Appendix). The instrument also correlates little with wealth (0.03), aid by province (0.01), or economic activity by district (0.007), see Figure A3 in Appendix. Admittedly, it could be argued that Pashto speakers are heavily concentrated close to the selected border crossings, meaning that common group characteristics may invalidate the instrument. Given that Pashto speakers make up the large part of the Taliban movement, perhaps as much as 95%, this spatial correlation is not anomalous (Giustozzi, 2010); however, the common characteristics for Pashto speaking households are not likely to have any subsequent effect on child health. That is, although Pashtuns share a common cultural heritage and a strong feeling of ethnic belonging; in practice, they cannot be considered a homogeneous ethnic group. On the one hand, wars, alliances, intermarriages, migrations, common religion, and shared culture have led to their constant integration with other groups over the centuries, making it unlikely that Pashto speakers share sufficient common genetics to affect the dependent variable (Dupaigne, 2012). On the other hand, Pashto speaking households differ strongly in socioeconomic characteristics and livelihood strategies, with some living in urban contexts and some in rural areas, while others being nomadic or semi-nomadic (Kuchi).

TABLE 2 Falsification Tests for the IV (OLS)

	Dependent variable:				
	WAZ	Wealth	Debt/ Income	Debt/ Wealth	Debt/ Sheeps
	(1)	(2)	(3)	(4)	(5)
Z	0.006	0.001	−0.0002	13.585	−2.833
	(0.004)	(0.003)	(0.0003)	(18.878)	(11.925)
Observations	7,453	11,335	10,413	20,000	5,650
R^2	0.069	0.480	0.021	0.024	0.100
Adjusted R^2	0.066	0.480	0.018	0.021	0.094
Residual Std. Error	16.744	11.335	66.959	9,228,390	786,095
F Statistic	***	***	***	***	***

Notes: All models are computed using survey sampling weights. Controls: child age, sex, birth season, mother's BMI, mother's age at time of pregnancy, number of pregnancies, mortality rate, dependency ratio, hunger scale index, wealth index, district economic activity, district natural disasters, and provincial aid, and dummies for mother's literacy, interviewed after Ramadan, head of household marital status, head of household literacy, urban household, and ethnic minority. Robust standard errors clustered at the district level in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Validity of the instrument Given the possible transmission channels that would invalidate the instrument, I jointly test the assumptions above by constructing two set of falsification tests (cf. Pizer, 2015) and a two place tests. First, I use a subsample of 7,453 children whose districts experienced no fatalities during the in utero period but in part did experience them at other times to estimate the instrument's (Z) direct effect on the outcome variable (WAZ) while controlling for the full set of regressors from the main model (model (1) in Table 2). Moreover, I estimate the instrument's effect on household wealth which should not have been affected by conflict intensity during the last pregnancy but might be correlated with potential instrument confounders like conflict levels at time of interview (see model (2) in Table 2). In this setting, if the instrument correctly explains conflict intensity during pregnancy but not in other periods, it should have no effect on both child health and household wealth.

Second, given the protracted nature of the Afghan conflict, it may be possible that households self-selected closer to the Afghan-Pakistani border according to their degree of risk aversion. In order to exclude the non-random nature of the instrument into respect to the latter selection by leveraging 2014 ALCS data (CSO Afghanistan, 2016) I identify several proxies for risk aversion (validated in Brown et al. and adapted for the case of Afghanistan), namely value of debt over annual income, wealth index (assets), or number of sheep (rural assets), and I estimate the potential effect of the instrument on these latter.

If the instrument's coefficients in all falsification tests are not statistically significant, the exclusion restriction cannot be rejected. In fact, as Tables 2 and 2 show, the instrument coefficient is never statistically significant, which further confirms the instrumental variable's validity.

Finally, in Table 3, I run a set of first-stage placebo tests where measures of conflict in periods different than pregnancy (i.e. conflict one year before interview and in the period 2001-interview date) are regressed against the full set of controls of the main model with the addition of the instrument (models (1) and (2)). Results of these placebo tests show that the instrument is not able to explain a statistically significant portion of variability of conflict intensity in periods different from the one in utero. In fact, only in model (3), when conflict during pregnancy is used as the dependent variable –the actual first-stage regression for the models presented below– the instrument coefficient shows high statistically significance.

TABLE 3 Effects of instrument on conflict in different points in time (First-Stage OLS)

	Dependent variable:		
	fat_{t-1}	$fat\ all$	$fat_{t=p}$
	(1)	(2)	(3)
Z	−0.008	−0.020	-0.038^{***}
	(0.012)	(0.013)	(0.010)
Observations	16,962	16,962	16,962
R^2	0.048	0.034	0.058
Adjusted R^2	0.047	0.032	0.056
Residual Std. Error	35.485	53.693	44.450
F Statistic	***	***	***

Notes: All models are computed using survey sampling weights. Model (2) uses all the total number of fatalities for the period 2001-interview date minus those experienced during pregnancy as dependent variable. Controls: child age, sex, birth season, mother's BMI, mother's age at time of pregnancy, number of pregnancies, mortality rate, dependency ratio, hunger scale index, wealth index, district economic activity, district natural disasters, and provincial aid, and dummies for mother's literacy, interviewed after Ramadan, head of household marital status, head of household literacy, urban household, and ethnic minority. Robust standard errors clustered at the district level in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Results

Main Results Table 4 reports the OLS estimations of the effect of in utero conflict exposure on the health (WAZ) of children aged 0-59 months, showing only the coefficients related to the conflict variables (full results in Table A1). The coefficient for conflict intensity during the in utero period ($fat_{t=p_i}$) is positive but not statistically significant (model 1), an outcome that does not change when conflict intensity in the preinterview year (fat_{t-1}) is included as an additional regressor (model 2). As stressed in Section , models (1) and (2) in Table 4 may suffer from omitted variable bias arising from the exclusion of price levels at the interview period, which are likely to be correlated with both current child health and present conflict levels. This omission would explain the positive (albeit not significant) association between child health and in utero conflict detected in all models.

TABLE 4 Effects of in utero conflict exposure (OLS)

	Dependent variable:				
	WAZ			WAZ <-2SD	WAZ <-3SD
	(1)	(2)	(3)	(4)	(5)
$fat_{t=p_i}$	0.005	0.003	-0.194^{**}	0.104^{***}	0.040^{***}
	(0.006)	(0.007)	(0.086)	(0.032)	(0.015)
fat_{t-1_i}		0.004			
		(0.013)			
Observations	16,962	16,962	16,962	16,962	16,962
Residual Std. Error	18.889	18.890	20.594	7.318	4.243
R^2	0.053	0.053	–	–	–
Adjusted R^2	0.051	0.051	–	–	–
F Statistic	***	***	–	–	–
First-stage F-stat	–	–	14.826	14.826	14.826
Wu-Hausman	–	–	***	***	***

Notes: All models are computed using survey sampling weights. Specifications (3)-(5) are estimated using 2SLS (specifications (4) and (5) with IV linear probability models). Controls: child age, sex, season of birth, mother's BMI, mother's age at time of pregnancy, number of pregnancies, mortality rate, dependency ratio, wealth index, hunger scale index, district economic activity, district natural disasters, district opium poppy, and provincial aid, and dummies for mother's literacy, interviewed after Ramadan, head of household marital status, head of household literacy, urban household, and ethno-linguistic minority. First stage F-statistics adjusted for the clustered structure of the data. Null for Wu-Hausman test: β_2 2SLS is consistent. Robust standard errors clustered at the district level in parenthesis; *p<0.1; **p<0.05; ***p<0.01.

Table 4 in specification (3)-(5) then shows the coefficients of interest for the IV regression models, which reveal a negative and statistically significant causal relation between in utero conflict exposure and child health. More specifically, an additional fatality per ten thousand inhabitants during pregnancy causes a 0.20 standard deviation loss in WAZ. In the linear probability models 2 and 3, a positive coefficient sign represents a higher probability of being underweight. The estimates for these models reveal that the probability of being moderately ($WAZ < -2$) and severely underweight ($WAZ < -3$) increases by 10.2% and 4%, respectively, with each extra fatality per ten thousand inhabitants occurring during the in utero period.

Heterogeneous Effects Within countries in protracted conflict, substantial difference exists in the actual frequency at which shocks occur at the subnational level. Hence, in regressions in Table 5 I test for homogeneous effects among households according to a long-term measure of conflict intensity, measured as per capita fatalities between late 2001 and the interview ($fat_{tot,d}$). To do so, I construct a dummy taking on the value one for districts in which the long-term conflict intensity is above the distribution's median, and zero otherwise (see equation 4).

$$\text{high conflict}_d = \begin{cases} 1, & \text{if } fat_{tot,d} > \widetilde{fat_{tot,d}} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where $\widetilde{fat_{tot,d}}$ is the median of the $fat_{tot,d}$ distribution.

Because the interaction terms are endogenous, their estimation exploits the exogenous interaction between the Z instrument and the exogenous dummy variable ($high\ conflcit_d$) as additional instrument in the first stage of the 2SLS regressions.

TABLE 5 Heterogeneous effects of in utero conflict exposure (IV)

	Dependent variable:		
	WAZ	WAZ <-2SD	WAZ <-3SD
	(1)	(2)	(3)
$fat_{t=p}$	−0.713**	0.298**	0.086
	(0.338)	(0.133)	(0.368)
$high\ conflict_d$	−0.192	0.060	0.012
	(0.169)	(0.067)	(0.027)
$fat_{t=p} * high\ conflict_d$	0.688**	−0.260*	−0.062
	(0.339)	(0.134)	(0.056)
First-stage F-stat (Z)	13.241	13.241	13.241
First-stage F-stat (I)	22.879	22.879	22.879
Wu-Hausman	***	***	***
Observations	16,962	16,962	16,962
Residual Std. Error	21.007	7.176	4.171

Notes: All models are computed using survey sampling weights; specification (2) and (3) are estimated using IV linear probability models. Controls: fatalities 365 days before interview, child age, sex, season of birth, mother's BMI, mother's age at time of pregnancy, number of pregnancies, mortality rate, dependency ratio, wealth index, hunger scale index, district economic activity, district natural disasters, district opium poppy, and provincial aid, and dummies for mother's literacy, interviewed after Ramadan, head of household marital status, head of household literacy, urban household, and ethno-linguistic minority. I refers to the interaction term of each regression. Robust standard errors clustered at the district level in parenthesis. First stage F-statistics adjusted for the clustered structure of the data. Null for Wu-Hausman test: β_2 2SLS is consistent; *p<0.1; **p<0.05; ***p<0.01.

Table 5 shows the interaction terms' coefficients differing significantly from zero and with signs opposite to the main effects for $fat_{t=p_i}$ in all specifications, except in model 3[14], signaling that heterogeneous effects are in place according to the households' long-term experience of conflict. In particular, holding all other factors constants, the negative effect on child health of an extra fatality per ten thousand inhabitants during the in utero period is lower for children born in comparatively higher conflict intensity districts[15]. Nonetheless, households affected by conflict must not be regarded as impotent actors (Zetter and Verwimp, 2011); rather, they learn and enact mitigation strategies capable of partly offsetting the consequences of the harmful environment in which they live. Households whose experience of conflict is more sudden and more intermittent may in fact be less prepared to cope with the immediate negative outcomes of these shocks. Indeed, research on this aspect finds that experience of conflict itself, at different degrees and in varying contexts, may reinforce collective action (Bellows and Miguel, 2009), solidarity links, and cooperative behaviors while producing different perceptions of assets (Justino et al., 2013). My findings are also in line with previous research analyzing the causal relations in Afghanistan between food price spikes and household food security. For example, D'Souza and Jolliffe (2013) find that households in provinces with higher versus lower levels of conflict experience âĂIJmore muted declines in food securityâĂİ because of increased food prices (p. 42).

Mechanism Different transmission channels that can affect early child health through in utero conflict exposure exist. In the Afghan context, the most relevant are pre- and post-partum health care access, household wealth, and stress experienced by mothers during and immediately after pregnancy. However, several limitations exist when assessing the effect of conflict on some of these channels. First, the NNS (2013) does not provide any information on mother's experienced stress. Second, despite the NNS (2013) does ask questions about health care practices during and after pregnancy, the lack of precise information on the index mothers' date of last pregnancy prevents me from testing the conflict's effect on these latter because the high number of miscarriages means that the latest child born need not correspond to last pregnancy date. Moreover, the availability of these information for the sole index mothers would cause sample selection because of the exclusion of other women from the study sample.

I thus estimate conflict's effect on household wealth, a strong conflict-to-health transmission channel, using the number of per capita fatalities in the 365 days before interview (fat_{t-1_i}) as a measure of short-term conflict. Given the cumulative process through which household wealth is generated, the omission of current price levels is unlikely to produce substantial bias in these estimates, so simple OLS models suffice. As Table A2 in Appendix shows, the violence experienced by the households in the year before interview (fat_{t-1_i}) has a negative and statistically significant effect on household wealth (model 1). Model 2 then tests for homogeneity in the conflict's short-term effect for household's living in high versus low long-term conflict intensity districts. In line with the analysis for the main dependent variable of this study (WAZ), results show an overall negative and statistically significant effect of conflict on household wealth and positive interaction effect, signaling once again the comparatively greater ability of households exposed to conflict for longer periods to offset violence's negative impact.

The mechanism behind these results is manifold. A possible explanation may lie in the ongoing dynamics between levels of conflict and illegal cultivations of opium poppy. That is, higher levels of conflict favor opium poppy cultivation by reducing the risk of eradication. Drug eradication teams report to face great security threats which often make them unable to successfully carry out eradication (e.g., 143 and 89 personnel were respectively killed and injured during the eradication activities in 2013 UNODC, 2013). Moreover, the UNODC reports that in 2013, compared to the previous year, opium poppy eradicated hectares decreased by 24%, whereas killed personnel increased by 40%.

I thus explicitly test for homogeneous effects of conflict intensity in both the short (fat_{t-1_i}) and long-term ($high\ confict_d$) on household wealth according to the per capita opium poppy cultivated area in hectares per district in the year of interview ($poppy_{ha,d}$), and alternatively, interacting the measures of conflict intensity[16] with a dummy taking on a value of one if in a given district opium poppy has been cultivated in 2013, and zero otherwise (equation 5).

$$\text{non-poppy free}_d = \begin{cases} 1, & \text{if } poppy_{ha,d} \geq 1\ ha \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

It must be noted that estimating the effect of opium poppy cultivation on household wealth does not pose concerns of bias due to reverse causality, especially if the former is measured at the district level. In fact, as stated by the UNODC (2008) in regard to Afghanistan, there is not evidence that the poorest farmers are more likely to cultivate opium poppy. On the contrary, existing research highlights factors such as the presence of insurgents, under-resource national government, corruption and difficulties in accessing to reliable and sustainable agricultural markets (UNODC, 2015) to be the key determinants of drug production.

Models 3 to 5 in Table A2 in Appendix show an overall negative effect of different measures of conflict on households living in non-poppy free districts. However, everything else constant, higher conflict intensity produce more muted negative effects on wealth for households living in non-poppy free districts. In particular, model 3 and 4 show positive effects for interactions between the dichotomous variable defining non-poppy free districts and conflict, in the short and long-term respectively. Finally, model 5 further confirms the robustness of these positive effects using the interaction between the long-term measure of conflict ($high\ conflict_d$) and per capita opium poppy cultivated area in hectares ($poppy_{ha,d}$). Results in this section highlight the complex and counter intuitive inter linkages among conflict, opium economy and development already discussed in previous studies. Although, the negative effects of the Afghan opium economy are evident (e.g., wide spread opium addiction and related deaths), Goodhand et al. (2012), for example, state that regarding it as just detrimental for development oversimplifies the actual dynamics, on the contrary, among the others, there are positive outcomes of the drug economy. Increases in employment and wages, and better access to credit in rural areas (Thompson, 2006), currency stabilization and greater national liquidity (Buddenberg and Byrd, 2006) are the main channels through which the drug business contributes ameliorating the condition of rural households. Moreover, counter-narcotics policies (e.g., eradication) may inadvertently hindered socio-economic conditions of the poorest, increasing profits of large landowners and traffickers to the detriment of the former (Goodhand et al., 2012).

Robustness of the analysis The identification strategy of this study, by employing a 2SLS estimation strategy, solves for biases due to omitted variables, reverse causality, and measurement errors. However, here after I discuss in detail the possible sources of biases and the reasons why these are of no concern for this study. Because families living in conflict areas may prefer to have more or less children and/or experience higher offspring mortality rates, selective fertility and mortality are potential sources of bias that could lead to a nonrandom sample. If the strongest children are more likely to survive, then the true negative effects of violence intensity will be understated if fertility in conflict areas is higher or lower than it would have been in the absence of conflict, leading to negative or positive selection. I therefore control for these potential sources of bias by including both the number of pregnancies and mortality rate in the regressions (cf. Kumar et al. (2016)). At the same time, the lack of information on each child's actual birth location (versus the assumed match with residency), in cases of birth district misidentification, could cause measurement error-induced bias. Although this bias is corrected by the 2SLS estimation strategy employed, by exploiting representative (internal and international) provincial-level migration data from the ALCS (2013/2014) I compute the probability that a random child aged 0-59 months in 2013 could have been born in a province different from that of residency at the time of interview (Table A3). Overall, only 1% of this children migrated from province of birth. I therefore judge the risk of bias due to birthplace misidentification to be marginal for this sample, especially as excluding observations from provinces with a comparatively higher proportion of migrated children (2 to 5.1 per cent) does not change the results. Lastly, the estimates presented in this study remain unbiased despite the fact that 2,962 children, for which information on mother characteristics were missing, were dropped from the final study sample. These missing information relate to motherless children, mothers who refused to participate in the women's dedicated module of the survey, or not present in the household at the time of interview. Although it may be argued that the exclusion of these observations from the study sample may partly correlate with both the outcome and the regressor of interest, the exogeneity of the instrument (as shown in Table 2) assures unbiasedness in the estimates, as it is correlated only to the conflict intensity at each specific in utero period and not to general conflict levels. Moreover, Figure A1 in Appendix shows the prevalence of maternal mortality by province (2008-2013), computed as the proportion of women aged 15-49 at time of death overall the total number of women per province. No clear pattern among the distance from the two selected conflict hot-spots and incidence of maternal mortality is shown. In fact, risk of maternal mortality is not only due to high levels of physical insecurity, but also to wide spread poverty, and occurrence of natural disasters. Finally, all the results reported are robust when substituting district/province controls in levels with provincial dummies fixed effects. However, due to the presence of multicollinearity when the latter are included in the model (detected by high VIF values), as in D'Souza and Jolliffe (2013), I present only the results employing district/province controls in levels.

Conclusions

This study not only makes a useful contribution to the stream of literature investigating Barker's fetal origins hypothesis but is the first to test the persistent effect of armed conflict during pregnancy on early child health for the case of countries in protracted conflict. In particular, by applying a 2SLS identification strategy to Afghanistan NNS (2013) data for a cross-sectional subsample of children aged 0-59 months, I show that in utero conflict exposure, measured as the per capita number of fatalities per district, has strong detrimental effects on child health.

In particular, and in contrast to studies that focus only on relatively short conflicts, this analysis assesses the heterogeneous effects of short-term conflict on child health based on the level of conflict experienced in the long-term. By doing so, it demonstrates that although armed conflict always has net detrimental effects on child health, households differ substantially in the effectiveness of the coping mechanisms they enact based on the degree of their experience in offsetting shocks, which in turn depends on the frequency at which these shocks occur. In other words, households that are most exposed to violent environments may be better able to counterbalance the effects of short-term conflict. These heterogeneous effects and the empirical evidences in their support highlight the need to carefully shape policies in the light of the complex dynamics among conflict, politics, opium economy and development. Nonetheless, the net effects of frequent shocks are context specific ad vary according to type of shock, intensity, and coping strategies enacted, implying that the results found in this study for Afghanistan may not be generalizable to other countries. Hence, future research into the coping strategies of, and the negative effects on, households stressed by frequent shocks should aim at identifying the mechanisms underlying their ability to mitigate negative shocks based on experience gained in a particularly unfavorable environment.

In addition, given previously mentioned evidence of conflict's ability to influence collective actions (Bellows and Miguel, 2009), solidarity links, cooperative behaviors, and perception of assets (Justino et al., 2013), and, the counter intuitive dynamics among the drug economy, conflict and development outcomes (Buddenberg and Byrd, 2006; Goodhand et al., 2012; Thompson, 2006) future studies should investigate the differential effects and determinants of household mitigation strategies within countries in protracted conflict such as Afghanistan which provide a particularly valuable opportunity for identifying and understanding these mechanisms.

Notes

[1]In this paper, I use the terms 'conflict', 'violence intensity', and 'physical insecurity' interchangeably and as referred to the number of fatalities at a specific period and geographical level.

[2]Missing data were handled using list-wise deletion, with 2,962 observations dropped because of missing information on mother characteristics.

[3]Opting for higher precision in the geolocalization does not significantly reduce the number of events. Including observations with province-level precision only increases the number of fatalities to 48,062 (+1.48%).

[4]Brazil, Ghana, India, Norway, Oman and the USA.

[5]District population in 10 thousands.

[6]For the variable $fat_{tot,d}$ I use the $_d$ (district) subscript because, despite the variable is computed considering the exact date of interview, and thus should vary among individuals, this source of variability is only marginal for long-term computations.

[7]The categories used for computing the wealth index are ownership of a bicycle, motorcycle, car, television, telephone, mobile phone, sewing machine, washing machine, refrigerator, computer, and livestock and availability of electricity (in the dwelling), house building materials, and safe water (at or immediately close to the dwelling).

[8]The NDID comprise information of occurrence and severity of earthquakes, floods and flash floods, landslides, extreme winters, and avalanches.

[9]The analytical results are robust to alternative specifications of the natural disasters variable.

[10]Additional sources of bias, including selective mortality, fertility, and migration, are discussed in Section , Paragraph .

[11]Mortality rate is computed for each mother

as the sum of dead children and miscarriages over the total number of pregnancies.

[12]The importance of the selected border crossings in determining the overall level of conflict in Afghanistan is further confirmed by the U.S. Army's concern on these areas. In fact, on April the 13th 2017, during an operation against Daesh militia with the aim to destroy an intricate net of bunkers and tunnels, the U.S. Air Force dropped its GBU-43/B Massive Ordnance Air Blast (also known as the Mother of All Bombs) on the Aichin district (Nangahar), approximately only 40 km from the Torkham border crossing.

[13]The distances are computed as Euclidean distances only taking into account for Earth curvature.

[14]In model 3, the failure in detecting any statistical significant effect of conflict intensity on child health may be due to the low number of children severely underweight (10%).

[15]The signs of the interaction coefficients are robust to different specifications of the variable high conflict$_d$, for example, classifying as high conflict intensity districts those in the two or three highest quintiles of the distribution of long-term conflict respectively.

[16]Note that the alternative inclusion of these variables in the models in Table A2 in Appendix is justified by the risk of multicollinearity. In fact, the measure of long-term conflict intensity ($high\ confict_d$) comprises the fatalities count in the short-term (fat_{t-1_i}).

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Appendix

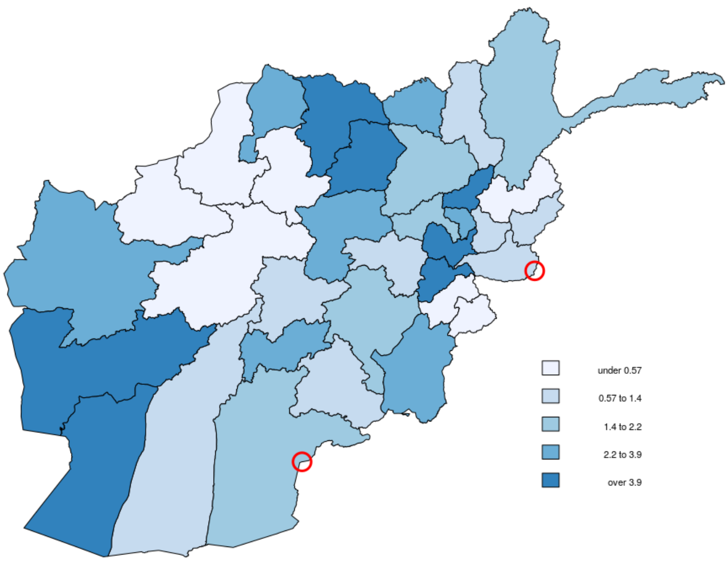

FIGURE A1 Proportion of dead women of reproductive age (15-49) by province every 1,000 women (2008-2013), quintile cuts. Author's computations on provincial representative AfDHS, 2015 data (CSO Afghanistan, 2015). Estimates based on the count of each respondent's sisters died at age 15-49 in the period 2008-2013, excluding duplicates (i.e. respondents born to the same mother) and using survey sampling weights. The red circles in the south-west and south-east of the map, respectively, represent the Chaman (Kandahar) and Torkham (Nangahar) border crossings used in Section to compute the instrumental variable.

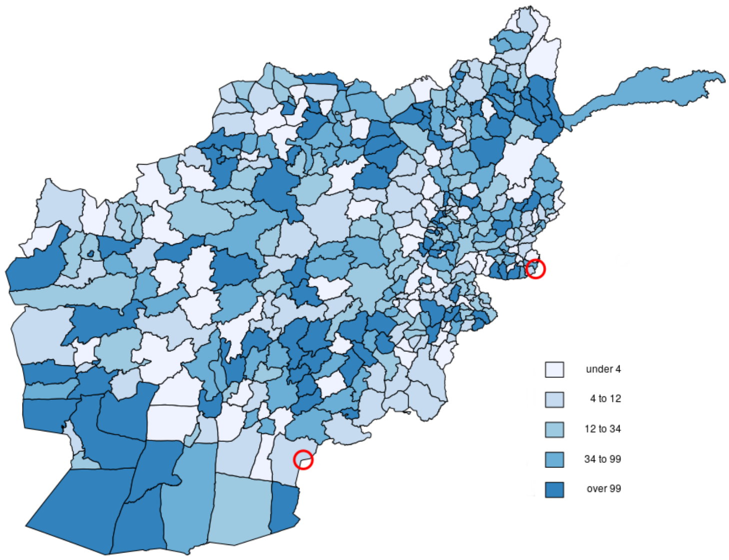

FIGURE A2 Natural disasters index per district, quintile cuts. Author's computations on data taken from Natural Disaster Incidents Database (OCHA Afghanistan, 2013). The natural disasters index is computed by adding the number of damaged houses weighted by 0.5 with the number of houses destroyed. Natural disasters considered are earthquakes, floods and flash floods, landslides, extreme winters, and avalanches. The red circles in the south-west and south-east of the map, respectively, represent the Chaman (Kandahar) and Torkham (Nangahar) border crossings used in Section to compute the instrumental variable.

FIGURE A3 Afghanistan average visible stable lights (2013), based on author's computations of images and data provided by the U.S. Air Force Weather Agency's (NOAA, 2013).

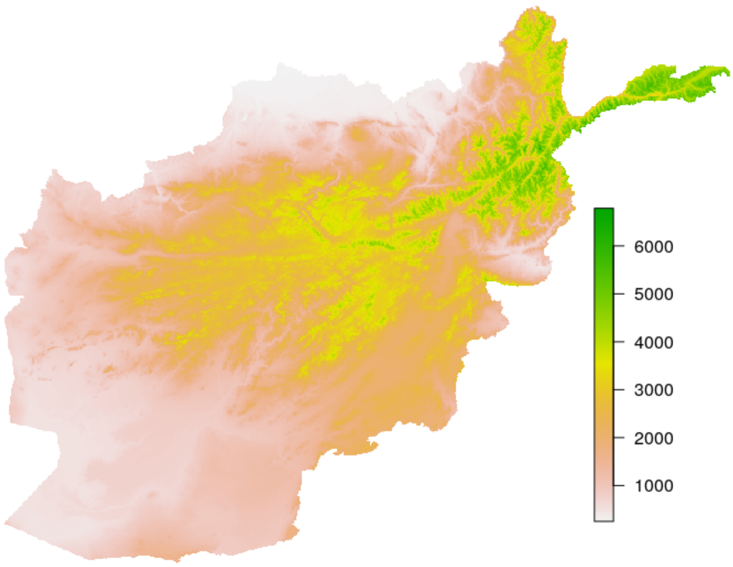

FIGURE A4 Elevation of Afghanistan in meters, based on author's computations of images and data from the DEM SRTM 90m resolution image (NASA, 2016).

TABLE A1 Effects of in utero conflict exposure and heterogeneous effects (Full results, IV)

	Dependent variable:					
	WAZ	WAZ <-2SD	WAZ <-3SD	WAZ	WAZ <-2SD	WAZ <-3SD
	(1)	(2)	(3)	(4)	(5)	(6)
$fat_{t=p}$	−0.194** (0.086)	0.104*** (0.032)	0.040*** (0.015)	−0.713** (0.338)	0.298** (0.133)	0.086 (0.055)
high $conflict_d$				−0.192 (0.169)	0.060 (0.067)	0.012 (0.027)
$fat_{t=p_i}$*high $conflict_d$				0.688** (0.339)	−0.260* (0.134)	−0.062 (0.056)
Child age (months)	−0.009*** (0.002)	−0.0001 (0.001)	−0.0004 (0.0002)	−0.011*** (0.002)	0.001 (0.001)	−0.0002 (0.0002)
Child sex (male)	−0.157*** (0.030)	0.043*** (0.011)	0.010* (0.005)	−0.136*** (0.029)	0.034*** (0.011)	0.008 (0.005)
Mother age at pregnancy	0.005 (0.003)	−0.001 (0.001)	0.0001 (0.0005)	0.0003 (0.004)	0.001 (0.001)	0.001 (0.001)
Mother is literate	−0.017 (0.052)	−0.002 (0.020)	0.009 (0.008)	−0.017 (0.050)	−0.002 (0.019)	0.008 (0.008)
Mother BMI	0.023*** (0.005)	−0.005*** (0.002)	−0.001 (0.001)	0.025*** (0.005)	−0.006*** (0.002)	−0.001 (0.001)
Pregnancies number	0.002 (0.008)	−0.002 (0.003)	−0.002 (0.002)	0.014 (0.010)	−0.006* (0.003)	−0.004** (0.002)
Mortality	−0.123 (0.097)	0.066** (0.033)	0.026 (0.017)	−0.164 (0.104)	0.082** (0.034)	0.030* (0.017)
Interview taken after Ramadan	0.001 (0.082)	−0.035 (0.030)	−0.0001 (0.014)	0.138 (0.132)	−0.085* (0.049)	−0.012 (0.021)
Urban	−0.145 (0.115)	0.056 (0.038)	0.005 (0.016)	−0.119 (0.101)	0.046 (0.031)	0.003 (0.014)
Ethnic minority belonging	−0.140** (0.057)	0.053** (0.024)	0.007 (0.012)	−0.175* (0.090)	0.064* (0.037)	0.010 (0.015)
Wealth index	0.066** (0.029)	−0.009 (0.010)	−0.008* (0.004)	0.083*** (0.028)	−0.016 (0.010)	−0.009** (0.004)
Dependency ratio	−0.0004 (0.0002)	0.0001 (0.0001)	0.0001 (0.0001)	−0.001** (0.0002)	0.0001 (0.0001)	0.0001* (0.0001)
Head is male	0.031 (0.098)	−0.032 (0.028)	0.009 (0.018)	−0.003 (0.103)	−0.018 (0.030)	0.012 (0.019)
Head is married	−0.176* (0.090)	0.060** (0.029)	0.017 (0.016)	−0.143 (0.092)	0.047 (0.029)	0.013 (0.017)
Head is literate	0.139*** (0.047)	−0.042** (0.017)	−0.024** (0.010)	0.135*** (0.047)	−0.039** (0.017)	−0.023** (0.010)
HS-mild (ref.: no hunger)	−0.158* (0.082)	0.022 (0.029)	0.036* (0.018)	−0.191** (0.086)	0.035 (0.030)	0.039** (0.019)
HS-severe	−0.503*** (0.153)	0.192** (0.077)	0.047 (0.031)	−0.286 (0.248)	0.106 (0.108)	0.026 (0.032)
Disaster $index_d$	−0.002 (0.003)	0.001 (0.001)	0.0003 (0.0004)	−0.002 (0.003)	0.001 (0.001)	0.0003 (0.0004)
Stable night $lights_d$	0.008* (0.005)	−0.002 (0.002)	−0.001 (0.001)	0.007 (0.004)	−0.001 (0.001)	−0.001 (0.001)
Committed aid_p	−0.0009 (0.001)	0.00004 (0.0005)	−0.0001 (0.0002)	−0.003** (0.001)	0.008 (0.005)	0.00006 (0.0002)
$Poppy_{ha/d}$	0.001** (0.0004)	−0.0005*** (0.0002)	−0.0002** (0.0001)	0.0002 (0.0002)	−0.0001** (0.0001)	−0.0001** (0.00004)
Constant	−0.959*** (0.180)	0.215*** (0.064)	0.060** (0.030)	−0.744*** (0.246)	0.141 (0.096)	0.044 (0.039)
First-stage F-stat (Z)	14.826	14.826	14.826	13.241	13.241	13.241
First-stage F-stat (I)	–	–	–	22.879	22.879	22.879
Wu-Hausman	**	***	***	***	***	***
Observations	16,962	16,962	16,962	16,962	16,962	16,962
Residual Std. Error	20.594	7.318	4.243	21.007	7.176	4.171

Notes: All models are computed using survey sampling weights. Season of birth omitted from the table. I refers to the interaction term of each regression. Robust standard errors clustered at the district level in parenthesis. First stage F-statistics adjusted for the clustered structure of the data. Null for Wu-Hausman test: β_2 2SLS is consistent; *p<0.1; **p<0.05; ***p<0.01.

TABLE A2 Effects of short-term conflict on household wealth and heterogeneous effects (Full results, OLS)

	Dependent variable:				
	Wealth index				
	(1)	(2)	(3)	(4)	(5)
$fat_{t\text{-}1}$	−0.036***	−0.131***	−0.054***		
	(0.010)	(0.045)	(0.019)		
high $conflict_d$		−0.227***		−0.278***	−0.256***
		(0.082)		(0.091)	(0.076)
non-poppy $free_d$			−0.312***	−0.416***	
			(0.075)	(0.090)	
$poppy_{ha,d}$	−0.00003	−0.00002			−0.006***
	(0.0001)	(0.0001)			(0.002)
$fat_{t\text{-}1_i}$*high $conflict_d$		0.116**			
		(0.046)			
$fat_{t\text{-}1_i}$*non-poppy free $_d$			0.041*		
			(0.022)		
high $conflict_d$*non-poppy $free_d$				0.277**	
				(0.131)	
high $conflict_d$*$poppy_{ha,d}$					0.006***
					(0.002)
Urban	1.700***	1.696***	1.677***	1.633***	1.672***
	(0.121)	(0.108)	(0.111)	(0.109)	(0.111)
Ethnic minority belonging	−0.266***	−0.266***	−0.272***	−0.275***	−0.270***
	(0.067)	(0.068)	(0.064)	(0.064)	(0.067)
Dependency ratio	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)
Head is male	−0.062	−0.049	−0.063	−0.052	−0.044
	(0.097)	(0.096)	(0.097)	(0.095)	(0.096)
Head is married	−0.053	−0.058	−0.045	−0.041	−0.057
	(0.109)	(0.105)	(0.107)	(0.103)	(0.105)
Head is literate	0.340***	0.329***	0.320***	0.308***	0.325***
	(0.036)	(0.036)	(0.035)	(0.034)	(0.036)
Oldest mother (wra) age	0.011***	0.011***	0.011***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Oldest mother (wra) is literate	0.693***	0.674***	0.669***	0.654***	0.673***
	(0.075)	(0.074)	(0.073)	(0.072)	(0.073)
Disaster $index_d$	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Committed aid_p	−0.001	−0.002	−0.001	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	−0.284**	−0.200*	−0.198*	−0.092	−0.158
	(0.112)	(0.114)	(0.111)	(0.112)	(0.115)
Observations	11,335	11,335	11,335	11,335	11,335
R^2	0.463	0.467	0.471	0.474	0.467
Adjusted R^2	0.462	0.466	0.470	0.474	0.466
Residual Std. Error	13.844	13.786	13.741	13.690	13.789
F Statistic	812.018***	708.665***	718.725***	786.267***	762.438***

Notes: All models are computed using survey sampling weights. Robust standard errors clustered at the district level in parenthesis; *p<0.1; **p<0.05; ***p<0.01.

TABLE A3 Children under age-5 emigrated from Province of birth

Province	Emigrated	Population under-5	Probability
Badakhshan	0	205, 598	0.000
Badghis	0	143, 608	0.000
Baghlan	1, 311	181, 872	0.007
Balkh	2, 242	227, 113	0.010
Bamyan	4, 181	84, 969	0.049
Daykundi	557	76, 682	0.007
Farah	3, 631	132, 125	0.027
Faryab	1, 824	213, 033	0.009
Ghazni	0	266, 121	0.000
Ghor	8, 883	175, 158	0.051
Helmand	523	233, 873	0.002
Herat	3, 387	358, 058	0.009
Jawzjan	454	81, 282	0.006
Kabul	12, 423	715, 034	0.017
Kandahar	286	272, 384	0.001
Kapisa	125	81, 592	0.002
Khost	0	148, 884	0.000
Kunarha	3, 664	113, 705	0.032
Kunduz	637	211, 222	0.003
Laghman	663	127, 465	0.005
Logar	0	127, 260	0.000
Nangarhar	10, 965	424, 806	0.026
Nimroz	827	34, 169	0.024
Nooristan	0	35, 031	0.000
Paktika	0	85, 922	0.000
Paktya	3, 019	131, 186	0.023
Panjsher	170	24, 160	0.007
Parwan	1, 247	138, 518	0.009
Samangan	250	77, 331	0.003
Sar-e-Pul	286	117, 666	0.002
Takhar	211	215, 900	0.001
Urozgan	0	103, 924	0.000
Wardak	0	163, 545	0.000
Zabul	1, 779	98, 770	0.018
Total	63,545	5,827,966	0.010

Note: author's computations based on data from ALCS 2014 (CSO Afghanistan, 2016). Emigrated children are identified as those aged 1 to 6 years old (in 2014) and living in a province different from the one of birth. Individual sampling weights have been used to compute provincial representative estimates.