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Health and Fertility among Afghan Women of Reproductive Age

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Chapter I

Introduction

This doctoral thesis is a collection of three empirical studies which aim at assessing the effect of external shocks, both man-made and natural, on health and fertility of Afghan women of reproductive age. The scope of this thesis is limited to investigate some of the most relevant aspects of the severe and frequent shocks in the Afghan setting, namely conflict and natural disasters.

For the last 38 years, Afghanistan has suffered from an almost uninterrupted conflict situation. High levels of violence in the country started in 1979 with the Soviet invasion of Afghanistan, and continued after the Soviet withdrawal (1992), first with the rise of the Taliban regime in 1996, and then with the NATO invasion of Afghanistan in late 2001. Nowadays the country still experience high levels of physical insecurity, a large proportion of the population lives below the national poverty line (35.8%) and another relevant part is internally or externally displaced (World Bank, 2015b). Moreover, as consequence of this protracted conflict, basic infrastructures, including roads, hospitals and schools, are largely inefficient and underdeveloped.

Natural disasters are also of serious concern in Afghanistan. High frequency of earthquakes, floods, landslides and severe winters cause loss of life and injuries, crop losses, problems accessing markets, and depletion of household wealth, all of which ultimately determine food insecurity and related micronutrient deficiencies. In particular, floods are the most frequent natural shock in Afghanistan; in 2013 they accounted for 70% of all the natural disasters (OCHA, 2014). Moreover, the effect of floods is particularly strong in Afghanistan, where they accounted for over 5,000 recorded deaths and about 400,000 displaced people between 1988 and 2006, over 200,000 of these in the 2002–2006 period alone (Hagen and Teufert, 2009).

Understanding the effects of these shocks and their underling mechanism is of particular importance, especially as, despite relevant, they remain quite understudied. Moreover, given that woman of reproductive age and children are particularly likely to suffer the most from these shocks, I present three empirical studies focusing on this subsample of population. In fact, Afghanistan, with an under-5 child mortality and mother mortality rates of 42.5 per 1,000 live births and 396 per 100,000 women, respectively World Bank (2015b), remains one of the country worst performing in terms of health statistics. In particular, anemia among Afghan women of reproductive age is a major public health problem that affects 40.4% of reproductive age women, 13.8% of them suffering from iron deficiency anemia (UNICEF, 2014). As extant research for Southeast Asia shows, not only nearly every second pregnant women is anemic, but this condition causes about 20% of all maternal deaths (Noronha et al., 2012). Malnutrition among children aged 0-59 months is quite relevant as well, with 26% and 10% of them suffering moderate-(WAZ < 2s.d.) and severe-under nutrition, respectively.

In Chapter II, the first study, by employing a quasiexperimental strategy, investigates the effect of in utero exposure to protracted-armed conflict on later child (0-59 months) health, measured in terms of Weight-for-Age Zscores (WAZ). As in extant studies, also for Afghanistan I find an overall negative effect of in utero exposure to conflict on WAZ. However, models accounting for interactions between short- and long-term exposure to conflict show that households residing in historically high conflict intensity districts are better capable of offsetting the negative consequences of short-term conflict, compared to their counterparts exposed in an intermittent and sudden way. These results shed light on the Afghan households' ability to offset the negative consequences of the shocks they are exposed to, which in turn depends on the frequency at which these occur.

The second study, presented in Chapter III, tests the effect of conflict on the recent drop in Afghan Total Fertility Rate (TFR). In the fifteen-year period from 2000 to 2015 TFR in Afghanistan dropped dramatically from 7.5 to 4.6. By employing a quasi-experimental strategy, I find that conflict reduce both the total number of pregnancies and living children per woman. Estimates of the models employing ideal number of children a woman would have wanted (if she could go back in time), or she is willing to have (if she has none yet) in her whole life as dependent variable show a statistically significant effect, but rather small in magnitude. Hence, at the light of the low women empowerment in terms of volitional fertility's drivers, it follows that if conflict ceases the Afghan negative TFR trend would slow down.

Finally, in Chapter IV, the third study of this doctoral thesis uses biomarker information and satellite imagery to analyze how floods affect the probability of anemia in Afghan women of reproductive age (15-49). The models estimated show a positive effect of exposure to floods on probability of anemia. However, interestingly, despite iron deficiency is known to be the most common cause of anemia, floods cause anemia through other transmission channels, that is Vitamin A deficiency and infections, with the latter probably due to water borne diseases. Although, households in the sample suffered barely any hunger, and thus integrated iron from wheat - the main staple in Afghanistan – floods may had caused shortages of fresh vegetables and fruit. This results is of particular relevance as vitamin A supplementation may be more needed than iron in case of natural disasters such as floods, at least for Afghan reproductive age woman.

The remainder of this doctoral thesis unfolds as follows: Chapter II presents the empirical analysis on the effects of in utero exposure to short- and long-term conflict on child healh, after which Chapter III studies the effect of protracted conflict on fertility outcomes and preferences. Finally, Chapter IV assesses how floods affect anemia and related transmission channels in a sample of Afghan reproductive age women. At the end of each Chapter, Appendices present full regressions' results and additional supporting information.

Chapter II

Less is Too Much: Afghan Child Health and In Utero Exposure to Conflict $\stackrel{\Rightarrow}{\Rightarrow}$

Abstract

No extant study addresses the persistent detrimental effect of in utero exposure to conflict in countries experiencing protracted conflict. I therefore estimate the impact of in utero conflict exposure on weight-for-age z-score (WAZ) by applying instrumental variable regression to information on Afghan children aged 0-59 months merged with data on district-level fatalities during the intrauterine period. Although like previous research, I find an overall negative effect of violence on WAZ, the effect is stronger for children born in districts where long-term conflict is on average comparatively lower. I attribute these heterogeneous effects to the fact that households living in environments of constant conflict have developed more effective coping strategies. I support this result by showing that physical insecurity in districts in which opium poppy is cultivated, a coping strategy for rural farmers, has a comparatively smaller negative effect on household wealth because of the lower risk of eradication.

Keywords: Afghanistan, Protracted Conflict, Child Health, Fetal Origins Hypothesis, Instrumental Variables JEL Classification: D74; I15; O1

1. Introduction

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; Torche and Kleinhaus, 2012), armed conflict (Abeliansky and Strulik, 2017; Akresh et al., 2012, 2014; Kesternich et al., 2014; 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 conflict¹ 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

¹In 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.

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.

2. 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 (Maley, 2009; Barfield, 2010). As Figure 2 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 3). 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, 2015a). 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; Thompson, 2006; Goodhand et al., 2012). 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 undis-



Figure 2: Total number of fatalities by year based on author computations using number of fatalities in thousands from UCDP GED 2.0.

puted 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).

3. 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, 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 children². 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 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 coordi-

 $^{^2{\}rm Missing}$ data were handled using list-wise deletion, with 2,962 observations dropped because of missing information on mother characteristics.



Figure 3: 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 4 to compute the instrumental variable.

nates 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 civilians³.

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 countries⁴ 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 capita⁵ fatalities at the district level, measured for each child over the exact in utero period. As an additional control, I compute violence intensity right

³Opting 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%).

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

⁵District population in 10 thousands.



Figure 4: Time line of relevant events

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 4 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 durables⁷, 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 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 8). 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 houses⁸. I compute the natural district intensity index by adding the number of damaged houses weighted by 0.5 with the number of houses destroyed⁹. Figure 7 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).

⁶For 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.

⁷The 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).

 $^{^{8}{\}rm The~NDID}$ comprise information of occurrence and severity of earthquakes, floods and flash floods, landslides, extreme winters, and avalanches.

 $^{^{9}\}mathrm{The}$ results are robust to alternative specifications of the natural disasters variable.

Table 1: Characteristics of the main sample 10 .

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
$fat_{t=p}$	14.779	30.400
fat _{t-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 light _d	7.254	9.035
disaster index _d	3.964	12.716
poppy (ha) _d	542.9	2516.439
$non-poppy-free_d$	0.357	0.479
committed aid_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 $(fat_{t=p})$ and the 365 days before interview (fat_{t-1}) are reported in absolute values. The subscripts $_{p}$ and $_{d}$ refer to variables computed at the province and district level, respectively.

4. 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 cannot 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 level¹¹. 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 5, 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 5, bottom).



Figure 5: Bias from the omission of short-term conflict and price levels. Full stretch and dashed two-ways arrow represent correlation and reverse causality, respectively.

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.

 $^{^{10}\}mathrm{All}$ tables had been created using the star gazer package for R (Hlavac, 2015).

¹¹Additional sources of bias, including selective mortality, fertility, and migration, are discussed in Section 5, Paragraph 5.

The first and second stages of this IV estimation are expressed by equations 1 and 2, respectively:

$$fat_{t=p_i} = \alpha_1 + \alpha_2 Z_i + \delta_{\mathbf{c}} \mathbf{C} \mathbf{C}_{\mathbf{i}} + \delta_{\mathbf{h}} \mathbf{H} \mathbf{C}_{\mathbf{i}} + \delta_{\mathbf{m}} \mathbf{M} \mathbf{C}_{\mathbf{i}} + \delta_{\mathbf{p}} \mathbf{P} \mathbf{D} + \eta_i$$
(1)

$$WAZ_{i} = \beta_{1} + \beta_{2} \widehat{fat_{i=p,i}} + \gamma_{\mathbf{c}} \mathbf{CC_{i}} + \gamma_{\mathbf{h}} \mathbf{HC_{i}} + \gamma_{\mathbf{m}} \mathbf{MC_{i}} + \gamma_{\mathbf{p}} \mathbf{PD} + \epsilon_{i}$$
(2)

where $fat_{t=p_i}$ and $\widehat{fat_{t=p_i}}$ are a measure of conflict intensity for child i at in utero 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 $rate^{12}$. **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 3). 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 latter¹³. After first computing the minimum true distance¹⁴ 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. Although this instrument correlates to the measure of conflict at pregnancy (the Pearson's correlation coefficient statistically significant at $\alpha = 5\%$ equals -0.12), Z is valid only if it also satisfies the exclusion restriction (i.e., it must affect child health only through conflict during pregnancy). Most important, 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 occurrence of natural disasters are exogenous to the distance from the selected border crossings (see Figures 9 and 7 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 8 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%,

 $^{^{12}{\}rm Mortality}$ rate is computed for each mother as the sum of dead children and miscarriages over the total number of pregnancies.

¹³The 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.

 $^{^{14}{\}rm The}$ distances are computed as Euclidean distances only taking into account for Earth curvature.

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: : Effects of instrument on child health and household wealth (OLS) $% \left(\left(OLS\right) \right) =0$

	Dependent variable:			
	WAZ	Wealth index		
	(1)	(2)		
$\overline{Z_i}$	$0.006 \\ (0.004)$	0.001 (0.003)		
Observations	7,453	11,335		
\mathbb{R}^2	0.069	0.480		
Adjusted \mathbb{R}^2	0.066	0.480		
Residual Std. Error	16.744	11.335		
F Statistic	21.956^{***}	805.047^{***}		

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 falsification tests (cf. Pizer, 2015). In the 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. In this setting, if the instrument correctly explains conflict intensity during pregnancy but not in other periods, it should have no effect on child health. In the second test, 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. If the instrument's coefficients in both falsification tests are not statistically significant, the exclusion restriction cannot be rejected. In fact, as Table 2 shows, the instrument coefficient is never statistically significant, which further confirms the instrumental variable's validity¹⁵.

5. Results

Main Results. Table A1 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. 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 4, all models in Table A1 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 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).

$$\text{high conflict}_{d} = \begin{cases} 1, & \text{if } fat_{tot,d} > f\widetilde{at_{tot,d}} \\ 0, & \text{otherwise} \end{cases}$$
(4)

¹⁵These results also hold when the short-term measure of conflict intensity (fat_{t-1_i}) is excluded from the set of controls.

Table 3: : Effects of in utero conflict exposure (OLS)

	Dependent variable:				
	WAZ				
	(1)	(2)			
$fat_{t=p_i}$	0.005	0.003			
- • • •	(0.006)	(0.007)			
fat_{t-1_i}		0.004			
		(0.013)			
Observations	16,962	16,962			
\mathbb{R}^2	0.053	0.053			
Adjusted \mathbb{R}^2	0.051	0.051			
Residual Std. Error	18.889	18.890			
F Statistic	37.567^{***}	36.15 ***			

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

Table 4: Effects of in utero conflict exposure (IV)

	Dependent variable:				
	WAZ	WAZ <<-2SD	WAZ <-3SD		
	(1)	(2)	(3)		
$fat_{t=p_i}$	-0.194^{**} (0.086)	$\begin{array}{c} 0.104^{***} \\ (0.032) \end{array}$	$\begin{array}{c} 0.040^{***} \\ (0.015) \end{array}$		
First-stage F-stat Wu-Hausman	14.826 ***	14.826 ***	14.826 ***		
Observations Residual Std. Error	$\frac{16,962}{20.594}$	$16,962 \\ 7.318$	$16,962 \\ 4.243$		

Notes: All models are computed using survey sampling weights; specification (2) and (3) are estimated using 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. I refers to the interaction terms 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.

where $fat_{tot,d}$ 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 $(high \ conflicit_d)$ 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)		
$\overline{fat_{t=p_i}}$	-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)		
$fat_{t=p_i} * high \ conflict_d$	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 3¹⁶, 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 districts¹⁷. 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

 $^{^{16}}$ 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%).

 $^{^{17}}$ 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.

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 "more muted declines in food security" because of increased food prices (p. 42).

Mechanism. To identify channels that can affect early child health through in utero conflict exposure, I estimate conflict's effect on household wealth¹⁸.

I assess the impact of conflict on household wealth 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 intensity¹⁹ 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).

non-poppy free_d =
$$\begin{cases} 1, & \text{if } poppy_{ha,d} \ge 1 \ ha \\ 0, & \text{otherwise} \end{cases}$$
(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

¹⁸Although the NNS (2013) does ask questions about antenatal care and reproductive behaviors, the lack of precise information on the index mothers' date of last pregnancy prevents me from testing the conflict's effect on health care access and parental care because the high number of miscarriages means that the latest child born need not correspond to last pregnancy date.

¹⁹Note 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}) .

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 5.1per 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 6 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.

6. 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 shortterm 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 (Thompson, 2006; Buddenberg and Byrd, 2006; Goodhand et al., 2012) 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.



Figure 6: 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 4 to compute the instrumental variable.



Figure 7: 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 4 to compute the instrumental variable.



Figure 8: 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 9: 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)

			Dependen	t variable:		
	WAZ	WAZ <-2SD	WAZ <-3SD	WAZ	WAZ <-2SD	WAZ <-3SD
$\overline{\mathrm{fat}_{\mathrm{t=p_i}}}$	(1) -0.194^{**} (0.086)	(2) 0.104*** (0.032)	(3) 0.040*** (0.015)	(4) -0.713^{**} (0.338)	(5) 0.298** (0.133)	(6) 0.086 (0.055)
high $\operatorname{conflict}_d$	(0.000)	(0.002)	(01010)	-0.192	0.060	0.012
${\rm fat}_{t=p_i}{}^*\!\!{\rm high \ conflict}_d$				(0.109) 0.688^{**} (0.339)	(0.007) -0.260^{*} (0.134)	(0.027) -0.062 (0.056)
child age (months)	-0.009^{***} (0.002)	-0.0001 (0.001)	-0.0004 (0.0002)	(0.005) -0.011^{***} (0.002)	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)
born in 2nd quarter (ref.: Spring)	-0.036 (0.054)	0.005 (0.017)	-0.002 (0.010)	-0.021 (0.060)	-0.001 (0.020)	-0.003 (0.010)
born in 3rd quarter	-0.039 (0.054)	-0.018 (0.017)	-0.014 (0.010)	-0.005 (0.055)	-0.031^{*} (0.016)	-0.017^{*} (0.010)
born in 4th quarter	-0.065 (0.052)	$0.006 \\ (0.019)$	-0.008 (0.010)	-0.038 (0.057)	-0.004 (0.022)	-0.011 (0.010)
mother age at pregnancy	$ \begin{array}{c} 0.005 \\ (0.003) \end{array} $	-0.001 (0.001)	$\begin{array}{c} 0.0001\\ (0.0005) \end{array}$	$\begin{array}{c} 0.0003 \\ (0.004) \end{array}$	$ \begin{array}{c} 0.001 \\ (0.001) \end{array} $	$\begin{array}{c} 0.001 \\ (0.001) \end{array}$
mother is literate	-0.017 (0.052)	-0.002 (0.020)	$ \begin{array}{c} 0.009 \\ (0.008) \end{array} $	-0.017 (0.050)	-0.002 (0.019)	$ \begin{array}{c} 0.008 \\ (0.008) \end{array} $
mother BMI	0.023^{***} (0.005)	-0.005^{***} (0.002)	-0.001 (0.001)	$\begin{array}{c} 0.025^{***} \\ (0.005) \end{array}$	-0.006^{***} (0.002)	-0.001 (0.001)
pregnancies number	$ \begin{array}{c} 0.002 \\ (0.008) \end{array} $	-0.002 (0.003)	-0.002 (0.002)	$\begin{array}{c} 0.014\\ (0.010) \end{array}$	-0.006^{*} (0.003)	-0.004^{**} (0.002)
mortality	-0.123 (0.097)	0.066^{**} (0.033)	$ \begin{array}{c} 0.026 \\ (0.017) \end{array} $	-0.164 (0.104)	0.082^{**} (0.034)	0.030^{*} (0.017)
interview taken after Ramadan	$ \begin{array}{c} 0.001 \\ (0.082) \end{array} $	-0.035 (0.030)	$\begin{array}{c} -0.0001 \\ (0.014) \end{array}$	$\begin{array}{c} 0.138\\ (0.132) \end{array}$	-0.085^{*} (0.049)	-0.012 (0.021)
urban	-0.145 (0.115)	$\begin{array}{c} 0.056 \\ (0.038) \end{array}$	$ \begin{array}{c} 0.005 \\ (0.016) \end{array} $	-0.119 (0.101)	$ \begin{array}{c} 0.046 \\ (0.031) \end{array} $	$ \begin{array}{c} 0.003 \\ (0.014) \end{array} $
ethnic minority belonging	-0.140^{**} (0.057)	$\begin{array}{c} 0.053^{**} \\ (0.024) \end{array}$	$\begin{array}{c} 0.007\\ (0.012) \end{array}$	-0.175^{*} (0.090)	$\begin{array}{c} 0.064^{*} \\ (0.037) \end{array}$	$ \begin{array}{c} 0.010 \\ (0.015) \end{array} $
wealth index	0.066^{**} (0.029)	-0.009 (0.010)	-0.008^{*} (0.004)	$\begin{array}{c} 0.083^{***} \\ (0.028) \end{array}$	-0.016 (0.010)	-0.009^{**} (0.004)
dependency ratio	-0.0004 (0.0002)	$\begin{pmatrix} 0.0001\\ (0.0001) \end{pmatrix}$	$\begin{pmatrix} 0.0001\\ (0.0001) \end{pmatrix}$	-0.001^{**} (0.0002)	$\begin{array}{c} 0.0001 \\ (0.0001) \end{array}$	$\begin{array}{c} 0.0001^{*} \\ (0.0001) \end{array}$
head is male	$\begin{array}{c} 0.031 \\ (0.098) \end{array}$	-0.032 (0.028)	$ \begin{array}{c} 0.009 \\ (0.018) \end{array} $	-0.003 (0.103)	-0.018 (0.030)	$\begin{array}{c} 0.012\\ (0.019) \end{array}$
head is married	$\begin{array}{c} -0.176^{*} \\ (0.090) \end{array}$	0.060^{**} (0.029)	$\begin{array}{c} 0.017\\ (0.016) \end{array}$	-0.143 (0.092)	$\begin{array}{c} 0.047\\ (0.029) \end{array}$	$\begin{array}{c} 0.013\\ (0.017) \end{array}$
head is literate	$\begin{array}{c} 0.139^{***} \\ (0.047) \end{array}$	-0.042^{**} (0.017)	-0.024^{**} (0.010)	$\begin{array}{c} 0.135^{***} \\ (0.047) \end{array}$	-0.039^{**} (0.017)	-0.023^{**} (0.010)
HS-mild (ref.: no hunger)	-0.158^{*} (0.082)	$\begin{array}{c} 0.022\\ (0.029) \end{array}$	$\begin{array}{c} 0.036^{*} \\ (0.018) \end{array}$	-0.191^{**} (0.086)	$\begin{array}{c} 0.035 \\ (0.030) \end{array}$	$\begin{array}{c} 0.039^{**} \\ (0.019) \end{array}$
HS-severe	-0.503^{***} (0.153)	0.192^{**} (0.077)	$\begin{array}{c} 0.047\\ (0.031) \end{array}$	-0.286 (0.248)	$ \begin{array}{c} 0.106 \\ (0.108) \end{array} $	$\begin{array}{c} 0.026\\ (0.032) \end{array}$
disaster $index_d$	-0.002 (0.003)	$\begin{array}{c} 0.001 \\ (0.001) \end{array}$	$\begin{array}{c} 0.0003\\ (0.0004) \end{array}$	-0.002 (0.003)	$\begin{array}{c} 0.001 \\ (0.001) \end{array}$	$\begin{array}{c} 0.0003\\ (0.0004) \end{array}$
stable night lights _d	0.008^{*} (0.005)	-0.002 (0.002)	-0.001 (0.001)	$\begin{array}{c} 0.007\\ (0.004) \end{array}$	-0.001 (0.001)	-0.001 (0.001)
committed aid_p	-0.0009 (0.001)	$ \begin{array}{c} 0.00004 \\ (0.0005) \end{array} $	-0.0001 (0.0002)	-0.003^{**} (0.001)	$ \begin{array}{c} 0.008 \\ (0.005) \end{array} $	$\begin{array}{c} 0.00006\\ (0.0002) \end{array}$
$poppy_{ha/d}$	0.001^{**} (0.0004)	-0.0005^{***} (0.0002)	-0.0002^{**} (0.0001)	$\begin{pmatrix} 0.0002\\ (0.0002) \end{pmatrix}$	-0.0001^{**} (0.0001)	-0.0001^{**} (0.00004)
Constant	-0.959^{***} (0.180)	$\begin{array}{c} 0.215^{***} \\ (0.064) \end{array}$	$\begin{array}{c} 0.060^{**} \\ (0.030) \end{array}$	-0.744^{***} (0.246)	$\begin{array}{c} 0.141 \\ (0.096) \end{array}$	(0.044) (0.039)
First-stage F-stat (Z) First-stage F-stat (I)	14.826	14.826	14.826	13.241 22.879	13.241 22.879	13.241 22.879
Wu-Hausman Observations Residual Std. Error	$16,962 \\ 20.594$	$^{***}_{16,962}_{7.318}$	$16,962 \\ 4.243$	$16,962 \\ 21.007$	$16,962 \\ 7.176$	$^{***}_{4.171}$

Notes: All models are computed using survey sampling weights. 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.

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

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

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.

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

Table A3: Children under age-5 emigrated from Province of birth

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.

Chapter III

"If I Could Only Have More": Protracted Armed Conflict and Fertility in Afghanistan

Abstract

Although Afghanistan experienced a slight rise in female literacy and some decline in female and infant mortality between 2000 and 2015, these improvements were not great enough to explain the simultaneous dramatic drop in total fertility, from 7.5 to 4.6. In this study, therefore, I test the previously unverified hypothesis that long-term conflict has a negative causal impact on both fertility outcomes and fertility preferences. More specifically, by applying 2SRI GLM Poisson regressions to cross-sectional data for a subsample of ever-married women of reproductive age (15-49) combined with georeferenced information on district level conflict from 1979 to 2015, I estimate the causal impact on fertility of conflict experienced since the time of first union. I find that although long-term conflict does indeed reduce the number of pregnancies and living children, when a woman's ideal number of children desired over the lifetime is used as the dependent variable, conflict is a relatively small (albeit still statistically significant) determinant of fertility preferences. This finding implies that, given the only modest improvements in women's health and development, the drop in Afghanistan's total fertility rate would slow down if the conflict were to cease.

Keywords: Afghanistan, Protracted Conflict, Fertility, Instrumental Variables JEL Classification: J13; D74; J16

1. Introduction

For many years, the total fertility rate (TFR) in Afghanistan has been one of the highest in the world, staying mostly stable at 7.46 children per woman but increasing slightly right after the Soviet withdrawal from Afghanistan and reaching a peak of 7.64 in 1997 after the Taliban came to power (1996) (World Bank, 2015b). Between 2000 and 2015, the TFR decreased substantially from 7.5 to 4.65 (World Bank, 2015b), but this decline was accompanied by only marginal improvements in wellestablished volitional fertility determinants like female literacy and labor market participation (cf. Basu, 2002). In fact, even though female literacy in adult women (15 and over) has increased since 2007, it remains at very low levels, with only 19% of women able to read and write in 2014 and a similarly low female labor participation rate in 2015 of 19.1% (World Bank, 2015b). Hence, as the extant research shows (Doepke, 2005; Huber et al., 2010), it is likely that other factors such as improved health and the implementation of a national family planning program that have contributed to the recent drop in Afghan TFR.

When the Islamic Republic of Afghanistan was established in 2002, it had among the worst health statistics globally, with a maternal mortality ratio of 1,600 per 100,000 women, and an infant and child mortality ratio of der et al., 2014). To address this problem, the Ministry of Public Health (MoPH) (MoPH Afghanistan, 2015) implemented a basic package of health services (BPHS) that, despite several shortcomings (see Frost et al., 2016), reduced both under-5 child mortality and mother mortality rates to 42.5 per 1,000 live births and 396 per 100,000 women, respectively (World Bank, 2015b). In addition to child immunization, public nutrition, control of communicable diseases, and provision of mental health and disability related services, the BPHS provides maternal and newborn care and a family planning program (Roberts et al., 2008). Nevertheless, even though the use of modern contraceptive methods among Afghan women of reproductive age (15-49) increased from 3.6% to 19.9% in the 2000-2015period (World Bank, 2015b), the provision of contraceptives alone, although crucial, is only marginally effective in reducing TFR. Important as access to contraceptive methods is the BPHS's provision of community-based information, education, and communication in both urban and rural areas. Such provision is important because although Islam is generally open to family planning (Roudi-Fahimi, 2004) and its religious leaders actively advocate contraceptive use and birth spacing (Huber et al., 2010; Sato, 2007), the degree of acceptance of the national birth control pol-

165 and 257 per 1,000 live births, respectively (Newbran-

icy varies greatly with cultural background and ethnicity. For example, whereas Hazaras, regardless of whether Shi'a or Sunni, are more likely to use family planning services to avoid unwanted pregnancies (Sato, 2007), Pashtun households are less likely to do so, probably because of adherence to Pashtunwali, their pre-Islamic code of honor. Relative to these two groups, minorities like the Nuristanis and Pashai prefer a statistically significant ($\alpha = 5\%$) larger number of children, an average of 10.03 and 6.9 offspring, respectively, compared to the 6.1 and 5.2 children per woman of Pashtuns and Hazaras. Overall, however, as few qualitative studies suggest (e.g., Brown, 2004), the Afghan population's perception of the protracted physical, political, and economic insecurity as a valid reason to have smaller families may have shaped current fertility decisions. In fact, since 1979, with the soviet invasion of Afghanistan, the country experiences high levels of physical insecurity which continued, first with the civil war started in 1992 and the subsequent rise of the Taliban regime in 1996, and then with the NATO invasion in late 2001. Figure 10 shows the distribution of conflict intensity at the district level for the period 1989-2015. Although southern districts faced a greater level of violence since the beginning of the NATO invasion in late 2001, violence has gradually spread out to the northern part of the country as well. Particularly, after the partial withdrawal of NATO troops (2014), violence has never been so intense and widespread.

Thus, understanding the role of the Afghan protracted conflict on fertility is particularly relevant, especially in light of the important, albeit modest, improvements over the 2000-2015 period in various dimensions of human development, including overall health, mother and infant mortality rates, and access to family planning materials and information. Specifically, by applying an IV estimation strategy to cross-sectional data on a sample of evermarried, reproductive age Afghan women, I assess whether the protracted armed conflict since 1979 has affected her number of pregnancies, number of living children, and the number of children she would ideally have liked to have. I show that greater levels of conflict, measured for each woman since the age of her first union (i.e., during marriage), do decrease the number of pregnancies and living children; however, when (ideal) fertility preferences are used as the dependent variable, the effect is very small, signaling that the drop in TFR depends greatly on the current context of violence. This research makes several valuable contributions to current understanding of the conflictfertility nexus. First, unlike previous studies of the negative trend in Afghan fertility, which focus mainly on average birth intervals, sex ratio at birth by parity, parity progression ratios, and synthetic lifetime average parity (see Spoorenberg, 2013), my causal analysis is the first to assess the effect of conflict on fertility in Afghanistan. Filling this knowledge gap is particularly important not only for measuring the conflict's contribution to the fertility drop but also for predicting how persistent this negative trend

would be in the absence of conflict. Methodologically, it is unique not only in its exploitation of ideal family size preferences to predict this counterfactual and its measurement of conflict over the entire duration of a marriage, but in its use of country-specific evidence to test the hypothesis that households, in response to situations of protracted insecurity, increase their fertility as an insurance mechanism.

2. Review of the Literature

Not only are causal analyses of the relation between armed conflict and fertility rare, but very few studies address this issue in the context of protracted conflict. Extant research finds that the direction of the relation between armed conflict and fertility is likely to vary across countries and contexts (Urdal and Che, 2013; Hill, 2004). Lindstrom and Berhanu (1999), for example, use National Family and Fertility Survey (1990) data to assess the effects of the Ethiopian war and famine events of 1974-1991 on year-specific probabilities of conception. These authors observe a decline in these probabilities during the major crisis years of the 1970s (which were only transitorily perceived as such), with an increase immediately after each event. Since 1982, however, with the civil war significantly worsening the country's overall economy, the probabilities of conception have declined in a steady and gradual pattern. In fact, levels of armed conflict, especially during 1978, 1980, and 1988, significantly lowered the probability of conceptions that ended in live births.

Similarly, Schindler and Brück (2011), using pooled cross-sectional data before and after the 1994 genocide in Rwanda, show that in the short term (5 years post event), women who lost at least one child during the genocide gave birth to more children in the period immediately after it than women who lost no children. Nevertheless, in the long term (10 years post genocide), the coefficient of interest, although slightly smaller in magnitude, maintains the same direction. When the authors substitute the women's widowhood status for the child lost variable, however, they observe the opposite result: those registered as widows after the genocide have lower fertility, not only compared to nonwidows but also to those identified as widows before 1994. They further demonstrate that a more unbalanced age group-specific sex ratio at the provincial level lowers fertility both before and after 1994.

Several micro level studies, in contrast, show that short-term conflict decreases fertility, with Woldemicael (2008) and Agadjanian and Prata (2002) demonstrating a negative association during both the 1998-2000 Ethiopia-Eritrea border war and the Angolan civil strife (1992-1996), respectively, with a subsequent postwar rebound in the latter case. Nevertheless, although in their study Agadjanian and Prata (2002) use war-related fertility preferences on the desire to have a child in the coming 12month period as their outcome variable, they admit that their findings of a negative effect vary significantly accord-



Figure 10: Fatalities by district (1989-2015) using quintile cuts, based on author computations using UCDP GED 17.1 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 4 to compute the instrumental variable.

ing to degree of war exposure and other socioeconomic characteristics.

Similar divergence characterizes results at a higher level of aggregation; for example, Urdal and Che (2013) analysis of cross-national time-series for 1970-2005 and 1990-2005 reveals no statistically significant short-term effect of conflict on either fertility rates or maternal mortality but rather indicates that long-term conflict may increase fertility. On the other hand, Iqbal (2010), using 1960-1999 panel data for both developed and developing countries, finds no statically significant effect of long-term conflict on fertility but does identify a negative effect of short-term conflict.

This extant literature points to several important considerations, including how dependent the effect's direction is on the way in which conflict is measured. For example, in Schindler and Brück (2011), the coefficient of interest changes direction depending on whether conflict is approximated by the number of dead offspring or becoming a widow during the genocide. This result, although seemingly contradictory, makes sense contextually. That is, although couples that lose an offspring may compensate by having an extra child or interrupted lactation (and resulting lactational amenorrhea) may shorten a women's birth intervals during her reproductive years (Nur, 1982), a woman who loses her husband might not find another.

In addition to the ultimate direction of the war's effect on fertility being unclear, if the authors use low precision conflict data, it raises concerns about the estimates' robustness. For instance, the yearly data in Agadjanian and Prata (2002) are measured only at the broad regional level and coded as medium or high intensity, while those in Lindstrom and Berhanu (1999) measure conflict only as the number of yearly military attacks at the national level. There also appear to be no studies of conflict's effect on fertility that employ a quasi-experimental strategy that can account for the multiple potential sources of endogeneity.

3. Data

The study sample is drawn from two primary sources; the Afghanistan Demographic and Health Survey (AfDHS) 2015 (CSO Afghanistan, 2017) for household and individual level information, and the Uppsala Conflict Data Program Georeferenced Event Dataset 17.1 (UCDP-GED) for spatially and temporally disaggregated data on conflict intensity (Sundberg and Melander, 2013). I merge these data sets by projecting the number of fatalities from the UCDP-GED onto an AGCHO (2012) shapefile for the second administrative division and then assigning these counts to each observation in the resulting database according to district of residence and the period from the date of first union until the day of interview. Once missing and nonnumeric values for the outcome variable and controls are deleted, the final sample comprises 9,860 ever-married women of reproductive age (WRA). Relevant constructs from, and detailed information on, these data sources are described in the paragraphs below.

Household and WRA Information. The AfDHS 2015, for which the DHS program provides technical support, was founded by USAID and implemented by the Afghanistan Central Statistics Organization (CSO) and the Afghan Ministry of Public Health (MoPH). This survey provides information on basic household characteristics, nutrition and health outcomes of women and children, fertility preferences and related behaviors, and domestic violence. The relevant data were collected from June 15, 2015, to February 23, 2016 using the CSO Household Listing Frame (developed in 2003 and updated in 2009) and a stratified twostage sampling design. The information covers both rural and urban households and is representative at the provincial level (34 provinces).

Conflict Information. UCDP-GED 17.1 contains information on violent events since 1979 for both Africa and Asia. The database not only provides precise date, location, and estimated number of fatalities but indicates precision levels for events whose exact location is unknown: a 25 km approximation from the actual event location, coordinates for the centroid of the second administrative division (district level), or lower precision (province, national, or international level). For the purposes of this study, I retain only events identifiable at least at the district level for the period from 1979 to the interview date.

Outcome Variables. Because the AfDHS 2015 provides detailed information on fertility outcomes and related behavior, I select three outcome variables of interest: total number of pregnancies, number of living children, and ideal number of children, defined as the number of offspring a woman would have wanted if she could go back in time or, if she has none yet, is willing to have over her lifetime. These data were collected by trained female interviewers assigned to field teams operating in their own province of residence, with the exception of Helmand, Zabul, and Urozgan, for which suitable local candidates could not be found and were replaced by interviewers hired from nearby provinces.

Conflict Measure. Conflict is measured as the per capita yearly average number of fatalities experienced during the marriage (fat marriage) in each woman's district of residence. The comparability of the conflict measure among observations is guaranteed by the fact that the overall

number of these fatalities is adjusted for the length of the marriage in years. The final variable used in the regressions is then further adjusted for district population in order to reflect the actual intensity experienced by each WRA in the study sample.

Other Constructs. The empirical models control for conflict confounders at three different levels: the woman's, partner's, and household's characteristics. These controls comprise the woman's and partner's ages, partner's years of education, number of dead sons and daughters, and dummies equal to one if the woman is literate, has ever had at least one pregnancy that ended in a non-live birth, has never used any contraceptive method during her entire life, and currently works outside of the household dwelling. It should be noted that, despite women's years of education are available in the original data and their inclusion in the models does not change neither the statistical significance or magnitude of the coefficients, I use the AfDHS-defined dummy literacy variable, (a woman is coded as literate if able to read a whole sentence or part of a sentence in her own language at the moment of interview), due to very low average number of years of schooling for the reproductive age women sub-sample. Controls at the household level include a binary variable equal to one if the household resides in a rural area, and zero otherwise; a dependency ratio; and a wealth index, computed by DHS using polychoric principal component analysis (see Rutstein (2008), for details of its construction and dimensions). Province and ethnicity fixed effects are also controlled for using 33 and 8 dummies, respectively.

4. Empirical Strategy

To address the possibilities of sample selection and measurement errors in the variable of interest, I assess the causal relation between number of pregnancies and conflict intensity experienced since the date of first union using a two-stage residual inclusion (2SRI) control function (CF) approach. In the first stage (equation 1), I regress the main variable of interest on the full set of exogenous regressors with the addition of an exogenous instrument Z_i (defined in the next section) and save the residuals $\widetilde{v_i}$. These residuals capture the endogenous component of the outcome variable from the first stage regression. In the second stage (equation 2), I estimate the relations of interest, including the residuals \tilde{v}_i obtained in the first stage to control for the correlation between ϵ_i and v_i , leaving the coefficient estimates unbiased. Because both the main outcome and the variable of interest follow a Poisson distribution, I estimate the first and second stages of the proposed model using Poisson GLM regressions. In my approach, the 2SRI first stage, rather than being linear in both variables and parameters, which would lead to the usual 2SLS estimator, is nonlinear and thus cannot assure that ϵ_i is normally distributed. Such a nonlinear 2SRI produces unbiased estimates only under the additional assumption that the instrument Z is not correlated with the vector of unobserved omitted variables $(\mathbf{U_i})$ (Terza et al., 2008; Wooldridge, 1997, 2010, 2015).

$$h(fat_i) = \alpha_0 + \alpha_1 Z_i + \alpha_w \mathbf{CW}_i + \alpha_p \mathbf{CP}_i + \alpha_h \mathbf{HC}_i + \alpha_p \mathbf{Prov}_p + v_i$$
(6)

$$g(Preg_i) = \alpha_0 + \beta_1 fat_i + \beta_w \mathbf{CW}_i + \beta_p \mathbf{CP}_i + \beta_h \mathbf{HC}_i + \beta_p \mathbf{Prov}_p + \beta_v \hat{v}_i + \epsilon_i$$
(7)

In the analytical formulation of the CF estimation strategy given above, $h(\cdot)$ and $g(\cdot)$ are the log-link functions employed to estimate the first- and second-stage GLM Poisson regressions, respectively. \mathbf{CW}_i and \mathbf{CP}_i are vectors of the women's and partner's characteristics, respectively, including the woman's and partner's ages, partner's years of education, number of dead daughters and sons, and dummies for the woman being literate, having experienced at least one pregnancy that ended in a non-live birth, having never used contraceptive methods, and working outside the household dwelling. \mathbf{HC}_i is a set of household characteristics comprising the wealth index, a dependency ratio, and dummies for ethnic group; \mathbf{Prov}_{p} describes the household's province of residence; and ϵ_i is an idiosyncratic error term. Given that some controls may be endogenous because of joint determination (i.e., number of dead daughters and sons, miscarriages, age at first marriage, and woman working outside the household dwelling), I run the main regressions with these variables excluded. Then, to test the robustness of the estimates, I include them as explanatory variables in a set of auxiliary regressions. It should be noted that women's literacy status is treated as exogenous because it is assumed that, on average, individuals learn to read and write before becoming fertile. In any case, replicating all the models with women's literacy status excluded changes neither the coefficients of interest nor their statistical significance.

Exogenous Instrument. Not only does missing information in the original data set make it impossible to construct a fat marriage variable that accounts for migration paths and timings, but if migration is on average nonrandom in conflict level (i.e., if individuals move from violent to safer districts), then there is a risk of systematically assigning lower fat marriage values to women that experience greater than observed physical insecurity. This systematic measurement error is likely to be attenuated by several factors. First, because IDPs are counted as "persons or groups of persons who have been forced or obliged to flee or to leave their homes or places of habitual residence" (Kalin, 2008, p. 2), the estimated number of conflictinduced IDPs in Afghanistan, 1.2 million as of December 2015 (UNHCR, 2016), does not reflect the probability of misassigning fat marriage. In fact, this count also includes individuals that did not move far from their original

place of residence (i.e., remained in the original residence district), implying no measurement error. Second, internal migration occurs for many reasons other than conflict, including natural disasters, job searches, access to education, and family reunification. Third, most IDPs are concentrated in or close to urban areas, an estimated 40%of which are in Kabul province (CSO Afghanistan, 2016). This concentration is methodologically useful, however, in that it allows robustness checks that exclude the areas in which IDPs are clustered. Fourth, not only has the CSO sampling frame of the AfDHS 2015 not been updated since 2009, but it does not include the population residing in barracks, which basically excludes a portion of the recent and short-term IDPs from the sample. Given that approximately 800,000 conflict-induced IDPs were generated in the 2012-2015 period (OCHA Afghanistan, 2013), this exclusion may lead to sample selection bias.

To address the above sources of endogeneity, I construct an exogenous instrument Z that is strongly correlated with the endogenous regressor fat marriage (-0.12, at $\alpha = 5\%$) but related to the outcome of interest only through the instrumented regressor. More specifically, I define Z as the minimum true distance between each district center of mass and two border crossings, Torkham and Chaman (which belong administratively to the districts of Nangahar and Kandahar, respectively), both crucial to the inflow into the country of NATO soldiers, insurgents, and we apons –see the red circles in Figure 10. In general, higher (lower) Z values approximate lower (higher) levels of conflict because of the greater (lesser) district-to-hot-spot distance. Nonetheless, if Z is nonrandom in IDP movement, even the 2SRI strategy will produce biased estimates. Hence, Z is a valid instrument only if, in addition to being non-weak in respect to the instrumented variable, it fully satisfies the exclusion restriction by having no direct effect on the outcome variable and being uncorrelated with either the vector of omitted variables or any unobservables, including the IDP status of those excluded from the sampling frame. Because individuals and households choose their displacement destinations based on a complex set of constraints, potential opportunities, and family ties unlikely to coincide with moving away from the two selected hot-spots, even in the presence of individuals who moved from high to low conflict intensity districts, the instrument is unlikely to systematically take higher values (greater distance). Another possible source of bias, given the protracted nature of the Afghan conflict, is the likelihood of households self-selecting into districts closer to (further away from) the border crossings based on their degree of risk aversion. Although unable to determine whether more risk-averse households move away from the Afghan-Pakistani border because of too much conflict or because migrating itself is seen as too risky, I can exclude potential endogeneity of the instrument in respect to migration based on household risk-aversion.

Thus, I use several falsification tests to assess the exogeneity of the distance from the selected conflict hot-spots.

Table 1: Falsification Tests

		Dependent variabl	e:			
	Pregnancies	Living Children	Ideal Children			
	(1)	(2)	(3)			
Z	0.0001 (0.001)	0.0002 (0.001)	$0.001 \\ (0.001)$			
Observations	884	884	723			
Log Likelihood	-1,217	-1,244	-1,300			
Akaike Inf. Crit.	2,528	2,583	2,694			
	Dependent variable:					
	Debt/	Debt/	Debt/			
	Income	Wealth	Sheeps			
	(4)	(5)	(6)			
Z	-0.0002	13.585	-2.833			
	(0.0003)	(18.878)	(11.925)			
Observations	10,413	20,000	5,650			
\mathbb{R}^2	0.021	0.024	0.100			
Adjusted R ²	0.018	0.021	0.094			
Residual Std. Error	66.959	9,228,390	786,095			
F Statistic	7.814^{***}	10.953***	14.558^{***}			

Notes: All models are computed using survey sampling weights; specifications (1) to (3) are estimated using Poisson GLM and control for woman's and partner's age, partners' years of education, dependency ratio, wealth index, province and ethnicity fixed effects. and dummies for the woman being literate and married after BPHS implementation. Specification (3) also controls for number of pregnancies. Specification (4) includes only household reported yearly income, with missing values dropped from the analysis; specification (5) includes the full sample of households after list-wise deletion of missing basic household characteristics; and specification (6) includes only households owning at least one sheep. The OLS regressions for specifications (4) to (6) regress the outcome variable against the instrument Z computed as the sole minimum distance from the selected conflict hot-spots, dependency ratio, age of household head, coping strategy index, provincial and ethnicity fixed effects, and dummies for rural households, female head of household, and employed and married head of household. Additional controls are number of sheep owned in specifications (4) and (5) and wealth index in specifications (4) and (6). Robust standard errors (in parenthesis) are clustered at the district level; *p<0.1; **p<0.05; ***p<0.01.

In the first, I select a subsample of women that did not experience any fatality during the marriage period and then regress each outcome variable of interest on the full set of regressors from the main analysis including instrument Z. In the second, by leveraging 2014 ALCS data (CSO) Afghanistan, 2016) and the proxies validated in Brown et al., (2013) study of U.S. household attitudes toward risk and debt level, I separately regress the risk aversion proxies of share of debt over total yearly household income (both in 2014 Afghani), wealth index, and number of sheep owned (assets) against Z and a set of pertinent control variables. If the Z coefficient has no statistically significant effect on the outcome variables in any of the falsification test, then the exclusion restriction cannot be rejected, and as Table 1 shows, this coefficient is in fact not statistically significant in any specification, providing no evidence against its exogeneity.

5. Results

Descriptive statistics. The analytic sample (see Table 2), which covers all 34 provinces and 309 out of the total 398 districts, comprises woman living mostly (79%) in rural areas, with an average age of 30 and a relatively low level of AfDHS-defined literacy (only 13.4% able to read and write). One third of the sample has never used any modern or traditional contraceptive methods over the lifetime (33%), and only 10% are currently working outside the household dwelling. On average, Afghan women have 4.2 pregnancies resulting in 4.1 living children per woman, and 19% have experienced at least one miscarriage. Child mortality is higher for male than for female offspring, 0.19 and 0.15 children per woman, respectively. Interestingly, the ideal number of children wanted exceeds both the actual average number of pregnancies and living children (5.8 children per woman), implying the presence of a factor preventing women from meeting desired fertility levels. On average, the women experienced 22.8 fatalities per year; however variability in the sample is substantial (SD = 42.1). The women's partners are on average 4 years older, and have 4 years of education.

Table 2: Characteristics of the Sample

Statistic	Mean	St. Dev.
Number of pregnancies	4.183	2.734
Number of living chidlren	4.103	2.467
Ideal number of children	5.843	2.366
Fatalities during marriage (yearly)	22.796	42.116
Woman's age	29.838	7.686
Woman's age at first union	17.9	3.33
Woman is literate (dummy)	0.134	0.341
Woman works (dummy)	0.103	0.304
Never used contraceptives (dummy)	0.329	0.470
Miscarriages (dummy)	0.188	0.391
Married after BPHS implementation	0.614	0.487
Number of dead daughters	0.147	0.429
Number of dead sons	0.184	0.490
Partner's age	33.997	8.233
Partner's years of education	3.916	5.001
Household is rural (dummy)	0.791	0.406
Dependency Ratio	123.778	77.215
Wealth index (PCA)	-0.265	8.036
Number of districts	309	
Observations	9,860	

Notes: The only variable for which observations are missing is the ideal number of children (8,126 obs.).

Multivariate analysis. Although GLM Poisson regression is a natural candidate for the analysis of the dependent variables used in this study, formal tests for equidispersion show some degree of underdispersion (low varianceto-mean ratio) in all models (ranging from a 0.60 to 0.80). In GLM Poisson models, if equidispersion is not met, the estimated standard errors and test statistics would be distorted, whereas the potential effect on the coefficients' estimates is only minor. Specifically, underdispersion would increase the estimated standard errors, and thus decrease the estimation power. Controlling for the cluster-specific structure of the data or estimating a GLM Negative Binomial model solve for this problem if the conditional mean function is correctly specified (Cameron and Trivedi, 2009, p.561). In fact, lack of equidispersion may be also due to the omission of relevant explanatory variables, an issue that cannot be corrected by the approaches suggested above.

Predicted count means from all GLM Poisson regression are not statistically different from the actual sample means, and three quartiles of the observations show predicted probabilities greater than 0.79-0.88, confirming that the Poisson estimation fits well the data.

Table B1 reports the models' full estimates using the complete sample of both urban and rural households, alternatively considering number of pregnancies (models (1) and (2), number of living children (models (3) and (4)), and ideal number of children (models (5) and (6)) as dependent variables. It also shows the coefficients obtained using both the one-stage Poisson GLM (models (1), (3), and (5)) and the 2SRI Poisson GLM (models (2), (4), and (6)). Because these models are estimated using Poisson GLM estimations with a log-link function, Table 3 reports the coefficients in terms of rate ratios percentage changes (i.e. $e^{\beta_j} - 1$). The appendix tables show the original coefficients from the Poisson regressions for the full set of controls, and marginal effects from the GLM Poisson models for the conflict variable keeping all other controls at their mean value are reported in Figure 11 (Panel A and B present these effects for the models with and without controlling for the vector of transmission channels, respectively). One particularly noteworthy finding, signaled by the statistical significance of the coefficients relative to the estimated first-stage generalized residuals (\tilde{v}) in all models, is that the simple Poisson GLM regressions are biased in the coefficient of interest. On the one hand, the 2SRI strategy, under the condition of strict exogeneity, solves for migration-related measurement errors in the variable of interest (fat marriage) and sample selection (i.e., recent migrants and IDPs are excluded).

Under the assumption that migration occurs from high to low conflict intensity districts, measurement errors in the conflict variable – that is, lower conflict levels systematically assigned to women who were in fact most exposed to it – would understate conflict's true effect on fertility. However, in the case of sample selection, the bias's direction in the coefficient of interest because of the exclusion of recent internal migrants and IDPs would not be trivial. In fact, a substantial body of literature shows that forced migration causes increased fertility as a result of poor access to health care and contraceptives and higher exposure to sexual violence (Creel, 2002; Verwimp and Van Bavel, 2005), while another research stream demonstrates that IDP fertility may decline because of spousal separation, reduced nuptiality, and/or a drop in coital frequency due to stress and perceived insecurity (Hill, 2004). The effect of forced migration on fertility may also vary in the short, medium, and long term: for example, Hill (2004) concludes that despite drops in fertility in the immediate aftermath of a forced migration shock, in the long term, when IDPs resettle, their fertility levels are comparable to those of the rest of the population.

Table 3: Effect of Conflict on Fertility (Rate ratios percentage change)

		Dependent variable:				
	Pregnancies	Living Children	Ideal Children			
	(1)	(2)	(3)			
Fatalities (marriage)	-0.145^{***} (0.044)	-0.113^{***} (0.034)	-0.034^{***} (0.013)			
\widetilde{v}	0.033^{***} (0.010)	0.025^{**} (0.010)	0.017^{**} (0.008)			
Age	0.040^{***} (0.002)	0.035^{***} (0.002)	0.001 (0.002)			
Woman is literate	$\begin{array}{c} 0.045 \\ (0.032) \end{array}$	0.043 (0.032)	-0.006 (0.024)			
Marriage after BPHS	-0.221^{***} (0.021)	-0.188^{***} (0.018)	0.016 (0.018)			
Never contracept.	$\begin{array}{c} 0.112^{***} \\ (0.018) \end{array}$	0.092^{***} (0.017)	-0.071^{***} (0.019)			
Pregnancies			0.031^{***} (0.005)			
Ethnicity Province	Yes Yes	Yes Yes	Yes Yes			
Observations	9,860	9,860	8,126			
Log Likelihood	-18,216	-17,976	-17,704			
Akaike Inf. Crit.	36,538	36,057	35,517			
F-Stat (Robust VCovV).	13.28	13.28	16.42			

Notes: All models are computed using survey sampling weights and the following controls: is the error term from the first stage regression (\tilde{v}) , woman's and partner's age, partners' years of education, dependency ratio, wealth index, province and ethnicity fixed effects, and dummies for the woman being literate and being married after BPHS implementation, and for the household being rural. Specification (3) also controls for number of pregnancies. Robust standard errors (in parenthesis) are clustered at the district level; *p<0.1; **p<0.05; ***p<0.01.

Because internal migrants in Afghanistan are likely to choose urban or suburban areas as their intermediate and final destinations (CSO Afghanistan, 2016), excluding these areas from the study sample is likely to reduce, or even eliminate, biases stemming from either migrationrelated measurement errors or IDP exclusion. This assumption is confirmed by the not statistically significant coefficients of the first-stage generalized error (\tilde{v}) in all the model estimates reported in Table B2 (for the rural subsample only). In fact, not statical significance of the first stage error's coefficient signals lack of endogeneity Wooldridge (1997). Moreover, the consistently decreasing gaps between the coefficients estimated both with and without the IV corroborate the hypothesis that the bias detected in the one-stage Poisson GLM models in Table B1 but controlled for in the models using the 2SRI strategy is due more to sample selection than systematic measurement error.

In Table B1 the coefficients of fat marriage (denoting conflict exposure since time of first union) is always negative and statistically significant in all specifications except model (5). For instance, based on the unbiased 2SRI estimates (see Table 3), with all else kept constant, one additional yearly fatality per 1,000 inh. decreases a woman's number of pregnancies and living children rate ratios by 14.5% (model (1)) and 11.3% (model (2)), respectively, while also lowering the ideal number of children rate ratio by 3.4% (model (3)). For all models, these estimates are robust to the inclusion of conflict-to-fertility transmission channel variables, such as number of dead sons or daughters, the woman's work status, age at first marriage, and a dummy controlling for at least one pregnancy ending in a non-live birth (see Table B3). As expected, a higher number of dead children increases the number of pregnancies but has negative effect on the number of living children and ideal family size (see Table B3), which confirms that the effect detected when regressing the former on fertility outcomes solely represents replacement effects. Nonetheless, these results, although in line with the existing literature, are likely to suffer from endogeneity because of reverse causality, which prevents any claim of a causal relation. Similarly, because of the suspected reverse causality in the relation of women's work status to fertility and of miscarriage to fertility, these estimates represent only statistical associations.

Being married after the 2002 implementation of the Afghan BPHS, which includes a family planning program, although it always has a statistically significant and large negative effect on fertility outcomes, has no effect on fertility preferences. Also noteworthy is that this result remains robust to controlling for women's age. At the same time, although women with no contraceptive use over the lifetime have a greater number of pregnancies and children, when the ideal number of children is regressed against the no contraceptives dummy, the coefficient of this latter changes sign. Although the reason could be bias from reverse causality, the result could also signal an insufficient supply of contraceptives or sociocultural constraints on access to birth control methods, a hypothesis beyond the scope of the present study but worthy of further investigation. Not surprisingly, women's literacy has no effect on either fertility outcomes or ideal family size, a finding attributable to the very low educational level of reproductive age women in general (13.4%) able to read and write, only 68.6% of whom complete primary school). As might also be expected, number of pregnancies and living children decrease with older age at first union, and rural households prefer and have larger families.

Robustness checks. In order to rule out any possibility of bias due to violation of the equidispersion assumption, I alternatively replicate all models by means of Conway-Maxwell-Poisson (CMP) and GLM Negative Binomial regressions. These two strategies relax the equidispersion assumption. Specifically, the CMP estimation strategy allows for underdispersion (as well as overdispersion) by modelling the variance as a function of the mean $(var(y|x) = \theta)$, where $\theta < 1$ in case of underdispersion). The results produced by these two alternative estimation approaches are virtually no different in terms of coefficients sizes, and show the same level of statistical significance for the coefficients of interest -CMP regressions' standard errors are corrected by parametric bootstrap. Interestingly, post-estimation CMP regression diagnostics do not show any evidence against equidispersion, confirming the robustness of the estimates presented in this study.

One may argue that when regressing the number of ideal children against the full set of regressors including a woman's number of pregnancies would reduce the potential effect of the conflict variable effect on the former dependent variable, especially as this study demonstrates a clear causal link between conflict and fertility outcomes. A similar argument could be raised for the fact that equations modeling the effect of conflict on fertility outcomes exclude from the set of controls the proxy for fertility preferences. I thus run auxiliary regressions excluding the variable for number of pregnancies, and including the proxy for fertility preferences in the models where the dependent variable is the ideal number of children wanted and a fertility outcome, respectively. Noteworthy, the results of this additional specifications do not change neither in coefficient size nor statistical significance.

Finally, in all the models additionally controlling for the vector of transmission channels (Table B3), the dummy taking value one if a woman married after the implementation of the BPHS is omitted because of strong multicollinearity. This multicollinearity is due to the simultaneous inclusion of woman's age and age at first marriage among the regressors. However, this issue does not affect the magnitude and statistical significance of the conflict variable relative coefficients.

6. Discussion

Overall, this study finds that the Afghan protracted conflict is a downward shaping determinant of both fertility outcomes and preferences. Nevertheless, the conflict's negative effect on ideal family size, although statistically significant, is very small, which contrasts with the larger effects obtained using number of pregnancies or living children as the dependent variable. The study findings thus highlight two major country-specific considerations. First, contrary to the risk-insurance approach to fertility, Afghans opt for smaller families in order to cope with the country's persistent and unwavering level of conflict-led socioeconomic disruption (see Brown, 2004). Results in the



Figure 11: Marginal effects for the conflict intensity experienced during marriage. Estimates from GLM Poisson, all other variable kept at their mean level. Panel A reports the results for the models (2),(4) and (6) of Table B1. Panel B reports the results for the models (2),(4) and (6) of Table B3, where the vector of transmission channels is included among the controls.

same direction are reported and similar conclusions drawn by studies on comparable contexts of widespread physical insecurity, poverty, and famine such as the Ethiopian Civil War of 1974-1991 (Lindstrom and Berhanu, 1999). Second, the conflict's minimal direct effect on fertility preferences strongly suggests that the downward trends in Afghan TFR would probably slow if conflict were to cease, especially given the only marginal improvements in health and human development. It should be noted that the interpretation of this result does not change even when women reveal their ideal number of children given peace in their district. In fact, in this case, the model's coefficient would not only be free from any bias but would provide further evidence for the hypothesis that conflict does not modify long-term family size preferences. Finally, despite the endogeneity of the conflict variable -solved implementing a 2SRI approach- the results of this study are robust as the sign of this variable's coefficient does not change when only the rural subsample, for which I demonstrate that no bias exists, is analyzed.

Noteworthy, these results are robust to the inclusion

of a dummy controlling for being married after the implementation of the BPHS which, among the others, includes a family planning program. This study is not able to evaluate the effectiveness of the BPHS family planning program, and the relative coefficients must be interpret as statistical associations. However, the empirical evidence presented, as well the fact that the average number of children a woman is willing to have exceeds the observed fertility outcomes, suggest that the Afghan authorities should improve their family planning program not only by assuring access to contraceptives, but also by developing better information campaigns able to reach both men and women belonging to different ethnic groups and particularly focusing on contraceptive safety, effectiveness and their non-harmful side-effects Huber et al. (2010).

In fact, as shown by the successful implementation of the Iranian birth control policy, the provision of family planning services alone, despite crucial, is only marginally effective in reducing TFR. Iran, which before the approval of its family planning program by Ayatollah Khamene'i showed a TFR as high as 5.5 birth per women, managed to reach a TFR of 1.68 by 2015 (World Bank, 2015b). In fact, the Iranian drop in TFR would have been inconceivable without the population's wide acceptance of the family planning education campaign that was carried extensively throughout the country. Even today, for example, in Iranian clinics and health posts can be found posters reading "not too late, not too soon, not too many" (*nah kheli dir, nah kheli zoud, nah kheli ziad*) (Tober et al., 2006). Islam (Shi'a Islam in particular) and its general openness toward family planning (Roudi-Fahimi, 2004) worked as a catalyst for the Iranian birth control policy population's acceptance.

In Afghanistan, however, ethnic-specific factors may be constraining the family planning program effectiveness. Noteworthy, Pashtuns, the largest ethnic group in Afghanistan, are more likely to have and prefer a greater number of children, probably because of adherence to Pashtunwali. At the best of my knowledge, to date no systematic study exists on the Afghan population's reception and relative limitations of the birth control policy, a gap that, if filled, would contribute in improving the general quality of life for this war-torn population.

7. Conclusions

Given the recent sharp drop in Afghan TFR despite modest improvements in the population's overall health and human development, this study assesses the contribution of protracted conflict to fertility trends by applying a quasi-experimental strategy to a combined data set of cross-sectional data on reproductive age women and georeferenced information on district level conflict intensity. The results show that long-term conflict significantly reduces the numbers of both pregnancies and living children, with households limiting births to better cope with conflict-related shocks. This finding, although contrary to the hypothesis that households increase their fertility in situations of socioeconomic insecurity, is in line with the conclusions of extant empirical studies. At the same time, however, estimates of the conflict's coefficient when fertility preferences are the dependent variable, although negative and statistically significant, are very small in magnitude. Given the low level of women's empowerment in terms of volitional fertility drivers, these findings imply that if the conflict were to cease, Afghanistan's negative TFR trend would slow down.

Table B1:	Effect o	of Conflict	on	Fertility ((Urban	and	Rural	Areas))
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	Dependent variable:					
	Pregn	ancies	Living (Children	Ideal C	hildren
	(1)	(2)	(3)	(4)	(5)	(6)
Fatalities during marriage	-0.057^{**} (0.027)	-0.157^{***} (0.043)	-0.048^{**} (0.023)	-0.120^{***} (0.033)	-0.007 (0.008)	-0.035^{***} (0.013)
\widetilde{v}		$\begin{array}{c} 0.031^{***} \\ (0.010) \end{array}$		0.025^{**} (0.010)		0.017^{**} (0.008)
Age	$\begin{array}{c} 0.041^{***} \\ (0.002) \end{array}$	0.040^{***} (0.002)	$\begin{array}{c} 0.035^{***} \\ (0.002) \end{array}$	0.034^{***} (0.002)	$\begin{pmatrix} 0.002\\ (0.002) \end{pmatrix}$	$\begin{array}{c} 0.001 \\ (0.002) \end{array}$
Woman is literate (dummy)	$\begin{array}{c} 0.046 \\ (0.034) \end{array}$	$\begin{array}{c} 0.049 \\ (0.035) \end{array}$	$ \begin{array}{c} 0.040 \\ (0.031) \end{array} $	$\begin{array}{c} 0.042 \\ (0.032) \end{array}$	-0.005 (0.024)	-0.006 (0.024)
Marriage after BPHS implementation	-0.235^{***} (0.021)	-0.235^{***} (0.021)	-0.208^{***} (0.018)	-0.209^{***} (0.018)	$ \begin{array}{c} 0.020 \\ (0.018) \end{array} $	$\begin{array}{c} 0.016\\ (0.018) \end{array}$
Never used contraceptives	0.108^{***} (0.018)	0.106^{***} (0.018)	0.090^{***} (0.017)	0.088^{***} (0.017)	-0.071^{***} (0.019)	-0.074^{***} (0.019)
Number of pregnancies					$\begin{array}{c} 0.032^{***} \\ (0.005) \end{array}$	$\begin{array}{c} 0.031^{***} \\ (0.005) \end{array}$
Partner's age	$\begin{array}{c} 0.009^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.009^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.009^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.009^{***} \\ (0.002) \end{array}$	$\begin{array}{c} -0.0004 \\ (0.002) \end{array}$	-0.001 (0.002)
Partner's years of education	-0.001 (0.002)	-0.001 (0.002)	$ \begin{array}{c} 0.0002 \\ (0.001) \end{array} $	0.0001 (0.001)	-0.003^{**} (0.001)	-0.003^{**} (0.001)
Rural (dummy)	0.070^{*} (0.036)	0.072^{**} (0.035)	0.071^{**} (0.029)	0.073^{**} (0.028)	0.072^{*} (0.039)	0.071^{*} (0.038)
Dependency ratio	0.002^{***} (0.0001)	0.002^{***} (0.0001)	0.002^{***} (0.0001)	0.002^{***} (0.0001)	0.0002^{**} (0.0001)	0.0002^{**} (0.0001)
Wealth index	-0.009 (0.014)	-0.011 (0.014)	-0.008 (0.011)	-0.010 (0.011)	-0.061^{***} (0.010)	-0.062^{***} (0.010)
Tajik (ref: Pashtun)	$ \begin{array}{c} -0.020 \\ (0.017) \end{array} $	-0.031^{*} (0.017)	-0.029^{*} (0.017)	$\begin{array}{c} -0.037^{**} \\ (0.017) \end{array}$	$egin{array}{c} -0.067^{***} \ (0.019) \end{array}$	$\begin{array}{c} -0.071^{***} \\ (0.019) \end{array}$
Hazara	-0.037 (0.032)	-0.054 (0.034)	-0.070^{*} (0.040)	-0.082^{*} (0.043)	-0.052^{*} (0.029)	-0.058^{**} (0.029)
Uzbek	$\substack{-0.062^{**}\\(0.027)}$	$^{-0.070^{**}}_{(0.028)}$	$\begin{array}{c} -0.051^{*} \\ (0.029) \end{array}$	$egin{array}{c} -0.057^{*} \ (0.030) \end{array}$	$\begin{pmatrix} 0.014 \\ (0.024) \end{pmatrix}$	$\begin{pmatrix} 0.009\\ (0.024) \end{pmatrix}$
Turkmen	$\begin{array}{c} -0.138^{***} \\ (0.037) \end{array}$	$\substack{-0.157^{***}\(0.039)}$	${-0.161^{***}\atop (0.031)}$	$\substack{-0.175^{***}\(0.032)}$	$\begin{array}{c} 0.108^{**} \\ (0.045) \end{array}$	$\begin{array}{c} 0.100^{**} \\ (0.045) \end{array}$
Nuristani	$^{-0.004}_{(0.060)}$	$\begin{array}{c} -0.008 \\ (0.086) \end{array}$	$\begin{array}{c} -0.001 \\ (0.057) \end{array}$	$\begin{array}{c} -0.004 \\ (0.074) \end{array}$	$\begin{pmatrix} 0.019 \\ (0.136) \end{pmatrix}$	$\begin{pmatrix} 0.012\\ (0.141) \end{pmatrix}$
Baloch	$^{-0.130^{***}}_{(0.040)}$	$^{-0.143^{***}}_{(0.043)}$	$\begin{array}{c} -0.149^{***} \\ (0.042) \end{array}$	$\begin{array}{c} -0.159^{***} \\ (0.045) \end{array}$	$\begin{pmatrix} 0.030 \\ (0.083) \end{pmatrix}$	$\begin{pmatrix} 0.022\\ (0.081) \end{pmatrix}$
Pashai	$\begin{pmatrix} -0.029\\ (0.026) \end{pmatrix}$	$\begin{array}{c} -0.036 \\ (0.027) \end{array}$	$\begin{array}{c} -0.047 \\ (0.037) \end{array}$	$\begin{array}{c} -0.052 \\ (0.037) \end{array}$	$\begin{pmatrix} 0.001 \\ (0.034) \end{pmatrix}$	$\begin{pmatrix} -0.001 \\ (0.035) \end{pmatrix}$
Other ethnicity	$ \begin{array}{c} -0.067 \\ (0.056) \end{array} $	-0.067 (0.055)	-0.062 (0.044)	-0.062 (0.044)	$\begin{array}{c} -0.071 \\ (0.044) \end{array}$	-0.069 (0.044)
Constant	$\begin{array}{c} -0.550^{***} \\ (0.087) \end{array}$	$\begin{array}{c} -0.501^{***} \\ (0.081) \end{array}$	$\begin{array}{c} -0.321^{***} \\ (0.079) \end{array}$	$\begin{array}{c} -0.282^{***} \\ (0.078) \end{array}$		$(0.087)^{1.479^{***}}$
Observations Log Likelihood Akaike Inf. Crit. First Stage F-Stat (Robust VCovV).	$9,860 \\ -18,227 \\ 36,559 \\ -$	$9,860 \\ -18,216 \\ 36,538 \\ 13.28$	$9,860 \\ -17,983 \\ 36,069 \\ -$	$9,860 \\ -17,976 \\ 36,057 \\ 13.28$	$^{8,126}_{-17,710}_{35,526}$	$^{8,126}_{-17,704}_{35,517}_{16.42}$

Notes: All models are computed using survey sampling weights; Specifications (2), (4) and (6) are estimated by means of 2SRI approach, where \tilde{v} is the error term from the first stage regression. Controls: woman's and partner's age, partners' years of education, dependency ratio, wealth index, dummies for woman being literate, being married after the implementation of the BPHS, the household being rural, province and ethnicity fixed effects. Moreover, specification (5) and (6) controls for number of pregnancies. Robust standard errors clustered at the district level in parenthesis; *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:						
	Pregn	ancies	Living (Children	Ideal C	hildren	
	(1)	(2)	(3)	(4)	(5)	(6)	
Fatalities during marriage	-0.083^{***} (0.029)	-0.125^{***} (0.048)	$\begin{array}{c} -0.071^{***} \\ (0.022) \end{array}$	-0.084^{**} (0.033)	-0.010 (0.006)	$\begin{array}{c} -0.032^{**} \\ (0.014) \end{array}$	
\widetilde{v}		$\begin{array}{c} 0.015 \\ (0.014) \end{array}$		$\begin{array}{c} 0.005 \ (0.011) \end{array}$		$\begin{array}{c} 0.015 \ (0.009) \end{array}$	
Age	$\begin{array}{c} 0.041^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.041^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.037^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.036^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.002 \\ (0.002) \end{array}$	$\begin{array}{c} 0.002 \\ (0.002) \end{array}$	
Woman is literate (dummy)	$\begin{array}{c} 0.048 \\ (0.040) \end{array}$	$\begin{array}{c} 0.049 \\ (0.041) \end{array}$	$\begin{array}{c} 0.044 \\ (0.037) \end{array}$	$\begin{array}{c} 0.044 \\ (0.037) \end{array}$	-0.018 (0.027)	-0.019 (0.027)	
Marriage after BPHS implementation	$\begin{array}{c} -0.219^{***} \\ (0.022) \end{array}$	$\begin{array}{c} -0.218^{***} \\ (0.022) \end{array}$	$\begin{array}{c} -0.193^{***} \\ (0.018) \end{array}$	$egin{array}{c} -0.193^{***} \ (0.018) \end{array}$	$\begin{array}{c} 0.024 \\ (0.021) \end{array}$	$\begin{array}{c} 0.021 \\ (0.021) \end{array}$	
Never used contraceptives	$\begin{array}{c} 0.098^{***} \\ (0.017) \end{array}$	$\begin{array}{c} 0.096^{***} \\ (0.017) \end{array}$	$\begin{array}{c} 0.079^{***} \\ (0.017) \end{array}$	$\begin{array}{c} 0.078^{***} \\ (0.017) \end{array}$	$\begin{array}{c} -0.042^{***} \\ (0.016) \end{array}$	$\begin{array}{c} -0.045^{***} \\ (0.017) \end{array}$	
Number of pregnancies					$\begin{array}{c} 0.031^{***} \\ (0.004) \end{array}$	$\begin{array}{c} 0.030^{***} \ (0.005) \end{array}$	
Partner's age	$\begin{array}{c} 0.009^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.009^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.007^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.007^{***} \\ (0.002) \end{array}$	-0.001 (0.002)	-0.001 (0.002)	
Partner's years of education	$ \begin{array}{c} -0.002 \\ (0.001) \end{array} $	$\begin{array}{c} -0.002 \\ (0.001) \end{array}$	$\begin{array}{c} -0.0001 \\ (0.001) \end{array}$	$\begin{array}{c} -0.0001 \\ (0.001) \end{array}$	$\begin{array}{c} -0.003^{**} \\ (0.001) \end{array}$	$^{-0.003^{**}}_{(0.001)}$	
Dependency ratio	0.002^{***} (0.0001)	0.002^{***} (0.0001)	0.002^{***} (0.0001)	0.002^{***} (0.0001)	0.0002^{**} (0.0001)	0.0002^{**} (0.0001)	
Wealth index	$\begin{pmatrix} 0.001 \\ (0.003) \end{pmatrix}$	$\begin{array}{c} 0.0003 \\ (0.002) \end{array}$	$\begin{array}{c} -0.0002 \\ (0.002) \end{array}$	$-0.0003 \\ (0.002)$	-0.007^{***} (0.002)	-0.007^{***} (0.002)	
Tajik (ref: Pashtun)	-0.011 (0.019)	-0.017 (0.019)	-0.017 (0.019)	-0.019 (0.018)	$\begin{array}{c} -0.075^{***} \\ (0.018) \end{array}$	-0.078^{***} (0.018)	
Hazara	$\begin{array}{c} 0.009 \\ (0.029) \end{array}$	$\begin{pmatrix} 0.001 \\ (0.030) \end{pmatrix}$	-0.007 (0.028)	-0.010 (0.028)	-0.093^{***} (0.024)	-0.098^{***} (0.025)	
Uzbek	$\begin{array}{c} -0.042 \\ (0.027) \end{array}$	$ \begin{array}{c} -0.045 \\ (0.028) \end{array} $	$ \begin{array}{c} -0.027 \\ (0.028) \end{array} $	$-0.028 \\ (0.028)$	$\begin{pmatrix} 0.009\\ (0.026) \end{pmatrix}$	$\begin{array}{c} 0.007 \\ (0.026) \end{array}$	
Turkmen	$^{-0.121^{***}}_{(0.041)}$	$\substack{-0.124^{***}\\(0.041)}$	$\substack{-0.137^{***}\\(0.032)}$	$egin{array}{c} -0.138^{***} \ (0.032) \end{array}$	$\begin{array}{c} 0.110^{**} \\ (0.045) \end{array}$	$\begin{array}{c} 0.107^{**} \\ (0.045) \end{array}$	
Nuristani	$ \begin{array}{c} -0.008 \\ (0.069) \end{array} $	$\begin{array}{c} -0.011 \\ (0.079) \end{array}$	$\begin{array}{c} -0.004 \\ (0.064) \end{array}$	$\begin{array}{c} -0.005 \\ (0.067) \end{array}$	$\begin{pmatrix} 0.029\\ (0.137) \end{pmatrix}$	$\begin{pmatrix} 0.023 \\ (0.141) \end{pmatrix}$	
Baloch	$\begin{array}{c} -0.115^{***} \\ (0.029) \end{array}$	$\begin{array}{c} -0.123^{***} \\ (0.029) \end{array}$	$\begin{array}{c} -0.118^{***} \\ (0.042) \end{array}$	$\begin{array}{c} -0.121^{***} \\ (0.043) \end{array}$	$\begin{pmatrix} 0.037 \\ (0.067) \end{pmatrix}$	$\begin{pmatrix} 0.027 \\ (0.067) \end{pmatrix}$	
Pashai	$\begin{array}{c} -0.036 \\ (0.025) \end{array}$	$\begin{array}{c} -0.039 \\ (0.025) \end{array}$	$\begin{array}{c} -0.052 \\ (0.036) \end{array}$	$\begin{array}{c} -0.053 \\ (0.036) \end{array}$	$\begin{pmatrix} 0.012 \\ (0.037) \end{pmatrix}$	$\begin{pmatrix} 0.010 \\ (0.038) \end{pmatrix}$	
Other ethnicity	$ \begin{array}{c} -0.079 \\ (0.066) \end{array} $	$\begin{array}{c} -0.079 \\ (0.066) \end{array}$	$\begin{array}{c} -0.063 \\ (0.055) \end{array}$	$\begin{array}{c} -0.062 \\ (0.055) \end{array}$	$\begin{array}{c} -0.071 \\ (0.049) \end{array}$	-0.068 (0.049)	
Constant	$\begin{array}{c} -0.365^{***} \\ (0.097) \end{array}$	$\begin{array}{c} -0.343^{***} \\ (0.093) \end{array}$	$-0.138 \\ (0.102)$	$-0.130 \\ (0.097)$	$\begin{array}{c} 1.465^{***} \\ (0.089) \end{array}$	$\begin{array}{c} 1.487^{***} \\ (0.087) \end{array}$	
Observations Log Likelihood Akaike Inf. Crit. First Stage F-Stat (Robust VCovV).	$7,801 \\ -14,820 \\ 29,741 \\ -$	$7,801 \\ -14,818 \\ 29,739 \\ 15.40$	$7,801 \\ -14,629 \\ 29,359 \\ -$	$7,801 \\ -14,629 \\ 29,360 \\ 15.40$	$6,331 \\ -14,103 \\ 28,308 \\ -$	$\begin{array}{r} 6,331 \\ -14,100 \\ 28,304 \\ 19.24 \end{array}$	

Notes: All models are computed using survey sampling weights; Specifications (2), (4) and (6) are estimated by means of 2SRI approach, where \tilde{v} is the error term from the first stage regression. Controls: woman's and partner's age, partners' years of education, dependency ratio, wealth index, dummies for woman being literate, being married after the implementation of the BPHS, province and ethnicity fixed effects. Moreover, specification (5) and (6) controls for number of pregnancies. Robust standard errors clustered at the district level in parenthesis; *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:						
	Pregn	ancies	Living (Children	Ideal C	Children	
	(1)	(2)	(3)	(4)	(5)	(6)	
Fatalities during marriage	-0.065^{**} (0.027)	-0.152^{***} (0.042)	$\begin{array}{c} -0.047^{**} \\ (0.023) \end{array}$	-0.121^{***} (0.032)	$-0.006 \\ (0.008)$	$\begin{array}{c} -0.035^{**} \\ (0.014) \end{array}$	
\widetilde{v}		$\begin{array}{c} 0.027^{***} \\ (0.010) \end{array}$		$\begin{array}{c} 0.025^{***} \ (0.010) \end{array}$		$\begin{array}{c} 0.018^{**} \\ (0.009) \end{array}$	
Age	$\begin{array}{c} 0.037^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.037^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.035^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.034^{***} \\ (0.002) \end{array}$	$\begin{pmatrix} 0.002\\ (0.002) \end{pmatrix}$	$\begin{pmatrix} 0.001 \\ (0.002) \end{pmatrix}$	
Woman is literate (dummy)	$\begin{array}{c} 0.041 \\ (0.031) \end{array}$	$\begin{array}{c} 0.043 \ (0.032) \end{array}$	$\begin{array}{c} 0.041 \\ (0.031) \end{array}$	$\begin{array}{c} 0.043 \ (0.033) \end{array}$	-0.011 (0.022)	-0.012 (0.023)	
Marriage after BPHS implementation	$egin{array}{c} -0.211^{***} \ (0.018) \end{array}$	-0.211^{***} (0.018)	${-0.209^{***} \atop (0.017)}$	$\begin{array}{c} -0.210^{***} \\ (0.017) \end{array}$	$\begin{array}{c} 0.022 \\ (0.019) \end{array}$	$\begin{array}{c} 0.019 \\ (0.019) \end{array}$	
Never used contraceptives	$\begin{array}{c} 0.119^{***} \\ (0.016) \end{array}$	$\begin{array}{c} 0.117^{***} \\ (0.016) \end{array}$	$\begin{array}{c} 0.089^{***} \\ (0.017) \end{array}$	$\begin{array}{c} 0.087^{***} \\ (0.017) \end{array}$	$\begin{array}{c} -0.072^{***} \\ (0.018) \end{array}$	$egin{array}{c} -0.074^{***} \ (0.018) \end{array}$	
Had a miscarrige (dummy)	$\begin{array}{c} 0.013 \ (0.011) \end{array}$	$\begin{array}{c} 0.011 \\ (0.011) \end{array}$	$\begin{array}{c} 0.021^{*} \ (0.012) \end{array}$	$\begin{array}{c} 0.020 \\ (0.012) \end{array}$	$\begin{array}{c} 0.045^{*} \\ (0.026) \end{array}$	$\begin{array}{c} 0.044^{*} \\ (0.026) \end{array}$	
Woman works (dummy)	-0.003 (0.017)	$\begin{array}{c} 0.001 \\ (0.017) \end{array}$	$\begin{array}{c} 0.010 \\ (0.018) \end{array}$	$\begin{array}{c} 0.013 \\ (0.018) \end{array}$	$\begin{array}{c} 0.034 \\ (0.030) \end{array}$	$\begin{array}{c} 0.035 \ (0.030) \end{array}$	
Numb. of dead sons	$\begin{array}{c} 0.131^{***} \\ (0.010) \end{array}$	$\begin{array}{c} 0.131^{***} \\ (0.011) \end{array}$	-0.016 (0.012)	-0.016 (0.012)	-0.017 (0.017)	-0.016 (0.017)	
Numb. dead dauthers	0.140^{***} (0.014)	0.140^{***} (0.014)	-0.010 (0.014)	-0.010 (0.014)	$\begin{array}{c} 0.004 \\ (0.025) \end{array}$	$ \begin{array}{c} 0.006 \\ (0.026) \end{array} $	
Number of pregnancies					$\begin{array}{c} 0.032^{***} \\ (0.006) \end{array}$	$\begin{array}{c} 0.032^{***} \\ (0.006) \end{array}$	
Partner's age	$\begin{array}{c} 0.010^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.009^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.009^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.008^{***} \\ (0.002) \end{array}$	$\begin{array}{c} -0.001 \\ (0.002) \end{array}$	-0.001 (0.002)	
Partner's years of education	$\begin{array}{c} -0.0004 \\ (0.001) \end{array}$	$egin{array}{c} -0.0005 \ (0.001) \end{array}$	$\begin{array}{c} 0.0001 \\ (0.001) \end{array}$	$\begin{array}{c} 0.00005 \\ (0.001) \end{array}$	$egin{array}{c} -0.003^{**} \ (0.001) \end{array}$	$egin{array}{c} -0.003^{**} \ (0.001) \end{array}$	
Rural (dummy)	$\begin{array}{c} 0.068^{**} \\ (0.032) \end{array}$	$\begin{array}{c} 0.070^{**} \\ (0.032) \end{array}$	$\begin{array}{c} 0.072^{**} \\ (0.029) \end{array}$	$\begin{array}{c} 0.073^{***} \\ (0.028) \end{array}$	$\begin{array}{c} 0.071^{*} \ (0.037) \end{array}$	$\begin{array}{c} 0.070^{**} \\ (0.036) \end{array}$	
Dependency ratio	0.002^{***} (0.0001)	$\begin{array}{c} 0.002^{***} \\ (0.0001) \end{array}$	0.002^{***} (0.0001)	$\begin{array}{c} 0.002^{***} \\ (0.0001) \end{array}$	$\begin{array}{c} 0.0002^{**} \\ (0.0001) \end{array}$	$\begin{array}{c} 0.0002^{**} \\ (0.0001) \end{array}$	
Wealth index	$\begin{array}{c} 0.0001 \\ (0.002) \end{array}$	$\begin{array}{c} -0.0002 \\ (0.002) \end{array}$	$\begin{array}{c} -0.001 \\ (0.001) \end{array}$	-0.001 (0.001)	$\begin{array}{c} -0.007^{***} \\ (0.001) \end{array}$	$\begin{array}{c} -0.008^{***} \\ (0.001) \end{array}$	
Constant	-0.518^{***} (0.085)	-0.477^{***} (0.082)	-0.327^{***} (0.077)	-0.288^{***} (0.076)	$ \begin{array}{c} 1.441^{***} \\ (0.092) \end{array} $	$\begin{array}{c} 1.472^{***} \\ (0.083) \end{array}$	
Observations Log Likelihood Akaike Inf. Crit. First Stage F-Stat (Robust VCovV).	$9,860 \\ -17,942 \\ 35,996 \\ -$	$9,860 \\ -17,933 \\ 35,981 \\ 13.08$	$9,860 \\ -17,979 \\ 36,070 \\ -$	$9,860 \\ -17,971 \\ 36,057 \\ 13.08$	$8,126 \\ -17,699 \\ 35,512 \\ -$	$8,126 \\ -17,693 \\ 35,502 \\ 16.47$	

Notes: All models are computed using survey sampling weights; Specifications (2), (4) and (6) are estimated by means of 2SRI approach, where \tilde{v} is the error term from the first stage regression. Controls: woman's and partner's age, partners' years of education, dependency ratio, wealth index, dummies for woman being literate, being married after the implementation of the BPHS, the household being rural, woman currently working, had at lest one miscarriage, never used contraceptive methods, province and ethnicity fixed effects. Moreover, specification (5) and (6) controls for number of pregnancies. Robust standard errors clustered at the district level in parenthesis; *p<0.1; **p<0.05; ***p<0.01.

Chapter IV

The Effect of Floods on Anemia among Reproductive Age Women in Afghanistan

Abstract

This study uses biomarker information from the 2013 National Nutrition Survey Afghanistan and satellite precipitation driven modeling results from the Global Flood Monitoring System to analyze how floods affect the probability of anemia in Afghan women of reproductive age (15–49). In addition to establishing a causal relation between the two by exploiting the quasi-random variation of floods in different districts and periods, the analysis demonstrates that floods have a significant positive effect on the probability of anemia through two possible transmission mechanisms. The first is a significant effect on inflammation, probably related to water borne diseases carried by unsafe drinking water, and the second is a significant negative effect on retinol concentrations. Because the effect of floods on anemia remains significant even after we control for anemia's most common causes, we argue that the condition may also be affected by elevated levels of psychological stress.

1. Introduction

As the most common type of disaster worldwide, floods, which account for 47% of all catastrophic events, resulted in approximately 57,000 deaths between 2006 and 2015 UNIDSR & CRED (2016). Future prospects are even bleaker: the frequency and intensity of floods are expected to increase because of global warming through rising sea levels and more extreme precipitation Ahern et al. (2005); Costello et al. (2009); Haines and Patz (2004); Ramin and McMichael (2009). Exposure to floods will also increase because of rapid urbanization Du et al. (2010). The effect of floods is particularly strong in Afghanistan, where they accounted for over 5,000 recorded deaths and about 400,000 displaced people between 1988 and 2006, over 200,000 of these in the 2002–2006 period alone Hagen and Teufert (2009). In 2013, the data year for this study, floods accounted for 70% of all the natural disasters in Afghanistan OCHA (2014).

The most evident effects of floods, besides loss of life and injuries, are crop losses, problems accessing markets, and depletion of household wealth, all of which ultimately determine food insecurity and related micronutrient deficiencies. According to one systematic review of 197 studies Du et al. (2010), floods also have significant and often lasting health consequences, including disability, social disruption, and mental health problems. These negative health outcomes are underscored by an earlier review of 212 epidemiologic studies evidencing their influence on common mental disorders, posttraumatic stress disorder (PTSD), and suicide Ahern et al. (2005), results which hold also in the long-run as shown in a study on early chilhood exposure to natural disasters and mental health disorders and substance use as adults Maclean et al. (2016). The negative mental health effects of flooding caused by hurricanes Sandy and Katrina have also been documented Moise and Ruiz (2016); Gruebner et al. (2015).

Floods may also explain the incidence of anemia (low hemoglobin) in Afghanistan, a major public health problem that, in 2013, affected 40.4% of reproductive age women, 13.8% of them suffering from iron deficiency anemia UNICEF (2014). In fact, studies for Southeast Asia show not only that nearly every second pregnant women is anemic, but that this condition causes about 20% of all maternal deaths Noronha et al. (2012). The most common form of the condition is iron deficiency anemia, which in Southeast Asia is caused primarily by inadequate intake of iron, dietary deficiency, and infectious diseases Noronha et al. (2012). An additional but as yet little studied cause of such anemia could be severe psychological stress, already shown to heavily impact menstrual disorders Gordley et al. (2000); Neinstein (1985); Shapley et al. (2003), which in turn may lead to anemia. In this paper, therefore, we analyze the possible effects of floods on anemia among a particularly susceptible group: Afghan women of reproductive age.

Our primary hypothesis is that floods can affect anemia through a number of channels, including infections, poor diet (leading to iron, zinc, and vitamin deficiencies), and psychological stress associated with the consequences of flooding. In testing this hypothesis, we contribute to the existing literature in several ways: first, as emphasized by other studies (e.g., Du et al. (2010)), there is a dearth of research on the health consequences of floods in developing countries. This scarcity is particularly true for Afghanistan, a country for which, to the best of our knowledge, no research on this topic exists. Second, little of the existing research on the health effects of flooding focuses on reproductive age women even though this population is particularly vulnerable to natural disasters Alderman et al. (2012). As pointed out in Alderman et al. (2012), "women's elevated risk for worse mental health outcomes following disaster exposure, combined with negative impacts of prenatal stress on maternal health, calls for a greater attention to women's reproductive health following flood events" (p. 46). Finally, this study can serve as a primer for combining rich biomarker information and satellite imagery to identify the causal relations between flood exposure and the prevalence of anemia.

2. Data and Measures

2.1. Data sources

Information on the health and other relevant characteristics of reproductive age Afghan woman, together with household level information, are taken from the 2013 National Nutrition Survey (NNS) Afghanistan. The NNS (2013) was undertaken through a cooperative agreement between the Aga Khan University, Pakistan, the Afghan Ministry of Public Health and UNICEF Afghanistan. The NNS data are publicly available from UNICEF. The NNS collects data on the nutritional status of the Afghan population and related factors, such as consumption frequency of specific food groups during the week and month before interview and the unavailability of any food during the month prior to interview. The survey sample is obtained using a two-stage cluster sampling technique based on the Afghan Central Statistical Office (CSO) sampling frame and includes both urban and rural households.

In addition to general information on household characteristics – including measures related to wealth, food diversity and frequency, and anthropometric measures – the 2013 NNS provides biomarker data for children (0– 59 months), unmarried adolescent girls (10–19), and married women of reproductive age (15–49). We restrict our sample to this latter group for whom the survey data record hemoglobin, ferritin, retinol, vitamin D, zinc, C-reactive protein (CRP), and alpha-1-acid glycoprotein (AGP) blood levels, as well as urinary iodine excretion. The serum and blood samples were collected by trained phlebotomists, placed in gel ice-packs and dry ice, and transported first to Kabul via airline cargo and then to Karachi UNICEF (2014). Hemoglobin levels were tested on site using a HemoCue machine, thereby avoiding the (common) destruction of erythrocytes during blood sample transportation UNICEF (2014). Although the Nutritional Research Laboratory of Aga Khan University also analyzed other biomarkers, the data set includes no information on the target group's vitamin B12 (folic acid) levels, whose deficiency, together with that of iron and vitamin A, is the most common cause of anemia from inadequate food intake. We overcome this limitation by exploiting individual level information on the intake frequency of vitamin B12 rich food groups (meat/fish, dairy/eggs) in the week prior to interview.

Although the survey sample is provincially representative, because of budget limitations, the biomarker information was collected only for a nationally representative subsample. It should further be noted that the 2013 NNS is not seasonally representative in that data collection was carried out between the second week of June 2013 and the end of October 2013, with a 50-day suspension during Ramadan to avoid biases from changed eating behaviour during this observance. After deletion of missing and implausible values (observations showing serum ferritin > 150 $\mu g/dL$, and CRP > 10 mg/dL are dropped from the final study sample), the final analytic sample comprises 1,128 observations, which decreases to 979 when we drop observations for which data on serum ferritin, retinol, zinc, and CRP are unavailable. The original sample included 1,237 married woman of reproductive age, 100 of them missing values for hemoglobin levels and 9 missing information on basic household characteristics.

The Global Flood Monitoring System (GFMS) database, a NASA-founded project developed at the University of Maryland, provides real-time (3-hour interval) quasi-global $(50^{\circ}N - 50^{\circ}S)$ flood detection and intensity estimates using TRMM Multi-satellite Precipitation Analysis (TMPA) precipitation information, hydrological runoff, and routing models at 0.125° longitude/latitude grid resolution. Routing is a widely used technique in hydrology that enables the prediction of changes in surface water state. Runoff routing is the process of routing excess rainfall to produce a hydrograph of accumulated surface water Laurenson (1964). For each grid location, floods are reported in millimeters of accumulated water above the historical threshold derived from 13 years of retrospective statistics on surface water storage Wu et al. (2014). A flood is detected for each grid's cell when $R > P_{95} + 0.5 * \delta$ and Q > 10, where R is the routed runoff in millimeters for each 3-hour interval. P_{95} is the 95th percentile value, δ is the temporal standard deviation of the routed runoff derived from the retrospective simulation time series at the grid cell, and Q is the corresponding value of discharge in m^3/s Wu et al. (2014). Particularly relevant for the case of Afghanistan is the ability of GFMS's cold season process to detect snowmelt-related floods, which, because of heavy winter snowfalls combined with warm summers, make up a large part of the country's inundation USGS (2013).

2.2. Dependent variable: anemia

The outcome of interest is the anemia status of married women of reproductive age (15-49), defined by the WHO threshold of hemoglobin concentration levels less than 12mg/dl (<11mg/dl for pregnant women) WHO (2011b) and adjusted in the original data for altitude. We thus define a binary variable equal to 1 if low concentration is observed and 0 otherwise. To identify the channels through which floods affect anemia, we also regress a selection of characteristics known to influence anemia on flooding. In doing so, we use the following known causes of anemia as dependent variables: ferritin ($Fer_i < 12\mu g/dL$), serum retinol ($Ret_i < 20\mu g/dL$), current inflammation status $(CRP_i > 1mq/dL)$, and availability of safe drinking water. This latter – defined as piped water; bottled water; water from hand pumps, protected springs, or wells; or water brought by tanker trucks – is a binary variable equal to 1 if the household has access to safe drinking water, 0 otherwise.

2.3. Flood variable

A main explanatory variable in this study is the district level daily average of accumulated land surface water in millimeters above the flood threshold measured one and two months before the interview date $(Flood_{i,t-m})$. Its construction involves cropping each GFMS file based on Afghanistan's national borders and then obtaining daily flood values for each grid cell by computing the average flood estimate for the 3-hour interval flood estimates (8 files per day). This process yields a georeferenced database of daily flood estimates whose values are assigned to each observation in the 2013 NNS based on the interview date and district of residence by projecting them onto the AG-CHO shapefile for the second administrative division (districts) AGCHO (2012). Although the spatial disaggregation level of the GFMS data is relatively high, flood estimates cannot be assigned to 9 of the 398 Afghan districts because of their relatively small area. Hence, to prevent missing values in the variable of interest, we increase the resolution from 0.125° to 0.0625° longitude/latitude by dividing each grid's cell in the GFMS data by four, and assigning to these subcells the same flood estimate as given by the original corresponding cell. We also eliminate uninhabited areas from the flood variable estimations by exploiting the high spatial resolution (0.0083°) global population estimates from the Gridded Population of the World (GPWv4) 2010 raster image CIESIN (2016). Lastly, we assure comparability of the one and two-month flood coefficients by computing these variables as daily averages; that is, we divide the count of floods in millimeters at t-1 and t-2 by 30.4 and 60.8 days, respectively. We then adjust the final measures for district population density $(1,000 \text{ inh.}/100 \text{ km}^2)$. District population data are taken

from CSO Population Statistics by Civil Division and Sex, 2013 CSO (2013). Equation 1 expresses the flood measure construction for t-1,t-2, where $F_{h,d,r}$ are 3-hour interval (h) flood estimates (in mm above the flood threshold) for all the grid's cells corresponding to the district of residence (r_i) of the i^{th} observation relative to a single day (d), int_i is date of interview, $dens_{r,i}$ is population density of district r_i , and m = 1, 2 is the time span in months.

$$Flood_{i,t} = \frac{\sum_{d=int_i-30*m}^{int_i} \sum_{h=1}^{8} \frac{F_{h,d,r_i,}}{8}}{30.4*m} \frac{1}{dens_{r_i}}$$
(8)

2.4. Biomarkers and nutrition characteristics

These characteristics are computed as a set of dummy variables equal to 1 for observations deficient in serum ferritin ($Fer_i < 12 \ \mu g/dL$), serum retinol ($Ret_i < 20 \ \mu g/dL$), and serum zinc $(Zn_i < 60\mu g/dL)$, or with a low intake frequency of vitamin B12/B9 rich food groups (meat/fish, dairy products) in the week before interview $(B12/B9_i \leq$ 7days), 0 otherwise. All thresholds are based primarily on WHO criteria WHO (2011a,c, 2014). The original data set provides ferritin, retinol, and zinc levels adjusted for inflammation status as measured by CRP and AGP. CRP, however, can be differentiated into a more severe $(CRP_i > 3mq/dL)$ and a more moderate $(CRP_i > 1mq/dL)$ condition. Although the WHO recommends the former WHO (2014), we adopt the latter also used in the official UNICEF NNS report UNICEF (2014) – because it covers a more meaningful proportion of our sample. Lastly, to control for the possible effects on anemia of fasting during the month of Ramadan, we construct a dummy variable equal to 1 if an individual was interviewed after August 7, 2013, 0 otherwise.

2.5. Other relevant constructs

We further control for a set of women's, household, and provincial characteristics, including age of respondent and household head in years, a dummy equal to 1 if a woman is currently pregnant (0 otherwise), dummies for the educational level of both the reproductive age women and corresponding household head equal to 1 if an individual is literate, 0 otherwise, and another equal to 1 if the household head is currently married, 0 otherwise. Although the raw data includes information about the highest educational level achieved, because of the extremely high illiteracy rate, especially among women (74%), we choose to measure only whether an individual can at least read and write. Additional controls at the household level are the dependency ratio, computed as the proportion of economically inactive members in the household (individuals aged 0-14 and over 65) divided by the number of active members (15–64); a set of eight dummy variables identifying ethnolinguistic group (Baluchi, Dari, Hazarai, Nuristani, Pashaee, Pashtu, Turkmeni, and Uzbeki), and the household wealth index. This latter is computed by a polychoric



Figure 12: Daily average floods in millimeters (April-October 2013). Drawn by the authors using GFMS data. Resolution 0.125° longitude/latitude.

principal component analysis applied to a set of relevant characteristics; namely, household dwelling building material; and dummy variables for ownership of bicycle, motorcycle, car, television, telephone, mobile phone, sewing and washing machines, and livestock, as well as availability of electricity and safe water in the dwelling Rutstein et al. (2004). Note that in models where safe drinking water is used as the dependent variable, this variable is excluded from the computation of the wealth index. Safe drinking water is a dichotomous variable equal to 1 if the household has access to the protected drinking water sources enumerated earlier, 0 otherwise. Finally, we control for committed aid at the provincial level for 2013 (in 100 thousand USD) by exploiting information from the Afghan National Budget and Aid Management Systems DAD (2015).

3. Empirical Model

The study aims to identify the causal relations among the occurrence and intensity of floods and anemia in reproductive age Afghan women by exploiting the quasi-random flood variation among different districts and periods. We estimate this effect by means of the following linear probability model:

$$Y_{i} = \alpha + \beta_{1}Flood_{i,t} + \beta_{2}Aid_{p,} + \gamma_{w}\mathbf{CW}_{i} + \gamma_{h}\mathbf{CH}_{i} + \gamma_{p}\mathbf{P} + \varepsilon_{i}$$

$$(9)$$

where Y_i is a binary variable equal to 1 if the i^{th} woman's hemoglobin concentration is less than 12mg/dL (< 11mg/dL for pregnant women), 0 otherwise. The controls are a set of woman (CW) and household characteristics (CH), namely woman's age, literacy, and current pregnancy status; household location type (urban vs. rural), wealth index, dependency ratio, ethnolinguistic group; and age, sex, literacy, and marital status of the household head. We also control for province fixed effects (P) and provincial committed aid (Aid_{p} ,). ε_i is an idiosyncratic error term.

$$Y_{i} = \alpha + \beta_{1}Flood_{i,t} + \beta_{2}Aid_{p} + \gamma_{b}\mathbf{BNC}_{i} + \gamma_{w}\mathbf{CW}_{i} + \gamma_{h}\mathbf{CH}_{i} + \gamma_{n}\mathbf{P} + \varepsilon_{i}$$
(10)

Equation (3) models the causal relation between floods and anemia status while directly controlling for a vector of the following biomarkers and nutrition characteristics (**BNC**): serum ferritin (Fer_i), serum retinol (Ret_i), and serum zinc (Zn_i) deficiencies; inflammation status

	$ \begin{array}{c} \text{Flood}_{t-1} \text{ (pop)} \\ (1) \end{array} $	$ \begin{array}{c} Flood_{t-1} \ (den) \\ (2) \end{array} $	$ \begin{array}{c} \text{Flood}_{t-2} \text{ (pop)} \\ (3) \end{array} $	$ \begin{array}{c} Flood_{t-2} \ (den) \\ (4) \end{array} $
$\operatorname{Fat}_{t-1}(\operatorname{pop})$	$\begin{array}{c} 0.019 \\ (0.523) \end{array}$	-0.009 (0.768)	_	_
$Fat_{t-2} (pop)$	-	-	$0.038 \\ (0.195)$	-0.006 (0.837)
Pop. Density	-0.025 (0.400)	-0.023 (0.425)	-0.037 (0-214)	-0.029 (0.327)
Rural (dummy)	-0.135 (0.000)	-0.140 (0.000)	-0.086 (0.000)	-0.121 (0.000)

Table 1: Measures of flood, conflict and urbanization: correlation analysis

Notes: Table reports Pearson correlation coefficients for all variables with the exception of the rural dummy for which tetrachoric correlations coefficients are shown. P-values in parenthesis are computed using a 95% confidence interval.

 (CRP_i) ; and meat, fish, and dairy product intake frequencies in the week before interview $(B12/B9_i)$. This specification allows us to determine which biomarkers and nutritional characteristics are associated with anemia in our sample, and also to what extent the inclusion of these variables attenuates the flood effect on anemia. Once we identify the former, we use the same estimation strategy as in equation (2) to regress the significant characteristics on floods to determine the mechanisms through which floods affect anemia.

For this analysis, linear probability models are preferable to their nonlinear probit or logit counterparts Hellevik (2009) for three methodological reasons. First, because of its design, the NNS (2013) tends to within-cluster similarities that may bias the coefficients' standard errors. We overcome this shortcoming by computing robust standard errors clustered at the (53) district levels. At the same time, in the presence of heteroscedasticity, the maximum likelihood estimator is inconsistent, meaning that its point estimates are biased even when computing a robust covariance matrix (Greene, 2012, pp. 692–693). Linear models, in contrast, provide consistent estimates despite heteroscedasticity of the error term, while also yielding easily interpretable coefficients.

Although occurrence and intensity of floods could be assumed to be quasi-random, there is the possibility that some degree of correlation exists between these and human-made disasters. In particular, in a country such as Afghanistan, the possible role of conflict as a confounder must be considered when establishing causality for the floods-health nexus. In this respect, using data from Uppsala Conflict Data Program Georeferenced Database (version 17.1) Sundberg and Melander (2013) we computed a set of district level measures of conflict intensity for the same time span for which the floods variables are computed (i.e. one and two months before the interview). Conflict intensity is measured as the total number of per capita fatalities. Moreover, a similar argument could be raised in respect to the environmental characteristics in which the households live. In fact, as shown by extant literature (e.g., Hejazi and Markus (2009)), urbanization is a direct determinant of the occurence and intensity of floods.

Correlation analysis (Table 1) shows that neither our flood measures nor population density are significantly correlated with conflict intensity, ruling out the possibility that omitting these variables from the set of controls causes bias in the estimates of interest. It should be noted that the dicothomus variable controlling for households living in rural vs. urban locations is negatively correlated with flood, confirming that these natural disasters are more likely to happen in urbanized areas. Moreover, we anticipate that using these variables as additional controls does not change either the size of the flood's coefficients or their statistical significance in all models. However, due to the possible endogeneity of the conflict variable (e.g., we find that greater levels of conflict decreases the probability of anemia), we report only the models excluding this control. These additional results are available from the authors upon request.

Finally, we argue that although floods may be sometimes predictable and thus households could move away from their habitual residence, these latter are unlikely to migrate outside their district of residence when a flood occurs. However, even in presence of such an error in measuring our flood variable we would underestimate the true negative effect of floods on anemia.

4. Results

A comparison of the descriptive statistics for the full versus the reduced sample (because of missing biomarker values) reveals no abnormal divergence (Table 2). In fact, the absence of statistically significant differences in variable means suggests that the unavailability is completely random. This assumption is further confirmed by the fact

that the total number of districts in the reduced sample does not change. In general, the descriptive statistics indicate that 43% of reproductive age Afghan women suffer moderate anemia. Only 26% of those in the sample (average age 30.4 years) are literate, as opposed to 48% of the household heads. Most of the women (91%) are married, with the rest being widows (8%) or separated (1%). The reproductive age female population also tends to suffer from micronutrient deficiencies, with 30%, 13%, and 21%being deficient in iron, vitamin A, and zinc, respectively. In half the sample, the intake frequency of meat/fish or dairy/eggs is less than seven times per week. About 4% of the sample has a $CRP_i > 1mg/dL$ with only 0.7% having a $CRP_i > 3mg/dL$. Finally, 18% and 32% of the reproductive age women experienced at least one day of flooding during t-1 and t-2, respectively.

The spatial variation in flood intensity among the districts is outlined in Fig 1. A considerable area of the country has been affected by floods in 2013. This is also highlighted by the fact that 32% of the observations in our sample experienced at least a day of flooding in the two months before the interview. Most of the floods occurred in the south-east and north-east of the country. Floodprone areas are located close to large rivers, such as the Amu Darya, a major river in Central Asia that marks the border between Afghanistan and Tajikistan, and the Helmand River in the south-west. Floods have been particularly intense in the area south-west of the Kabul province and north of Kunduz where values between 1 and 5 mm of flood per day have been recorded.

Table 3 reports the coefficients of interest for the restricted and full models employing a binary dependent variable that captures whether or not a woman is anemic (hemoglobin concentration < 12 mg/dL; < 11 mg/dL for pregnant women). Here, the coefficients capturing floods are always statistically significant, and we observe no abnormal changes in magnitude among different specifications (see Table C1 for complete model estimates and models using floods adjusted by 1,000 inh.). Specifications 1 and 2 (equation 2) show the effect of floods occurring one and two months before the interview, measured in millimeters per day adjusted by district population density. All else kept constant, one extra millimeter of flood per 1,000 inhabitants per 100 km² increases the probability of anemia by 0.039 and 0.054 at *t-1* and *t-2*, respectively.

The table also presents the results of applying specifications 3 and 4 (equation 3) to the full model. Here, the inclusion of the **BNC** vector variables increases the goodness-of-fit, from an adjusted *R*-squared of 0.048 in the restricted model to a value of 0.096 in the full model. As expected, iron and vitamin A deficiency increase the probability of anemia by a substantial 0.22 and 0.20, respectively, but we identify no statistically significant effect of inflammation, zinc deficiency, or low frequency intake of vitamin B12 rich foods (< 7 times/week) on the probability of becoming anemic. If we use the more stringent WHO definition of inflammation ($CRP_i > 3mq/dL$) Table 2: Characterics of the sample

	Mean	Mean	Difference
		<i></i>	(p values)
	(1)	(2)	(3)
Anemia ^a	0.43	0.43	0.499
	(0.50)	(0.50)	
Age	30.36	30.29	0.417
TT7 • 1• 9	(7.97)	(7.87)	0.451
Woman is literate ^a	(0.26)	(0.26)	0.451
Woman is programt ^a	(0.44) 0.13	(0.44) 0.14	0 755
woman is pregnant	(0.13)	(0.34)	0.155
Interviewed after Ramadan ^a	0.35	0.37	0.732
	(0.47)	(0.48)	
Wealth index ^b	0.00	-0.02	0.362
	(1.25)	(1.25)	
Dependency ratio ^c	1.27	(1.30)	0.741
C - f +à	(0.83)	(0.83)	0.469
Sale water	(0.39)	(0.38)	0.408
Head is literate ^a	(0.49) 0.48	(0.49) 0.47	0.478
	(0.50)	(0.50)	0.110
Head age	45.12	44.94	0.393
	(14.51)	(14.67)	
Head is married ^a	(0.91)	(0.91)	0.477
	(0.28)	(0.28)	0 500
Flood: 1 month (mm) ^d	(1.69)	(1.70)	0.568
Electric de la constitución (march)d	(1.08)	(1.70)	0.200
Flood: 2 months $(mm)^2$	(1.08)	(4.28)	0.399
Flood: 1 month ^a	(4.38)	0.18	0.576
	(0.38)	(0.38)	0.010
Flood: 2 months ^a	0.32'	$0.33^{'}$	0.652
	(0.47)	(0.47)	
Iron def. $(Fer_i < 12 \ \mu g/dL)^a$		0.30	
D19 low (D10 (D0 (FL)))		(0.46)	
D12 IOW $(B12/B9_i \leq 7days)$		(0.51)	
Vit. A def. $(Bet_i < 20\mu q/dL)^a$		0.13	
(100 11 doi: (1000 (20µg/al))		(0.34)	
Zinc def. $(Zn_i < 60 \mu g/dL)^a$		0.21	
T 0		(0.41)	
Inflam. $(CRP_i > 1mg/dL)^a$		(0.04)	
Inflam $(CPR > 2ma/dL)^{a}$		(0.21)	
$11111a111. (CKP_i > 3mg/aL)^2$		(0.007)	
Number of districts	53	53	
Number of observations	1128	979	

Notes: Column (5) is calculated using *t*-tests. ^aDummy variables. ^bComputed by a polychoric principal component analysis applied to a set of assets, as well as the availability of electricity and safe water. ^cThe proportion of economically inactive members in the household (individuals aged 0-14, and over 65) over the number of active members (15–64). ^dThe district level daily average count of accumulated land surface water in millimeters above the flood threshold measured at one and two months before the interview date. Standard Deviation in parenthesis.

WHO (2014), however, then we observe a positive association between this latter and inflammation (see Table C2). Thus, severe inflammation is significantly related to anemia in our sample but moderate inflammation is not. Lastly, despite directly controlling for the most common causes of anemia that are likely to be correlated with floods, the coefficients of interest remain statistically significant, although smaller in magnitude than their restricted model counterparts (0.23 and 0.33 for t-1 and t-2, respectively). These results indicate that floods may affect anemia through mechanisms other than nutritional deficiencies and inflammation conditions (e.g., floods may cause psychological stress, which in turn may cause prolonged and abnormal uterine bleeding among women of reproductive age) or that our variables are subject to a certain degree of measurement error (especially given our inability to account directly for folate levels).

Table 4 then depicts the effect of floods on levels of serum ferritin (regressions 1 and 2) and serum retinol (regressions 3 and 4) measured in $\mu g/dL$, revealing no statistically significant flood effects on the former. One plausible explanation is that only a small proportion of households suffered severe hunger in the month before the interview (0.08%). We derive this result by computing the Hunger Scale Index for our sample Ballard et al. (2011a). This result suggests that households exposed to floods are able to maintain a constant consumption of cereals, particularly wheat, which is not only the main food staple in Afghanistan but also the main source of iron Flores-Martinez et al. (2016). In fact, Afghan wheat varieties are rich in iron Manickavelu et al. (2017), concentrations range between 5.5 and 12.2mg/100gr, as compared with a recommended daily intake of iron of 30mg and 60mg for pregnant women WHO (2012). The intake of vitamin A rich foods (i.e., fresh fruit and vegetables, and food from animal sources) may also diminish as a consequence of natural disasters like floods: in regressions 3 and 4, all else being equal, one extra millimeter per day of flooding at t-1 and t-2 causes decreases in serum retinol of 2.2 and $3.2\mu g/dL$, respectively (Table 4).

A major reason for floods being a known cause of infectious diseases is impaired household access to safe drinking water Alderman et al. (2012). Table 5 summarizes the causal relations between floods and inflammation status – as measured by elevated concentrations in the blood of CRP (1mg/dL) – and between floods and the availability to the household of safe water. Regressions 1 and 2 show that, all else being equal, an extra millimeter per day of flood at t-1 and t-2 causes a 0.015 and 0.023 increase, respectively, in the probability of inflammatory conditions, severe cases of which are associated with anemia (Table C2). Floods also greatly reduce the probability of access to safe drinking water: a 0.12 and 0.18 decrease for floods measured at t-1 and t-2, respectively.

Lastly, we consider additional covariates (reported in Appendix C), including a flood variable adjusted for population in 1,000 inh. The models using this latter (regressons 5–8 in Table C1) confirm the main results presented in Table 2. In all regressions, we note that younger women are less likely to be anemic (Table C1 and C2) while also having higher levels of serum ferritin (regressions 1–2, Table C3). We find no statistically significant effect for any of the dependent variables on female literacy, either because very low education levels do not actually affect health outcomes or because this effect is too small to observe. As all

models in Table C1 show, being pregnant increases the probability of low hemoglobin levels and has a negative effect on serum ferritin and serum retinol levels (regressions 1-4, Table C3).

Interestingly, we observe a strong increase in the anemia probability for women interviewed after Ramadan. Although unable to determine whether or not a woman fasted during this period, we can safely assume that the post-Ramadan interview is random in both observable and nonobservable characteristics, meaning that our estimates are not biased by any systematic error. Anemia is also more likely among women in rural households, who on average have a lower level of serum retinol. The positive association between household wealth and anemia probability, however, cannot be taken at face value because it is influenced by the wealth variable's correlation with other model covariates, particularly the literacy status of both the woman and the head of household. When these variables are dropped, the wealth coefficient becomes statistically insignificant.

Table 3: Effect of floods on anemia: OLS estimates

	Dependent variable Anemia					
	(1)	(2)	(3)	(4)		
$\operatorname{Flood}_{t=1}$	0.039^{***}		0.024^{***}			
$\operatorname{Flood}_{t=2}$	(0.000)	0.054^{***}	(0.009)	0.033^{***} (0.013)		
Iron deficiency		(0.000)	0.219^{***} (0.037)	(0.010) (0.219^{***}) (0.037)		
Inflammation (WHO)			0.129 (0.099)	0.129 (0.099)		
Vit. A deficiency			0.202^{***} (0.062)	0.202^{***} (0.062)		
Zinc deficiency			0.009 (0.070)	0.009 (0.070)		
Vit. B12 low intake			0.043 (0.048)	0.043 (0.048)		
Province f.e.	Yes	Yes	Yes	Yes		
Ethnicity f.e.	Yes	Yes	Yes	Yes		
Observations	1,128	1,128	979	979		
R^2	0.084	0.084	0.139	0.139		
Adjusted \mathbb{R}^2	0.048	0.048	0.096	0.096		
Residual std. error	9.384	9.384	9.007	9.007		
F statistic	2.356^{***}	2.355^{***}	3.202^{***}	3.201^{***}		

Table 4: Notes: The dependent variable is equal to 1 if the respondent's hemoglobin concentration is less than 12mg/dL (< 11mg/dL for pregnant women) and 0 otherwise. The regressions control for woman's age, literacy, and current pregnancy status; household location type (urban vs. rural), wealth index, dependency ratio, and ethnolinguistic affiliation; and age, sex, literacy, and marital status of household head, while also including provincial dummies and provincial aid. All models are estimated using sampling survey weights, and the flood variable in all specifications is adjusted for district population density. Robust standard errors (in parenthesis) are clustered at the district level.* p < 0.1, ** p < 0.05, *** p < 0.01.

5. Discussion

The empirical research on flooding's effect on health in developing countries is limited Du et al. (2010), and particularly so for Afghanistan, where floods have been a common occurrence in the past decade, claiming thousands of lives and displacing many more. In fact, about one third of our representative sample of reproductive age women experienced a flood in the two-month period prior to the survey, leading us to argue that these floods are a cause of anemia among this population. We test this proposition by using GFMS satellite imagery to accurately capture flood locations and intensity, and by exploiting the quasi-random variation of floods among different districts and time periods to capture their causal relation with the incidence of anemia.

Our results show that the flood effect on anemia is not only significant but also quite large: an extra millimeter per day of population density-adjusted flooding increases anemia probability by 0.039–0.054. Floods influence anemia via several channels but particularly by reducing the intake of such vital nutrients as iron, zinc and, vitamins through the destruction of crops and livestock. They also have a well-documented effect on water borne diseases including gastrointestinal and respiratory diseases, skin infections, and leptospirosis Alderman et al. (2012) – which can also result in anemia. Lastly, given the damage that floods wreak on lives and livelihoods (especially in developing countries like Afghanistan where insurance is rare), they generate psychological stress in those affected Alderman et al. (2012) that itself can cause a decrease in serum iron and/or affect erythropoiesis Wei et al. (2008). Psychological stress can also negatively affect menstrual cycles Gordley et al. (2000); Neinstein (1985); Shapley et al. (2003), which in turn may result in anemia.

Our analysis identifies two main transmission mechanisms of floods on anemia: inflammation or water-related infections and vitamin A intake. As regards the first, not only is anemia clearly associated with severe inflammation but an extra millimeter per day of floods in the previous two months induces a 2.3% increase in the probability of moderate inflammation. At the same time, floods' negative affect on the availability of potable water is often an important cause of infections related to water-borne diseases. Flooding's negative impact on the intake of vitamin A rich foods (i.e., fresh fruit and vegetables) is reflected by the fact that one extra millimeter per day of flooding in the previous two months decreases serum retinol by 3.2 $\mu g/dL$. Flooding does not, however, appear to influence ferritin intake, which probably implies that floods have no strong effect on the consumption of wheat, which is the primary iron rich staple in the Afghan diet. This result suggests that, in the case of floods, vitamin A supplementation may be more needed than iron, at least for Afghan reproductive age women.

Although biomarker information and nutrition characteristics can partly explain the probability of anemia, the

Table 5: Effect of floods on serum ferritin and serum retinol: OLS estimates

	Dependent variable						
	Ferritin	$(\mu g/dL)$	Retinol (μ	(4) (4)			
	(1)	(2)	(5)	(+)			
$\operatorname{Flood}_{t=1}$	-0.544		-2.209***				
	(2.934)		(0.383)				
$Flood_{t=2}$		-0.735		-3.208***			
		(4.283)		(0.543)			
Province f.e.	Yes	Yes	Yes	Yes			
Ethnicity f.e.	Yes	Yes	Yes	Yes			
Observations	979	979	979	979			
R^2	0.097	0.097	0.099	0.099			
Adjusted R^2	0.054	0.054	0.057	0.058			
Residual std. error	577.950	577.951	240.588	240.581			
F statistic	2.271^{***}	2.270^{***}	2.386^{***}	2.388^{***}			

Table 6: Notes: In regressions 1 and 2, the dependent variable is level of serum ferritin in μ g/dL, whereas in regressions 3 and 4, it is serum retinol in μ g/dL. These regressions control for woman's age, literacy, and current pregnancy status; household location type (urban vs. rural), wealth index, dependency ratio, ethnolinguistic affiliation; and age, sex, literacy, and marital status of household head, while also including provincial dummies and provincial aid. Only for regressions 1 and 2 is inflammation status (CRP > 1 mg/dL) used as a regressor. All models are estimated using sampling survey weights, and the flood variable in all specifications is adjusted for district population density. Robust standard errors (in parenthesis) are clustered at the district level. * p < 0.1, ** p < 0.05, *** p < 0.01.

effect of floods on this condition remains significant even after we include these variables in our regressions. This interesting finding indicates that floods may be affecting anemia beyond the most common determinants of inadequate iron intake, dietary deficiency, and infectious diseases. The most obvious explanation for our sample of reproductive age Afghan women is that floods, through their effect on stress, affect menstrual cycles, including prolonged and abnormal uterine bleeding. Admittedly, our data set provides no information with which to test this assumption – although the relation is empirically supported by prior research – however, given the breadth of our explanatory analytic variables, it seems a plausible explanation.

Two other study limitations include the fact that although our flood exposure measure is known for its high precision, the unavailability of household GPS coordinates limits its accuracy in our case. Knowing the exact location of a household, and, in particular, the household's proximity to the flood, would be useful as previous research has shown that mental health problems are predominantly clustered in regions that are geographically more exposed to a natural disaster Gruebner et al. (2015). Likewise, the absence from the NNS (2013) of data on folate levels prevents our directly controlling for this vitamin, especially when interpreting the persistent statistically significant effect of floods after main transmission channels are

controlled for.

	Dependent variable					
	Inflam	mation	Safe water			
	(1)	(2)	(3)	(4)		
$\mathrm{Flood}_{t=1}$	0.015^{***}		-0.124^{***}			
	(0.005)		0.035			
$Flood_{t=2}$		0.023^{***}		-0.179^{***}		
		(0.006)		(0.050)		
Province f.e.	Yes	Yes	Yes	Yes		
Ethnicity f.e.	Yes	Yes	Yes	Yes		
Observations	979	979	889	889		
R^2	0.063	0.064	0.289	0.289		
Adjusted \mathbb{R}^2	0.021	0.021	0.256	0.256		
Residual std. error	4.352	4.351	7.550	7.550		
F statistic	1.511**	1.511**	8.624***	8.625***		

Table 7: Effect of floods on inflammation and availability of safe water: OLS estimates

Notes: In regressions 1 and 2, the dependent variable is inflammation status (CRP > 1 mg/dL), whereas in regressions 3 and 4, it is access to safe water (1 if yes, 0 otherwise). These regressions control for woman's age; household location type (urban vs. rural), wealth index, dependency ratio, and ethnolinguistic affiliation; and age, sex, literacy, and marital status of household head, while also including provincial dummies and provincial aid. Only specifications 1 and 2 also control for woman's current pregnancy status. All models are estimated using sampling survey weights, and the flood variable in all specifications is adjusted for district population density. Robust standard errors (in parenthesis) are clustered at the district level.. * p < 0.1, ** p < 0.05, *** p < 0.01.

6. Conclusions

Because both floods and anemia are serious and concomitant problems in South East Asia, and particularly in Afghanistan, this study assumes a relation between the two. We test this assumption using 2013 NNS data, which includes rich biomarker information, combined with GFMS satellite imagery that accurately captures the incidence of floods. Not only do our results demonstrate that floods are associated with anemia among Afghan women of reproductive age but, because of the quasi-randomness of flood occurrence, they can be interpreted as causal. These findings fill the knowledge gap left by a prior research focus on floods' negative effects on health with no specific attention to their impact on anemia.

Our analysis identifies two channels through which floods influence anemia, the first being a significant effect on inflammation and a possible effect, through unsafe drinking water, on infections related to water-borne diseases. This latter is important because it underscores that anemia can be influenced by flood-related infections. Floods also significantly and negatively affect retinol concentrations, a recognized cause of anemia. Even with the inclusion of effective controls for anemia's most common causes, our analysis still shows that floods affect anemia. Hence, given the empirical evidence of both flooding's inducement of psychological stress and such the effect of stress on anemia, we speculate that this effect may be (at least partly) attributable to psychological stress.

Table C1: Effect of floods on anemia: OLS estimates

				Depender	nt variable			
	Anemia						(9)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\operatorname{Flood}_{t=1}$	0.039***		0.024***		0.054^{***}		0.033**	
	(0.006)		(0.009)		(0.012)		(0.015)	
$Flood_{t=2}$		0.054^{***}		0.033^{***}		0.066^{**}		0.036
Iron deficiency		(0.009)	0.910***	(0.013) 0.210***		(0.027)	0.910***	(0.028) 0.210***
from denciency			(0.037)	(0.037)			(0.037)	(0.037)
Inflammation $(CRP_i > 1mg/dL)$			0.129	0.129			0.129	0.129
			(0.099)	(0.099)			(0.099)	(0.099)
Vit. A deficiency			0.202^{***}	0.202^{***}			0.202^{***}	0.202***
			(0.062)	(0.062)			(0.062)	(0.062)
Zinc deficiency			(0.009)	(0.009)			(0.009)	(0.009)
) Vit B12 low intako			(0.070) 0.043	(0.070) 0.043			(0.070) 0.043	(0.070) 0.043
1 VII. D12 IOW IIItake			(0.043)	(0.043)			(0.043)	(0.043)
Age	-0.005**	-0.005**	-0.004*	-0.004*	-0.005**	-0.005**	-0.004*	-0.004*
0	0.002	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Woman is literate	-0.042	-0.042	-0.048	-0.048	-0.042	-0.043	-0.048	-0.049
	(0.045)	(0.045)	(0.055)	(0.055)	(0.045)	(0.045)	(0.055)	(0.055)
Woman is pregnant	0.102^{*}	0.102^{*}	0.079	0.079	0.102^{*}	0.102^{*}	0.079	0.079
Interviewed often Demoder	(0.055) 0.120***	(0.055) 0.120***	(0.055) 0.107***	(0.055) 0.107***	(0.055) 0.120***	(0.055) 0.120***	(0.055) 0.107***	(0.055) 0.107***
Interviewed after Kamadan	(0.120)	(0.120)	(0.107)	(0.107)	(0.120)	(0.034)	(0.107)	(0.107)
Urban	-0.168^{***}	(0.054) -0.167***	-0.164^{***}	-0.164^{***}	(0.054) -0.167***	(0.054) -0.167***	(0.041) -0.164***	-0.163^{***}
	(0.036)	(0.036)	(0.054)	(0.054)	(0.036)	(0.036)	(0.054)	(0.054)
Wealth index	0.031^{**}	0.031**	0.032**	0.032**	0.031**	0.031^{**}	0.032**	0.032^{**}
	(0.014)	(0.014)	(0.016)	(0.016)	(0.014)	(0.014)	(0.016)	(0.016)
Dependency ratio	0.005	0.005	0.006	0.006	0.005	0.005	0.005	0.005
T	(0.016)	(0.016)	(0.019)	(0.019)	(0.016)	(0.016)	(0.019)	(0.019)
Head is literate	-0.022	-0.022	-0.017	-0.017	-0.022	-0.022	-0.017	-0.017
Hoad ago	(0.029)	(0.029)	(0.036)	(0.036)	(0.029)	(0.029)	(0.036)	(0.036)
neau age	(0.001)	(0.001)	(0.0001)	(0.0001)	(0.001)	(0.001)	(0.0001)	(0.0001)
Head is male	-0.034	-0.033	0.006	0.006	-0.034	-0.034	0.006	0.006
	(0.111)	(0.111)	(0.103)	(0.103)	(0.111)	(0.111)	(0.103)	(0.103)
Head is married	0.114	0.114	0.163^{*}	0.163^{*}	0.114	0.114	0.163^{*}	0.163^{*}
	(0.093)	(0.093)	(0.089)	(0.089)	(0.093)	(0.093)	(0.089)	(0.089)
Provincial aid	-0.043**	-0.041**	-0.04*	-0.039*	-0.042**	-0.04**	-0.039*	-0.038*
a	(0.018)	(0.018)	(0.021)	(0.022)	(0.018)	(0.018)	(0.022)	(0.021)
Constant	2.009^{***}	1.973^{***}	1.612^{**}	1.590^{**}	2.000^{***}	1.917^{***}	1.606^{**}	1.562^{**}
Ethnicity fixed offects	(0.011) Voc	(0.011) Voc	(0.790) Voc	(0.788) Voc	(0.612) Voc	(0.613) Voc	(0.790) Voc	(0.788) Voc
Province fixed effects	Vos	Ves	Ves	Vos	Ves	Ves	Ves	Tes Vos
	105	105	105	105	105	105	105	105
Observations	1,128	1,128	979	979	1,128	1,128	979	979
R^2	0.084	0.084	0.139	0.139	0.084	0.083	0.139	0.139
Adjusted \mathbb{R}^2	0.048	0.048	0.096	0.096	0.048	0.048	0.096	0.096
Residual std. error	9.384	9.384	9.007	9.007	9.385	9.385	9.007	9.007
F statistic	2.356^{***}	2.355^{***}	3.202^{***}	3.201^{***}	2.354^{***}	2.352^{***}	3.201^{***}	3.200^{***}

Notes: The dependent variable is equal to 1 if the respondent's hemoglobin concentration is less than 12mg/dL (< 11mg/dL for pregnant women) and 0 otherwise. The regressions control for woman's age, literacy, and current pregnancy status; household location type (urban vs. rural), wealth index, dependency ratio, and ethnolinguistic affiliation; and age, sex, literacy, and marital status of household head, while also including provincial dummies and provincial aid. All models are estimated using sampling survey weights. Flood variable specifications (1)-(4) is adjusted for district population density, and for the sole population in specification (5)-(8). Robust standard errors (in parenthesis) are clustered at the district level.* p < 0.1, ** p < 0.05, *** p < 0.01.

	Depender	nt variable
	(1)	emia (2)
$\mathrm{Flood}_{t=1}$	0.028*	
Flood	(0.009)	0 030***
$r_{100}d_{t=2}$		(0.039)
Iron deficiency	0.226***	0.226***
non donoioney	(0.037)	(0.036)
Inflammation $(CRP_i > 3mq/dL)$	0.483***	0.483***
	(0.130)	(0.130)
Vit. A deficiency	0.183***	0.182**
U U	(0.062)	(0.061)
Zinc deficiency	0.004	0.004
v	(0.070)	(0.066)
Vit. B12 low intake	0.039	0.039
	(0.048)	(0.044)
Age	-0.004*	-0.004
5	(0.002)	(0.003)
Woman is literate	-0.042	-0.042
	(0.055)	(0.055)
Woman is pregnant	0.077	0.077
	(0.055)	(0.055)
Interviewed after Ramadan	0.105^{**}	0.105^{**}
	(0.041)	(0.041)
Urban	-0.163^{***}	-0.163**
	(0.054)	(0.054)
Wealth index	0.030^{*}	0.030^{*}
	(0.016)	(0.016)
Dependency ratio	0.0001	0.0001
	(0.0002)	(0.0002)
Head is literate	-0.020	-0.020
	(0.036)	(0.036)
Head age	0.0003	0.0003
	(0.002)	(0.001)
Head is male	-0.020	-0.020
TT 1	(0.103)	(0.107)
Head is married	0.209**	0.209**
	(0.089)	(0.103)
Provincial aid	-0.047	-0.040
Constant	(U.U2U) 1.705**	(0.020)
Constant	1.(95)	$1.(09^{\circ})$
Ethnigity fixed offects	(0.790) Vog	(0.729) Voc
Province fixed effects	Tes Voc	Tes Vos
	100	103
Observations	979	979
R^2	0.149	0 149
Adjusted R^2	0.106	0.106
Residual std. error	8.953	8 953
E statistic	9 477***	3 477***

Table C2: Effect of floods on anemia using the WHO inflammation definition: OLS estimates

Notes: The dependent variable is equal to 1 if the respondent's hemoglobin concentration is less than 12 mg/dl (< 11 mg/dl for pregnant women) and 0 otherwise. All models are estimated using sampling survey weights, and all specifications use a flood variable adjusted for district population density. Robust standard errors (in parenthesis) are clustered at the district level. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table C3:	Effect of floods	on drivers	of anemia:	OLS estimates
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	Dependent variable							
	Ferritin $(\mu g/dL)$		Retinol	$(\mu g/dL)$	Inflam	mation	Safe	water
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\operatorname{Flood}_{t=1}$	-0.544		-2.209^{***}		0.015^{***}		-0.124^{***}	
$\mathrm{Flood}_{t=2}$	(2.001)	-0.735 (4.283)	(0.000)	-3.208^{***} (0.543)	(0.000)	0.023^{***} (0.006)	(0.000)	-0.179^{***} (0.050)
Inflammation	0.438 (3.789)	0.438 (3.789)	2.045 (2.576)	2.047 (2.576)		· · /		~ /
Age	0.464^{*} (0.239)	0.464^{*} (0.239)	0.036 (0.077)	0.036 (0.077)	0.001 (0.002)	0.001 (0.002)	-0.0001 (0.002)	-0.0001 (0.002)
Woman is literate	-3.229 (4.295)	-3.228 (4.295)	1.534 (1.732)	1.536 (1.731)	0.034 (0.024)	0.034 (0.024)	-0.103^{*} (0.055)	-0.103^{*} (0.055)
Woman is pregnant	-5.900^{**} (2.292)	-5.901** (2.292)	-5.101^{***} (1.637)	-5.101^{***} (1.637)	0.043 (0.038)	0.043 (0.038)	· · /	()
Interviewed after Ramadan	-9.775*** (3.356)	-9.773*** (3.357)	-2.425^{*} (1.249)	-2.421^{*} (1.251)	-0.007 (0.013)	-0.007 (0.013)		
Urban	-0.247	-0.257	(1.2.10) -2.287^{*} (1.204)	-2.294^{*}	(0.013) (0.014)	(0.014)	-0.054	-0.054
Wealth index	(0.164) -1.323 (2.054)	(0.004) -1.323 (2.054)	(1.234) 0.063 (0.636)	(1.252) 0.061 (0.636)	(0.010) 0.005 (0.006)	(0.010) (0.005)	(0.001) 0.040^{*} (0.024)	(0.001) 0.040^{*} (0.024)
Dependency ratio	(2.054) 0.544 (1.155)	(2.054) 0.544 (1.155)	(0.030) 1.360 (0.012)	(0.030) 1.361 (0.012)	(0.000) - 0.038^{***}	(0.000) - 0.038^{***}	(0.024) 0.006 (0.020)	(0.024) 0.006 (0.020)
Head literate	(1.135) -5.028 (2.420)	(1.155) -5.029 (2.420)	(0.912) 1.561 (1.222)	(0.912) 1.561 (1.222)	(0.013) 0.021 (0.017)	(0.014) 0.021 (0.017)	(0.029) 0.154^{***}	(0.029) 0.154^{***}
Head age	(3.439) 0.112^*	(3.439) 0.112^*	(1.322) 0.018	(1.323) 0.018	(0.017) -0.001	(0.017) -0.001	(0.055) 0.001	0.001
Head is male	(0.064) 14.016*** (5.031)	(0.064) 14.013*** (5.028)	(0.028) -2.836 (4.220)	(0.028) -2.839 (4.221)	(0.001) 0.091 (0.086)	(0.001) 0.091 (0.086)	(0.001) -0.075 (0.092)	(0.001) -0.075 (0.092)
Head is married	(5.001) -8.336 (5.117)	(5.020) -8.334 (5.114)	(1.220) 4.368 (4.458)	(1.221) 4.371 (4.458)	(0.000) -0.122 (0.102)	(0.000) -0.122 (0.102)	(0.052) -0.031 (0.058)	(0.052) -0.030 (0.058)
Provincial aid	(1.699)	(1.711) (1.250)	(0.632^{*})	(0.685^{**})	(0.002) (0.002)	(0.002) (0.006)	0.0001^{***} (0.00002)	0.0001^{***}
Constant	(11201) -18.592 (26.308)	(11200) -18.838 (26.625)	(6.523) (6.544)	(6.526) (6.534)	(0.000) 0.117 (0.187)	(0.1000) (0.125) (0.186)	(0.00002) -1.340^{***} (0.520)	(0.00000) -1.400^{***} (0.521)
Ethnicity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	979	979	979	979	979	979	889	889
R2	0.097	0.097	0.099	0.099	0.063	0.064	0.289	0.289
Adjusted R2	0.054	0.054	0.057	0.058	0.021	0.021	0.256	0.256
Residual std. error	577.950	577.951	240.588	240.581	4.352	4.351	7.550	7.550
F statistic	2.271***	2.270***	2.386^{***}	2.388^{***}	1.511^{**}	1.511^{**}	8.624***	8.625***

Notes: The dependent variable is level of serum ferritin in $\mu g/dL$ in regressions 1 and 2, serum retinol in $\mu g/dL$ in regressions 3 and 4, inflammation status (CRP > 1 mg/dL) in regressions 5 and 6, and an indicator equal to 1 if the respondent's household has access to safe water in regressions 7 and 8 (0 otherwise). All models are estimated using sampling survey weights, and all specifications use a flood variable adjusted for district population density. Robust standard errors (in parenthesis) are clustered at the district level. * p < 0.1, ** p < 0.05, *** p < 0.01.

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