Bombs and babies: Terrorism increases fertility in Nigeria*

Valentina Rotondi* Michele Rocca†

March 20, 2019

Abstract

This paper studies the association between exposure to Boko Haram's attacks and households' fertility choices in Nigeria. In our model, parents decide not only how many children they want to have, but also how much they want to invest on them. The predictions of the model suggest that households exposed to terrorism increase the number of children as a way to insure against future unexpected shocks and reduce investment in their offspring. We test the predictions of the model by resorting on geolocalized panel data linked to information on terrorist attacks occurred in the region. Consistent with the theory, terrorism is found to increase fertility (proxied by the number of surviving children per household) and decrease parental investment (proxied by child malnutrition). While the first association is robust to the use of difference-in-differences and instrumental variables models – and therefore can be given causal interpretation –, the second is not.

Keywords: Terrorism; Fertility; Parental investment; Boko Haram; Nigeria;
JEL classification: J13,I15 ,D19.

*This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement n. 694262), project DisCont - Discontinuities in Household and Family Formation. The authors wish to thank Lucia Corno, Selim Guleshi, Gianluca Femminis, Francesco Billari, Nicoletta Balbo, Vincenz Frey, Luca Stella, Simone Ghislandi, Massimo Anelli, Aart C. Liefbroer, Asli Ebru Sanliturk, Simone Spinelli, Elia Boschetti, Paolo Pinotti, Gianmarco Daniele, Marco Le Moglie, Rebecca Graziani, Vytenis Deimantas, Selin Koksal, Luca M. Pesando, Ridhi Kashyap, the participants to Do Re Mee Bocconi Seminar, the participants to PAA 2019 conference, the participants to PopDays 2019, + discussant at PAA.

*Bocconi University. Email: valentina.rotondi@unibocconi.it
†Catholic University of Milan. Email: michele.rocca@unicatt.it

1 Introduction

The aim of terrorism is to let fear rule over the lives of people. Terrorist groups share this aim all over the world, irrespective of the context in which they operate. The consequences of terrorist attacks, however, can be substantially different depending the context in which the attacks are perpetrated.

In developing countries, terrorism poses a *direct* threat to the achievement of the sustainable development goals (SDGs henceforth) by undermining "peace, justice and strong institutions" (SDG 16). However, terrorism can also constitute an *indirect* threat to the achievement of the SDGs by generating psychological, social and political effects upon the population that are generated by the climate of fear that the attacks evoke (Metcalfe et al., 2011; Romanov et al., 2012; Becker et al., 2004). In this paper, we study one of these *indirect* consequences by focusing on the impact in terms of households' fertility choices of Boko Haram's attacks in Nigeria.

From a theoretical standpoint terrorism could be both positively or negatively related to fertility choices. On the one hand, terrorism increases the feeling of uncertainty and changes individuals' risk assessments with a resulting *negative* effect in terms of fertility choices, as it has been shown to be the case for famine, political events, economic decline (e.g., Lindstrom and Berhanu, 1999), and war (e.g., Agadjanian and Prata, 2002; Woldemicael, 2008). On the other hand, terrorism can also have a *positive* effect in terms of fertility, as it has been shown to be the case for other shocks such as war (Easterlin, 1961; Van Bavel and Reher, 2013), bombings (Rodgers et al., 2005), or natural disasters (Nobles et al., 2015). In developing countries – in particular –, children may still be considered as an insurance on future income against unexpected shocks (Pörtner, 2001; Lambert and Rossi, 2016). Parents can therefore react to the increased instability brought about by terrorist attacks by having more children.

While there is a long history of research relating reproductive outcomes to conflicts and violence (e.g., Agadjanian and Prata, 2002; Woldemicael, 2008; Heuveline and Poch, 2007), and only a relatively small body of literature studying the relationship between terrorism and birth outcomes (e.g., Camacho, 2008; Quintana-Domeque and Ródenas-Serrano, 2017), the implications of terrorist attacks in terms of fertility choices have been largely neglected in the existing literature, with few relevant exceptions being Rodgers et al. (2005), Berrebi and Ostwald (2014), and Sanso-Navarro et al. (2018).

With this paper, we innovate with respect to the existing literature by studying the effect of Boko Haram in Nigeria on both i) parents' fertility choices (the *quantity* of children proxied by the number of surviving children per household) and ii) parental *investment* in their children (proxied by anthropocentric measures of babies below the age of 2 operationalized as weight-for-age z-scores, the most appropriate descriptor of malnutrition as for the World Health Organization). We do so, by exploiting micro-level geolocalized longitudinal data collected from 2009 to 2017 in Nigeria matched with data on terror events from the Armed Conflict and Location Event Dataset (ACLED).

Our theoretical model produces two hypotheses that we test in the empirical analysis. First, households exposed to terrorist attacks *increase* the *quantity* of children as a way to insure against future unexpected shocks, and, second, for a given budget constraint, they decrease *investment* in their children. Our empirical analysis builds on Bertoni et al. (2018) and adds to this contribution by exploiting not only the location of the events (in a panel data fixed effect model) but also the timing of the events (in a difference-in-differences design). We furthermore employ instrumental variables estimation techniques to deal with the possibly endogenous nature of terrorist attacks. Our empirical findings confirm our first hypothesis by showing that a 1 standard deviation increase in the number of fatalities increases the probability that a household hit by terrorism has a newborn by 1%, with this effect being robust to the use of empirical models aimed at tackling the issue of endogeneity. Terrorism is also found to be negatively associated with parental investment in their children (our second hypothesis). This association, however, cannot be given causal interpretation.

The remainder of this paper is organized as follows: section 2 briefly presents the background on which this paper is built. Section 3 presents a theoretical model whose predictions are tested with the data and methods presented in Section 4. Section 5 presents the results of the empirical analysis. Section 6 concludes.

2 Literature and background

There are reasons why fertility can be expected to rise in the aftermath of a shock such as an eruption of violence or after a war. Van Bavel and Reher (2013), for instance, show that the mid-twentieth-century baby boom experienced by several Western countries can be explained not only by a recuperation of the births postponed during the the Great Depression and World War II, but also by a rise of nuptiality. Heuveline and Poch (2007) show that the baby-boom experienced in Cambodia around the time of the Khmer Rouge regime – when 25% of the Cambodian population died –, was coupled to an increase in marriages and to a surge in marital fertility. Fertility can increase also due to the desire to replace own-child deaths – as it has shown to be the case for Rwanda (Kraehnert et al., 2017)–, or as a way to insure against future mortality shocks, –as it has been shown to be the case for Bangladesh (Hossain et al., 2007).[1]

[1] An increasing evidence shows that fertility can also surge in the aftermath of a natural disaster (See, for instance, Nobles et al., 2015). This branch of literature is only

Terrorism is a form of violence carrying peculiar characteristics.

There is no unanimous definition of terrorism. The most frequently used one combines two main features. First, terrorism is the use of extreme violence to obtain political, religious, or ideological objectives and, second, terrorism has the aim to intimidate a large audience, larger with respect to the one directly touched by the event itself (Friedland and Merari, 1985; Enders and Sandler, 2000). In many ways, terrorism is random: the incidents should take place without any warning and the timing of the event should be unpredictable in order to reach the goal of shock and disrupt (Berrebi and Ostwald, 2014). This is the main feature of terrorism that makes it conceptually different from any other form of violence and from war.

Terrorism can be domestic or transnational (Enders et al., 2011). While in the former and most common form of terrorism both perpetrators and victims come from the venue country hosting the attack, in the latter, two or more countries are involved. The two forms of terrorism have different implications (Enders et al., 2011) and different causes (Piazza, 2011). In this paper we focus on domestic terrorism, as it is usually the case in developing countries, and in Nigeria in particular.

Demography has been often included among the causes of terrorism and violence, instead that among its consequences. While Goldstone (2002) argued that demographic transformations can be linked to grievances and violent conflicts, Urdal (2006) showed that youth bulges potentially increase political violence, what have been claimed to be the case, recently, for the Arab Spring (LaGraffe, 2012) where an increasingly educated population has faced a lack of adequate economic opportunities (Campante and Chor, 2012). Apart from the population age composition, and the related youth employment opportunities, also gender imbalance (henceforth, a higher ratio of men to women) has been recently related to (reduced) terrorism in developing countries (Younas and Sandler, 2017). In this paper, we focus on the opposite relationship by studying the association between terrorism and demography. Notice that, the very fact that the relationship between terrorism (demography) and demography (terrorism) is *a priori* bi-univocal poses a problem of reverse causality that must be clearly tackled in the empirical analysis. We refer the reader to section 4 for a detailed discussion of this issue.

To the best of our knowledge, only few papers to date have studied the relationship between terrorism and fertility. Rodgers et al. (2005) study the consequences in terms of fertility of the Oklahoma City bombing occurred in downtown Oklahoma City on April 19, 1995 that caused 168 deaths and injured more than 680 people. By employing two different empirical methodologies (a control-group interrupted time-series design and a difference-in-differences design) they show that fertility in Oklahoma County increased

tangentially related to our work and, therefore, is not reviewed in deep in this paper.

after the attack. Berrebi and Ostwald (2014) exploit a longitudinal macro-level data set comprising 170 countries from 1970 to 2007 and different empirical models, including instrumental variables regressions, and find that terrorist attacks decrease both total fertility rates and crude birth rates. Sanso-Navarro et al. (2018) make use of a difference-in-differences approach to estimate the impact of terrorism on population growth in the municipalities of the Basque Country and Navarre autonomous communities in Spain from 1986 to 2014, and show that terrorism had a negative and transitory effect on the population growth rates of the municipalities in the regions studied. The three papers focus largely on developed countries.

Against this background, in this paper we expect fertility to increase in the aftermath of a terrorist attack in a developing country, such as Nigeria, as a consequence of an insurance (or "hoarding") mechanism. Before proceeding with the description of the model from which we derive two hypotheses that we test in the empirical analysis, let us briefly present Boko Haram and the demographic context in which it operates.

2.1 Boko Haram

Boko Haram, whose English translation can be "Western education is forbidden", is a terrorist group active in Nigeria since 2002. From April 2011 to June 2017, the group deployed 434 bombers to 247 different targets during 238 suicide-bombing attacks (Warner and Matfess, 2017) and has killed more than 30,000 people in north-east Nigeria and neighboring countries and contributed to the displacement of 2.1m.

Figure 1 shows the aggregated ACLED data for Nigeria from 2009 to 2017. The red circles are proportional to the total number of fatalities occurred in the area. The crosses (plotted in different colors according to the year, as indicated in the legend) show the exact location of the attacks, even those that did not result in any fatality.

The turning point for Boko Haram was july 2009 when the founder, Mohammed Yusuf, was killed in unclear circumstances during imprisonment by Nigerian security forces. After his death, the leadership of Abubakar Shekau began. The new leadership coincided with a rapid escalation of terrorist attacks during late summer of 2010. The terrorist attacks increased even more intensely in summer 2011 when a suicide bomber detonated at a United Nations compound killing at least 21 people. In 2014 and 2015 the violence escalated forcing the Nigerian government to postpone presidential elections by six weeks in order to guarantee the safety of voters in the region. The three states most affected by Boko Haram's attacks are situated in the North-East: Borno, Adamawa and Yobe. Of those forcibly displaced, about 84% remained within these three states, 8% moved to Northern and Central Nigeria, and 8% moved to Cameroon, Chad and Niger (Bertoni et al., 2018).

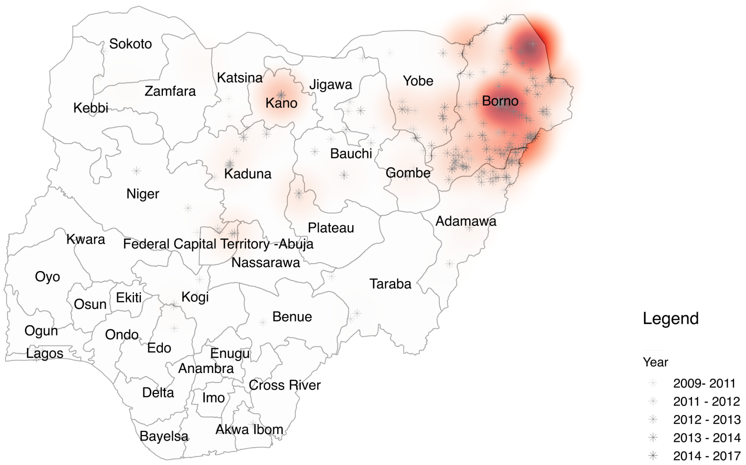


Figure 1: Total number of Boko Haram fatalities in Nigeria 2009-2017 (ACLED data)

To the best of our knowledge, only two papers to date have studied the micro-level effects of Boko Haram attacks in Nigeria: Bertoni et al. (2018), focusing on educational outcomes, and Nwokolo (2014), focusing on prenatal exposure to Boko Haram and birth weight.[2] Bertoni et al. (2018) make use of individual panel fixed-effects and difference-in-differences models to show that Boko Haram fatalities in North-East Nigeria during the period 2009–2016, reduced school enrolment especially for children who were no longer of mandatory school age. Nwokolo (2014) exploit variation in timing and geography of attacks in a difference-in-differences design to estimate the effect of in-utero exposure to terrorism and birth weight. The results show that terrorism is negatively related to birth weight for cohorts exposed within six months of pregnancy.

2.2 Demography in Nigeria

Nigeria's demographic transition is stalling (e.g., Bongaarts, 2006, 2008). According to the latest estimates by the United Nations with a population of 190 million people in 2017, an average annual population growth rate of 2.7%, and a total fertility rate of 5.7 children per woman, Nigeria has the largest population in Africa (United Nations, 2017). This population is young, a scenario typical of countries with high fertility rates: 46% of Nigeria's popu-

[2] Notice that there is a growing literature studying the consequences of in-utero exposure to terrorism and violence that are not reviewed in this paper due to space constraints.

lation is under the age of 15, while the proportion of individuals aged 65 and older is 4% (NPC/Nigeria and International, 2014). Life expectancy at birth was 52.6 and 51.2, for males and females, respectively, in 2017, while infant mortality rate amounted to 64.6 deaths per 1,000 live births in 2017. When looking at desired fertility rates, overall, Nigerian women have about one child more than the number they want. This implies that the total fertility rate of 5.7 children per woman is around 15% higher than it would be if all unwanted births were avoided. 15% of currently married women use a contraceptive method, only 2 percentage points more that in 2003 (NPC/Nigeria and International, 2014). According to the UN World Population Prospects 2017 (United Nations, 2017), the population of Nigeria, currently the world's 7th largest, is projected to become – by 2050 – the third largest in the world. This projected population growth is, however, unlikely to be economically sustainable. In fact, despite Nigeria's HDI value increased from 0.465 to 0.532 between 2005 and 2017, the current HDI value of 0.532 put the country in the low human development category (United Nations Development Programme, 2018).

The ethnic composition of Nigeria is outnumbered by the Hausa-Fulani ethnicity, accounting for two-thirds of the population. As far as religion is concerned, Nigeria's population is nearly equally divided between Christians, mainly living in the south, and Muslims, mainly living in the north. Ethnicity and religion play a very important role in shaping fertility patterns in the country (Mberu and Reed, 2014; Mobolaji et al., 2017) with fertility rates being in general higher among Hausa–Fulani–Kanuri ethnic groups and among Muslim communities. Yoruba and Igbo girls tend to marry later with respect to Hausa–Fulani (Odimegwu and Somefun, 2017) with a resulting increase in the age at first birth. Male privilege in terms of entitlements and inheritance rules are prevalent across ethnicity and religions.

Let us now proceed with the presentation of the theoretical model from which we obtain the two hypotheses we test in the empirical analysis.

3 Households' fertility choices

In developing countries children are often seen more as an *investment good* (which indirectly increases parents' utility by increasing their life-time income or life-time consumption – as in, among others, Neher (1971), Cigno (1993), and Pörtner (2001)) –, more than a *consumption good* (which increases the utility of parents as in Becker (1960)), as it is usually the case in developed countries.[3] In fact, when institutions such as social security are missing and markets (credit, insurance) are imperfect, parents have an expected return

[3] For a non-technical introduction of the analyses of fertility based on a rational-choice paradigm see Werding (2014).

from their children in the form of child labor or/and the provision of financial support for parents in older age to such an extent that having an additional child can be seen as a secure minimum level of income (e.g., Agadjanian and Prata, 2002; Lambert and Rossi, 2016).

When parents decide their optimal number of children,[4] they weigh benefits and costs. The parents live in two periods (present,p, and future,f). For simplicity, let us assume that benefits include the expected income from child labor at time future (W) while costs include the opportunity cost of the mother's time and the costs associated with raising each child (i) at time present. Parents are subject to a budget constraint that depends on the present output (Y_p), family endowments acquired at time present (H), the number of children (N), and the cost (investment) per child (i). Assuming that there can be no inter-period transfer of income except through children this means that:

$$Y_p = C_p + iN + H \tag{1}$$

Where C_p is the part of the current output (Y_p) that is consumed at time present (p). Consumption at time future (f) is instead given given by:

$$C_f = WN + Y_f \tag{2}$$

Where Y_f is the household's future output.

Notice that, as in Becker and Lewis (1973), from (1) we know that, for a given income constraint and a given level of present consumption (C_p), the costs associated to rising children (i) imply a trade-off between having fewer high-quality and high-cost children, versus having more low-quality and low-cost children characterized by a lower earning potential in the future.

Households can, therefore, resort on two equivalent strategies:

1. Increase the number of children (N) and reduce the investment in each of them (i)

2. Keep constant[5] the number of children (N) and the investment in each one of them (i)

[4]Implicitly we assume that parents can (wish to) control the number of births, which is not always the case in developing countries where traditions and cultural heritage often play a decisive role in terms of adoption of contraceptive methods. We also assume that the cost of controlling fertility is negligible. For a description of contraceptive prevalence and desired fertility among Nigerian women see section 2.2. Notice that, we leave also apart any emotional component coming from rising children and any psychological cost from sending children to work. We are aware that this is a simplification of the true value of children.

[5]For ethical reasons it is possible to consider the possibility of reducing the quantity of children

Which one of the two strategies will prevail is an empirical question, and crucially depends on the relationship between the expected income from child labor and from parents' investment, i.e., W and i, respectively.

We can assume that, similarly to Del Carpio et al. (2016), the expected wage of a child in the labor market W is a (positively) function of 1) family endowments (H) such as productive assets in the household (e.g., tools, land, and capital), and 2) parents' investment (cost) in each children in period present (i), such that: $W(i, H) = Hw^i$, where w is the salary that the child gains in the labor market and it is assumed to be exogenously given.

Solving (1) for N and substituting into (2) we obtain:

$$C_f = Hw^i \frac{Y_p - C_p + H}{i} + Y_f \tag{3}$$

Parents wish to pick i and N so as to maximize their chosen combination of present and future consumption. Therefore:

$$\frac{\partial C_f}{\partial i} = \frac{Hw^i \left(Y_p - H - C_p\right)\left(\ln\left(w\right) i - 1\right)}{i^2} = 0 \tag{4}$$

By solving equation (4) for i we obtain: $i^* = \frac{1}{\ln(w)}$. Assuming that w is exogenous, substituting i^* in equation (1) and solving for N we obtain: $N^* = \ln\left(w\right)\left(+Y_p - C_p - H\right)$. Therefore, a reduction in H due to a terrorist attack increases N^* ($\frac{\partial N^*}{\partial H} < 0$).

Obviously this is not the only possibility. If we consider a case where $W(i, H) = w^{iH}$,[6] we obtain:

$$i^* = \frac{1}{H \ln\left(w\right)}. \tag{5}$$

Assuming that w is exogenous, substituting (5) in equation (1) and solving for N we obtain: $N^* = \ln\left(w\right)\left(+Y_p - C_p - H\right) H$. Assuming that terrorist attacks might damage households' endowments (H), a reduction in H due to a terrorist attack increases N^* ($\frac{\partial N^*}{\partial H} < 0$).[7]

Given the simple model sketched above, we can formulate the following hypothesis:

Hp1 In the aftermath of a terrorist attack households increase the *quantity* of children as a way to insure against future unexpected shocks

Hp2 For a given budget constraint, in the aftermath of a terrorist attack parents decrease the *investment* in their children if they increase their *quantity*

[6] Notice that the same predictions holds for a different function such as: $W(i, H) = w^{i\left(\frac{H}{N}\right)}$

[7] Another example comes from $Y_c = C_p + iN + H$. In this case, a reduction in H due to a terrorist attach does not affect i^* while it increases N^*.

So far, we have considered a world where boys and girls earning potentials are exactly the same. This is usually not the case in developing countries where children play different roles in household production: while girls usually look after their siblings, and help in household's chores, boys are usually employed in cultivating family's land, or in waged jobs.[8] The opportunity costs of boys and girls therefore crucially depend on the relative importance of each one of these two roles. As a result, parents may react to the increased instability brought about by terrorist attacks by preferring boys to girls if their returns on the labor market are higher (if $w_b > w_g$ where w_b is the salary of boys and w_g is the salary of girls). This effect would translate, for instance, in a better average parents' investment for boys with respect that for girls (i.e., a *preference-driven effect*), especially in times of economic hardship, as a vast literature on imbalances in developing countries show (See among others: Friedman and Schady, 2013; Iqbal et al., 2018). However, while son preference has been widely documented in South and East Asia, in Sub-Saharan Africa boys and girls seem to be treated rather equally (e.g., Garenne, 2003). Indeed, Rabassa et al. (2014) showed that the impact of weather shocks is the same for young boys and girls in Rural Nigeria, which suggests that there is no gender-based discrimination in the allocation of resources within households even in times of economic hardship.[9] Indeed, it is also plausible to expect exactly the opposite relationship. Parents might in fact react to the increased instability brought about by terrorist attacks by investing more on girls given their higher chances of surviving (i.e., a *reinforcing effect*). The sex difference in genetic and biological makeup makes, in fact, infant boys biologically weaker, more susceptible to diseases and more likely to die in infancy premature death than girls (e.g., Naeye et al., 1971). Since it is not possible to establish *a priori* which of the two effects prevails, this remains an open empirical question.

4 Data and methods

4.1 Data

Our empirical analysis is based on the combination of three micro data sources. First, we exploit the richness of the three waves (2011, 2013, and 2016) of the Nigeria General Household Survey Panel (GHS-Panel), a nationally representative survey of approximately 5,000 households conducted by the Nigeria National Bureau of Statistics as a part of the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) project

[8] See for instance: https://data.unicef.org/topic/child-protection/child-labour

[9] Notice that son preference might also affect women fertility behavior, health and well-being (Milazzo et al., 2014). This aspect is, however, behind the scope of this paper.

(World Bank, 2019). The households included in the GHS-Panel are a random sub-sample of the overall GHS sample households. The demographic composition of each household can be derived each wave from the household roster. Besides information on household's assets and durables, the GHS-Panel provides information on education, labor force participation, health and child development within households. Our estimation sample comprises 12,488 household-year observations resulting from 4,998 households at wave 1. The crucial feature of the GHS-Panel is that it provides village-level GPS information which allows us to link it to our second source of data: the PRIO/Uppsala Armed Conflict and Location Event (ACLED) dataset, which covers conflict events through the 1997–2018 period (ACLED). The third data source is the geo-referencing of ethnic groups (GREG) dataset (Weidmann et al., 2010) containing geo-referenced information on ethnic groups around the world. The GREG main source of information is based on data and maps from the Atlas Narodov Mira, a project by Soviet Ethnographers dating back to the 60s. Similarly to (Alfano, 2017) we allocate households from the GHS-panel to their ethnic homelands of Nigeria's ethnicities by matching the GHS-panel latitude and longitude to the centroid latitude and longitude of the ethnicity in the GREG.[10]

We now proceed with the presentation of the methods used along the empirical analysis.

4.2 Methods

Our analysis comprehends one baseline empirical model corroborated by a number of sensitivity and robustness checks.

4.2.1 Fixed-effect panel data model

First, we exploit the longitudinal nature of our dataset to implement a fixed effect panel data regression.[11]

We therefore estimate the following regression model:

$$Y_{j,l,t} = \alpha + \beta Conflictintensity_{l,t-1} + \gamma * X'_{j,l,t-1} + \mu_j + \theta_t + \gamma_{st} + \epsilon_{j,l,t} \quad (6)$$

We test **Hp1** of the model in Section 3, by using as dependent variable ($Y_{j,l,t}$) a dummy variable taking value 1 if the household has at least one newborn ($NewBorn_{j,l,t}$), a baby below the age of two.[12] We test **Hp2** by

[10] This process in implemented by using the programs *shp2dta* and *geonear* in Stata.

[11] Notice that, the Hausman test suggests that under the current specification, individual-level effects are not adequately modeled by a random-effects model.

[12] Notice that this variable measures the probability that the household has at least one surviving child. This measure is conceptually different from fertility *per se*. Along the paper we will present some models in which we will explicitly control for child mortality.

using weight-for-age z-score (WAZ, henceforth) for each child below the age of 2 (males and females) in the household. WAZ is a proxy for short term malnutrition defined by the World Health Organization as wasting (low weight for height). For each child, depending on their sex and age, the z-score expresses anthropocentric values in terms of standard deviations below or above the median of an international reference group. The World Health Organization defines as "healthy" those children whose z-score ranges from -1 to +1, "under risk" those whose z-score ranges from -1 to -2, and "severe risk" those whose z-score is below -2. Notice that, in terms of economic perspectives, empirical evidence shows that potential low health outcomes in early life affect labor productivity, income-earning potential and social skills later in life, with consequences beyond the individual level (e.g., Maccini and Yang, 2009). This variables therefore is well suited for capturing parental investment in their children and their future income prospects.

The matrix $X'_{h,t}$ includes a set of (time-varying) household-level controls as depicted in table 1. μ_j and θ_t are household and time fixed effects while γ_{st} are state-specific linear time trends. $\epsilon_{j,l,t}$ is the error term. Consistently with Bertoni et al. (2018), $ConflictIntensity_{h,t-1}$ is the household-specific evolution of conflict intensity over time and space. First, we define a buffer distance measure around each household (5 km). Second, we compute the total number of fatalities occurred within each buffer zone in the period starting from 12 months prior to the date of the interview to the latest wave so as to account for pregnancy and delivery. This means that if the information on the dependent variable ($NewBorn_{j,l,t}$) is collected in March 2011, the information on the independent variable ($ConflictIntensity_{h,t-1}$) is the number of fatalities that occurred in the radius of 5 km from the household's location before March 2010:

$$Conflictintensity_{l,t-1} = \sum_{t-1}^{t-2} Fatalities(5Km)_l \tag{7}$$

As a robustness check we re-run our baseline regression by using as dependent variable a dummy variable taking value 1 if there has been at least one fatality within the 5km radius and by changing the buffer zone from 5km to 10km. The results of the latter exercise are available upon request.

All regressions are estimated using robust standard errors clustered at the household level.

Summary statistics for the variables used along the paper are presented in Table 1.

Attrition As already mentioned above, our sample includes 4998 households of which 67% are interviewed three times. Attrition might potentially invalidate the analysis when it is systematically related to exposure to the

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Dependent variables					
Newborn(d)	0.351	0.477	0	1	12487
WAZ	-1.561	1.404	-4	4	3711
WAZ (F)	-1.521	1.446	-4	3.94	2140
WAZ (M)	-1.597	1.415	-4	4	2191
Severe risk	0.413	0.492	0	1	3711
Severe risk (M)	0.423	0.494	0	1	2191
Severe risk (F)	0.406	0.491	0	1	2140
Explanatory variable					
Conflict Intensity	0.166	2.278	0	187	12488
Covariates					
HH size	3.898	2.23	1	30	12487
# of HH members able to read and write	0.499	0.318	0	1	12487
Urban	0.312	0.463	0	1	12487
Share of Islamic in the HH	0.178	0.375	0	1	12487
HH wealth index	0.019	0.642	-0.914	13.319	12458
# of HH members occupied	0.436	0.283	0	1	12357

treatment. In order to check how attrition bias might affect our results we build a dummy taking value 1 if the household is not interviewed in wave three and zero otherwise, and we regress it on the level of conflict intensity. The results of this exercise are depicted in table 8 in the Appendix. Reassuringly for our analysis, we find no significant correlation between exposure to terrorism and the probability of leaving the sample at wave 3, not even when conditioning on the covariates used along the empirical analysis. However, the results of the model reported in column 2 of table 8 show that attrited households tend to be more numerous, have a higher number of employed members, and to have a higher share of Islamic relative to households that remained in the panel. These results suggest that selection bias would unlikely affect the results of the analysis. At the same time, the fact that attrited households seem to be wealthier with respect to households remaining in the panel can lead to an overestimation of the true causal effect since our measures of fertility choices are likely to be negatively correlated with wealth.

4.2.2 Difference-in-differences

Our second empirical analysis is a Difference-in-Differences (DID, henceforth) model whereby we exploit the timing of the change in Boko Haram's leadership. When in 2009 the Nigerian army attacked one of the bases of Boko Haram, Mohammed Yusuf, the historical leader who founded the movement at the turn of the century, was captured and killed (Thomson, 2012). At that time, also Abubakar Shekau, the founder's right arm, was given for dead. Less

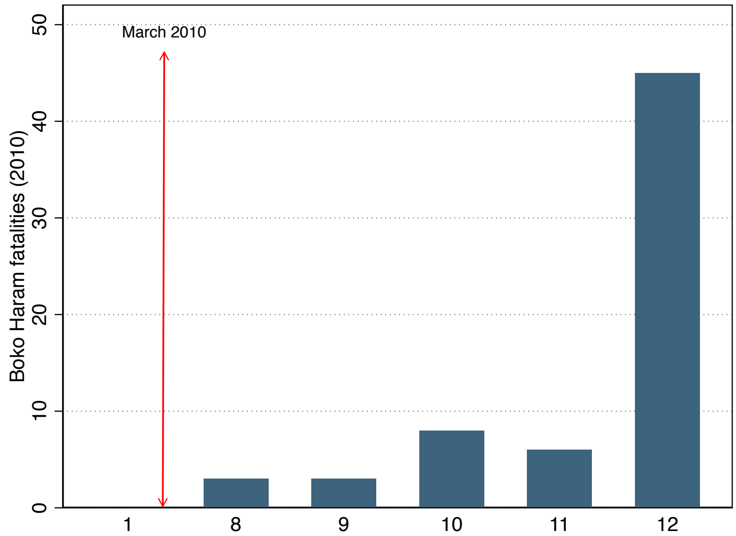


Figure 2: Total number of Boko Haram fatalities in 2011 by month (ACLED data).

than one year later, however, he appeared online and proclaimed himself as the new leader of Boko Haram. Under Shekau's leadership Boko Haram has changed not only its targets, but also its tactics and its geographic scope by passing from sporadic skirmishes with the army to unexpected terrorist attacks targeting civilians, schools and churches. This happened around the summer of 2010.

This change in leadership might act as a natural experiment within our dataset. Recall that our main explanatory variable ($Conflictintensity_{l,t-1} = \sum_{t-1}^{t-2} Fatalities(5Km)_l$) is built as the total number of fatalities occurred within a radius of 5 km from the household's location in the period starting from t-12 months to the previous wave (t-2). Considering that the interviews for the first wave of the GHS were conducted in March 2011, they were conducted in a pre-terrorism environment (see Figure 2).[13] Therefore we can exploit the variation of a pre-post terrorism together with the variation in the location of the events, in a difference-in-differences framework as depicted in equation (8):

$$Y_{j,l,t} = \alpha + \beta_1 T_{j,l,t-1} + \beta_2 P_{j,l,t} + \beta_3 T_{j,l,t} * P_{j,l,t} + \gamma X'_{j,l,t-1} + \mu_j + \theta_t + \epsilon_{j,l,t} \quad (8)$$

where $T_{j,l,t}$ is a dummy variable taking value one if the household (j) located in (l) is affected by a terrorist attack and $P_{j,l,t}$ is a dummy variable

[13]Notice that the ACLED dataset includes also information on general violence and riots. In this paper we only consider events classified in the dataset as being perpetrated by Boko Haram.

taking value 1 after the second wave. β_3 is, therefore, our coefficient of interest.

Parallel trend assumption The main identifying assumption for the difference-in-differences approach (the so-called parallel trend assumption) is that, absent the treatment, the demographic outcomes of treated and control households would have followed the same trend. By definition, this assumption cannot be verified. However, we can show that when looking the total fertility rates[14] in treated and non-treated states we can see that although treated states start, on average, from a higher initial level, they follow similar trends (see Figure 5 in the Appendix).

Endogeneity Although our specification includes state fixed effects and state-specific time trends, the difference-in-differences analysis might still be biased due to endogeneity concerns coming from time varying state-level characteristics that are not accounted for in the estimated model. We can partially test for this source of endogeneity, by analyzing the correlation between pre-terrorism fertility rates and conflict intensity at the state level. To this aim, we regress pre-conflict state-specific TFR on the number of fatalities occurred at the state-level. The results of this exercise (shown in Table 9 in the Appendix) show no statistically significant correlations across specifications even when controlling for child mortality, the presence of on shore petroleuem, and the intensity of light sources detected during nighttime as a proxy for local development.[15]

4.2.3 Instrumental variables

Under the assumption that there are no omitted household-level time-varying variables correlated with terrorism (i.e., under the assumption that terrorism is exogeneous) the estimated β in equation 6 gives the true causal effect of conflict exposure on fertility choices. However, if terrorism is predetermined (terrorism respond to past terrorism shocks) or endogenous, the fixed effect estimator is inconsistent. According to Warner and Matfess (2017), Boko Haram seems to have no discernible pattern regarding date, target, or nature of the bomber. This makes unlikely that these terrorist attacks are endogenous. However, although the question of causal ordering is teased out by panel data models, these models typically can still be biased by omitted

[14]We make use of total fertility rate obtained through the Nigeria Demographic and Health survey. This measure refers to the 5 years preceding the survey and it is computed as the age-period fertility rate for a synthetic cohort of women. It therefore measures the average number of births a group of women would have by the time they reach age 50 if they were to give birth at the current age-specific fertility rates.

[15]Data have been retrieved through the AidData's GeoQuery tool (Goodman et al., 2019).

variables. Accordingly, the estimated β_3 in equation (8) is a measure of the causal effect when, absent the treatment, the difference between the treatment and control group is constant over time (the so-called parallel trend assumption). The violation of the parallel trend assumption leads to biased estimation of the causal effect.

One way to overcome these problems is to implement a model with instrumental variables. It is not easy to find an appropriate instrument, i.e., a variable associated with the probability of experiencing terrorism (i.e., relevant), but not related to demographic outcomes (i.e., exogenous) except through its influence on terrorism. To the best of our knowledge, the instruments used in the empirical literature relate to lagged domestic terrorism incidents in neighboring countries as in Berrebi and Ostwald (2016, 2014); Enders et al. (2011), or to distance from the border, as in Rehman and Vanin (2017). Indeed, Boko Haram initially concentrated its suicide-bombing attacks in Nigeria's more remote border areas where the group appears to be concentrating larger proportions of its resources (Foyou et al., 2018). This is evident also from Figure 1. Our first candidate instrument for terrorism is, therefore distance from the border (*Distance from border*).

According to Pieri and Zenn (2016), Boko Haram's rhetoric is based on the reference to two precolonial empires: the ethnic Fulani and Hausa-led caliphate of Usman Dan Fodio (1804–1903) and the ethnic Kanuri-led Kanem-Borno Empire (700–1900). More specifically, while Boko Haram seems to seek legitimacy in the former Fulani caliphate, its leaders and members are predominantly Kanuri operating in the areas of the latter empire (the States of Borno and Yobe in figure 1). Obviously, it is easier to commit an attack in areas where you can count on more and better support. However, ethnic belonging *per se* does not reach the requirements for a good instrument. In particular, it cannot be considered exogeneous with respect to fertility choices. In fact, differences between ethnic groups might play a role in determining son preference (Fayehun et al., 2011; Alfano, 2017) as– although the majority of ethnic groups in Nigeria are predominantly characterized by patrilineality and patrilocality whereby inheritance rules provide that only male children are allowed to inherit a large part of the father's property (Milazzo et al., 2014) –, some minority ethnic groups (e.g., the Ijaw) has marriage and other practices often associated with matrilineal systems. Furthermore, different ethnic groups are often characterized by different socio-cultural values that have been shown to impact on children health metrics (Adedini et al., 2015). Mberu and White (2011) show, for instance, that ethnicity is a key determinant of premarital sexual initiation in Nigeria, and Becker (2018) finds that the strength to which a woman's ancestral ethnic group depended on pastoralism is positively associated with how strong son preference is. It is also plausible to expect that persistent horizontal inequality (Archibong, 2018) by ethnic group might affect households' fertility choices.

In order to address this concern, as in Michalopoulos and Papaioannou (2013b), Michalopoulos and Papaioannou (2013a), Cogneau and Moradi (2014), and Alfano (2017) we exploit the exogeneity coming from the arbitrary partitioning among European powers of African ethnicities into states during the so-called "scramble for Africa" in the end of the 19th century. This arbitrary division of territories into administrative borders was conducted disregarding traditional ethnic homelands (Englebert et al., 2002) and led to the partitioning of several ethnicities across newly created states. We claim that it should be more difficult for terrorist groups to find support in partitioned territories with respect to more homogeneous ones. Our second candidate instrument for terrorism is, therefore, living in a territory where a traditional ethnic homeland has been partitioned across two or more states (*Partitioned ethnicity*).

As a further instrument in our empirical analysis we include distance from the market. As any other terrorist movement, the declared goal of Boko Haram is to shock and disrupt. To this aim the attacks are often directed towards those areas with a higher concentration of population. Our third candidate instrument for terrorism is therefore the household's distance from the market (*Distance from market*). Notice that, since the three instruments do not vary between one wave and the other we interact them with terrorism.

5 Results

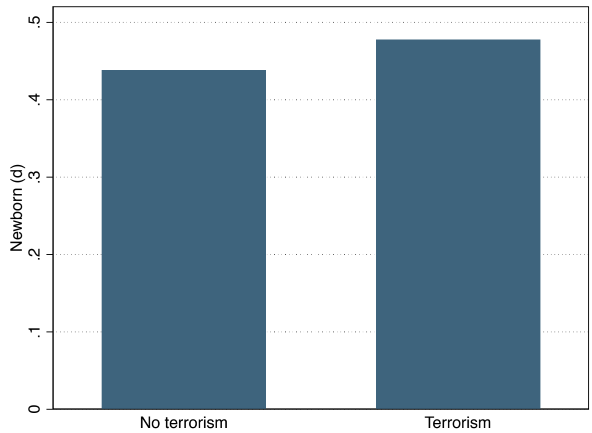


Figure 3: Total number of newborn by terrorism (ACLED-GHS data).

This section presents the results of the empirical analysis. We start by presenting bivariate evidence of the relationship between exposure to terrorism and households' fertility choices. Figure 3 and Figure 4 provide a simple bivariate assessment of the patterning of fertility choices (the frequency of households having at least a child below the age of 2) and malnutrition (as proxied by WAZ scores), respectively.

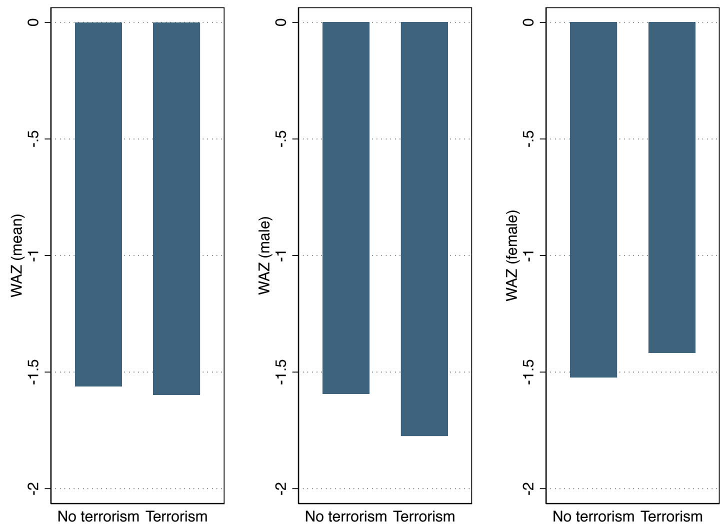


Figure 4: WAZ scores by terrorism (ACLED-GHS data).

Figure 3 shows that households that have experienced at least one terrorist attack have a higher probability of having at least one child below 2 with respect to households that did not experience terrorism. The paths emerging from figure 4 are less clear-cut. While we can notice that malnutrition is extremely widespread in our sample, with on average more than 40% of the girls and more than 45% of the boys being severely malnourished (i.e, a WAZ score below -2), there seems to be no clear pattern related to terrorism in terms of children malnutrition. When looking at gender differences in malnutrition, however, it seems that boys living in households that have experienced terrorism seem to be more malnourished with respect to their female counterparts. Of course, these paths might be driven by either selection on observable traits (like education, socio-economic status, age), or selection on unobservable traits (like genetic differences, motivation, forward looking behavior), or they might be driven by a true causal effect. In what follows, we leverage a variety of estimation tools to further unpack and explain these differences.

Quantity Table 2 depicts the household panel fixed-effects estimates for the association between Boko Haram attacks and households' fertility choices in Nigeria using as main measure for terrorism the total number of fatalities occurred (*Conflict Intensity*) or using as dependent variable a dummy variable taking value 1 if there has been at least one fatality within each buffer zone (column 1 and 2, respectively).

Table 2: Boko Haram and *quantity* of children: Panel data fixed effect

	(1)	(2)
	Newborn(d)	
	b/se	b/se
Conflict Intensity	0.0044***	
	(0.001)	
At least 1 death		0.0983**
		(0.045)
HH size	-0.0137**	-0.0136**
	(0.005)	(0.005)
# of HH members able to read and write	-0.3337***	-0.3337***
	(0.023)	(0.023)
Urban	0.0298	0.0325
	(0.063)	(0.063)
Share of Islamic in the HH	0.0618**	0.0625**
	(0.025)	(0.025)
HH wealth index	0.0048	0.0040
	(0.008)	(0.007)
# of HH members occupied	-0.0570***	-0.0571***
	(0.020)	(0.020)
Constant	0.8839**	0.8846**
	(0.419)	(0.419)
N.	12327	
Mean of dep. var.	0.3526	
S.D. of dep. var	0.4778	

Note: Fixed effects panel data model. Covariates as described in Table 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

The positive coefficients reported in the first and third line of table 2 suggest that an increase in exposure to terrorism is positively related to fertility. Although the magnitude of the coefficients seem to be small, when computing standardized coefficients for the model depicted in column 1 we find that a 1 standard deviation increase in the number of fatalities (+2.4 fatalities) occurred in the 5 km radius from household in the previous year resulted, on average, in around 1% increased probability to have a newborn for each household, *ceteris paribus*. In a context characterized by high birth rates and high incidence of poverty and malnutrition, this result is not as small as it might seem at a first sight. As an example, in relative terms, the coefficient for conflict intensity is comparable to half the size of increasing by one standard deviation the share of occupied in the HH (β_c=0.01 and β_o=-.02 for conflict intensity and number of household members occupied, respectively). These results (not reported due to space and time constraints) hold also when accounting for ethnic-specific time trends. The results from the control variables suggest, as expected, that fertility choices are negatively related to education, while they are positively related to being Islamic.

Table 3: Boko Haram, *quantity* of children, child mortality

	(1)	(2)
	Newborn(d)	
	b/se	b/se
Conflict Intensity	0.0044***	0.0044***
	(0.001)	(0.001)
# of children death	-0.0320	-0.0312
	(0.025)	(0.025)
Conflict Intensity × # of children death		-0.0037
		(0.014)
Constant	0.8829**	0.8821**
	(0.419)	(0.419)
N.	12327	12327

Note: Fixed effects panel data model. Covariates as described in Table 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

Our measure of fertility choices is a measure of the probability that the household has at least one surviving newborn. This measure therefore may be thought of as an indicator of recent fertility net of child mortality. This is an imperfect measure that tend to understate the actual fertility levels. In the context of this study, this aspect could be particularly disabling if we consider the fact that women and children – especially children in school age– have often been the target of Boko Haram's attacks (UN Security Council, 2017).[16] Our dataset does not include any information about whether the household was a victim of an attack in which a child died. However, we have information about whether the family has experienced the death of a child. If child mortality is indeed a mechanism by which terrorism operates, we expect the estimated β in equation (6) to be no longer significant when controlling for child mortality in our estimated model. The coefficients depicted in column 1 and 2 of Table 3 show that this is not the case.[17]

Parental investment Table 4 reports regression results obtained when using as dependent variables weight-for-age z-scores (Columns 1-3) or a dummy

[16]The United Nations (UN Security Council, 2017) documented 3,909 children (1,428 boys, 1,021 girls and 1,460 unknown sex) killed and 7,333 children (2,101 boys, 1,459 girls and 3,773 unknown sex) maimed during 474 conflict-related incidents between 2013 and 2015.

[17]Notice also that when we estimate a model using child mortality as a dependent variable, the coefficient for $ConflictIntensity$ is not significant. The results of this exercise are available upon request.

for severe malnutrition (Columns 4-6) as a proxy for parents' *investment* in their children. Column 1 and column 4 depict the results for all children in the household, column 2 and column 5 consider only boys, while column 3 and column 6 consider only girls. The upper and the lower panel of Table 4 use as main measure for terrorism the total number of fatalities occurred within each buffer zone (*Conflict Intensity*) or a dummy variable taking value 1 if there has been at least one fatality, respectively.[18]

Table 4: Boko Haram and parental *investment*: Panel data fixed effect.

	(1) WAZ b/se	(2) WAZ (M) b/se	(3) WAZ (F) b/se	(4) Severe risk b/se	(5) Severe risk (M) b/se	(6) Severe risk (F) b/se
Conflict Intensity	-0.0964**	-0.0637	-0.1057	0.0170	0.0182	-0.0031
	(0.041)	(0.047)	(0.095)	(0.011)	(0.017)	(0.022)
HH size	0.0057	0.0928	-0.1194	0.0083	-0.0023	0.0487*
	(0.045)	(0.064)	(0.076)	(0.017)	(0.028)	(0.025)
# of HH members who know to read and write	-0.1002	0.4119	0.1717	0.0245	0.0434	-0.1398
	(0.197)	(0.307)	(0.353)	(0.076)	(0.126)	(0.135)
Urban	1.9916***	0.6867	1.7502	-0.1329	0.1384	-1.1615**
	(0.637)	(0.847)	(1.192)	(0.241)	(0.377)	(0.497)
Share of Islamic in the HH	-0.1391	0.4094	-0.2425	0.0142	-0.1278	0.0746
	(0.187)	(0.355)	(0.307)	(0.066)	(0.115)	(0.116)
HH wealth index	0.0403	0.0495	0.0265	-0.0173	-0.0073	-0.0269
	(0.052)	(0.084)	(0.080)	(0.023)	(0.042)	(0.031)
# of HH members occupied	-0.0754	-0.4673*	-0.0217	-0.0829	0.0706	-0.0568
	(0.195)	(0.274)	(0.303)	(0.073)	(0.108)	(0.111)
Constant	-2.1584***	-2.3261***	-1.7710***	0.3861***	0.3293**	0.6287***
	(0.271)	(0.375)	(0.502)	(0.103)	(0.164)	(0.193)
N.	3710	2191	2139	3710	2191	2139
Mean of dep. var.	-1.5625	-1.5974	-1.5233	0.4129	0.4226	0.4063
S.D. of dep. var	1.4031	1.4149	1.4434	0.4924	0.4941	0.4912
At least 1 death	-0.9842***	-1.2893***	-0.3840	0.1230	0.3383**	-0.1744
	(0.322)	(0.388)	(0.504)	(0.109)	(0.136)	(0.155)

Note: Fixed effects panel data model. Covariates as described in Table 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

The coefficient depicted seem to suggest that when households react to terrorism by increasing the number of children, they reduce the investment on them. In fact, a one standard deviation increase in the number of fatalities in each buffer zone corresponds, on average, to a 4% increase in the probability of having severely malnourished children in the household, with this result being mainly driven by a reduced investment in boys with respect that in girls.

One could argue that this result is driven by sex selection at birth, the attempt to control the sex of the offspring to achieve a desired sex. As suggested in section 3, households might have a preference for sons with respect to daughters whose economic returns in the labor market are expected to be lower. If this is the case, there might be evidence of distorted sex ratio at (or soon after) birth especially where terrorism has been more severe and households need to insure against future shocks. Our calculations suggests that we cannot detect distorted sex ratio at birth in the sample of households exposed to terrorism nor in the sample of households not exposed.

[18] For simplicity the bottom panel of Table 4 does not report the results for the covariates.

The results of the analysis conducted so far seem to confirm Hp1: in the aftermath of a terrorist attack households increase the quantity of children as a way to insure against future unexpected shocks. As far as Hp2 is concerned, there appear to be mild evidence of a reduction in parental investment in children and, above all, in male children (*i.e., a reinforcing effect*). This result is, however, less robust than the previous one and suggests being cautious.

5.1 Heterogeneous effects and mechanisms

The results depicted in table 2 and table 4 might be interpreted as evidence that Boko Haram is dictating high fertility through terrorism in Nigeria. Indeed, Boko Haram's rhetoric deems contraception to be forbidden and pushes women to avoid school, marry early and have numerous children. If our results were only driven by an attempt to dictate religious preferences for larger families, we would expect to find a greater effect of terrorism in those 12[19] states that in 2000 introduced Sharia law and the institutions aimed at enforcing it.

The Sharia covers and regulates a wide spectrum of the interrelations between parents and their children that might impact on parental decisions about the *quantity* of children as well as about parental *investment* in their offspring. First of all, Sharia law changes the expected costs and the economic returns of children. In fact, while parents are obliged to maintain their children (boys and girls alike) until adulthood, children have the duty to maintain their parents in old age. This duty slightly differs between boys and girls but only after marriage. In fact, while married girls are expected to move with their husband from whom they are typically maintained and cannot transfer money to their family without the spouse's permission, boys act as the main caretakers of their parents. Indeed Alfano (2017) shows that the introduction of Sharia law increased fertility by 38% and the duration of breastfeeding by 19% therefore increasing the survival rate of newly born babies.

Table 5, first panel, depicts the results of estimating equation (6) by adding an interaction term between $ConflictIntensity_{h,t-1}$ and a dummy variable taking value 1 for those states that introduced Sharia law in 2000. The insignificant interaction term depicted in column 1 suggests that it is unlikely that our results are driven only by Boko Haram attempt to dictate higher fertility through terrorism. The negative and significant interaction term depicted in column 4 is instead in line with the results reported in Alfano (2017) and with the fact that, despite pro-natalist beliefs are widespread, Islamic leaders recognize the importance of matching family size with economic

[19]Bauchi, Borno, Gombe, Jigawa, Kaduna, Kano, Katsina, Kebbi, Niger, Sokoto, Yobe and Zamfara

resources (Mberu and Reed, 2014).

Panel 2 and 3 of table 5 aim at dig deeper into the interpretation of our results by adding to the model depicted in equation (6) an interaction term between $ConflictIntensity_{h,t-1}$ and the number of household members occupied and the number of children already living in the household, respectively. Column 3 of panel 2 suggests that households having a higher share of occupied adults cope better with terrorist attacks with respect to households having fewer occupied adults, in line with our hypothesis. However, the negative and significant interaction term depicted in column 1 of the third panel suggests that the positive association between terrorism and the *quantity* of children is smaller for households having already more children. Not surprisingly, boys in households with a higher number of children have a higher probability to be malnourished with respect to their counterparts with fewer siblings (column 3 of panel 3). These two latter results do not allow us to fully exclude (at least from an empirical standpoint) the hypothesis, however remote, that Boko Haram is specifically targeting smaller families with the specific aim to dictate fertility through terrorism. Recall that, however, Warner and Matfess (2017) suggest that Boko Haram does not have any discernible pattern regarding date, target, or nature of the bomber.

Table 5: Heterogeneous effects

	(1) Newborn(d) b/se	(2) Severe risk b/se	(3) Severe risk (M) b/se	(4) Severe risk (F) b/se
1. Conflict Intensity × Sharia states	0.0072	-0.0469	-0.0867	-0.1010**
	(0.004)	(0.034)	(0.054)	(0.051)
2. Conflict Intensity × # of HH members occupied	0.0037	-0.0951	-0.2782**	-0.1512
	(0.008)	(0.101)	(0.131)	(0.197)
3. Conflict Intensity × # of children already in HH	-0.0018*	0.0040	0.0293*	0.0152
	(0.001)	(0.012)	(0.017)	(0.024)

Note: Fixed effects panel data model. Covariates as described in Table 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

5.2 Addressing endogeneity

5.2.1 Difference-in-differences

Table 6 depicts the results of a difference-in-differences model as described in section 4.2.2. The upper panel of table 6 reports the results of a simple difference-in-differences while the lower panel reports the results of a kernel propensity score matching difference-in-differencs whereby the weights derived from the kernel density function are used to implement a propensity score matching on the covariates by imposing common support. Notice that when combining DID with matching techniques the aim is to differencing out the permanent confounders of the true causal effect (as in the DID) while capturing transitory shocks (as in matching techniques).[20]

Table 6: Robustness: DID.

	(1) Newborn (d) b/se	(2) Severe risk b/se	(3) Severe risk (M) b/se	(4) Severe risk (F) b/se
DID	0.3614***	-0.0159	0.1045	-0.1299
	(0.040)	(0.084)	(0.102)	(0.109)
N.	12327	3710	2191	2139
Kernel PSM DID	0.3182***	-0.0061	0.2089*	-0.1635
	(0.039)	(0.087)	(0.107)	(0.110)
N.	12321	1808	667	844

Note: DID. Covariates as described in Table 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

The results of the average treatment effect on the treated are in line with the main findings in table 2.

5.2.2 Instrumental variables

As a final robustness check we present the results of our instrumental variables approach. The results are depicted in table 7. Good instruments should be both relevant and valid: i.e., they should be correlated with the endogenous regressors and orthogonal to the errors.

We cannot test whether our instruments are truly exogenous. The discussion provided in section 4.2.3 is intended to justify our claims of exogeneity by reasoning. What can be tested is, instead, the strength of our selected set of instruments. The bottom panel of Table 7 reports the F statistics for the first stage regression and the Hansen J overidentification test. The F-statistics reported in Table 7 let us reasonably maintain that the selected instruments are not weak, while the fact that Hansen J statitic is far from the rejection of its null (i.e., the instruments are valid instruments, i.e., uncorrelated with the error term), gives us the confidence that our set of selected instruments is appropriate.

The results of Table 7 confirm our main finding with respect to fertility choices. Yet, given the joint results of the IV and DID models, reasonable doubts can be raised with respect to the causal interpretation of the effect of terrorism on parental investment.

[20]Notice that in the remaninder of this paper we report only results from severe malnutrition. Results for the WAZ scores are unchanged.

Table 7: Robustness: Instrumental Variables

	(1) Newborn(d) b/se	(2) Severe risk b/se	(3) Severe risk (M) b/se	(4) Severe risk (F) b/se
Conflict Intensity	0.0033**	0.0197	0.0202	0.0069
	(0.002)	(0.013)	(0.016)	(0.020)
F-stat. (first stage)	40.16***	37.72***	15.54***	127.29***
Hansen J stat. χ^2 (p-value)	0.4675	0.1007	0.6613	0.1418
Observations	11491	2547	1148	1117

Note: Panel data IV fixed effect model. Covariates as described in Table 1.
Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

6 Conclusions

In this paper, we have proved theoretically and empirically that terrorism might have a positive impact on the *quantity* of children that parents decide to have. More specifically, our empirical analysis of the impact of Boko Haram attacks in Nigeria shows that, *ceteris paribus*, a 1 standard deviation increase in the number of fatalities (+2.4 fatalities) occurred in a radius of 5 km from where the household lives, resulted, on average, in around 1% increased probability to have a newborn. This result can be given causal interpretation. Terrorism is also associated with an increase in the likelihood that children, especially males, are malnourished. However, this result cannot be interpreted as evidence of a true causal effect.

The policy implications of our work are substantial. In a context of already high fertility and extreme poverty the instability brought about by terrorism might exacerbate an already dramatic situation resulting in a self-perpetuating poverty trap. When this young population will enter the working age, the ratio of the non-working age population to the working age population will decline. If the labor market will be able to absorb the increased number of working age individuals, other things being equal, the per capita income will increase as well. Nigeria could exploit the potentials of this youth bulge in order to avert this youth population away from ongoing violence. However, if those young adults will stay unemployed, the demographic bomb that is created by high fertility coupled with increased life expectancy and no jobs, will lead to further social and political instability. Notice that Boko Haram is actually recruiting children in Nigeria (UN Security Council, 2017). While much of these children were abducted, others were gave up by their parents to obtain security guarantees or for economic gain. While this fact might offer a competing interpretation (competing with respect to our explanation of children as an insurance through labor market participation) of the positive association between terrorism and fertility, it surely shows that these dramatic choices are rooted into poverty and would ultimately undermine the achievement of the sustainable development goal

16: achieve peace, justice and strong institutions by 2030.

While the demographic literature distinguishes between the quantum and tempo of fertility, in this paper we have only considered a (limited) measure of the quantum of fertility. Bongaarts and Feeney (1998) refer to the quantum as the average number of children born to women in a cohort, and to the tempo as to the timing of births by age of mother within the cohort. It is possible to imagine that terrorism affects not only the quantum but also the tempo of fertility. Due to data limitations this aspect was left out in this work and offers an excellent starting point for future research.

References

ACLED. Acled data. https://www.acleddata.com/. 4.1

Adedini, S. A., Odimegwu, C., Imasiku, E. N., and Ononokpono, D. N. (2015). Ethnic differentials in under-five mortality in Nigeria. *Ethnicity & health*, 20(2):145–162. 4.2.3

Agadjanian, V. and Prata, N. (2002). War, peace, and fertility in Angola. *Demography*, 39(2):215–231. 1, 3

Alfano, M. (2017). Islamic law and investments in children: Evidence from the Sharia introduction in Nigeria. Technical report, Centre for Research and Analysis of Migration (CReAM). 4.1, 4.2.3, 5.1

Archibong, B. (2018). Historical origins of persistent inequality in Nigeria. *Oxford Development Studies*, 46(3):325–347. 4.2.3

Becker, A. (2018). On the origins of son preference and female genital cutting. *Mimeo*. 4.2.3

Becker, G. S. (1960). An economic analysis of fertility. In *Demographic and economic change in developed countries*, pages 209–240. Columbia University Press. 3

Becker, G. S. and Lewis, H. G. (1973). On the interaction between the quantity and quality of children. *Journal of political Economy*, 81(2, Part 2):S279–S288. 3

Becker, G. S., Rubinstein, Y., et al. (2004). Fear and the response to terrorism: An economic analysis. *University of Chicago mimeo*, 93. 1

Berrebi, C. and Ostwald, J. (2014). Terrorism and fertility: Evidence for a causal influence of terrorism on fertility. *Oxford Economic Papers*, 67(1):63–82. 1, 2, 4.2.3

Berrebi, C. and Ostwald, J. (2016). Terrorism and the labor force: Evidence of an effect on female labor force participation and the labor gender gap. *Journal of Conflict Resolution*, 60(1):32–60. 4.2.3

Bertoni, E., Di Maio, M., Molini, V., and Nisticò, R. (2018). Education is forbidden: The effect of the Boko Haram conflict on education in North-East Nigeria. *Journal of Development Economics*. 1, 2.1, 4.2.1

Bongaarts, J. (2006). The causes of stalling fertility transitions. *Studies in family planning*, 37(1):1–16. 2.2

Bongaarts, J. (2008). Fertility transitions in developing countries: Progress or stagnation? *Studies in family planning*, 39(2):105–110. 2.2

Bongaarts, J. and Feeney, G. (1998). On the quantum and tempo of fertility. *Population and development review*, pages 271–291. 6

Camacho, A. (2008). Stress and birth weight: Evidence from terrorist attacks. *American Economic Review*, 98(2):511–15. 1

Campante, F. R. and Chor, D. (2012). Why was the Arab world poised for revolution? Schooling, economic opportunities, and the Arab Spring. *Journal of Economic Perspectives*, 26(2):167–88. 2

Cigno, A. (1993). Intergenerational transfers without altruism: Family, market and state. *European Journal of Political Economy*, 9(4):505–518. 3

Cogneau, D. and Moradi, A. (2014). Borders that divide: Education and religion in Ghana and Togo since colonial times. *The Journal of Economic History*, 74(3):694–729. 4.2.3

Del Carpio, X. V., Loayza, N. V., and Wada, T. (2016). The impact of conditional cash transfers on the amount and type of child labor. *World Development*, 80:33–47. 3

Easterlin, R. A. (1961). The american baby boom in historical perspective. *The American Economic Review*, 51(5):869–911. 1

Enders, W. and Sandler, T. (2000). Is transnational terrorism becoming more threatening?: A time-series investigation. *Journal of Conflict Resolution*, 44(3):307–332. 2

Enders, W., Sandler, T., and Gaibulloev, K. (2011). Domestic versus transnational terrorism: Data, decomposition, and dynamics. *Journal of Peace Research*, 48(3):319–337. 2, 4.2.3

Englebert, P., Tarango, S., and Carter, M. (2002). Dismemberment and suffocation: A contribution to the debate on African boundaries. *Comparative Political Studies*, 35(10):1093–1118. 4.2.3

Fayehun, O., Omololu, O., and Isiugo-Abanihe, U. (2011). Sex of preceding child and birth spacing among Nigerian ethnic groups. *African journal of reproductive health*, 15(2). 4.2.3

Foyou, V. E., Ngwafu, P., Santoyo, M., and Ortiz, A. (2018). The Boko Haram insurgency and its impact on border security, trade and economic collaboration between Nigeria and Cameroon: An exploratory study. *African Social Science Review*, 9(1):7. 4.2.3

Friedland, N. and Merari, A. (1985). The psychological impact of terrorism: A double-edged sword. *Political Psychology*, pages 591–604. 2

Friedman, J. and Schady, N. (2013). How many infants likely died in Africa as a result of the 2008–2009 global financial crisis? *Health Economics*, 22(5):611–622. 3

Garenne, M. (2003). Sex differences in health indicators among children in African dhs surveys. *Journal of biosocial science*, 35(4):601–614. 3

Goldstone, J. A. (2002). Population and security: How demographic change can lead to violent conflict. *Journal of international affairs*, pages 3–21. 2

Goodman, S., BenYishay, A., Lv, Z., and Runfola, D. (2019). Geoquery: Integrating hpc systems and public web-based geospatial data tools. *Computers & Geosciences*, 122:103–112. 15

Heuveline, P. and Poch, B. (2007). The Phoenix population: Demographic crisis and rebound in Cambodia. *Demography*, 44(2):405–426. 1, 2

Hossain, M. B., Phillips, J. F., and LeGrand, T. K. (2007). The impact of childhood mortality on fertility in six rural thanas of Bangladesh. *Demography*, 44(4):771–784. 2

Iqbal, N., Gkiouleka, A., Milner, A., Montag, D., and Gallo, V. (2018). Girls' hidden penalty: analysis of gender inequality in child mortality with data from 195 countries. *BMJ global health*, 3(5):e001028. 3

Kraehnert, K., Brück, T., Di Maio, M., and Nisticò, R. (2017). The effects of conflict on fertility: Evidence from the genocide in Rwanda. Technical report, Centre for Studies in Economics and Finance (CSEF), University of Naples, Italy. 2

LaGraffe, D. (2012). The Navarrelge in Egypt: An intersection of demographics, security, and the Arab Spring. *Journal of Strategic Security*, 5(2):9. 2

Lambert, S. and Rossi, P. (2016). Sons as widowhood insurance: Evidence from Senegal. *Journal of Development Economics*, 120:113–127. 1, 3

Lindstrom, D. P. and Berhanu, B. (1999). The impact of war, famine, and economic decline on marital fertility in Ethiopia. *Demography*, 36(2):247–261. 1

Maccini, S. and Yang, D. (2009). Under the weather: Health, schooling, and economic consequences of early-life rainfall. *American Economic Review*, 99(3):1006–26. 4.2.1

Mberu, B. U. and Reed, H. E. (2014). Understanding subgroup fertility differentials in Nigeria. *Population review*, 53(2):23. 2.2, 5.1

Mberu, B. U. and White, M. J. (2011). Internal migration and health: Premarital sexual initiation in Nigeria. *Social science & medicine*, 72(8):1284–1293. 4.2.3

Metcalfe, R., Powdthavee, N., and Dolan, P. (2011). Destruction and distress: Using a quasi-experiment to show the effects of the september 11 attacks on mental well-being in the United Kingdom. *The Economic Journal*, 121(550):F81–F103. 1

Michalopoulos, S. and Papaioannou, E. (2013a). National institutions and subnational development in Africa. *The Quarterly Journal of Economics*, 129(1):151–213. 4.2.3

Michalopoulos, S. and Papaioannou, E. (2013b). Pre-colonial ethnic institutions and contemporary African development. *Econometrica*, 81(1):113–152. 4.2.3

Milazzo, A. et al. (2014). Son preference, fertility and family structure: evidence from reproductive behavior among Nigerian women. Technical report, The World Bank. 9, 4.2.3

Mobolaji, J. W., Bisiriyu, L., and Bamiwuye, S. O. (2017). Contraceptive discontinuation among Nigerian women: Exploring the ethnic variations. *Ife Research Publications in Geography*, 14(1):47–58. 2.2

Naeye, R. L., Burt, L. S., Wright, D. L., Blanc, W. A., and Tatter, D. (1971). Neonatal mortality, the male disadvantage. *Pediatrics*, 48(6):902–906. 3

Neher, P. A. (1971). Peasants, procreation, and pensions. *The American Economic Review*, 61(3):380–389. 3

Nobles, J., Frankenberg, E., and Thomas, D. (2015). The effects of mortality on fertility: population dynamics after a natural disaster. *Demography*, 52(1):15–38. 1, 1

NPC/Nigeria, N. P. C. and International, I. (2014). Nigeria demographic and health survey 2013. 2.2

Nwokolo, A. (2014). Terror and birth weight: Evidence from Boko Haram attacks. 2.1

Odimegwu, C. and Somefun, O. D. (2017). Ethnicity, gender and risky sexual behaviour among Nigerian youth: An alternative explanation. *Reproductive health*, 14(1):16. 2.2

Piazza, J. A. (2011). Poverty, minority economic discrimination, and domestic terrorism. *Journal of Peace Research*, 48(3):339–353. 2

Pieri, Z. P. and Zenn, J. (2016). The Boko Haram paradox: Ethnicity, religion, and historical memory in pursuit of a caliphate. *African Security*, 9(1):66–88. 4.2.3

Pörtner, C. C. (2001). Children as insurance. *Journal of Population economics*, 14(1):119–136. 1, 3

Quintana-Domeque, C. and Ródenas-Serrano, P. (2017). The hidden costs of terrorism: The effects on health at birth. *Journal of health economics*, 56:47–60. 1

Rabassa, M., Skoufias, E., and Jacoby, H. (2014). Weather and child health in rural Nigeria. *Journal of African Economies*, 23(4):464–492. 3

Rehman, F. U. and Vanin, P. (2017). Terrorism risk and democratic preferences in Pakistan. *Journal of Development Economics*, 124:95–106. 4.2.3

Rodgers, J. L., John, C. A. S., and Coleman, R. (2005). Did fertility go up after the Oklahoma city bombing? An analysis of births in metropolitan counties in Oklahoma, 1990–1999. *Demography*, 42(4):675–692. 1, 2

Romanov, D., Zussman, A., and Zussman, N. (2012). Does terrorism demoralize? Evidence from Israel. *Economica*, 79(313):183–198. 1

Sanso-Navarro, M., Sanz-Gracia, F., and Vera-Cabello, M. (2018). The demographic impact of terrorism: Evidence from municipalities in the Basque country and Navarre. *Regional Studies*, pages 1–11. 1, 2

Thomson, V. (2012). Boko Haram and Islamic fundamentalism in Nigeria. *Global Security Studies*, 3(3). 4.2.2

UN Security Council (2017). Report of the secretary-general on children and armed conflict in Nigeria (s/2017/304). http://undocs.org/S/2017/304. 5, 16, 6

United Nations (2017). World population prospects: The 2017 revision, key findings and advance tables. *Department of Economic and Social Affairs, Population Division*, Working Paper No. ESA/P/WP/248. 2.2

United Nations Development Programme (2018). Human development indices and indicators. 2018 statistical update. *United Nations Development Programme*. 2.2

Urdal, H. (2006). A clash of generations? Youth bulges and political violence. *International studies quarterly*, 50(3):607–629. 2

Van Bavel, J. and Reher, D. S. (2013). The baby boom and its causes: What we know and what we need to know. *Population and Development Review*, 39(2):257–288. 1, 2

Warner, J. and Matfess, H. (2017). Exploding stereotypes: The unexpected operational and demographic characteristics of Boko Haram's suicide bombers. Technical report, Combating Terrorism Center at West Point, United States Military Academy. 2.1, 4.2.3, 5.1

Weidmann, N. B., Rød, J. K., and Cederman, L.-E. (2010). Representing ethnic groups in space: A new dataset. *Journal of Peace Research*, 47(4):491–499. 4.1

Werding, M. (2014). Children are costly, but raising them may pay: the economic approach to fertility. *Demographic Research*, 30:253. 3

Woldemicael, G. (2008). Recent fertility decline in Eritrea: Is it a conflict-led transition. *Demographic Research*, 18(2):27–58. 1

World Bank (2019). Nigeria - general household survey. `http://microdata.worldbank.org/index.php/catalog/2734/study-description#page=export-metadata&tab=study-desc`. 4.1

Younas, J. and Sandler, T. (2017). Gender imbalance and terrorism in developing countries. *Journal of conflict resolution*, 61(3):483–510. 2

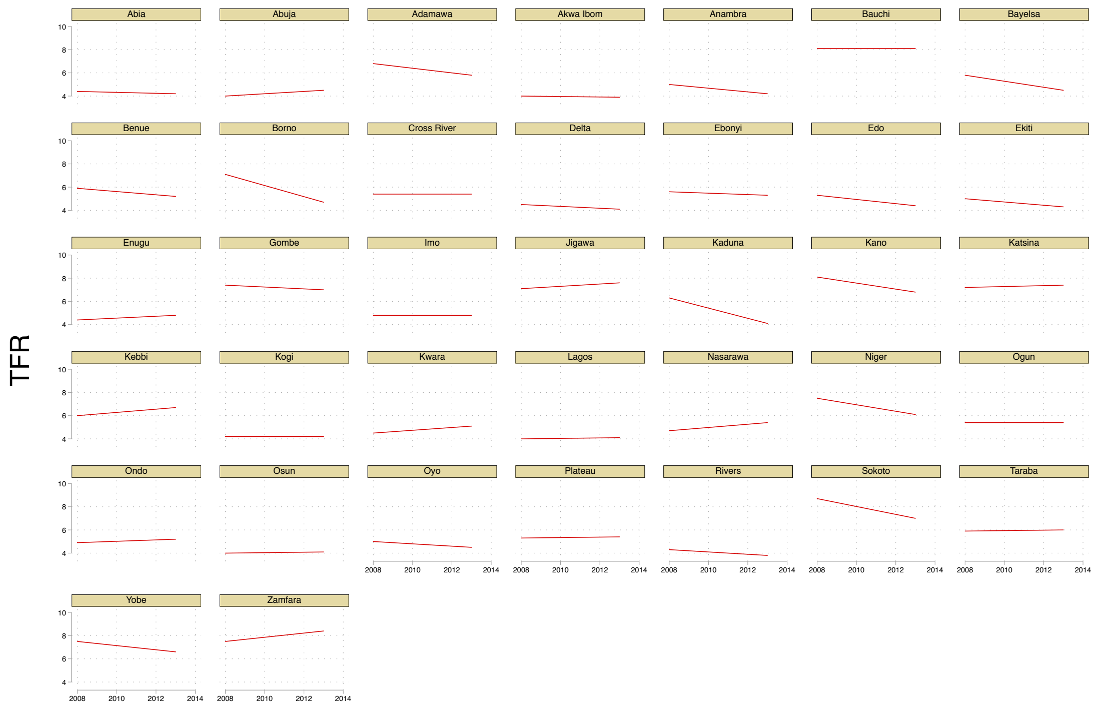
Appendix

Table 8: Attrition

	(1) Household interviewed in waves 1 and 2 b/se	(2) Household interviewed in waves 1 and 2 b/se
Conflict Intensity	0.0002	0.0007
	(0.001)	(0.001)
HH size		-0.0023*
		(0.001)
# of HH members who know to read and write		-0.0006
		(0.010)
Urban		0.0059
		(0.007)
Share of Islamic in the HH		0.0258***
		(0.006)
HH wealth index		-0.0018
		(0.003)
# of HH members occupied		0.0351***
		(0.010)
Observations	12488	12327

Note: Ols. Covariates as described in Table 1. Standard errors robust to heteroskedasticity reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

Figure 5: Total fertility rates from Nigeria's states (2008-2013)



Note: Total fertility rates are computed from the DHS for the 5 years preceding the survey.

Table 9: Pre-terrorism characteristics and conflict intensity at the state level.

	(1) Total Boko Haram Fatalities b/se	(2) Total Boko Haram Fatalities b/se	(3) Total Boko Haram Fatalities b/se	(4) Total Boko Haram Fatalities b/se	(5) Total Boko Haram Fatalities b/se
TFR (2008)	0.036	0.217			
	(0.073)	(0.164)			
Child mortality (2000)	0.185		0.218		
	(0.160)		(0.164)		
On shore petroleum	-0.095			-0.129	
	(0.074)			(0.091)	
Nightlights (2012)	-0.011				-0.106
	(0.023)				(0.082)
Constant	0.000	0.000	0.000	0.000	0.000
	(0.166)	(0.161)	(0.161)	(0.163)	(0.164)
R-squared	0.062	0.047	0.047	0.017	0.011
N	38.000	38.000	38.000	38.000	38.000
F	0.490	1.749	1.755	2.016	1.676

OLS. Robust standard errors in parentheses. Standardized coefficients. * $p<0.10$, ** $p<0.05$, *** $p<0.01$