WORKING PAPERS

N° 1127

August 2022

"The Cost of Fear: Impact of Violence Risk on Child Health During Conflict"

Augustin Tapsoba

Toulouse School of Economics

The Cost of Fear: Impact of Violence Risk on Child Health During Conflict*

Augustin Tapsoba†

August 28, 2022

Abstract

The fear of exposure to conflict events often triggers changes in the behavior of economic agents even before/without any manifestation of violence in a given area. It generates a treatment status (exposure to the adverse effects of conflict) that goes beyond violence incidence. This paper develops a new approach to capture such treatment. Violence is modeled as a space-time stochastic process with an unknown underlying distribution that is backed out of the observed pattern of conflict events. A new risk measure is built from this density and used to evaluate the impact of conflict on child health using data from Ivory Coast and Uganda. The empirical evidence suggests that conflict is a local public bad, with cohorts of children exposed to high risk of violence equally suffering major health setbacks even when this risk does not materialize in violent events around them.

JEL Codes: C1, O12, J13, I12

Keywords: Conflict - Insecurity - Kernel Density Estimation - Child Health

*Declarations of interest: none. I am grateful to my advisors, Joan Llull and Hannes Mueller, for their invaluable guidance and support. I also thank Matteo Bobba, Michael Creel, Ada Ferrer-i-Carbonell, Thierry Magnac, Josepa Miquel-Florensa, Pau Milan, and seminar/conference participants at Toulouse School of Economics, University of Amsterdam, NHH Bergen, ENS Lyon, Université Libre de Bruxelles, Universitat Autònoma de Barcelona, EUDN Ph.D. workshop at CERDI, and Barcelona GSE Ph.D. jamboree for useful comments and suggestions. Financial support from the Spanish Ministry of Economy and Competitiveness through an FPI Grant at Barcelona GSE is gratefully acknowledged. I also acknowledge funding from the French National Research Agency (ANR) under the Investments for the Future (Investissements d'Avenir) program, grant ANR-17-EURE-0010.

†Toulouse School of Economics. Email: augustin.tapsoba@tse-fr.eu

1 Introduction

Violent conflicts are serious humanitarian and economic threats to many developing countries.[1] Their impact on child health can substantially increase the overall cost of conflict and heavily affect the timing and nature of the recovery process. The early years of life are indeed crucial in influencing a range of health and socioeconomic outcomes across the life course. In particular, health in the fetal period, infancy, and early childhood determines most of our long-term health, education, and labor market outcomes (Black et al., 2007; Behrman and Rosenzweig, 2004; Maccini and Yang, 2009; Maluccio et al., 2009; Stein et al., 1975). Conflict-induced shocks experienced at this stage of life can, therefore, have persistent detrimental effects that we need to understand in order to devise the proper responses to protect children in conflict-prone areas.

Beyond the damage caused to direct victims of violence, conflict can lead to major health setbacks for young children through the consequences of insecurity. Economic agents (households and firms) react to violence risk in a given area with displacements or changes in their consumption/production behavior that can lead to disruptions in the supply and demand of goods and services (Bundervoet et al., 2009; Arias et al., 2019; Rockmore, 2017). They often engage in such risk-coping behavior before/without any manifestation of violence around them based on their expectations. In order to properly evaluate the consequences of conflict, it is, therefore, crucial to capture the risk perceived by agents on the ground beyond the incidence of violent events.

This paper investigates the impact of conflict on child health using a new metric that captures the perceived insecurity at the local level through a statistical model of violence. It is built on the intuition that economic agents react to the risk of being exposed to violence, and this generates a treatment status (exposure to conflict risk) that is unobserved but crucial for the short and long-term effects of conflict. To build a new metric that captures this treatment beyond the incidence of conflict events, violence is modeled as a space-time stochastic process that has two main characteristics. On the one hand, the occurrence of an

[1] More than 3/4 of countries in Sub-Saharan Africa have experienced civil war since 1960 (Blattman and Miguel, 2010; Gleditsch et al., 2002) and the Internal Displacement Monitoring Centre estimated that more than 2 million people were newly displaced in Africa during the first six months of 2017 alone due to conflict.

event increases the likelihood that another event will occur in the same area. On the other, violence can spread through the local environment via contagion.[2] This violence process has an unknown underlying distribution that, by assumption, drives the expectations of agents on the ground. Its density is backed out of the observed pattern of conflict events. To do so, each event observed on the ground is interpreted as a random realization of the underlying process. The density of this process can therefore be estimated from a representative sample of realizations using kernel density estimation methods (Li and Racine, 2007; Silverman, 1986). The integral of this density over a given space-time window gives the likelihood of occurrence of an event in that window and can be used to capture risk at a local level.

The basic principle behind this approach is that each observed event has its own contribution to the overall density at a given location. This contribution is given by a trivariate Gaussian kernel function. It is highest at the exact location of the event and fades out as we move away from it in space or time. The dispersion of the kernel mass is controlled by a matrix of smoothing parameters, with flatter kernels for events in low-intensity areas. The density at a given point in space and time is obtained by averaging all the contributions. The estimated density is proportional to the statistical risk of violence around this point.

This new measure of violence risk is then used to evaluate the impact of conflict on child health using data from Ivory Coast and Uganda.[3] The probability of exposure to violence in utero or during the first year of life across space for different cohorts of children is computed in order to estimate the impact of violence risk on infant mortality. The identification strategy relies on the spatial and temporal variation in the exposure of different birth cohorts to violence in a Difference-in-Differences setting. The observed pattern of events generates space-time windows with a high risk of violence but no violent events and windows with isolated events but a low risk of violence.

The main finding of this study is that violence risk significantly increases infant mortality

[2]An illustration of the first case is when battles between organized actors trigger waves of retaliatory or follow-up violence in a given area. In the second case, troops repeatedly attack clusters of nearby targets. This may happen because local vulnerabilities are well-known to them. Moreover, armed combatants can easily migrate from one area to another, and violence in a given city can disrupt regional economic stability.

[3]Ivory Coast has experienced a relatively low-intensity but highly disruptive conflict between 2002 and 2011 (Minoiu and Shemyakina, 2014). Uganda experienced an exogenous outburst of violence between 2002 and 2005 that put an end to a long-lasting ethnic conflict (Rohner et al., 2013).

even when this risk does not materialize in actual conflict events. A standard deviation increase in the probability of being exposed to violence between conception and the first anniversary increases infant mortality by 1 and 0.8 percentage points in Ivory Coast and Uganda, respectively. The estimated effect is quantitatively large. Children in the top risk quartile experience an increase in infant mortality of 6 and 3 percentage points in Ivory Coast and Uganda, respectively, which represents more than half of the average infant mortality rates in both countries. Interestingly, this effect is similar in magnitude and significance level when the analysis is restricted to the cohorts of children that have not been exposed to any violent event during the relevant time period. Relying on the incidence of conflict events in a given space-time window to define exposure to the adverse effects of conflict leads to an underestimation of the share of children that are treated and the magnitude of the treatment effect. Increasing mechanically the size of the spatial window for bigger cells also means including non-treated children in the treatment group. Any definition of treatment status based on violence incidence in a given window will, therefore, most likely lead to some attenuation bias due to misclassification (Lewbel, 2007).

The empirical evidence also suggests that the quality/availability of health care services, malnutrition, and maternal stress are important channels for the estimated effect. Mothers exposed to a high risk of violence during their pregnancy are more likely to deliver a baby with low birth weight, less likely to have access to basic health care services, and tend to have a longer duration of postpartum amenorrhoea.[4]

The main regressions in this paper control for child, mother, and household characteristics. They also account for weather shocks, location fixed effects, and birth cohort fixed effects. The estimates are robust to several alternative specifications and sample restrictions, including a very demanding one that controls for mother fixed effects. The estimated coefficients are also robust to controlling for the number of conflict events that occur within a certain distance from a given location during the relevant time window in a spatial lag model. Placebo tests confirm that the results are not driven by preexisting trend differences between high and low-risk areas. I also show evidence that suggests that the results are

[4] Postpartum amenorrhoea is the interval between the birth of a child and the subsequent return of menses. Its duration is often associated with maternal stress and malnutrition.

unlikely to be caused by factors such as selective migration and fertility or omitted variable bias.

The evidence documented above suggests that conflict is a local "public bad": being exposed to a high risk of violence leads to major setbacks in child health, even when the risk does not materialize in actual violence.[5] This is in line with the idea that economic agents engage in detrimental ex-ante coping strategies that lead to disruptions in the supply and demand of goods and services at the local level. From the policy perspective, this suggests that we should rethink both the scale and the target of interventions that aim at mitigating the consequences of conflict.

The new approach proposed in this paper to capture exposure to the adverse effects of conflict is more general than the standard approach. It captures violence risk beyond the incidence or not of conflict events in a given space-time window. The standard approach used so far in the literature consists of counting the number of events or fatalities within such a window to define exposure to the adverse effects of conflict. It relies only on the incidence of violent events to determine the risk. This implies that violence risk is high only for space-time windows in which we already observe violent events. In other words, violence is perceived by agents to be likely to happen only where it has already occurred. The cohorts that are not exposed to any event in their city or village in a given time period are therefore considered to be equally non-treated irrespective of the actual underlying risk perceived by the agents on the ground.

The density estimation method generalizes the standard approach in two important dimensions.[6] First, it fully incorporates the first order moment of the violence process (distance to events) by allowing for the use of all the information on the exact timing and location of conflict events when measuring violence risk. This is achieved by imposing some "desirable"

[5]Part of this result could also be coming from the fact that the new metric is more robust to measurement errors in the conflict event data. The estimation of the underlying density of the data generating process does not require the universe of events but just a representative sample. Moreover, space-time windows with isolated or misreported events will still have a low conflict risk with this new metric.

[6]Counting the number of events in a given space-time window is a special case of the kernel density estimation where we use a uniform kernel function around each event with "hand-picked" bandwidths that correspond to the size of the window. All the events that fall within the window have the same contribution to the risk, and all the other events have zero contribution.

structure on the extent to which the risk generated by each event spreads in space and time. The Gaussian kernel functional form implies that this risk fades out at an exponential rate. Second, this approach also takes into account higher moments of the underlying violence process, such as its variance/dispersion through the estimation of the matrix of smoothing parameters that control the dispersion of the kernel mass.

This new metric also addresses several measurement issues in the conflict event datasets. The kernel density estimation approach only requires a representative sample of realizations of the underlying process, while the standard approach assumes that we have an exhaustive list of conflict events. Moreover, isolated events that appear in the conflict event dataset because of measurement errors or just as rare realizations of the underlying violence process in low-risk areas can be captured as such with the new approach. This new approach is, therefore, more robust to the standard data limitations in the georeferenced, disaggregated events-level conflict datasets: non-exhaustivity and presence of coding errors (O'Loughlin et al., 2010; Eck, 2012).

This paper contributes to three main strands of the economics literature. First, it contributes to the previously mentioned literature on the importance of early life conditions (Lavy et al., 2016; Maccini and Yang, 2009; Maluccio et al., 2009; Black et al., 2007; Behrman and Rosenzweig, 2004; Stein et al., 1975). A substantial part of this literature has specifically examined the effects of conflict on child health. It has established that exposure to violence leads to worse birth outcomes (Quintana-Domeque and Ródenas-Serrano, 2017; Mansour and Rees, 2012; Camacho, 2008), increases infant and child mortality (Dagnelie et al., 2018; Valente, 2015), and decreases height-for-age z-scores (Akresh et al., 2016; Minoiu and Shemyakina, 2014; Akresh et al., 2012b; Bundervoet et al., 2009). All these papers rely on the incidence of violent events to proxy exposure to the adverse effects of conflict.[7] They were, therefore, unable to account for any of the cost induced by behavioral responses to risk in the absence of immediate violence. This is the first paper to provide evidence suggesting that children exposed to a high risk of violence suffer major health setbacks even when this risk does not materialize in actual violence around them.

[7] Papers that link conflict to other outcomes also use this approach (Ouili, 2017; Shemyakina, 2015; Leon, 2012; Akresh et al., 2012a; De Walque, 2005).

Second, this paper also contributes to a small but growing literature that studies the consequences of insecurity beyond the incidence of violent events in the conflict and the crime literature. In the conflict literature, Arias et al. (2019) investigate the changes in household production behavior and show that conflict affects land use and agricultural investment beyond violence incidence. Using data from Colombia, they show that during the initial years of presence of armed groups, farmers cut back production of perennial crops and pasture in favor of seasonal crops as a coping strategy against insecurity. Rockmore (2017) also shows that subjective risk (perceptions of survey respondents on difficulties in cultivating land due to insecurity) has a higher impact than violence incidence (actual attacks against a community) on household consumption in Northern Uganda. In fact, he finds that half of the welfare loss caused by conflict is related to risk and not to direct exposure to violence. My paper is built on similar intuitions, but the methodological approach used to capture risk is very different. I propose a framework in which violence risk can be derived from the observed location of violent events in space and time. Moreover, this paper is the first one within this literature to look at child health as an outcome. The existing articles have only looked at changes in household consumption or production behavior (Rockmore, 2017; Arias et al., 2014; Bozzoli and Brück, 2009; Deininger, 2003).

The idea that risk perception goes beyond the incidence of violent events has also been addressed in the crime literature. The fear of crime has been shown to affect housing prices even in the absence of any criminal event. Pope (2008) uses registry data that tracks sex offenders in Hillsborough County, Florida, and shows that nearby housing prices fall (rebound immediately) after a sex offender moves into (out of) a neighborhood irrespective of the seriousness of the threat that they pose. Fear of crime has also been measured with self-reported data on perceived insecurity (Buonanno et al., 2013) and urban property crime rates (Gibbons, 2004) to show its impact on housing prices. From the methodological perspective, kernel density estimation has been widely adopted in crime literature for hotspot mapping and crime prediction (Hu et al., 2018; Gerber, 2014; Chainey et al., 2008). The idea of using it to capture the perceived risk of crime on the ground is, however, to the best of my knowledge, new to this literature. Following the methodology proposed in this paper, one can study the consequences of behavioral responses to a specific type of criminal event beyond their incidence.

Finally, the third strand of literature related to my work looks at the role of expectations in conflict-prone environments. At the aggregate level, Zussman et al. (2008) and Willard et al. (1996) show, for instance, that asset prices during conflict react to important conflict events like battles or ceasefire agreements.[8] Besley and Mueller (2012) study the effect of violence on house prices in Northern Ireland. They show that the peace process and its corresponding decline in violence led to increased house prices in the most affected regions compared to other regions. Their paper offers a way to understand the heterogeneity of these changes across regions, which directly links to the role of expectations at a local level. The current paper contributes to this literature by showing that conflict can also affect child health and, therefore, long-term economic development at a local level through expectations.

The remainder of the paper is organized as follows. The next section gives some background on the Ivorian and Ugandan conflicts and describes the data. Section 3 presents the methodological approach used to measure violence risk across space and time. Section 4 presents the empirical strategy used for estimating the impact of conflict on infant mortality, followed by the results and some robustness checks in Section 5. Section 6 concludes.

2 Historical Background and Data

2.1 Data sources

I use the information on the exact timing and location of different conflict events from two data sources: the Uppsala Conflict Data Program Georeferenced Events Dataset -UCDP GED (Sundberg and Melander, 2013) and the Armed Conflict Location Events Dataset - ACLED (Raleigh et al., 2010).[9] These events are obtained from various sources, including press accounts from regional and local news, humanitarian agencies, and research publications during the conflicts in Ivory Coast and Uganda. I only keep all the events recorded

[8]See Mueller et al. (2017) for a full discussion on the role of expectations in conflict-affected countries.

[9]Main results in this paper use UCDP-GED dataset. Appendix Table A5 shows some robustness to using ACLED data. ACLED records all political violence, including battles between armed groups, violence against civilians, riots, and protests. I focus on war-related events: battles, explosions/remote violence, and violence against civilians.

with geographical precision at the municipality level or lower. Duplicates (events with the same location and time) are eliminated to have a list of different days and locations with at least one conflict event.

To assess the impact of exposure to violence risk on child health, I use Demographic and Health Survey (DHS) data collected in 2011-2012 in Ivory and 2006, 2011, and 2016 in Uganda. DHS surveys are repeated cross-sectional surveys run in most developing countries since the late 1980s. It gathers information on demographic topics such as fertility, child mortality, health service utilization, and nutritional status of mothers and young children from a nationally representative sample of households. Women (aged 15 to 49) are interviewed about the birth and survival of almost all the children they gave birth to in the past (up to 20 children), including those who died by the time of the interview. For the main analysis, I look at the survival of single-born female children.[10] I also use the information on child and maternal health short after birth combined with the availability of health care services for pregnancies that happened at most 5 years prior to each DHS interview in Uganda to shed some light on the potential mechanisms through which behavioral responses to violence risk can affect child health.

Given the emerging evidence on the links between weather shocks and violence (Harari and La Ferrara, 2017; Burke et al., 2015; Hsiang et al., 2013), I also introduce climatic variables to reduce the risk of confounding factors. Climate data comes from the Terrestrial Air Temperature and Precipitation: 1900–2014 Gridded Time Series database (Matsuura and Willmott, 2015). This dataset is a compilation of updated sources and provides monthly precipitation (and mean temperature) interpolated to a latitude/longitude grid of 0.5×0.5 decimal degrees (approximately 55×55 km at the equator). Following Kudamatsu et al. (2012), I compute the average rainfall and temperature for the last two years before birth and the first year of life, and I include them separately in the regressions to control for variations in maternal food supply induced by climate shocks.

[10] Multiple-birth babies face significantly higher chances of dying before turning one year old. Male fetuses are biologically more fragile than female ones, which leads to a higher selection in the sample of born males in the presence of shocks around the pregnancy period (Dagnelie et al., 2018; Pongou, 2013). My results on the male samples confirm this finding.

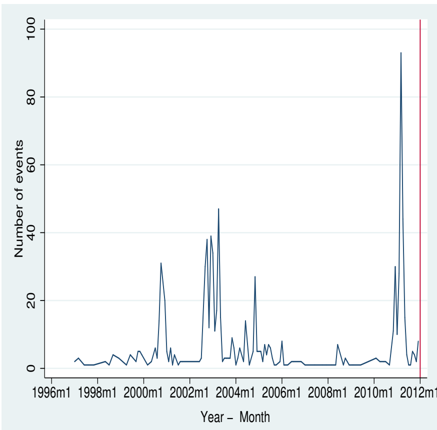
2.2 Conflict in Ivory Coast

Ivory Coast is a previous French colony that enjoyed a prolonged period of economic growth from its independence in 1960 until 1990. Political instability was sparked by the power struggle following the death of the country's first president, Felix Houphouet-Boigny, in 1993. To secure a win in the 1995 elections, the Interim President, Henri Konan Bedie, changed the electoral code to exclude his rival, Alassane Dramane Ouattara, from running for office based on his origins. The other opposition leaders then boycotted the election in protest against this discrimination, and Bedie was elected with 96% of the votes.

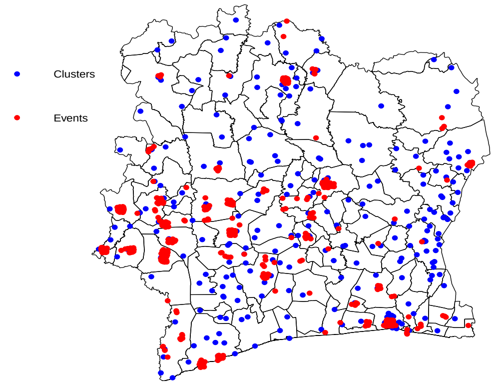
In July 1999, Alassane Ouattara returned to his country to run for the 2000 presidential elections. His plan to rechallenge Bedie split the country along ethnic and religious lines. This political turmoil gave a pretext to a group of army soldiers to intervene and overthrow Bedie by a coup in December 1999. Robert Guei, an army officer, was chosen to lead a transition to new elections and restore the order. New elections took place in October 2000, but Alassane Ouattara was still excluded from the process because of his challenged nationality. General Guei proclaimed himself president after announcing he had won the elections. However, he was forced to flee in the wake of a popular uprising and was replaced by his challenger Laurent Gbagbo. Fighting erupted between President Gbagbo's mainly southern Christian supporters and followers of his main opponent Alassane Ouattara, mostly Muslims from the north. Tensions lasted for almost a year before both challengers agreed to work towards reconciliation in March 2001.

This fragile reconciliation process was disrupted in September 2002 when a mutiny in Abidjan grew into a full-scale rebellion with the Ivory Coast Patriotic Movement rebels seizing control of the north. French interposition troops were sent to limit the clashes between the two armies, as shown in Figure A6. However, intense battles between the two sides lasted until March 2003, when the first peace agreement was signed, and rebels entered the government. Many other peace talks were held as actors were resuming clashes at one point or another during the implementation process. This went on until March 2007, when a power-sharing deal was signed. Under this deal, Guillaume Soro, leader of the rebel group, was made Prime Minister of Ivory Coast. The new government was put in charge of preparing

Figure 1: Distribution of Violent Events in Ivory Coast:1997 to 2012



(a) Monthly Events



(b) Spatial Distribution

Notes: The red bar in figure (a) is the DHS household survey year in Ivory Coast.

the election that would end the crisis and restore a stable constitutional order. After being postponed twice, this election was finally held in December 2010 but led to another crisis. The electoral commission declared Mr. Ouattara the winner of the presidential election run-off. Mr. Gbagbo refused to accept these results, and the dispute between the two camps soon escalated into extremely violent clashes until the capture of Mr. Gbagbo in April 2011, after the loyalist army was defeated by the rebels backed by the French troops under UN mandate.

Figure 1a shows the number of recorded violent events per month across the country. We can see that the recorded events are consistent with the timing described in the previous paragraphs, with violence peaks occurring after the 2000 elections, during the first months following the start of the first civil war in 2002, and the second civil war following the 2010 elections. Fewer events were recorded during the negotiations period until the comprehensive power-sharing treaty was signed in 2007. The spatial distribution of the events is also shown in Figure 1b. One can see that conflict incidents are mostly clustered in the central and western parts of the country.

2.3 Conflict in Uganda

Uganda has experienced multiple conflicts since its independence in 1962. It has been ruled by the National Resistance Movement (NRM) led by Yoweri Museveni since 1985, whose main constituency is the Bantu-dominated South. His government has faced opposition and armed rebellion in several parts of the country. This was the case in the North, where the Lord's Resistance Army (LRA) was active until 2006, and close to the border with the Democratic Republic of Congo, where the insurgency led by the Allied Democratic Forces (ADF) was active until 2004.

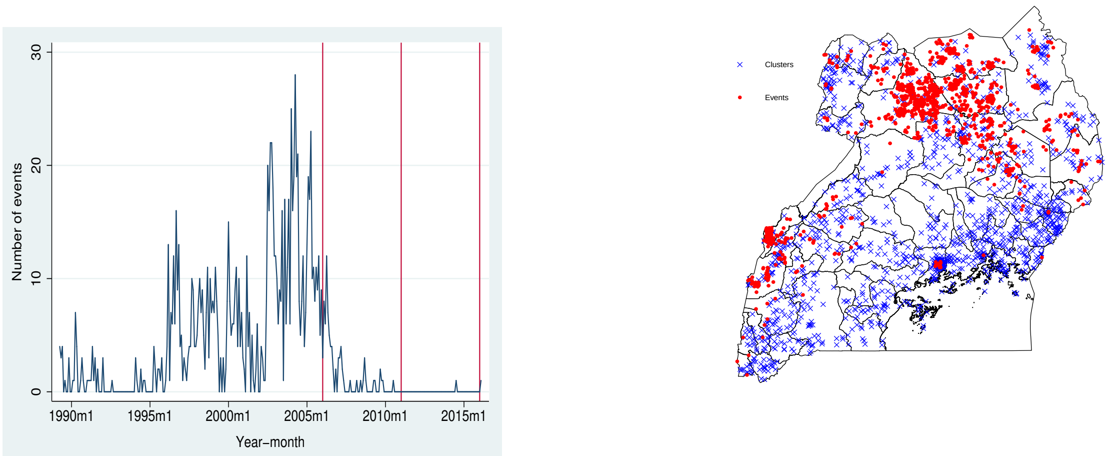
After September 11 terrorist attacks, LRA and ADF were declared terrorist organizations by the US Patriotic Act and lost support from their allies that feared retaliations and sanctions. LRA, in particular, lost support from the Sudanese government that was providing them sanctuary and military help. The ruling government in Uganda seized this opportunity to launch a military crackdown on these rebel groups. ADF was defeated by 2004. Military action against the LRA started in March 2002, when the army launched "Operation Iron Fist" against the rebel bases in South Sudan. The LRA responded by attacking villages and government forces in Northern Uganda. A cease-fire between the LRA and the government of Uganda was signed in September 2006, with the mediation of the autonomous government of South Sudan.

Figure 2a shows the monthly number of geo-referenced conflict events between 1988 and 2016 from the UCDP-GED dataset. Consistent with the narrative above, there was a sharp increase in 2002-05, followed by a decline, and very low levels of violence have been recorded after 2006.

2.4 Violence and Infant Mortality in Ivory Coast and Uganda

The conflicts in both Ivory Coast and Uganda had negative consequences on many outcomes. Economic activity, for instance, has been significantly affected. Both countries experienced a prolonged period of negative GDP growth during the years of intense violence. Another crucial indicator that has suffered from conflict in both countries is the infant mortality rate. This indicator, often used as a proxy for the quality of health services in a given country,

Figure 2: Distribution of Violent Events in Uganda Between 1989 and 2016



(a) Monthly Events

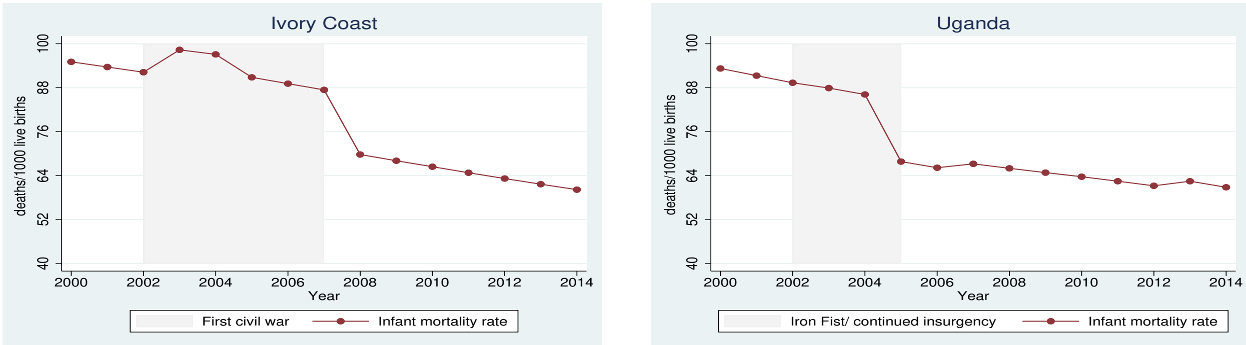
(b) Spatial Distribution

Notes: The red bars in figure (a) are the DHS household survey years in Uganda.

has gotten worse in Ivory Coast during the first civil war (2002-2007). It has improved substantially after the violence ended in Uganda following the government crackdown on rebel groups between 2002 and 2005 (see Figure 3). Beyond this apparent deterioration of the health system during the conflict, the aim of this is to provide causal evidence of the impact of behavioral response to violence risk on child health.

The anecdotal evidence suggests that fear of exposure to violence has been one of the key sources of the detrimental impact of conflict on child health. In Ivory Coast, for instance, it is estimated that 70 percent of professional health workers and 80 percent of government-paid teachers abandoned their posts in the northern and western parts of the country after the civil war started (UNOCHA, 2004; Sany, 2010). Survey data collected in the western province of Man showed that the three most important conflict-related problems reported by households were health problems (48 percent), lack of food (29 percent), and impaired public services (13 percent) (Fürst et al., 2009). The provision of goods and services has therefore been heavily disrupted in entire regions of the country and for many years due to expectations of economic agents on the ground and beyond the actual manifestation of violence. This is what the current paper is trying to capture.

Figure 3: Conflict and Infant Mortality



(a) Ivory Coast

(b) Uganda

Source: CIA World Factbook

3 Estimation of Violence Risk in Space and Time: Kernel Density Estimation Approach

To capture behavioral responses to violence risk, we need a way to quantify risk perceptions at the local level. Reliable measures of risk perceptions are rare, especially in conflict-prone areas where even standard surveys are hardly appropriately conducted. The approach used in this paper to address this issue is to assume that violence can be modeled as a stochastic process, across space and over time, with an unknown underlying distribution that drives expectations of economic agents on the ground. We can therefore capture risk perceptions at a local level through an estimation of the underlying density of the violence process.

Agents on the ground have access to a large information set (local news, observed movement of troops, violence history, etc.) to build expectations on the likelihood of occurrence of violent events in a given space-time window. By doing so, they predict variations in the density of the underlying violence process across space and time. These agents will then adjust their production or consumption decisions based on their risk perceptions.

As econometricians, we would ideally like to follow this same process to capture the perceived risk of violence on the ground. However, we often do not observe all the information that agents have access to, and we also do not know how they aggregate this information when they are building their beliefs. We can nonetheless estimate the density of the underlying violence process based on a representative sample of realizations of this process using density estimation methods. This can then be used to build a measure of the statistical risk of violence that will also capture risk perceptions at a local level if we assume that agents form beliefs that are consistent with the true underlying violence process.

In this section, I show how non-parametric density estimation methods can be used to capture variations in the statistical risk of violence at a local level. These methods have been initially used in the literature to assess basic characteristics of unknown distributions, such as their skewness, tail behavior, or the number, location, and shape of their modes (Silverman, 1986). Nowadays, they play a major role in machine learning, classification, and clustering.[11] They are popular methods in the crime literature for hotspot mapping and in the seismology literature for seismic hazard estimation. These methods can also be used (like in this paper) as input for more sophisticated analysis. DiNardo et al. (1996) used kernel density estimation methods to build counter-factual densities to study the effects of institutional and labor market factors on changes in the U.S. distribution of wages in the 80s. Kernel density estimation methods have also been extensively used in poverty analysis to measure poverty from grouped data (mean incomes of a small number of population quantiles) through the estimation of the underlying global income distribution (Sala-i-Martin, 2006; Minoiu and Reddy, 2014; Sala-i-Martin, 2002).

3.1 Principle of Kernel Density Estimation (KDE)

Let's assume violence is generated by a process X with an unknown probability density function (pdf) f. Density estimation consists of constructing an estimate of f based on a representative sample of random realizations $\{x_1, ..., x_n\}$ of X.

Let's begin with the simple case of a continuous, univariate random variable X.[12] Each observed event has its own contribution to the density at a given location x. This contribution

[11] For instance, some clustering methods are based on bump hunting, i.e., locating the modes in the density, and Bayes classifiers are based on density ratios that can be implemented via density estimation. Applications of density estimation in machine learning and classification are discussed in more depth in the books of Izenman (2008) and Hastie et al. (2009).

[12] To estimate violence risk across space and time, we need an extension to three dimensions (as shown below): latitude, longitude, and time.

is given by a Gaussian kernel function $k \sim \mathcal{N}(0,\, h)$.[13] The value of the kernel function is highest at the exact location of the data point and fades out at an exponential rate as we move away from it. The density estimate at x is obtained by summing up all the contributions according to Equation 1. Closer events have higher contributions to the density, and clustered events generate peaks corresponding to the modes of the underlying density function.

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} k\Big(\frac{x - x_i}{h}\Big). \tag{1}$$

Importance of the Smoothing Parameter

The choice of the smoothing parameter h is crucial in kernel density estimation. Small values of h reduce the bias by putting all the mass just around the data point and the density estimate displays spurious variations in the data. When h is too big, each individual kernel becomes flatter, and important details in the distribution can be obscured (see Appendix A.1 for an illustration).

The choice of the Optimal Smoothing Parameter

Optimal h is chosen to minimize the Mean Integrated Squared Error (MISE)

$$MISE(h) \;\; = \;\; \int [\hat{f}(x,h) - f(x)]^2 dx,$$

where $\hat{f}(x,h)$ is the kernel density estimate and $f(x)$ is the unknown density.

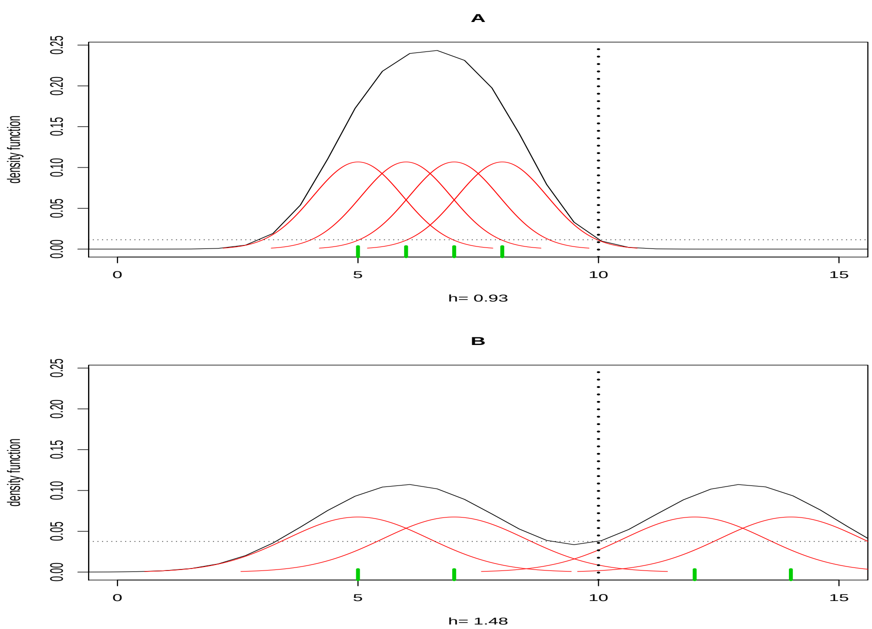
$MISE(h)$ can be evaluated and minimized without making any functional form assumption on $f(x)$ by using a bootstrap method (Taylor, 1989) as described in Appendix A.2.

The dispersion of the observed sample of events is a feature of the underlying process, so minimizing the $MISE(h)$ leads to a larger optimal smoothing parameter (h) for samples with more dispersion. The smoothing parameter is indeed an increasing function of the

[13] The bandwidth is the most crucial choice to make in KDE because it controls the degree of smoothing applied to the data. The kernel form is only responsible for the regularity of the resulting estimate (continuity, differentiability) and Gaussian kernels give an estimated density function that has derivatives of all orders (Silverman, 1986).

sample variance.[14] This is illustrated in Figure 4 where both panels show individual kernels and density estimates from 4 data points at equal distance from a given location $x = 10$. There is less dispersion in the event data in panel A compared to panel B, and the risk (density) should be higher for location x in panel B compared to A. The standard approach of counting the number of events within a certain distance from x as a proxy for risk (or exposure to adverse effects of violence) fails at making this distinction since it only relies on distances.[15] The kernel density estimation is able to generate higher risk in panel B because it takes into account the dispersion of conflict events on top of the distance to neighboring events.

Figure 4: Fixed KDE and Sample Variance in Separate Processes



[14] In the particular case of the underlying pdf being normally distributed, one can show that the optimal smoothing parameter (h_{opt}) is actually proportional to the sample variance (Silverman, 1986).

[15] The difference between standard approach and KDE approach is discussed in more detail below.

3.2 Adaptive KDE

Fixed bandwidth KDE has been shown to sometimes perform poorly with densities that exhibit significant changes in magnitudes, multi-modalities, or long tails (Silverman, 1986). In multi-dimensional cases, these issues are even more exacerbated by the scarcity of data over most of the effective estimation space (Terrell and Scott, 1992). Allowing for more flexibility in the choice of smoothing parameters can therefore be useful in the estimation of the density of the underlying violence process. This can be performed by using adaptive kernel density estimation methods.

This method combines features of the KDE method and the nearest neighbor density estimation approach. The idea is to construct a kernel estimate consisting of bumps or kernels placed at observed data points but allowing the smoothing parameter of the kernels to vary from one point to another. An observation in a low-intensity area will therefore have its mass spread out over a broader range than one in a high-intensity area (see Terrell and Scott (1992) for more details). The adaptive kernel approach is constructed in a three-stage procedure:

- First, find a pilot estimate $\tilde{f}(x)$ using classic kernel density estimation with fixed bandwidth $\tilde{f}(x) = \frac{1}{nh_p}\sum_{i=1}^{n} k\left(\frac{x-x_i}{h_p}\right)$, where $k \sim \mathcal{N}(0,\, h_p)$ is a Gaussian kernel function.

- Second, define a local bandwidth factor λ_i by $\lambda_i = [\tilde{f}(x_i)/g]^{-\alpha}$, where g is the geometric mean of the $\tilde{f}(x_i)$ and α is a sensitivity parameter such that $0 \leq \alpha \leq 1$.

- Finally, define the adaptive kernel estimate $\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{h\lambda_i}k(\frac{x-x_i}{h\lambda_i})\right)$

The optimal h is chosen to minimize the distance between the estimated density and the unknown density holding local bandwidth factors (λ_i's) constant. This can be done by bootstrap method as in the case of fixed bandwidth.

Allowing the local bandwidth factor to depend on a certain power of the pilot density gives some flexibility in the design of the method. The larger the power α, the more sensitive the method will be to variations in the pilot density, creating more differences in the smoothing parameters across different parts of the distribution. $\alpha = 0$ is equivalent to the fixed bandwidth method, while $\alpha = 1$ coincides with the nearest neighbor approach. $\alpha = 1/2$ is the standard choice in the statistics literature (see Terrell and Scott (1992)).

3.3 Generalization to more than One Dimension

The univariate kernel density estimation can easily be extended to the multivariate case. The estimated density is given by

$$\hat{f}(\bar{x}) = \sum_{i=1}^{n} \frac{1}{n \mid \lambda_i H \mid} K\Big((\lambda_i H)^{-1}(\bar{x}_i - \bar{x})\Big),$$

where $\bar{x}_i$ and $\bar{x}$ are d-dimensional vectors, H is a d x d symmetric matrix of parameters to be estimated and K is a multivariate kernel function.

To measure conflict risk in space and time, we need to consider three dimensions: latitude, longitude, and time. I assume independence between the three dimensions because of the relatively small number of conflict events given the estimation space. I also follow the space-time kernel density estimation literature and assume that latitude and longitude dimensions have the same smoothing parameter h_s. The matrix of smoothing parameters H is therefore parametrized in the most simplistic way possible as follows:[16]

$$H = \begin{pmatrix} h_s & 0 & 0 \\ 0 & h_s & 0 \\ 0 & 0 & h_t \end{pmatrix}.$$

The density at a given point $\bar{x} = (x, y, t)$ in space and time is therefore given by:

$$\hat{f}(x, y, t) = \sum_{i=1}^{n} \frac{1}{n\lambda_i^3 h_s^2 h_t} k\Big(\frac{x - x_i}{\lambda_i h_s}\Big) k\Big(\frac{y - y_i}{\lambda_i h_s}\Big) k\Big(\frac{t - t_i}{\lambda_i h_t}\Big), \tag{2}$$

where n is the number of events that occurred before time t.[17] The value of this function

[16]See Appendix A.3 for a discussion on the potential role of off-diagonal elements of the matrix H.

[17]Space-time kernel density estimation of this type have been used to study patterns of forest fire (Tonini et al., 2017), crime (Brunsdon et al., 2007; Nakaya and Yano, 2010), occurrence of disease (Eaglin et al., 2017), etc.

reflects the likelihood of occurrence of a violent event around (x, y, t). The integral of the estimated density over a given space-time window gives a measure of the probability of occurrence of an event in that window. This is a measure of the statistical risk of violence.[18] This new metric captures violence risk beyond the occurrence or not of an event in a given window.

3.4 Comparison with Standard Approach

The standard approach in the literature to define exposure or not to the adverse effects of conflict is based on counting the number of events or fatalities that have occurred within a given space-time window. This implicitly assumes that violence risk is high only in space-time windows where violent events have already occurred. In other words, violence is perceived to be likely to happen only where it has already occurred. Agents not exposed to any event in their city or village for a given time period are therefore considered to be equally non-treated irrespective of the actual violence risk they may perceive. Therefore, this approach cannot account for any of the costs induced by behavioral responses to risk in the absence of immediate violence.

The standard approach can also be seen as a special case of the kernel density estimation approach. The kernel approach is equivalent to counting the number of events that occurred during a given time period h_t within a certain distance h_s from $\bar{x}$ if we replace the Gaussian kernel function k in Equation (2) by a uniform distribution. Conflict-affected areas are, therefore, areas with high density, while non-affected areas are those with low or zero density. The parameters h_s and h_t are "handpicked". All the observations that fall within the relevant space-time window around $\bar{x}$ contribute equally to the measure of conflict exposure.[19] The kernel density estimation method generalizes the standard approach in two important aspects:

[18] In a companion paper (Tapsoba, 2019), I use the kernel density estimation method developed here to show that it does a relatively good job at predicting the occurrence of future conflict events based on violence history data. It outperforms, in particular, the standard space-time autoregressive methods used so far in the conflict prediction literature.

[19] h_s is usually handpicked as administrative areas, cells of a given size or rings of a given radius around location (x, y). h_t corresponds to the relevant time window.

- It better incorporates the first-order moment of the violence process by fully accounting for the distance from a given location $\bar{x}$ to each conflict event. This is done by imposing some structure on how the contribution of each event to the risk fades out in space and time. The Gaussian kernel function used here means that this contribution is highest at the exact point (in space and time) where the event occurred and fades out at an exponential rate as we move away from it.

- It also accounts for the second-order moment of the violence process (dispersion) through the data-driven approach used for choosing the optimal smoothing parameters h_s and h_t. This generates flatter Gaussian kernels when there is more dispersion in the sample of conflict events, as argued earlier.

These two simple generalizations of the standard approach lead to a better metric for measuring violence risk that goes beyond the occurrence or not of conflict events in a given space-time window. This new metric also addresses several measurement issues in the conflict event datasets. First, the kernel density approach only requires a representative sample of realizations of the underlying process, while the standard approach assumes that we have the exhaustive list of conflict events. Moreover, isolated events that appear in the conflict event dataset because of measurement errors or just as rare realizations of the underlying violence process in low-risk areas can be captured as such only with the new approach. The new approach is, therefore, more robust to the standard data limitations in the current georeferenced, disaggregated events-level conflict datasets: non-exhaustivity and presence of coding errors (O'Loughlin et al., 2010; Eck, 2012). The following sections will show how this new approach can be used to study the impact of violence risk on child health.

3.5 Accounting for the Number of Fatalities

The new methodology developed in this paper aims to capture variations in the distribution of the underlying violence process. So far, it relies on the timing and location of violent events and ignores the number of fatalities that they have caused. A simple interpretation of this assumption is that the timing and location of events are determined by the underlying violence process but not the number of casualties they could each generate. This is the case if the number of deaths caused by a given event is randomly determined or depends on idiosyncratic unobserved factors. This means that the number of fatalities is not a feature of the underlying violence process per se. Many other factors will play a role in determining how many people die in a given event. Therefore, we can ignore this component when trying to capture the density of the underlying process.

However, the number of casualties can also be interpreted as a measure of the intensity of conflict events. In this case, they can affect how the risk spreads in space and time. Therefore, accounting for the number of fatalities when estimating violence risk can be of interest.[20] If we take the estimates of the number of fatalities in the conflict event data sets at face value, the simplest way to account for the magnitude of events is to weigh the contribution to the risk of each event by the number of fatalities that it generated. This can be done in a two-step procedure:

- Estimate the optimal smoothing parameters of the kernel density estimation relying only on the timing and location of conflict events.

- Use these smoothing parameters and weight the contribution of each event with a function of the number of casualties that it generated:

$$\hat{f}_m(x,y,t) = \sum_{i=1}^{n} \varphi(m_i) \times \frac{1}{n\lambda_i^3 h_s^2 h_t} k\Big(\frac{x-x_i}{\lambda_i h_s}\Big) k\Big(\frac{y-y_i}{\lambda_i h_s}\Big) k\Big(\frac{t-t_i}{\lambda_i h_t}\Big), \tag{3}$$

  where m_i is the number of deaths caused by event i and φ is an increasing function that maps fatalities into weights for the kernel estimation.

In the empirical analysis, I implement this approach with $\varphi(m_i) = 1 + log(1 + m_i)$. This function handles well the fact that many events have zero reported deaths while few other events have a large number of deaths. Events with zero reported deaths have a "weight" of 1, and events that generate more deaths have higher "weights" on their contribution in a log scale.

[20]The fact that the number of deaths of each event is very poorly measured in conflict event data sets poses substantial problems that the kernel density estimation method cannot fix.

4 Empirical Strategy

In order to estimate the causal impact of exposure to the adverse effects of violence on child health, this paper uses a Difference-in-Differences identification strategy. The treatment is defined at the "location x birth cohort" level. All the variation in childhood exposure to treatment across enumeration areas (household clusters) and birth cohorts is fully exploited. I use infant mortality as the main measure of child health.

The choice of infant mortality as the main outcome variable is due to three main reasons. First, infant death is one of Africa's most prominent health problems. To this day, close to 10% of children born on the continent die before the age of one. Second, infant mortality is one of the standard proxies for economic development (Kudamatsu, 2012), and it captures well variations in factors such as quality of health care, water quality, and food supply. Finally, focusing on infant mortality has both empirical and methodological advantages: it is available for all children in retrospective fertility surveys (DHS), and the relevant period of potential exposure to conflict is relatively short (in utero or during the first year of life) which makes the distinction between risk and incidence of violence even more salient. This relatively short time window also decreases the likelihood that the estimated impact is driven by other confounding factors.

I estimate the following equation using ordinary least squares:

$$y_{i(m,t,e)} = \gamma conflict_{i(t,e)} + \mu_e + \beta_t + \theta_{hh} X_m^{(hh)} + \theta_1 X_{i(m,t,e)}^{(1)} + \theta_2 X_{i(t,e)}^{(2)} + \epsilon_{i(m,t,e)}, \tag{4}$$

where i denotes a child of cohort (year-month) t, born to mother m who lives in enumeration area e. $y_{i(m,t,e)}$ is a dummy equal 1 if child i dies during the first 12 months of her life. $conflict_{i(t,e)}$ is the measure of exposure to the adverse effects of violence for a child i (and her family) in utero or during her first year of life. μ_e and β_t are enumeration area and birth cohort fixed effects. $X_{i(m,t,e)}^{(1)}$ and $X_{i(t,e)}^{(2)}$ are observable characteristics at the individual level (birth order, age gap with direct older and younger siblings, etc.) and enumeration area level (climatic regressors like temperature and precipitations in the corresponding period and before), respectively. $X_m^{(hh)}$ are household level controls (gender and age of household head, wealth index of household, education of the mother, etc.). Standard errors are clustered at

55×55 km PRIO-GRID cell level, which is very conservative and allows for error correlation among enumeration areas within the same grid cell.[21]

In the case where I use the new metric proposed in this paper to build $conflict_{i(t,e)}$, the risk measure is computed in a first stage estimation and used in Equation (3) as a regressor. This may lead to a generated regressor bias, so I also estimate this specification's coefficients and standard errors using a bootstrap approach to show that the results are not substantially affected by such bias. Details on the bootstrap method can be found in Appendix B.

In the most basic version of the specification shown in Equation (3), I control for enumeration area fixed effects to account for permanent unobserved characteristics of the place of residence and cohort fixed effects to account for cohort-specific shocks.[22] The full version of the main specifications adds controls for the relevant mother and child characteristics.

The coefficient γ measures the average difference in changes in the probability of death of born babies between war and non-war areas, holding all the other relevant characteristics constant. The implicit assumption behind the identification strategy is that after controlling for cohort fixed effects, enumeration area and household characteristics (or mother fixed effects), and other relevant exogenous covariates, changes in infant mortality would be similar across war and non-war areas in the absence of conflict. The coefficient γ does not represent the national impact of conflict risk on infant mortality but the average effect with respect to local averages and cohort averages.

[21]Standard practice is to cluster at the enumeration area level since they are the units that are randomly sampled for the DHS survey. There are 101 and 87 Prio-Grid cells in Ivory Coast and Uganda, respectively.

[22]For the case of Uganda, since I'm using three different DHS survey waves, I aggregate enumeration areas to their corresponding PRIO-GRID cells in order to merge them.

5 Empirical Results

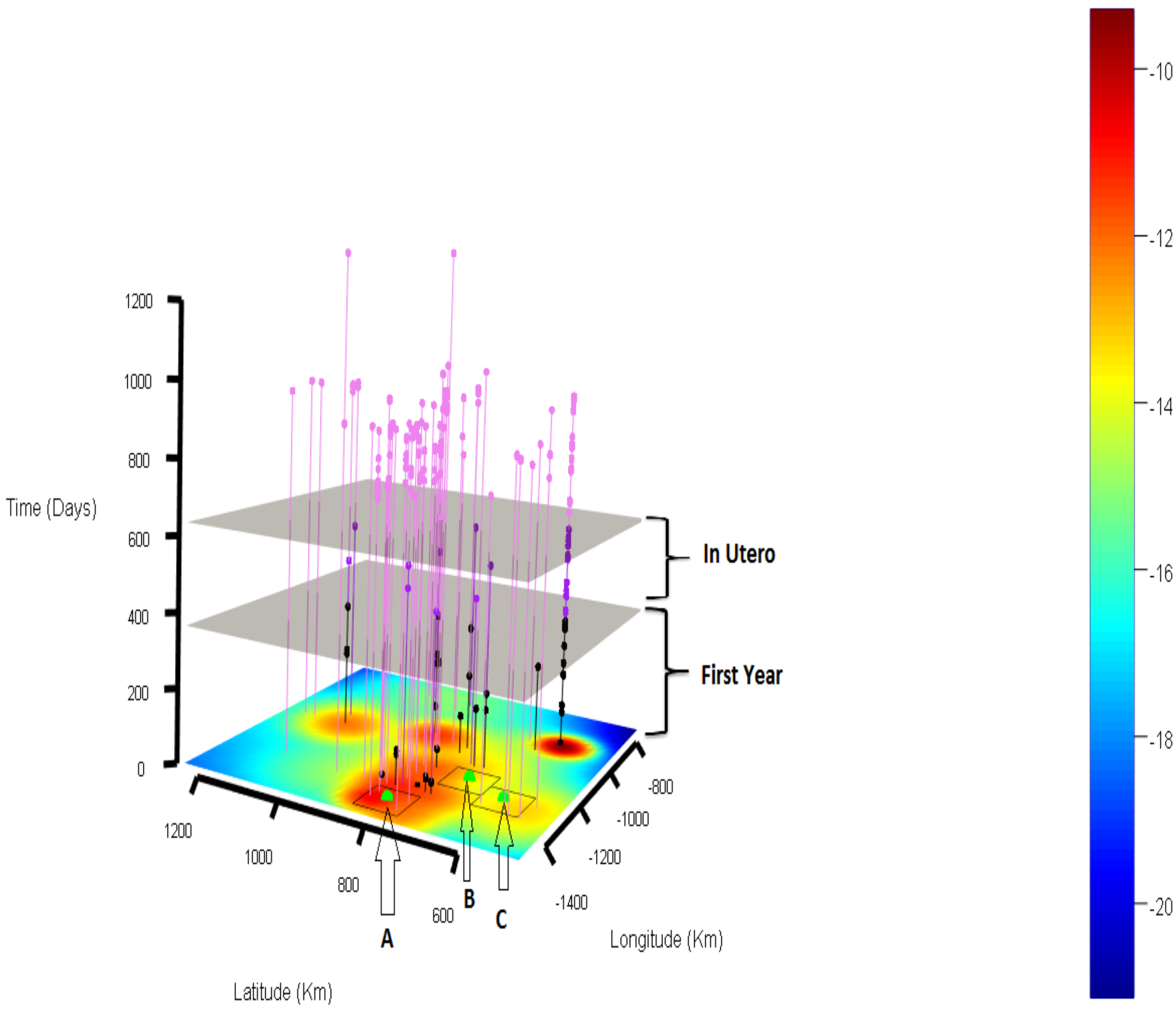
5.1 Estimated Conflict Risk

5.1.1 Illustration of the Risk Measure

The kernel density estimation method described above is performed on conflict event data for Ivory Coast and Uganda. The density of the underlying violence process is estimated for each "location $\times$ month." The risk of exposure to a conflict event between conception and the first year of life is obtained by integrating the estimated density over the relevant space-time window. As an illustration, Figure 5 shows the distribution of events in space and time and the probability of being exposed to an event in utero or during the first year of life for children conceived in September 2003 in Ivory Coast. The gray planes delimit the period in utero. Events in purple vertical bars occurred in utero, events in black vertical bars occurred during the first year of life, and the violet ones before conception. The heatmap at the bottom shows the likelihood that an event happens in utero or during the first year of life in a log scale.

For children born in locations A, B, and C, for instance, there was no event happening in the relevant time window (from conception to year 1) within 100 km, but the risk of occurrence of an event was high. Households living in location A have experienced many events just before their child's conception and during the relevant time window but beyond the 100 km radius. However, high risk in location B is only driven by events that occurred beyond the 100 km radius, both before and during the relevant time window. Risk in location C is caused by events that have happened before the relevant time window, both within the 100×100 km cell grid and beyond. These are examples of situations where the new approach can capture high violence risk while the standard approach of counting events or casualties in the relevant space-time window cannot. I show below that the children born in situations similar to those in A, B or C also suffer major health setbacks.

Figure 5: Risk for Children Conceived in September 2003 - Log Scale



5.1.2 Preliminary Observations

Before investigating the impact of violence risk on infant mortality, it is essential to discuss the empirical (dis)similarities between the proposed risk measure and the standard metrics used in the literature. Table 1 shows the distribution of my sample according to the risk of exposure to violence and the number of observed conflict events (in utero or during the first year of life) within 50 km around the place of birth of each child in Ivory Coast. The probability of being exposed to an event for children born after 1994 is grouped into four quartile groups.

There is some correlation between the proposed measure of violence risk and the standard metric used in the literature, but the two metrics also differ substantially. There was no event happening within 50 km around the place of birth of almost 90% of the observations in the two lowest quartiles of the violence risk. This percentage decreases to 60% and 15% respectively for the third and top quartiles of the risk distribution. Observations that experience at least 14 events within 50 km in utero or during their first year of life belong exclusively to the top quartile of the risk distribution. On the other hand, within the group of observations with no event within 50 km, only 36% belong to the lowest quartile of the distribution of violence risk. 35% and 23% of them are in the 2nd and 3rd quartiles of the risk measure respectively and the rest belongs to the top quartile. This leaves some room for refining the treatment status for many observations that the standard measures of conflict exposure cannot distinguish and would consider as equally non-treated.

By defining that violence risk is low if its estimated value belongs to the bottom quartile of the risk distribution, I have four different types of children in my sample. Children in the blue area of Table 1 are exposed to a low risk of violence and have not been exposed to any event within 50 km. Children in the yellow area also didn't experience any violence in the relevant space-time window, but they were exposed to a high risk of violence. This corresponds to children born during situations similar to A, B, or C in Figure 5. Children in the gray area had a low risk of violence but were exposed to some isolated events. These events, because they appear in areas with very few other events, do not generate a high risk of violence.[23] Children in the red area are both exposed to a high risk of violence and actual violence within the relevant space-time window.

If the kernel density estimation approach is the right metric for capturing exposure to the adverse effects of violence, we would expect children in the gray area of Table 1 to not suffer any health setbacks compared to the children in the blue area. We should also see that children in the yellow and red areas suffer major health setbacks compared to those in the blue area. This is indeed what I show in the next sections.

Table 1: Distribution of Children by Risk of Exposure to a Conflict Event and Levels of Observed Violence in Ivory Coast

	Conflict events within 50km					
Risk quartiles	0	[1 ; 2]	[3 ; 4]	[5 ; 13]	14 +	Total
Q1	1,144	114	24	1	0	1,283
Q2	1,118	109	22	6	0	1,255
Q3	723	224	141	141	0	1,229
Q4	183	176	170	274	393	1,196
Total	3,168	623	357	422	393	4,963

Rows represent the probability of exposure to at least one event in utero or during the first year of life. This probability is grouped in quartiles. Columns represent the number of observed conflict incidents in utero or during the first year of life within 50 km of children's place of birth.

Table 2 is equivalent of Table 1 for Uganda. It shows some correlation between the proposed violence risk measure and the standard metric used in the literature but also some substantial differences. Children exposed to some events also experienced high risk. However, a big share of children that did not experience any event had a high risk of exposure to violence in utero or during their first year of life.

[23]Isolated events in the gray area of Table 1 could come from measurement errors in the conflict dataset, or they could just be rare realizations of the underlying process in areas where its density is low.

Table 2: Distribution of Children by Risk of Exposure to a Conflict Event and Levels of Observed Violence in Uganda

	Conflict events within 50 Km					
Risk Quartiles	0	1	2	[3 ; 8]	9 +	Total
Q1	1,213	0	0	0	0	1,213
Q2	1,185	36	0	0	0	1,221
Q3	1,086	107	21	3	0	1,217
Q4	694	147	98	122	156	1,217
Total	4,178	290	119	125	156	4,868

Rows represent the probability of exposure to at least one event in utero or during the first year of life. This probability is grouped in quartiles. Columns represent the number of observed conflict incidents in utero or during the first year of life within 50 km of children's place of birth.

5.2 Violence Risk and Infant Mortality

5.2.1 Main Results and Heterogeneity

Table 3 shows the estimated effect of being exposed to a high risk of violence on the likelihood of dying within the first 12 months of life in Ivory Coast. Column (1) shows the estimated coefficient for the basic specification from Equation (3), in which I control only for enumeration area fixed effects and cohort fixed effects. The variable of interest is the standardized risk of exposure to a conflict event in utero or during the first year of life.[24] The estimated γ coefficient is positive and significant. This coefficient is stable and remains significant after progressively adding controls for child characteristics in column (2) and family characteristics in column (3). The main specification in column (3) suggests that a standard deviation increase in violence risk increases the likelihood of dying by 1 percentage point. Column (4) controls for the number of events that happen within each 10 km ring in the area between 20 and 100 km from the place of birth and the number of events between 100 and 150 km. The estimated γ remains stable and significant.

Column (5) splits the observations into the four groups of Table 1 to test some of the

[24] As main specification, I use adaptive kernel density estimation in which I consider all the events that have occurred before a given period t to compute the risk at t. I show some robustness to alternative ways of estimating the density in the robustness section.

implications of the risk model. The control group consists of children that are both exposed to low risk of violence and have not experienced any event within 50 km (blue cell in Table 1). Compared to this group, children that are exposed to low risk but experienced some events within 50 km (gray cells in Table 1) do not suffer any health setbacks. Children exposed to high risk of violence without any event (yellow cells in Table 1) suffer major health setbacks comparable to those exposed to high risk of violence with some events within 50 km (red cells in Table 1). Therefore, the relevant treatment metric is in line with the risk model. It avoids the false positives from isolated events that do not generate any fear. It also avoids the false negatives from cohorts not exposed to direct violence but born under high risk of conflict.

The magnitude of the estimated effect is substantial. The gap in infant mortality rate between children exposed to high and low violence risk is of 6 percentage points, representing more than 50% of the average infant mortality rate. Column (6) shows the estimated impact of violence when we use violence incidence as treatment variable (standard approach). It shows that being exposed to an event within 50 km increases infant mortality by 1.5 percentage points (4 times less than the estimated coefficient with the risk measure), and the coefficient is not statistically significant.[25]

Table 4 is the equivalent of Table 3 for Uganda. The qualitative results are pretty similar. A standard deviation increase in violence risk increases infant mortality by 0.8 percentage points in Uganda. Column (5) also shows that children exposed to a high risk of violence suffer major health setbacks even when the risk does not materialize in actual events. Column (6) shows that the estimated impact is close to zero when using violence incidence to define the treatment variable (5 times smaller than with the risk measure).

Table 5 shows the results of heterogeneity analysis that allows us to check whether the estimated impact of violence risk on child health is driven by specific subgroups of children. Column (1) shows the results of the main equation in Column (3) of Table 3 but for male children instead. The estimated impact is close to zero and insignificant. This result could be explained by in utero selection being stronger for male fetuses than female ones. This

[25]See Figure 6a for robustness on the 50 km threshold.

Table 3: Impact of Violence Risk on Infant Mortality in Ivory Coast

	Infant Mortality					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Standardized violence risk	0.010***	0.010***	0.010***	0.010***		
	(0.002)	(0.003)	(0.003)	(0.003)		
Low violence risk with at least 1 event within 50 km					-0.009	
					(0.019)	
High violence risk with no event within 50 km					0.053**	
					(0.023)	
High violence risk with at least 1 event within 50 km					0.068***	
					(0.026)	
At least 1 event within 50 km						0.015
						(0.012)
Observations	4,944	4,944	4,944	4,944	4,944	4,944
R-squared	0.145	0.190	0.191	0.192	0.193	0.190
Cohort FE	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES
Family characteristics	NO	NO	YES	YES	YES	YES
Child characteristics	NO	YES	YES	YES	YES	YES
Conflict events spatial lags	NO	NO	NO	YES	NO	NO

"High violence risk" is a dummy equal 1 if the risk is high enough not to belong to the bottom quartile of the distribution. The full set of controls includes the mother's height, education, gender and age of household head, household wealth index, 12 months of rainfalls (for each of the two years preceding the birth of the child and during her first year of life), birth order, the time gap between conception and the previous/following pregnancies. Robust standard errors in parentheses are clustered at 50 × 50 km PRIO-GRID cell level.

is in line with findings in Dagnelie et al. (2018). Columns (2) to (4) use the sample of female children and add an interaction term for the other sub-groups of the population that I consider. Column (2) shows that the estimated impact is stronger in urban areas compared to rural ones (the coefficient on the interaction term is sizable even though it is not significant). Column (3) shows no difference between poor and rich households while column (4) shows a slightly stronger but not significant effect for children born to non-educated mothers compared to those born to educated mothers.

Columns (5) to (8) of Table 5 are the equivalent of the first four columns for Uganda. Column (5) also shows that there is no detectable effect of violence risk on male children. Column (6) indicates a stronger effect for girls born in rural areas. Columns (7) and (8) show no differential effect for children born in rich/poor families or families with educated/uneducated mothers.

Table 4: Impact of Violence Risk on Infant Mortality in Uganda

	Infant Mortality					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Standardized violence risk	0.011**	0.008**	0.008**	0.008**		
	(0.004)	(0.004)	(0.004)	(0.004)		
High violence risk with no event within 50 km					0.019**	
					(0.010)	
High violence risk with at least 1 event within 50 km					0.026*	
					(0.015)	
At least 1 event within 50 km						0.005
						(0.012)
Observations	4,868	4,868	4,868	4,868	4,868	4,868
R-squared	0.109	0.155	0.160	0.161	0.160	0.158
Cohort FE	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES
Family characteristics	NO	NO	YES	YES	YES	YES
Child characteristics	NO	YES	YES	YES	YES	YES
Conflict events spatial lags	NO	NO	NO	YES	NO	NO

"High violence risk" is a dummy equal 1 if the risk is high enough not to belong to the bottom quartile of the distribution. The full set of controls includes the mother's height, education, gender and age of household head, household wealth index, 12 months of rainfalls (for each of the two years preceding the birth of the child and during her first year of life), birth order, the time gap between conception and the previous/following pregnancies. Robust standard errors in parentheses are clustered at 50 × 50 km PRIO-GRID cell level.

5.2.2 Robustness

Table 6 shows some robustness of the baseline specification in Column (3) of Table 3. Column (1) includes region-specific time trends, Column (2) runs a mother fixed effect specification, and Column (3) uses sampling weights to check that results are not biased by the sampling design of the survey. Column (4) uses only events that have occurred within 200 km from a given location and at most two years ago to compute the violence risk at each point in space and time. Column (5) uses fixed bandwidth in the kernel estimation, while Column (6) uses both past and future events in the density estimation stage.[26] The estimated effect is stable across all these specifications. The main result is also robust to taking into account the number of fatalities generated by events in columns (7) and (8). I follow the procedure

[26]The rationale behind using future events could come from assuming that agents anticipate the future violence process perfectly so we can use future events to estimate the density at a given location. Restricting the events that are used to compute the risk to past events is a more conservative approach where it's assumed that future violence (and its realizations) is not in the information set of agents at time t when they are making decisions.

Table 5: Heterogeneous Effects: Ivory Coast and Uganda

	Ivory Coast				Uganda			
	Boys	Girls			Boys	Girls		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Standardized violence risk	0.001	0.010***	0.010***	0.009***	0.001	-0.007	0.008*	0.008*
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.004)	(0.005)
Standardized violence risk x Rural		-0.005				0.015**		
		(0.009)				(0.007)		
Standardized violence risk x Rich			-0.000				-0.002	
			(0.016)				(0.011)	
Standardized violence risk x No education				0.002				-0.001
				(0.003)				(0.006)
Observations	5,086	4,944	4,944	4,944	5,060	4,868	4,868	4,868
R-squared	0.196	0.191	0.191	0.191	0.188	0.160	0.160	0.158
Cohort FE	YES	YES	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES	YES	YES
Family characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Child characteristics	YES	YES	YES	YES	YES	YES	YES	YES

"High violence risk" is a dummy equal 1 if the risk is high enough not to belong to the bottom quartile of the distribution. The full set of controls includes the mother's height, education, gender and age of household head, household wealth index, 12 months of rainfalls (for each of the two years preceding the birth of the child and during her first year of life), birth order, the time gap between conception and the previous/following pregnancies. Robust standard errors in parentheses are clustered at 50 × 50 km PRIO-GRID cell level.

described in Section 3.5 using fixed and adaptive bandwidths, respectively.[27] Table A4 (in appendix) is the equivalent of Table 6 for Uganda and shows very similar results.

5.3 Placebo Test

Table 7 shows some placebo analysis that tests whether the documented results are driven by pre-existing trends. First, I lag the risk measure for each child by 12 months and run placebo regressions with this "lagged" risk. The risk of exposure to violence 12 months before a child's birth should not affect his health outcome. This is what I find in columns (1) and (2) for Ivory Coast and (5) and (6) for Uganda. In columns (1) and (5) I use the treatment dummies from Column (5) of Table 3 and 4. Columns (2) and (6) use the continuous risk measure. All the estimated coefficients are statistically insignificant and close to zero.

Second, I randomly assign risk values within each enumeration area for Ivory Coast and Uganda in columns (3) and (7), respectively. The estimated coefficients are also close to

[27] The weight function $\varphi(m_i)$ is rounded to the nearest integer to minimize the effect of noisy variations in the number of fatalities.

Table 6: Robustness Ivory Coast

	Infant Mortality							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Standardized violence risk	0.012**	0.007*	0.008***					
	(0.005)	(0.004)	(0.003)					
Risk with space-time restriction				0.011***				
				(0.003)				
Risk with fixed bandwidth					0.012***			
					(0.003)			
Risk with past and future events						0.007**		
						(0.003)		
Risk with fatalities and fixed bandwidth							0.012***	
							(0.003)	
Risk with fatalities and adaptive bandwidth								0.010***
								(0.003)
Observations	4,944	4,944	4,944	4,944	4,944	4,944	4,944	4,944
R-squared	0.192	0.167	0.215	0.191	0.191	0.190	0.191	0.191
Cohort FE	YES	YES	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES	YES	YES
Region specific time trend	YES	NO	NO	YES	YES	YES	YES	YES
Family characteristics	YES		YES	YES	YES	YES	YES	YES
Child characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Number of family		2,658						
Family FE	NO	YES	NO	NO	NO	NO	NO	NO

"High violence risk" is a dummy equal 1 if the risk is high enough not to belong to the bottom quartile of the distribution. The full set of controls includes the mother's height, education, gender and age of household head, household wealth index, 12 months of rainfalls (for each of the two years preceding the birth of the child and during her first year of life), birth order, the time gap between conception and the previous/following pregnancies. Robust standard errors in parentheses are clustered at 50 × 50 km PRIO-GRID cell level. R-squared in FE specification is the within household R-squared.

zero and statistically insignificant. Finally, in column (4), I run a placebo test for Ivory Coast in which children born in 1995 and 1996 are used as fake war cohorts, and treatment intensity is given by the maximum risk in a given area over time.[28] Column (4) does a similar exercise for Uganda using children born between 2006 and 2011 as fake war cohorts.[29] The results confirm that there is no pre-existing trend difference between areas with high and low violence risk.

5.4 Potential biases

The causal interpretation of the estimated coefficient can be threatened by factors such as omitted variable bias, selective migration, and fertility. This section presents evidence that the main results found here are unlikely to be driven by such factors. The magnitudes of the estimated coefficients are, if anything, lower bounds of the true impact of conflict risk

[28]Children born before 1995 are the non-exposed cohorts in column (2) of Table 7.

[29]Children born after 2011 are the non-exposed cohorts in column (4) of Table 7.

Table 7: Placebo Test

VARIABLES	Ivory Coast (1)	(2)	(3)	(4)	Uganda (5)	(6)	(7)	(8)
High violence risk with no event within 50 km	-0.002				0.008			
	(0.017)				(0.012)			
High violence risk with at least 1 event within 50 km	-0.006				0.006			
	(0.019)				(0.013)			
Low violence risk with at least 1 event within 50 km	-0.027							
	(0.043)							
Standardized violence risk		0.003				0.002		
		(0.003)				(0.003)		
Standardized violence risk with random values			0.001				-0.001	
			(0.004)				(0.003)	
Maximum standardized violence risk × 1995-1996 cohorts				0.000				
				(0.011)				
Maximum standardized violence risk × 2011-2016 cohorts								0.004
								(0.003)
Observations	4,944	4,944	4,944	1,621	4,868	4,868	4,868	3,739
Cohort FE	YES	YES	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES	YES	YES
Family characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Child characteristics	YES	YES	YES	YES	YES	YES	YES	YES

"High violence risk" is a dummy equal 1 if the risk is high enough not to belong to the bottom quartile of the distribution. The full set of controls includes the mother's height, education, gender and age of household head, household wealth index, 12 months of rainfalls (for each of the two years preceding the birth of the child and during her first year of life), birth order, the time gap between conception and the previous/following pregnancies. Robust standard errors in parentheses are clustered at 50 × 50 km PRIO-GRID cell level.

on infant mortality.

5.4.1 Omitted Variable Bias

A possible threat to the Difference-in-Differences identification is the existence of time-varying omitted factors that drive the timing and location of violence and, at the same time, are correlated with infant health. I show in this section that this is not an issue for the empirical results presented above.

For the case of Ivory Coast, figure 1a shows that violence intensity varies drastically over time according to the political agenda, both increasing and decreasing sharply to the extent that contemporary changes in omitted determinants of health are less likely to be driving the estimated coefficients.[30]

One of the main drivers of conflict intensity in Sub-Saharan Africa is the value of lootable resources like valuable minerals (Berman et al., 2017; Dagnelie et al., 2018). An increase in

[30] The variations in violence intensity are even more drastic at the local level. The space and time variation in violence intensity also helps in the identification strategy. Treatment (being exposed to a high risk of violence) can happen to children of any birth order within the same family and at different periods in time, mitigating, even more, the effect of potential confounding factors.

prices of minerals can also affect child health through household income for instance, so it is worth exploring this channel specifically in theory. However, the context of the Ivorian conflict rules out such an option. Lootable resources play a minor role in the Ivorian economy, and there is no anecdotal evidence linking them to the conflict under scrutiny. The country's economy relies primarily on cash crops that require permanent and heavy infrastructure to be sent to the world market like cocoa (first world producer), coffee, raw cashew nuts, palm oil, etc.

The identification strategy in Uganda relies on the exogenous increase in violence intensity in Northern Uganda following the change in government strategy against the internal insurgency after the September 11, 2001, terrorist attacks in the US. Violence in Uganda between 2002 and 2005 happened as a consequence of this exogenous shock which led to the end of any significant activity from the active rebel groups in the country.

5.4.2 Fertility

Selective fertility decisions could be a threat to the identification strategy. If the fear of being exposed to conflict affects the fertility decisions of mothers differently depending on some specific mother/household characteristics, then any estimate of the consequences of the shock would be biased. One would expect households with high socio-economic status to be most likely to adjust their fertility decisions to violence risk.[31] The stability of the estimated effect when controlling for household and mother characteristics is a first signal that endogenous fertility is not an issue here.

In both Ivory Coast and Uganda, the empirical evidence suggests that households with at least one child exposed to high violence risk in utero or during their first year of life are similar to the other households living in the same area. Appendix Table A3 shows that there is no difference between these two groups of households in terms of observable characteristics such as mother's education, number of births, age at first birth, height, as well as household head's age, and the wealth index of the household.[32]

[31] High socioeconomic status households are more likely to have different preferences due to their education. They tend to have fewer children and invest more in them.

[32] The only significant difference in Appendix Table A3 is the number of children born in each family in

Many factors could explain the fact that it is unlikely to observe selective fertility behavior with respect to violence in countries affected by low-intensity conflicts. In general, Sub-Saharan Africa faces high infant and child mortality rates. This high probability of losing a child, the low cost of having an extra one, and deeply rooted pro-natalist religious/cultural beliefs have led to high birth rates and a somehow fatalistic view of children's survival. The conflicts in Uganda and Ivory Coast were also long-lasting, so it's harder for even sophisticated households to postpone fertility decisions in that case.

5.4.3 Migration and Recall Bias

Conflict-induced displacements could bias (most likely downward) the estimated impact of conflict on infant mortality since I do not observe migration history in my data. However, permanent migration is rare in countries like Ivory Coast and Uganda. In rural areas, for instance, the land is the most valuable asset, and the absence of property rights makes it risky for farmers to leave their lands unused for too long or to try to establish themselves in another locality. The Internal Displacement Monitoring Center (IDMC) estimated that, as of February 2015, over 80 % of the 2.3 million people displaced by violence since 2002 in Ivory Coast had managed to return to their homes (Norwegian Refugee Council/Internal Displacement Monitoring Centre, 2015). Moreover, conflict-induced temporary displacement is one of the channels through which conflict affects infant mortality. Displaced households often live in camps or host communities with limited access to basic needs like health services, clean water, or the ability to undertake an economic activity.

The DHS surveys usually collect information on how long households have been living in a given area. Unfortunately, this information is unavailable for the 2011 survey wave used in Ivory Coast. In the case of Uganda, this information is available only for the 2006 and 2016 survey waves (not for the one in 2011). However, the period of interest in this paper for Uganda came after almost 20 years of civil war, so keeping track of migration is much more complicated in this setting. The data shows that less than 17% of children in these

Uganda. The families with at least one child treated have more children, but this could be explained by the fact that the likelihood of having at least one child treated increases with the number of children that you have.

two samples were born in households that have never moved from their place of residence.

Other papers in the conflict literature with better data found that conflict-induced migration is not selective and does not affect much the estimated impact of conflict on child health (Dagnelie et al., 2018; Valente, 2015). They show, in particular, that the characteristics of women who migrate and those who do not migrate are similar. Restricting the analysis to households that remained in their initial place of residence does not change the estimation results.

I also use alternative sources of information to confirm that this is also the case in my setting. Figure A7 shows the main areas of internal displacement in Ivory Coast due to the conflict. Using this map, I split the localities into low and high displacement areas to check whether the estimated effect differs across the two areas.[33] Table A6 shows no significant difference in the estimated effects across both areas. The interaction term is close to zero and statistically insignificant in Column (1). Columns (2) and (3) run separate regressions for each sub-sample. The magnitude of the estimated effect is of 6.1 percentage points for low displacement areas (Column(2)) versus 4.4 percentage points for high displacement areas (Column(3)). This represents around 73% of the average infant mortality rate in both sub-samples.[34]

A related potential concern comes from measurement error in women's recollections of the timing of birth and eventual death of their children in the survey data. Errors in women's recollections will lead to greater imprecision in the estimates. Overall, validation studies of age and date variables in the DHS data have suggested that such measures are rather accurate (Pullum, 2006), limiting concerns about the effect of measurement errors.

5.5 Analysis of Transmission Channels

Understanding the specific mechanisms by which violence risk impacts child health is critical for developing adequate policy responses to protect children from this adverse effect. The

[33] I identify the departments (level 3 administrative units) with high and low displacement levels according to the map and merge them to the DHS clusters. 51% of the 341 DHS clusters are located in a high displacement area.

[34] Average infant mortality rate is 8.38% in high displacement areas versus 5.75% in low displacement areas.

timing of violence escalation and DHS survey years in Uganda allows me to investigate these channels partially. The DHS surveys provide a rich set of information on the use of health services but also on child and maternal health for pregnancies that happened at most 5 years before the survey year. Using this information, I focus on exposure to violence risk in utero and show how it affects key health inputs and outcomes.

Column (1) of Table 8 shows that exposure to a high risk of violence in utero increases infant mortality significantly. Column (2) suggests that violence risk increases the likelihood of being born with low birth weight. High violence risk also decreases the likelihood of receiving prenatal care during the first quarter of pregnancy (Column (3)), delivering in a health center (Column (4)), or having access to a C-section during delivery (Column (5)). Women exposed to a high risk of violence during a specific pregnancy also have a longer duration of postpartum amenorrhoea which is evidence of maternal stress and insufficient nutrition.[35]

These results suggest that conflict in Uganda affected the quality and availability of health services or their use by citizens during crucial times.[36] They also suggest that the conflict has induced maternal stress and short-term malnutrition in women.

Table 8: Channels

VARIABLES	(1) Infant Mortality	(2) BW<2.5 Kg	(3) Q1 Prenatal care	(4) Home delivery	(5) C-section	(6) Duration Amenorrhea
Standardized violence risk in utero	0.008*	0.017**	-0.010**	0.014**	-0.015***	
	(0.004)	(0.007)	(0.005)	(0.007)	(0.005)	
Standardized violence risk in utero and during 1st year						0.189**
						(0.078)
Observations	4,868	2,673	4,868	4,807	2,964	4,838
R-squared	0.115	0.125	0.197	0.264	0.133	0.264
Cohort FE	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES
Family characteristics	YES	YES	YES	YES	YES	YES
Child characteristics	YES	YES	YES	YES	YES	YES
Conflict events spatial lags	YES	YES	YES	YES	YES	YES

The full set of controls includes the mother's height, education, gender and age of household head, household wealth index, 12 months of rainfalls (for each of the two years preceding the birth of the child), birth order, the time gap between conception and the previous and following pregnancies. Robust standard errors in parentheses are clustered at 50 × 50 km PRIO-GRID cell level.

[35] All the results in Table 8 are robust to including or not controls for the incidence of conflict events between conception and the first birthday.

[36] Without further data, it is impossible to tell whether these results are due to supply side or demand side effects.

5.6 Comparison with Standard Approach

In theory, one of the benefits of the proposed measure of violence risk over the standard metrics used in the literature is its ability to discriminate between children that are exposed to high and low risk of violence even at equal levels of violence incidence in their relevant space-time window. This section confirms the empirical relevance of this benefit.

First, I show the estimated impact of conflict on infant mortality using the standard metrics in the literature. Figure 6a plots several values of the coefficient γ estimated from the main specification in Equation (3) for Ivory Coast. The conflict variable is defined as a dummy equal 1 if at least one event happened between conception and year one within a certain radius r from the place of birth of a given child. A new regression is run for each tick in the X-axis and the coefficient together with 95% confidence bands for γ are plotted and interpolated to give the continuous lines. The first regression considers a treatment area of 20 km around the household location (large enough to encompass a city).[37] Around 20% of children are classified as treated, and their likelihood of dying within their first year increases by 1 percentage point (not statistically significant). As the radius of the treatment area increases, we are moving more observations from the control to the treatment group and the magnitude increases slightly before declining towards zero after 50 km.[38]

The main question here is whether the proposed risk measure captures something that the standard approach does not. I, therefore, check whether the new risk measure is relevant enough to capture significant variations in the exposure to the adverse effects of conflict within a sample of children that the standard approach classifies as non-treated since they were not exposed to any event within their relevant space-time window. Figure 6b shows the estimated impact of conflict using the proposed risk measure as treatment variable and restricting the analysis to observations with no event within r km from their place of birth. These observations are not treated according to the standard approach used in the literature

[37]In DHS data, some noise is introduced in the GPS coordinates of the enumeration areas that are surveyed for privacy reasons. They are displaced by up to 2 km in urban areas and 10 km in rural ones. For this reason, I use at least 20 km to define geographic areas that contain (most likely) the enumeration area of the surveyed households.

[38]See Figure A5a for the equivalent graph with mother FE specification.

and presented in Figure 6a.[39] Small values of r mean more observations to split between treatment and control. The estimated coefficient when $r = 50$ km corresponds to the yellow coefficient in Column (5) of Table 3. This can therefore be seen as a robustness for this estimation result. The estimated coefficient of the impact of being exposed to high risk of violence is strikingly constant (increase of 5 percentage points in infant mortality) and falls apart only when the sub-sample becomes too small because we are looking at children with no event within more than 100 km around their area of birth.[40]

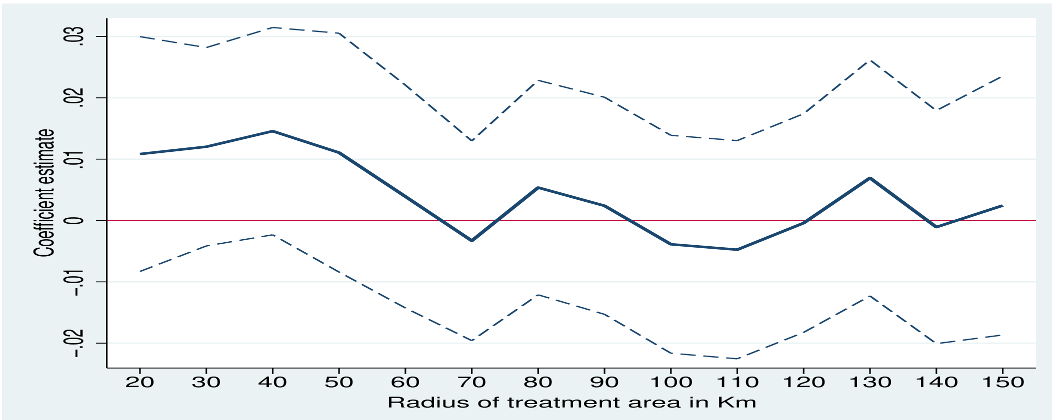
Results in Figure 6a and 6b taken together imply that the risk measure proposed in this paper is able to split an otherwise homogeneous group of non-treated children (according to the classic methods used in the literature) into treatment and control groups in such a relevant way that the estimated impact is positive, sizable and significant.

Equivalents of Figure 6a and 6b for Uganda are shown in Figure A4a and A4b (in appendix). The results are fairly similar qualitatively except for the fact that, due to the stronger persistence of violence across time in Uganda, the estimated impact in Figure A4b does not drop to zero even after increasing the size of the ring r up to 150 km.

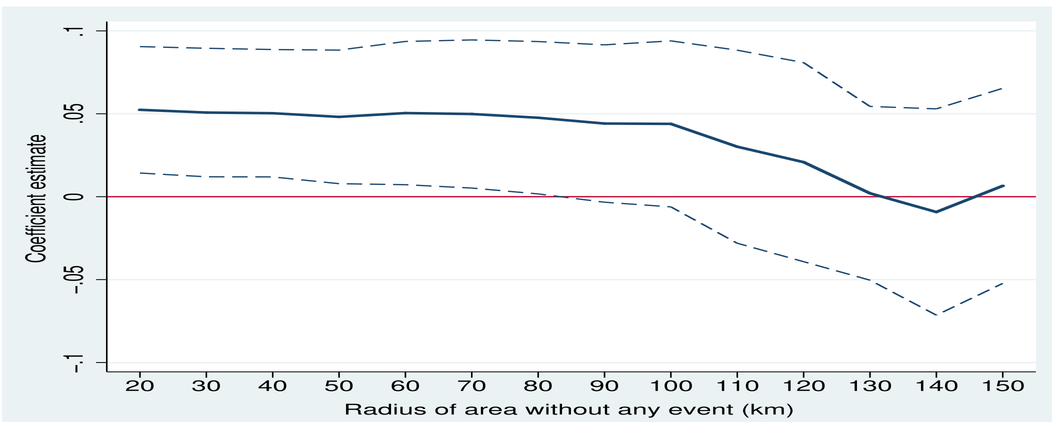
[39] Adding more spatial lags in each regression of Figure 6a always leaves the same children in the control group and this is what is used as sample in each regression in Figure 6b.

[40] The differences in the risk measure are just noisy in this sub-sample because they are all barely affected by the violence.

Figure 6: (a) Impact of Conflict on Infant Mortality using Observed Violence. (b) Impact of Violence Risk on Infant Mortality using Sub-sample of Children with no Event Within r km



(a)



(b)

Notes: Estimated impact of conflict on infant mortality in Ivory Coast using the main specification in Equation (3). In panel (a), the *conflict* variable is defined as a dummy equal 1 if there was at least one event that has happened within a certain radius r from the place of birth of each child (in utero or during the first year of life). In panel (b), the sample used for each regression is restricted to observations that had no event happening within a certain radius r from the place of birth (in utero or during the first year of life). The variable of interest is a dummy equal 1 if the risk of exposure to violence is high (belongs to the second quartile or higher). A new regression is run for each tick in the X-axis, and the γ coefficients together with 95% confidence bands are plotted and interpolated to give the continuous lines. Robust standard errors are clustered at 50 × 50 km PRIO-GRID cell level.

5.7 Discussion and Policy Implications

The evidence documented in this paper shows that exposure to the adverse effects of conflict goes beyond the mere incidence of violent events in a given space-time window. Some children were exposed to a high risk of violence with no event in the relevant window, while others were exposed to isolated events and low risk of violence. The standard approach leads, therefore, to two types of treatment misclassification. In the first one, some children that belong to the treatment group are wrongly classified in the control group (high risk with no incidence of violence). For the case of Ivory Coast, 40% of observations are in this situation (see Table 1). In the second one, some children exposed to low risk of violence are wrongly assigned to the treatment group because they have been exposed to isolated events. This is the case of 3% of the children in Ivory Coast. These treatment misclassifications lead to a substantial attenuation bias to the extent that the magnitude of the treatment effect is four times lower than when I use the risk measure for Ivory Coast (0.015 versus 0.06).[41] The new measure allows us to capture an additional cost of conflict that is sizable: the one due to the fear of being exposed to violence.

This evidence suggests that policy intervention in conflict-affected areas should target agents exposed to a high risk of violence, irrespective of whether there is actual violence around them. In other words, the coverage of these programs should be extended to areas at risk of violence even if this risk does not materialize immediately (or at all). This will often mean maintaining the provision of goods and services in these areas, making sure that displaced people still have access to basic goods (such as food) and services, etc. It is not only in areas where bullets are flying around that people need help coping with the adverse effects of conflict.

[41] This magnitude is ten times smaller for the case of Uganda.

6 Conclusion

This paper analyzed the impact of violence risk on child health using Ivory Coast and Uganda data. It is based on the intuition that economic agents often react to the risk of being exposed to violence in a given space-time window even before/without any manifestation of violence in this window. These behavioral responses to insecurity can lead to disruptions in the supply and demand of goods and services and affect households. A new metric that captures the statistical risk of violence is therefore proposed in the paper and used to evaluate the impact of violence risk on child health. The proposed measure of violence risk is based on an estimation of the underlying distribution of the violence process in space and time.

The empirical results show that cohorts of children exposed to high risk of violence suffer major health setbacks. In particular, violence risk increases infant mortality by more than 50% in both Ivory Coast and Uganda. This effect is similar in magnitude and significance level even when the violence does not manifest itself in the relevant space-time window. These results suggest that conflict is a public bad that affects entire communities through their risk coping behavior. An investigation into the potential channels through which this effect operates indicates that we cannot rule out factors such as maternal stress, malnutrition or a deterioration of the quality/availability of health care services (or a decrease in their demand).

This paper has important policy implications for different stages of violent conflicts. First, it strengthens the idea that we should focus even more on conflict prevention efforts to avoid the enormous humanitarian and economic costs that will arise if violence breaks out. Second, during conflict, governments and NGOs should address the fear/expectations of economic agents and prevent disruptions in the supply and demand of goods and services in order to minimize the cost of ongoing threats. Finally, in post-conflict reconstruction settings, the findings in this paper imply that policy interventions should include all the children born under violence stress and not just the direct victims of violence.

References

Akresh, Richard, German Caruso, and Harsha Thirumurthy, "Detailed Geographic Information, Conflict Exposure, and Health Impacts," 2016.

_ , Leonardo Lucchetti, and Harsha Thirumurthy, "Wars and Child Health: Evidence from the Eritrean–Ethiopian Conflict," *Journal of Development Economics*, 2012, *99* (2), 330–340.

_ , Sonia Bhalotra, Marinella Leone, and Una Okonkwo Osili, "War and Stature: Growing Up During the Nigerian Civil War," *The American Economic Review (Papers and Proceedings)*, 2012, *102* (3), 273–277.

Arias, María Alejandra, Ana Ibáñez, and Andres Zambrano, "Agricultural Production Amid Conflict: The Effects of Shocks, Uncertainty, and Governance of Non-State Armed Actors," Technical Report, Universidad de Los Aandes-Cede 2014.

_ , Ana María Ibáñez, and Andrés Zambrano, "Agricultural production amid conflict: Separating the effects of conflict into shocks and uncertainty," *World Development*, 2019, *119*, 165–184.

Behrman, Jere R and Mark R Rosenzweig, "Returns to Birthweight," *Review of Economics and Statistics*, 2004, *86* (2), 586–601.

Berman, Nicolas, Mathieu Couttenier, and Dominic Rohner, "This Mine is Mine! How Minerals Fuel Conflicts in Africa," *American Economic Review*, 2017, *107* (6), 1564–1610.

Besley, Timothy and Hannes Mueller, "Estimating the Peace Dividend: The Impact of Violence on House Prices in Northern Ireland," *The American Economic Review*, 2012, *102* (2), 810–833.

Black, Sandra E, Paul J Devereux, and Kjell G Salvanes, "From the Cradle to the Labor Market? The Effect of Birth Weight on Adult Outcomes," *The Quarterly Journal of Economics*, 2007, *122* (1), 409–439.

Blattman, Christopher and Edward Miguel, "Civil war," *Journal of Economic literature*, 2010, *48* (1), 3–57.

Bozzoli, Carlos and Tilman Brück, "Agriculture, Poverty, and Postwar Reconstruction: Micro-Level Evidence from Northern Mozambique," *Journal of Peace Research*, 2009, *46* (3), 377–397.

Brunsdon, Chris, Jonathan Corcoran, and Gary Higgs, "Visualising space and time in crime patterns: A comparison of methods," *Computers, environment and urban systems*, 2007, *31* (1), 52–75.

Bundervoet, Tom, Philip Verwimp, and Richard Akresh, "Health and Civil War in Rural Burundi," *Journal of Human Resources*, 2009, *44* (2), 536–563.

Buonanno, Paolo, Daniel Montolio, and Josep Maria Raya-Vílchez, "Housing Prices and Crime Perception," *Empirical Economics*, 2013, *45* (1), 305–321.

Burke, Marshall, Solomon M Hsiang, and Edward Miguel, "Climate and conflict," *Annual Review of Economics*, 2015, *7* (1), 577–617.

Camacho, Adriana, "Stress and Birth Weight: Evidence from Terrorist Attacks," *American Economic Review: Papers and Proceedings*, 2008, *98* (2), 511–15.

Chainey, Spencer, Lisa Tompson, and Sebastian Uhlig, "The Utility of Hotspot Mapping for Predicting Spatial Patterns of Crime," *Security Journal*, 2008, *21* (1-2), 4–28.

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

Deininger, Klaus, "Causes and Consequences of Civil Strife: Micro-Level Evidence from Uganda," *Oxford Economic Papers*, 2003, pp. 579–606.

DiNardo, John, Nicole M Fortin, and Thomas Lemieux, "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach," *Econometrica*, September 1996, *64* (5), 1001–1044.

Eaglin, Todd, Isaac Cho, and William Ribarsky, "Space-time kernel density estimation for real-time interactive visual analytics," in "Proceedings of the 50th Hawaii International Conference on System Sciences" 2017.

Eck, Kristine, "In data we trust? A comparison of UCDP GED and ACLED conflict events datasets," *Cooperation and Conflict*, 2012, *47* (1), 124–141.

Fürst, Thomas, Giovanna Raso, Cinthia A Acka, Andres B Tschannen, Eliézer K N'Goran, and Jürg Utzinger, "Dynamics of Socioeconomic Risk Factors for Neglected Tropical Diseases and Malaria in an Armed Conflict," *PLOS Neglected Tropical Diseases*, 2009, *3* (9), e513.

Gerber, Matthew S, "Predicting Crime using Twitter and Kernel Density Estimation," *Decision Support Systems*, 2014, *61*, 115–125.

Gibbons, Steve, "The Costs of Urban Property Crime," *The Economic Journal*, 2004, *114* (499).

Gleditsch, Nils Petter, Peter Wallensteen, Mikael Eriksson, Margareta Sollenberg, and Håvard Strand, "Armed Conflict 1946-2001: A new Dataset," *Journal of Peace Research*, 2002, *39* (5), 615–637.

Harari, Mariaflavia and Eliana La Ferrara, "Conflict, Climate and Cells: A Disaggregated Analysis," Technical Report, Working Paper 2017.

Hastie, Trevor, Robert Tibshirani, and Jerome Friedman, "Unsupervised Learning," in "The Elements of Statistical Learning," Springer, 2009, pp. 485–585.

Hsiang, Solomon M, Marshall Burke, and Edward Miguel, "Quantifying the Influence of Climate on Human Conflict," *Science*, 2013, *341* (6151), 1235367.

Hu, Yujie, Fahui Wang, Cecile Guin, and Haojie Zhu, "A Spatio-Temporal Kernel Density Estimation Framework for Predictive Crime Hotspot Mapping and Evaluation," *Applied Geography*, 2018, *99*, 89–97.

Izenman, Alan Julian, *Modern Multivariate Statistical Techniques: Regression, Classification and Manifold learning*, Springer, 2008.

Kudamatsu, Masayuki, "Has Democratization Reduced Infant Mortality in Sub-Saharan Africa? Evidence from Micro Data," *Journal of the European Economic Association*, 2012, *10* (6), 1294–1317.

_, Torsten Persson, and David Strömberg, "Weather and Infant Mortality in Africa," Technical Report, CEPR Discussion Papers 9222 2012.

Lavy, Victor, Analia Schlosser, and Adi Shany, "Out of Africa: Human Capital Consequences of In Utero Conditions," Working Paper 21894, National Bureau of Economic Research January 2016.

Leon, Gianmarco, "Civil Conflict and Human Capital Accumulation: The Long Term Effects of Political Violence in Perú," *Journal of Human Resources*, 2012, *47* (4), 991–1022.

Lewbel, Arthur, "Estimation of average treatment effects with misclassification," *Econometrica*, 2007, *75* (2), 537–551.

Li, Qi and Jeffrey Scott Racine, *Nonparametric econometrics: theory and practice*, Princeton University Press, 2007.

Maccini, Sharon and Dean Yang, "Under the Weather: Health, Schooling, and Economic Consequences of Early Life Rainfall," *American Economic Review*, 2009, *99* (3), 1006–26.

Maluccio, John A, John Hoddinott, Jere R Behrman, Reynaldo Martorell, Agnes R Quisumbing, and Aryeh D Stein, "The Impact of Improving Nutrition During Early Childhood on Education among Guatemalan Adults," *The Economic Journal*, 2009, *119* (537), 734–763.

Mansour, Hani and Daniel I Rees, "Armed Conflict and Birth Weight: Evidence from the Al-Aqsa Intifada," *Journal of Development Economics*, 2012, *99* (1), 190–199.

Matsuura, K and CJ Willmott, "Terrestrial Air Temperature and Precipitation: 1900–2014 Gridded Time Series (version 4.01)," 2015.

Minoiu, Camelia and Olga N Shemyakina, "Armed conflict, Household Victimization, and Child Health in Côte d'Ivoire," *Journal of Development Economics*, 2014, *108*, 237–255.

_ and Sanjay G Reddy, "Kernel Density Estimation on Grouped data: The Case of Poverty Assessment," *The Journal of Economic Inequality*, 2014, *12* (2), 163–189.

Mueller, Hannes Felix, Lavinia Piemontese, and Augustin Tapsoba, "Recovery from Conflict: Lessons of Success," *World Bank Policy Research Paper*, 2017, (7970).

Nakaya, Tomoki and Keiji Yano, "Visualising crime clusters in a space-time cube: An exploratory data-analysis approach using space-time kernel density estimation and scan statistics," *Transactions in GIS*, 2010, *14* (3), 223–239.

Norwegian Refugee Council/Internal Displacement Monitoring Centre, "Côte d'Ivoire: Internal displacement as of February 2015," 2015. https://www.refworld.org/docid/54f6ce954.html,Last accessed on 2021-05-1.

O'Loughlin, John, Frank DW Witmer, Andrew M Linke, and Nancy Thorwardson, "Peering into the fog of war: The geography of the wikileaks afghanistan war logs, 2004-2009," *Eurasian Geography and Economics*, 2010, *51* (4), 472–495.

Ouili, Idrissa, "Armed Conflicts, Children's Education and Mortality: New Evidence from Ivory Coast," *Journal of Family and Economic Issues*, 2017, *38* (2), 163–183.

Pongou, Roland, "Why Is Infant Mortality Higher in Boys than in Girls? A new Hypothesis Based on Preconception Environment and Evidence from a Large Sample of Twins," *Demography*, 2013, *50* (2), 421–444.

Pope, Jaren C, "Fear of Crime and Housing Prices: Household Reactions to Sex Offender Registries," *Journal of Urban Economics*, 2008, *64* (3), 601–614.

Pullum, Thomas W, *An assessment of age and date reporting in the DHS Surveys, 1985-2003*, Vol. 5, Macro International, 2006.

Quintana-Domeque, Climent and Pedro Ródenas-Serrano, "The hidden costs of terrorism: The effects on health at birth," *Journal of Health Economics*, 2017, *56*, 47–60.

Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joakim Karlsen, "Introducing Acled: An Armed Conflict Location and Event Dataset: Special Data Feature," *Journal of Peace Research*, 2010, *47* (5), 651–660.

Rockmore, Marc, "The Cost of Fear: The Welfare Effect of the Risk of Violence in Northern Uganda," *The World Bank Economic Review*, 2017, *31* (3), 650–669.

Rohner, Dominic, Mathias Thoenig, and Fabrizio Zilibotti, "Seeds of distrust: Conflict in Uganda," *Journal of Economic Growth*, 2013, *18* (3), 217–252.

Sala-i-Martin, Xavier, "The World Distribution of Income (Estimated from Individual Country Distributions)," Technical Report, National Bureau of Economic Research 2002.

_ , "The World Distribution of Income: Falling Poverty and ...Convergence, Period," *The Quarterly Journal of Economics*, 2006, *121* (2), 351–397.

Sany, Joseph, *Education and Conflict in Côte D'Ivoire*, United States Institute of Peace, 2010.

Shemyakina, Olga, "Exploring the Impact of Conflict Exposure during Formative Years on Labour Market Outcomes in Tajikistan," *The Journal of Development Studies*, 2015, *51* (4), 422–446.

Silverman, Bernard W, *Density Estimation for Statistics and Data Analysis*, Vol. 26, CRC press, 1986.

Stein, Zena, Mervyn Susser, Gerhart Saenger, and Francis Marolla, *Famine and Human Development: The Dutch Hunger Winter of 1944-1945.*, Oxford University Press, 1975.

Sundberg, Ralph and Erik Melander, "Introducing the UCDP georeferenced event dataset," *Journal of Peace Research*, 2013, *50* (4), 523–532.

Tapsoba, Augustin, "Measuring Violence Risk in Space and Time using Kernel Density Estimation," Technical Report, Working Paper 2019.

Taylor, Charles C, "Bootstrap Choice of the Smoothing Parameter in Kernel Density Estimation," *Biometrika*, 1989, *76* (4), 705–712.

Terrell, George R and David W Scott, "Variable Kernel Density Estimation," *The Annals of Statistics*, 1992, pp. 1236–1265.

Tonini, Marj, Mário Gonzalez Pereira, Joana Parente, and Carmen Vega Orozco, "Evolution of forest fires in Portugal: from spatio-temporal point events to smoothed density maps," *Natural Hazards*, 2017, *85* (3), 1489–1510.

UNOCHA, "Fighting in Côte d'Ivoire jeopardizes humanitarian aid," https://www.un.org/press/en/2004/afr1061.doc.htm 2004.

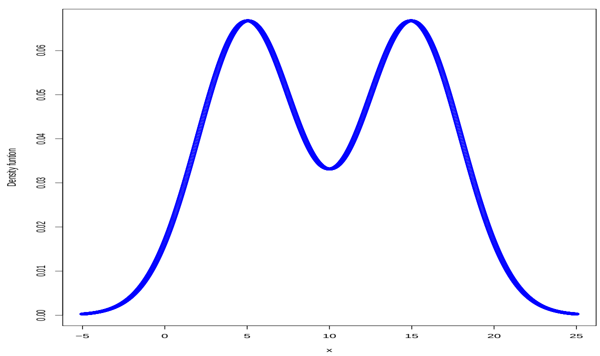
Valente, Christine, "Civil Conflict, Gender-specific Fetal Loss, and Selection: A new Test of the Trivers–Willard hypothesis," *Journal of Health Economics*, 2015, *39*, 31–50.

Walque, Damien De, "Selective Mortality during the Khmer Rouge Period in Cambodia," *Population and Development Review*, 2005, *31* (2), 351–368.

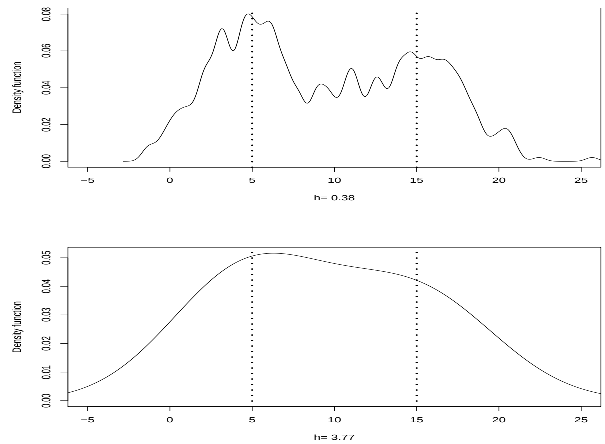
Willard, Kristen L, Timothy W Guinnane, and Harvey S Rosen, "Turning Points in the Civil War: Views from the Greenback Market," *American Economic Review*, September 1996, *86* (4), 1001–1018.

Zussman, Asaf, Noam Zussman, and Morten Ørregaard Nielsen, "Asset Market Perspectives on the Israeli–Palestinian Conflict," *Economica*, 2008, *75* (297), 84–115.

Figure A1: The Role of the Smoothing Parameter



(a) Underlying density



(b) KDE with small and large bandwidth

Appendix

A Estimation of Violence Risk using KDE

A.1 Importance of the Smoothing Parameter in KDE

To illustrate the importance of the smoothing parameter h in KDE, I draw 500 data points from a bi-modal distribution given by a mixture of 2 normal distributions with means 5 and 15 and a standard deviation of 3. The underlying distribution is shown in panel (a) of Figure A1. Panel (b) shows the estimated density with a small and large smoothing parameter h. The first graph still shows some spurious variations from the data, while the second one over-smooths the distribution to the extent of almost not reflecting its bi-modal nature.

A.2 Bootstrap Estimation of Smoothing Parameters

The idea of using bootstrap resampling to choose a smoothing bandwidth has been introduced by (Taylor, 1989). The bootstrap approach is used in conjunction with the $MISE(h)$ as a target criterion. The basic idea is to construct a "reference" density estimate of the data at hand, repeatedly simulate data from that reference density, and calculate the empirical integrated squared error at each iteration, doing so at different bandwidths. The bandwidth that minimizes the bootstrap-estimated MISE is taken as the optimal value.

- Select a pilot bandwidth g and compute estimator $\hat{f}_g$ of f

- Draw bootstrap samples X_1^*, ..., X_J^* from $\hat{f}_g$

- Compute the bootstrap version of the $MISE$ and minimize it over h:

$$J^{-1}\sum_{j=1}^{J}\int[\hat{f}_h(y|X_j^*) - f_g(y|X)]^2 dy$$

- Set new pilot bandwidth to the value h_0 that minimizes the $MISE$ and iterate until it converges

A.3 Parametrization of Smoothing Parameters in H

Given the relatively small number of realizations of the violence process in Ivory Coast and Uganda compared to the estimation space (entire country for over 10 years), I parametrize H in the most simplistic way possible. I only consider one smoothing parameter h_s for both latitude and longitude and another smoothing parameter h_t for time.

In multivariate kernel density estimation, the parametrization of the matrix of smoothing parameters H is crucial. Diagonal elements correspond to the smoothing parameter with respect to each dimension, and off-diagonal elements capture the trajectory of the process. The violence process could spread more on one dimension (latitude) rather than the other (longitude). Setting off-diagonal parameters to zero implies that the process spreads in symmetric way along both axis.

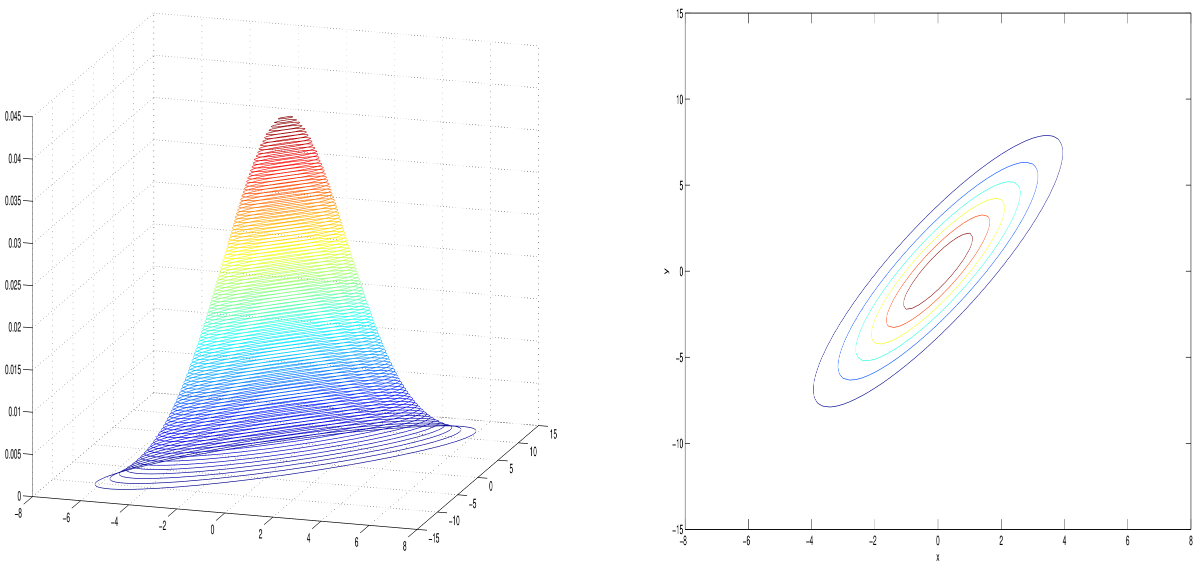
In theory, the trajectory/symmetry of the violence process in space can also play an important role. To illustrate that, let's ignore the time dimension and consider a 2-dimensional violence process that follows a bivariate normal distribution.

$$\begin{pmatrix} x \\ y \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 4 & 7 \\ 7 & 16 \end{pmatrix}\right]$$

Figure A2 shows the contour plots of the underlying density. I draw sample N=200 from this distribution and compare the performance of kernel density estimation when allowing for a full parametrization of matrix H or not.

Figure A3 shows that allowing for a full parametrization of H fits better the true density compared to the restricted parametrization. It also implies that everything else equal, locations that are on the trajectory of the violence process will have a higher density estimate.

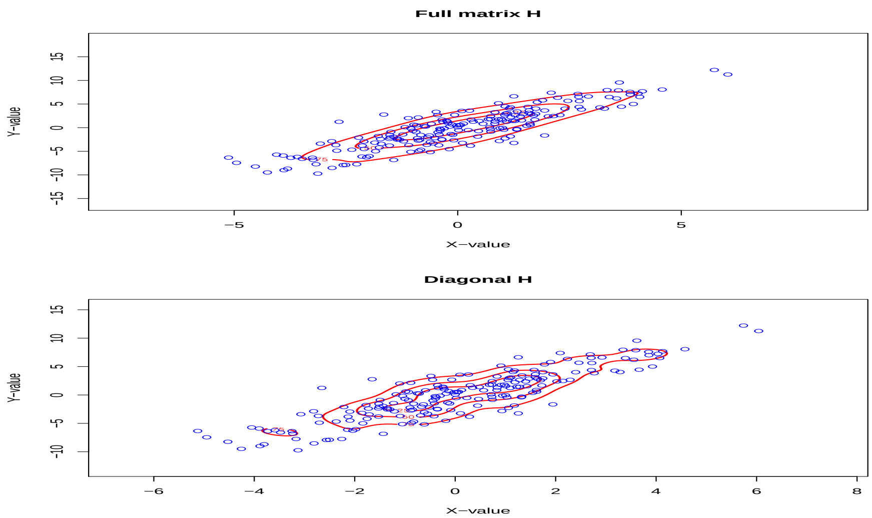
Figure A2: Density Contour Plot of Bivariate Normal Distribution



B 2-Stage Bootstrap of Estimated Impact of Violence Risk on Child Health

To check whether there is any substantial bias from using the risk measure as a generated regressor in Equation (3), a two-step bootstrapping algorithm is used to compute the estimates and standard errors for the main results. The bootstrap estimates are constructed in the following manner. A random sample with replacement is drawn from the conflict event dataset. This sample is used to estimate a new value for the optimal smoothing parameter in order to compute the risk measure for all space-time locations in each country.

Figure A3: Contour Plot KDE with Full and Diagonal Matrix H



The second stage regression (Equation (3)) is then estimated on a random sample drawn with replacement from the initial sample of children in the household survey, and the OLS coefficients are stored. To allow for dependence among children born in the same location, the bootstrap sampling in the second stage is clustered at PRIO-GRID cell level.[42] This process of two-step bootstrap sampling and least-squares estimation is repeated 1,000 times. If there is no substantial generated regressor bias in the simple OLS estimation of Equation (3), the average bootstrap coefficients should be close to the OLS estimates. The standard deviations of these 1,000 bootstrap coefficients represent the bootstrap standard errors of the point estimate.

Table A1 shows the distribution of the 1,000 bootstrap estimates of the smoothing parameters and the main coefficient of interest, γ, in Column (3) of Tables 3 and 4. The average of these estimates is very close to the original values for both countries. This suggests that the first stage generated regressor bias (for the estimation of γs) is not particularly important in this setting. Moreover, the t-stats computed using the standard deviation of the bootstrap estimates as standard errors show that the estimated coefficients remain significant at 5 percent level in both cases.

[42]This means in practice sampling with replacement PRIO-GRID cells. All the children in a sampled cell will be in the bootstrap sample.

Table A1: 2-Stage Bootstrap Estimation

Ivory Coast

Variable	Obs	Mean	Std.Dev.	Min	Max	Initial value	T-stat
Spatial smoothing parameter h_s (km)	1000	34.43	.875	32.266	37.433	34.275	
Temporal smoothing parameter h_t (days)	1000	493.176	58.374	247.488	617.596	508.856	
Estimated coefficient: Table 3 Column (3)	1000	.01	.003	.001	.019	0.01	3.333

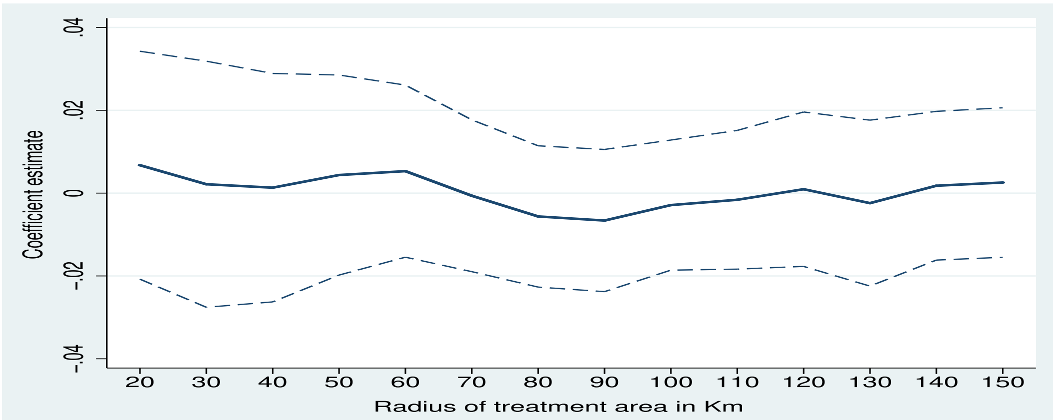
Uganda

Variable	Obs	Mean	Std.Dev.	Min	Max	Initial value	T-stat
Spatial smoothing parameter h_s (km)	1000	22.529	.877	19.835	25.941	22.802	
Temporal smoothing parameter h_t (days)	1000	326.17	8.131	300.368	354.177	329.302	
Estimated coefficient: Table 4 Column (3)	1000	.008	.004	-.004	.021	0.08	1.994

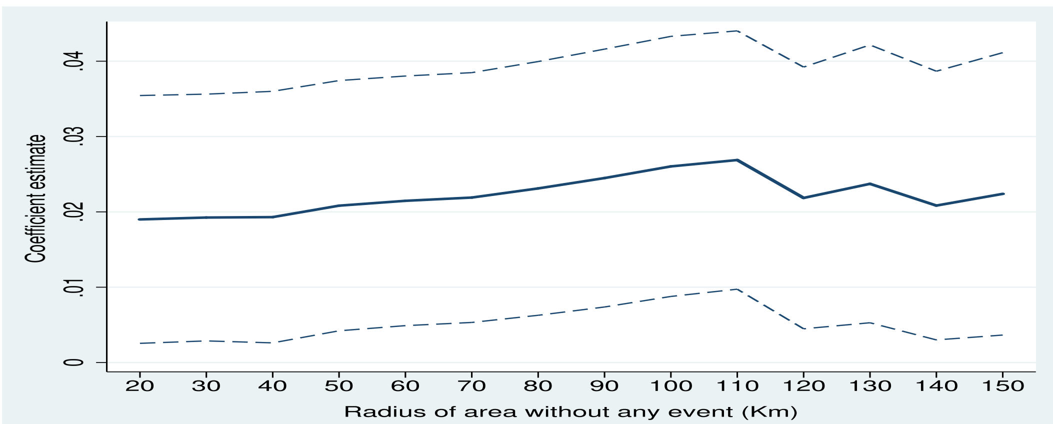
Spatial and temporal smoothing parameters correspond to the distribution of 1000 draws of conflict events with replacement that are used to compute the distribution of the estimated density. These estimated density values are then used in the second stage regression to compute the distribution of the estimated impact of violence risk on child health. Column "Initial value" represents the original estimation value for each parameter, and "T-stat" is obtained by dividing the initial coefficient $\hat{\gamma}$ by the standard deviation of the 1000 $\hat{\gamma}$ draws.

C Other Tables and Graphs

Figure A4: (a) Impact of Conflict on Infant Mortality using Observed Violence. (b) Impact of Violence Risk on Infant Mortality using Sub-sample of Children with no Event Within r km



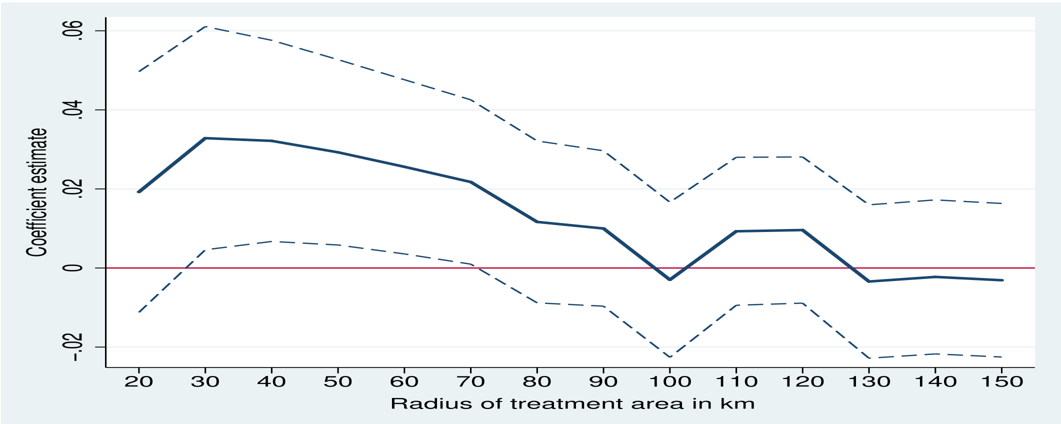
(a)



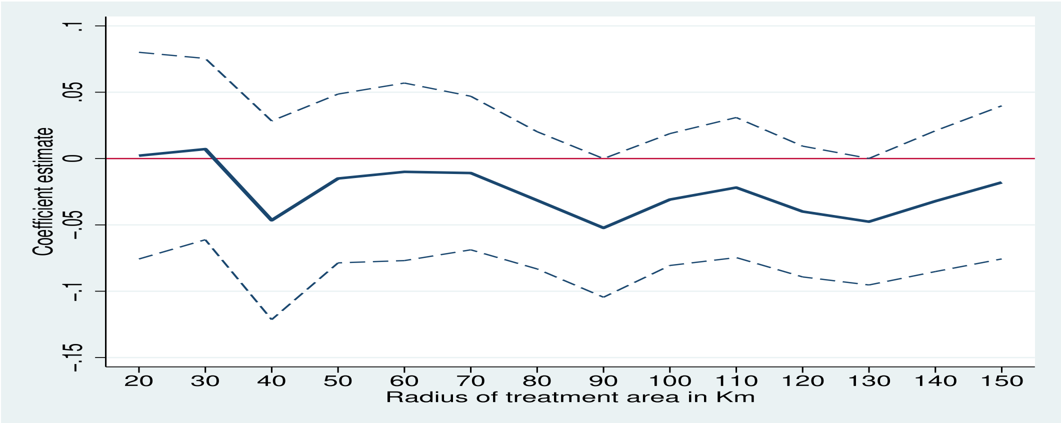
(b)

Notes: Estimated impact of conflict on infant mortality in Uganda using the main specification in equation (1). In panel (a), the $conflict$ variable is defined as a dummy equal 1 if there was at least one event that has happened within a certain radius r from the place of birth of each child (in utero or during the first year of life). In panel (b), the sample used for each regression is restricted to observations with no event happening within a certain radius r from the place of birth (in utero or during the first year of life). The variable of interest is a dummy equal 1 if the risk of exposure to violence is high (belongs to the second quartile or higher). A new regression is run for each tick in the X-axis, and the γ coefficients together with 95% confidence bands are plotted and interpolated to give the continuous lines. Robust standard errors are clustered at 50 $\times$ 50 km PRIO-GRID cell level.

Figure A5: Impact of Conflict on Infant Mortality using Violence Incidence in Mother Fixed Effect Specification.



(a) Ivory Coast



(b) Uganda

Notes: Estimated impact of conflict on infant mortality using the main specification in Equation (3). The $conflict$ variable is defined as a dummy equal 1 if at least one event happened within a certain radius r from the place of birth of each child (in utero or during the first year of life). A new regression is run for each tick in the X-axis, and the γ coefficients together with 95% confidence bands are plotted and interpolated to give the continuous lines. Robust standard errors are clustered at 50 $\times$ 50 km PRIO-GRID cell level.

Table A2: Endogenous Fertility: Characteristics of Households Having a Child Exposed to High Risk of Violence

Ivory Coast

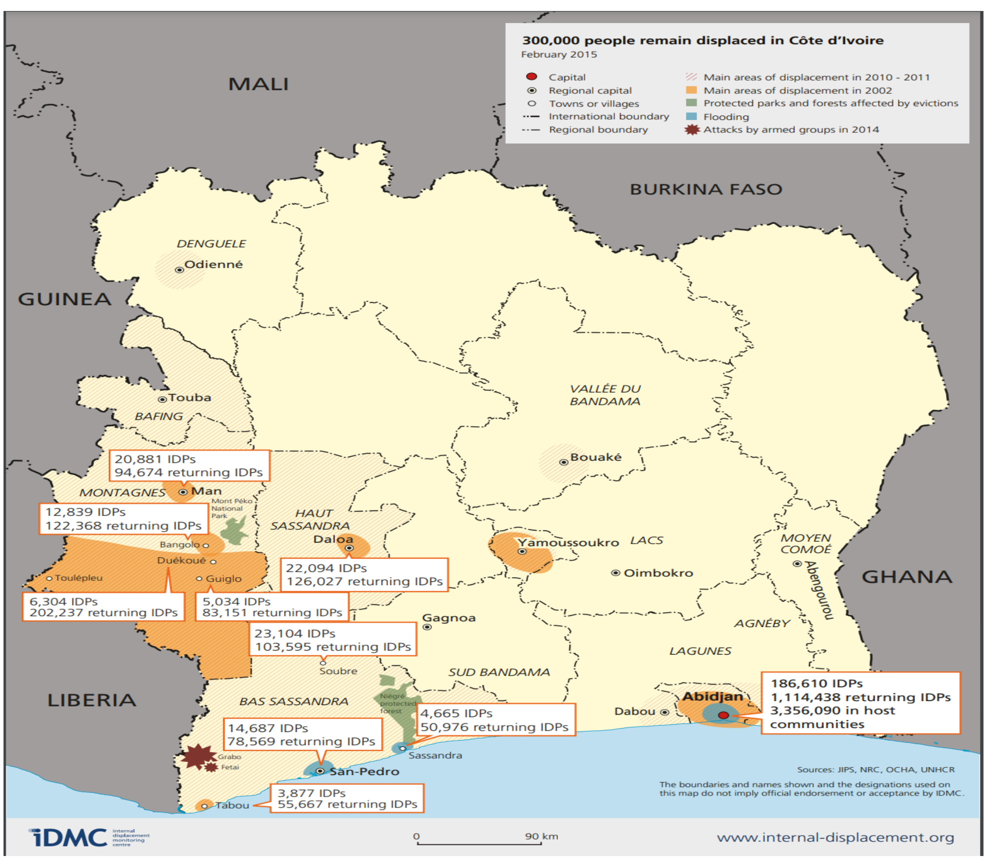
VARIABLES	(1) years of education	(2) Height (cm)	(3) Age at first birth	(4) Number of children	(5) Wealth Index	(6) Age HH head
Has a child exposed to high risk of violence	-0.053 (0.302)	0.793 (0.836)	0.479 (0.373)	0.078 (0.280)	0.030 (0.074)	-0.145 (1.185)
Observations	2,658	2,658	2,658	2,658	2,658	2,658
R-squared	0.319	0.175	0.171	0.206	0.782	0.228
Location FE	YES	YES	YES	YES	YES	YES

Uganda

VARIABLES	(1) years of education	(2) Height (cm)	(3) Age at first birth	(4) Number of children	(5) Wealth Index	(6) Age HH head
Has a child exposed to high risk of violence	-0.175 (0.262)	0.523 (0.575)	0.145 (0.260)	0.824*** (0.222)	0.030 (0.085)	-0.133 (0.944)
Observations	3,962	3,962	3,962	3,962	3,962	3,962
R-squared	0.566	0.417	0.427	0.373	0.717	0.361
Location FE	YES	YES	YES	YES	YES	YES

The first four columns correspond to mother characteristics. Robust standard errors in parentheses are clustered at 50 × 50 km PRIO-GRID cell level.

Figure A7: Areas of Internal Displacement due to Conflict in Ivory Coast



Source: Norwegian Refugee Council/Internal Displacement Monitoring Centre (NRC/IDMC), Internal displacement as of February 2015 in Ivory Coast

Table A3: Descriptive Statistics of Main Variables

Household Level

	Ivory Coast					**Uganda**				
Variable	Obs	Mean	Std.Dev.	Min	Max	Obs	Mean	Std.Dev.	Min	Max
years of education	2658	2.03	3.413	0	17	3962	5.291	3.91	0	20
No education	2658	.667	.471	0	1	3962	.157	.364	0	1
Height (cm)	2658	158.808	6.755	80	181.3	3962	159.059	6.76	82.5	194.6
Age at first birth	2658	18.555	3.608	12	39	3962	18.62	3.143	10	36
Number of children	2658	4.17	2.529	1	14	3962	4.275	2.648	1	14
Wealth Index	2658	2.749	1.376	1	5	3962	2.85	1.442	1	5
Poor	2658	.475	.499	0	1	3962	.446	.497	0	1
Age HH head	2658	45.585	13.725	17	92	3962	37.389	12.275	17	93
Rural	2658	.637	.481	0	1	3962	.822	.383	0	1
Has a child exposed to high risk of violence	2658	.82	.384	0	1	3962	.775	.418	0	1

Child Level

	Ivory Coast					**Uganda**				
Infant mortality	4944	.072	.258	0	1	4868	.044	.205	0	1
Exposed to a conflict event within 50 km	4944	.362	.481	0	1	4868	.142	.349	0	1
Violence risk	4944	21.909	130.897	0	1697.405	4868	3.029	16.438	0	229.451
BW<2.5 Kg						2673	.096	.295	0	1
Q1 Prenatal care						4868	.158	.365	0	1
home_delivery						4807	.38	.486	0	1
C section						2964	.089	.285	0	1
Duration Amenorrhea						4838	8.163	6.892	0	57

Figure A6: Partition of Ivory Coast During Conflict

Table A4: Impact of Violence Risk on Child Health: Robustness Uganda

	Infant Mortality					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Standardized violence risk	0.008**	0.010**	0.007*			
	(0.004)	(0.004)	(0.004)			
Risk with space-time restriction				0.007*		
				(0.004)		
Risk with fixed bandwidth					0.007**	
					(0.004)	
Risk with past and future events						0.009**
						(0.004)
Observations	4,863	4,868	4,868	4,868	4,868	4,868
R-squared	0.161	0.318	0.181	0.160	0.160	0.161
Cohort FE	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES
Region specific time trend	YES	NO	NO	NO	NO	NO
Family characteristics	YES		YES	YES	YES	YES
Child characteristics	YES	YES	YES	YES	YES	YES
Number of family		3,962				
Family FE	NO	YES	NO	NO	NO	NO

The full set of controls includes the mother's height, education, gender and age of household head, household wealth index, 12 months of rainfalls (for each of the two years preceding the birth of the child and during her first year of life), birth order, the time gap between conception and the previous and following pregnancies. Robust standard errors in parentheses are clustered at 50 × 50 km PRIO-GRID cell level.

Table A5: Impact of Violence Risk on Child Health: Robustness ACLED Dataset

	ACLED Ivory Coast			ACLED Uganda		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Standardized violence risk	0.007**	0.008***		0.007**	0.008**	
	(0.003)	(0.003)		(0.004)	(0.004)	
Q2 violence risk			0.004			0.005
			(0.018)			(0.012)
Q3 violence risk			0.019			0.012
			(0.023)			(0.013)
Q4 violence risk			0.021			0.034*
			(0.035)			(0.018)
Observations	4,944	4,944	3400	4,868	4,868	2,449
R-squared	0.190	0.192	0.208	0.160	0.161	0.221
Cohort FE	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES
Family characteristics	YES	YES	YES	YES	YES	YES
Child characteristics	YES	YES	YES	YES	YES	YES

The full set of controls includes the mother's height, education, gender and age of household head, household wealth index, 12 months of rainfalls (for each of the two years preceding the birth of the child and during her first year of life), birth order, the time gap between conception and the previous and following pregnancies. Robust standard errors in parentheses are clustered at 50 × 50 km PRIO-GRID cell level.

Table A6: Robustness Ivory Coast: Migration

	All sample	Low migration	High migration
VARIABLES	(1)	(2)	(3)
Standardized violence risk	0.056**	0.061**	0.044
	(0.025)	(0.028)	(0.038)
Standardized violence risk × high migration	0.003		
	(0.031)		
Observations	4,944	2,638	2,306
R-squared	0.186	0.236	0.214
Cohort FE	YES	YES	YES
Location FE	YES	YES	YES
Family characteristics	YES	YES	YES
Child characteristics	YES	YES	YES

High displacement areas correspond to the main areas of displacement around 2002 and 2010 based on data from IDMC(see figure A7). The full set of controls includes the mother's height, education, gender and age of household head, household wealth index, 12 months of rainfalls (for each of the two years preceding the birth of the child and during her first year of life), birth order, the time gap between conception and the previous/following pregnancies. Robust standard errors in parentheses are clustered at 50 × 50 km PRIO-GRID cell level. Column (1) uses the entire sample. Columns (2) and (3) split the sample between high and low displacement areas due to the conflict.