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

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Abstract: The impact of violence on child health has long-lasting consequences that increase the overall cost of conflict. Beyond the damage caused to direct victims of violence, behavioral responses to insecurity can lead to major health setbacks for young children. The fear of ex- posure to conflict events often triggers such responses even before/without any manifestation of violence in a given area. This generates a treatment status (exposure to conflict risk) that goes beyond violence incidence. In this paper, I develop new metrics that capture perceived insecurity at the local level through a statistical model of violence in order to investigate the impact of conflict on child health. Violence is modeled as a space-time process with an unknown underlying distribution that drives the expectations of agents on the ground. Each observed event is interpreted as a random realization of this process, and its underlying dis- tribution is estimated using adaptive kernel density estimation methods. The new measure of violence risk is then used to document the effects of conflicts in Ivory Coast and Uganda on child health. 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 the risk does not materialize in violent events around them.

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

JEL Codes: C1, O12, J13, I12

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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 the nature of the recovery process. The early years of life are indeed crucial in influencing a range of health and social outcomes across the lifecourse. 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 the next generations in conflict-prone environments.

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 react to violence risk with displacements or changes in consumption/production behavior that can lead to disruptions in supply and demand of goods and services. They sometimes engage in such risk coping behavior before/without any manifestation of violence in a given area 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 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) which is unobserved but crucial for the short and long-term effects of conflict. It develops new metrics that capture perceived violence risk at the local level through a statistical model of violence in order to investigate the impact of conflict on child health. In this model, violence is a space-time process with two characteristics. First, the occurrence of an event increases the likelihood that another event occurs in the same area. Second, violence can spread through the local environment via contagion.[2] This process has an unknown distribution that, by assumption, drives the expectations of agents on the ground. The density of this distribution is backed out of the observed pattern of violent events across space and over time.

[1] The Internal Displacement Monitoring Centre estimated, for instance, that 2.7 million people were newly displaced in Africa during the first six months of 2017, and three-quarters of those were allegedly due to conflict.

[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. For 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.

In order to estimate this density, a locally adaptive kernel method is implemented on the observed sample of violent events.[3] 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 location is obtained by averaging all the contributions.

This new measure of violence risk is then used to document the impact of conflicts in Ivory Coast and Uganda on child health.[4] 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 Ivory Coast and Uganda, in a Difference-in-Differences setting. The distribution of events in space and time generates space-time windows with high risk of violence but no violent events and windows with isolated events but low risk of violence.

My main finding is that violence risk significantly increases infant mortality even when the risk does not materialize in actual violence: 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 had no violent incident happening around their area of birth. The empirical evidence in Uganda also suggests that quality/availability of health care services, malnutrition and maternal stress are important transmission channels for this effect.

The baseline regressions control for household head, mother and child characteristics, weather shocks, enumeration area, and birth cohort fixed effects. The estimates are robust to many

[3]The observed events are interpreted as a sample of random realizations of the underlying violence process. The density estimation approach tries to estimate its unknown density based on the location of observed events in space and time. It is conceptually the opposite of drawing a sample from a given distribution.

[4]Ivory Coast has experienced a relatively low-intensity but highly disruptive conflict between 2002 and 2011. Uganda experienced an exogenous outburst of violence between 2002 and 2005 that put an end to a long-lasting ethnic conflict.

different specifications and sample restrictions, including a very demanding one that controls for mother fixed effects. Placebo tests confirm that results are not driven by preexisting trend differences between high and low risk areas.

The evidence documented above suggests that conflict is a local public bad and being exposed to 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 agents engage in detrimental ex-ante coping strategies that lead to disruptions in local economic activity and provision of goods and services.

The policy implications of this paper can be categorized in three groups. First, it shows that armed conflicts have substantial detrimental effects on an even larger share of population than we thought. We should, therefore, focus more on preventing them in order to avoid the huge humanitarian and economic cost that will arise if violence breaks out. Second, during conflict, governments and non-governmental organizations should address fears/expectations of economic agents and prevent disruptions in supply and demand of goods and services in order to minimize the cost of ongoing threats. For instance, the mandates of peace keeping missions could be extended to address expectations on the ground and governments could be encouraged to have a visible presence and control prices in conflict prone areas in order to send appeasing signals to economic agents whenever possible. Providing safe and decent living conditions to refugees and internally displaced populations will also help to minimize the overall cost of conflict. 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 atrocities.

This paper contributes to three main strands of economics literature. First, it contributes to the previously discussed 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 looked at the effects of conflict on child health. It has established that exposure to conflict leads to worse birth outcomes (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

[5]Part of this result could also be coming from measurement errors in the conflict event data since this issue is also partly addressed by the estimation of the underlying density of the data generating process.

rely on the incidence of violent events to proxy exposure to the adverse effects of conflict.[6] They were, therefore, unable to account for any of the cost induced by behavioral responses to risk in absence of immediate violence. Counting the number of events that happen in a given space-time window as a measure of conflict risk implies that violence risk is high only for windows in which we already observe violent events. In other words, violence is perceived to be likely to happen only where it has already happened. 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 risk perceived by the agents on the ground. The new approach proposed in this paper is more general and fixes these limitations by trying to capture violence risk beyond the incidence of conflict events. It uses the pattern of these events across space and over time to estimate the underlying distribution of the process that generated them. This is also the first paper to provide evidence suggesting that children exposed to high risk of violence suffer major health setbacks even when this risk does not materialize in actual violence around them.

Second, this paper also contributes to a small but growing literature that tries to evaluate the consequences of insecurity beyond the incidence of violent events in conflict and crime literature. In the conflict literature, Rockmore (2017) shows that subjective risk (perceptions of survey respondents on difficulties to cultivate land due to insecurity) has a higher impact than violence incidence (actual attacks against a community) on household consumption in Northen Uganda. In fact, he finds that half of welfare losses caused by conflict are related to risk and not to direct exposure to violence. Arias et al. (2014) investigate the changes in household production behavior and show that conflict affects land use and agricultural investment beyond violence incidence. Using data from Columbia, 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 to insecurity. 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 papers have only looked at changes in household consumption or production behavior (Rockmore, 2017; Arias et al., 2014; Bozzoli and Brück, 2009; Deininger, 2003).

[6]The standard approach in the literature is to count the number of events or fatalities within a given space-time window. Papers that link conflict to other outcomes also use this approach (Ouili, 2017; Shemyakina, 2015; Leon, 2012; Akresh et al., 2012a; De Walque, 2005).

The idea that risk perception goes beyond incidence has also been addressed in the crime literature. The fear of crime has been shown to affect housing prices even in 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 perceived risk of crime on the ground is however, to the best of my knowledge, new to this literature. One can study the consequences of behavioral responses to a specific type of criminal events beyond their incidence following the methodology proposed in this paper.

The third strand of literature related to my work looks at the role of expectations in conflict prone environments. At 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.[7] 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 an increase of 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 local level. The current paper contributes to this literature by showing that conflict can also affect child health and long term economic development at local level through expectations.

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

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

2 Historical Background and Data

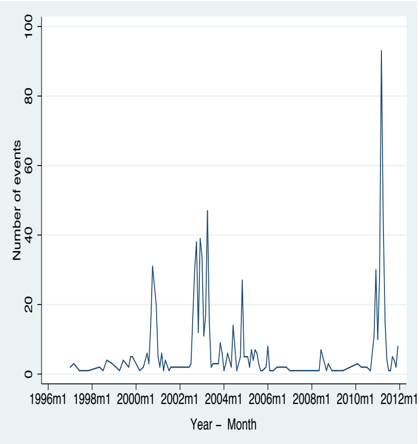
2.1 Conflict in Ivory Coast

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

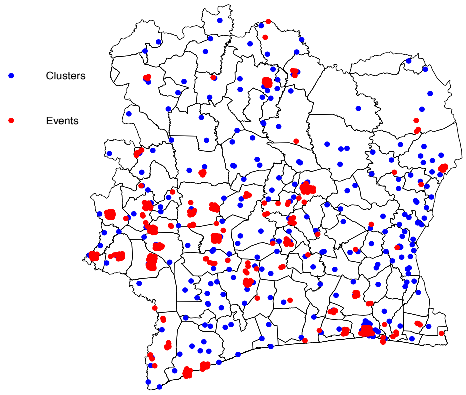
In July 1999, Alassane Ouattara, left his job at the International Monetary Fund and returned to run for the 2000 presidential elections. His plan to challenge Bedie again splits the country along ethnic and religious lines based on their own origins which determined their electoral basis. This political 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 Alasane Ouattara was still excluded from the electoral process because of not being "Ivorian enough". General Guei proclaimed himself president after announcing he had won the presidential elections, but 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 Alasane Ouattara, who were 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 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 A1 but intense battles between the two sides took place until March 2003 when the first peace agreement was signed and rebels made their entry into the government. Many other peace talks were held as actors were resuming clashes at one point or another during the implementations of the different peace agreements. 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 and the new government was put in charge of preparing the elections that would end the crisis and restore a stable constitutional order. The elections after being postponed twice were

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



(a) Monthly Number of Events



(b) Spatial Distribution of Events and Household Clusters

finally held in December 2010 but led to another crisis. The electoral commission declared Mr Ouattara the winner of 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 Gbagbo in April 2011 after the loyalist army has been defeated by the rebels backed by French troops under UN mandate.

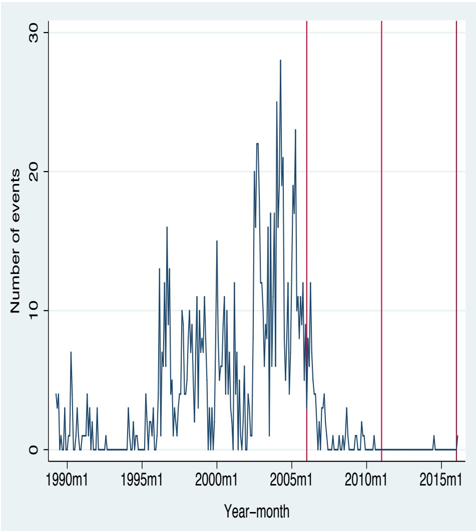
Figure 1a shows the number of recorded events per month across the whole country. We can see that the recorded events are consistent with the timing described in the preceding paragraphs with some violence peaks after the 2000 elections, during the first months following the start of the first civil 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 clustered along the French peace line and in the main cities in the south and the south-west. During the second civil war, rebel troops moved from their bases behind the peace line towards the capital and the recorded events also follow this pattern.

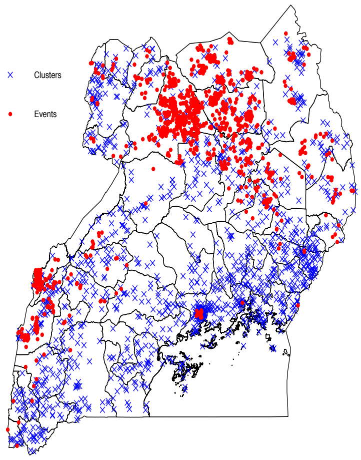
2.2 Conflict in Uganga

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

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



(a) Monthly Number of Events



(b) Spatial Distribution of Events and Household Clusters

Notes: Red bars in figure (a) are DHS household survey years in Uganda.

constituency is the Bantu-dominated South. His government has faced opposition and armed rebellion in several parts of the country, especially 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 attack, 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 has been 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 on September 2006, with the mediation of the autonomous government of South Sudan.

Figure 2a shows the monthly number of geo-referenced fighting events conflict between 1988 and 2016 from GED data. 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.

2.3 Violence and Infant Mortality in Ivory Coast and Uganda

The conflict in both Ivory Coast and Uganda had bad consequences on a wide range of outcomes. Economic activity for instance has been significantly affected. Both countries experienced a prolonged period of negative GDP growth during years of intense violence. Another crucial indicator that has suffered from conflict in both countries is infant mortality rate. This indicator, often used as proxy for the quality of health services in a given country, has gotten worse in Ivory Coast during the first civil war (2002-2007). It has improved substantially after violence ended in Uganda following the government crack down on rebel groups between 2002 and 2005 (see Figure 3). Beyond this apparent deterioration of health system during conflict, the aim of this is to provide causal evidence of the impact of behavioral response to violence risk on infant mortality.

The anecdotal evidence suggest 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). 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 actual manifestation of violence. This is what the current paper is trying to capture.

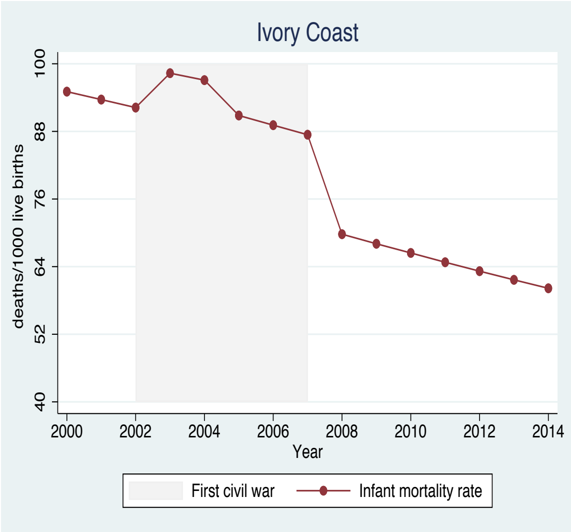
2.4 Data sources

To locate violence in space and time, I use information from conflict event datasets (ACLED and GED) on the exact dates and locations of violent incidents during the conflict, including armed battles, and violence against civilians.[8]

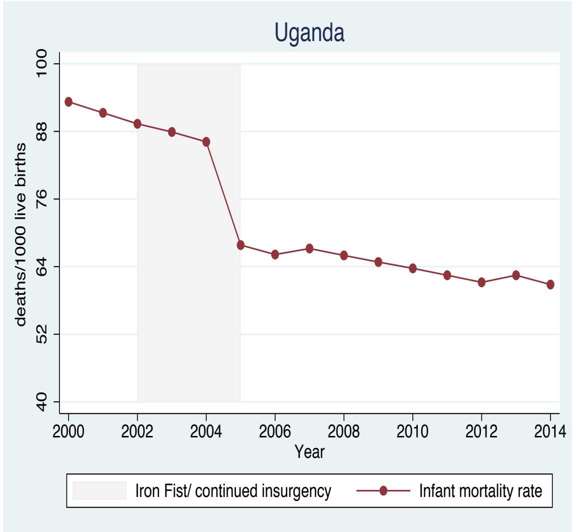
To assess the impact of exposure to violence risk on child health, I use Demographic and Health Survey (DHS) data collected in 2011-2012 in Ivory and 2006, 2011 and 2016 in Uganda.

[8] I exclude riots and protests from the conflict data and I keep all the events recorded with geographical precision at city level or lower. Duplicates (same location and time) are eliminated to have a count of the number of days with at least 1 event for a given location.

Figure 3: Conflict and Infant Mortality



(a) Ivory Coast



(b) Uganda

Source: CIA World Factbook

DHS surveys are a set of repeated cross-sectional surveys run in most developing countries since 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 exclusively at the survival of single born female children.[9] I also use information on use of child health services and maternal health during pregnancies that happened at most 5 years prior to a DHS interview 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 risk of confounding factors. Climate data comes from Terrestrial air temperature and precipitation: 1900–2014 gridded time series (Matsuura and Willmott, 2015). This dataset is

[9]Multiple birth babies face significantly higher chances of dying before turning one year old. Male fetuses are biologically more fragile compared to female ones and this leads to a higher selection in the sample of born males in presence of shocks around pregnancy period (Dagnelie et al., 2018; Pongou, 2013).

a compilation of updated sources and provides monthly precipitation (and mean temperature) interpolated to a latitude/longitude grid of 0.5 degree by 0.5 degree. Following Kudamatsu et al. (2012), I compute average rainfall and temperature for the last two years before birth and for the first year of life and include them separately in regressions to control for variations in maternal food supply induced by climate shocks.

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

In order to capture behavioral responses to violence risk, we need a way to quantify risk perceptions at the local level. To do this, I model the observed conflict events as random realizations of an underlying process which is observed by individuals on the ground but has to be backed out of the violence data. In this section, I show how non-parametric density estimation methods can be used to capture variations in violence risk at local level and describe beliefs on the ground.

Non-parametric density estimation methods have been initially used in the literature to assess basic characteristics of an unknown distribution such as skewness, tail behavior, number, location and shape of modes (Silverman, 1986). Nowadays, they play a major role in machine learning, classification and clustering.[10] They are popular methods in crime literature for hotspot mapping and in seismology literature for seismic hazard estimation. They can also be used (like in this paper) as input for more sophisticated analysis. DiNardo et al. (1996) used kernel density estimation method to build counter-factual densities in order 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).

[10]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).

3.1 Principle of Kernel Density Estimation (KDE)

3.1.1 A "Simple" Density Estimation

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

Let's begin with the simple case of a continuous, univariate random variable X.[11] Let $F(x)$ denote the cumulative distribution function of X. From the definition of the density, we know that

$$f(x) = \frac{d}{dx}F(x) = \lim_{h \to 0} \frac{F(x + \frac{h}{2}) - F(x - \frac{h}{2})}{h},$$

where h is the width of the interval. The simplest estimator would be to count the number of observations around the point x and divide that number by nh. The resulting estimator can be formally written as

$$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h}\mathbb{1}\Big(-\frac{1}{2} < \frac{x_i - x}{h} < \frac{1}{2}\Big),$$

where $\mathbb{1}(A)$ takes the value 1 if the argument A is true and 0 otherwise.[12] The indicator function can be replaced with the more general notation of a kernel function $k(*)$ and the estimator is now given as

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

The previous equation shows that each observed event, x_i, has a given contribution to the density estimate at x. This contribution is only a function of its distance to x. All the points falling within an interval h around x will contribute equally $(1/nh)$ to the density and all the other points will have zero contribution. The density $f(x)$ is just the sum of all the contributions.

Moreover, this "simple" density estimator is equivalent to counting the number of events that occurred during a given time period within a certain distance from x which is similar to the way the current literature measures exposure to conflict. Conflict affected areas are areas with

[11] To estimate violence risk across space and time, an extension to 3 dimensions (latitude, longitude and time) is shown below.

[12] This is the common histogram.

high density while non-affected areas are those with low or zero density. The parameter h is "handpicked" (administrative areas, cells of a given size or rings of a given radius around x), and all the observations falling within a distance h from x contribute equally to the measure of conflict exposure.

However, this approach has the following limitations:

- The distance from location x to a given conflict event is not fully incorporated into this "simple" density estimate since all events falling within a certain distance have equal contributions. One would like events that are closer to x in space or time to have higher contributions to the density, everything else equal.

- Beyond distance, the dispersion of conflict events should also affect the density. More dispersion in observed violent events should lead to a higher risk everywhere as opposed to very clustered events where the high risk is very localized.

- The trajectory/orientation of the conflict process in space could also matter for the underlying density: At equal distance and dispersion, people living on the trajectory of the violence process will be more threatened as compared to those that are off the trajectory, exactly like the case of cyclones.

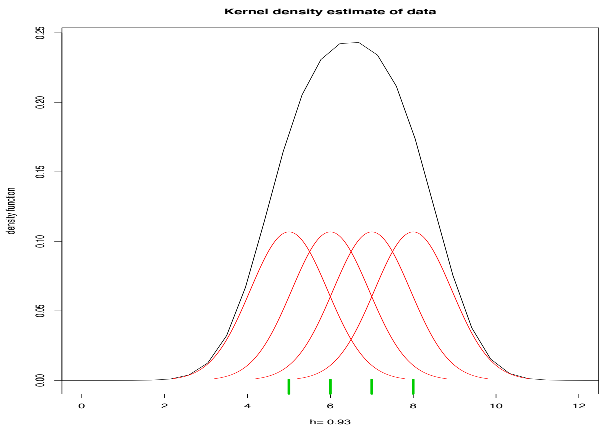
The rest of this section will show how the "simple" density estimation approach can be generalized to overcome these limitations.

3.1.2 Standard Kernel Density Estimation

A more sophisticated estimator of the underlying density can be obtained by replacing the indicator function with a smooth kernel function. The Gaussian functional form is a standard choice in the economics literature.[13] In this case, a Gaussian function $k \sim \mathcal{N}(0, h)$ is placed over each data point to measure its contribution to the density for all the locations around. The value of the kernel function is highest at the location of the data point, and diminishes at an exponential rate as we move away from it. The density estimate at x is obtained by summing up all the contributions. Closer events have higher contributions to the density and clustered events generate peaks corresponding to the modes of the underlying density function as shown in Figure 4.

[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 estimated density function that has derivatives of all orders (Silverman, 1986).

Figure 4: Aggregation of individual kernels in KDE



Notes: Kernel density estimation with 4 data points (in green). The Red Gaussian functions are individual kernels aggregated to get the density estimate in black.

Importance of 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 Section A for an illustration).

The choice of the smoothing parameter

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

$$\begin{aligned} MISE(h) &= \int [\hat{f}(x,h) - f(x)]^2 dx \\ &= \int \hat{f}(x,h)^2 dx - 2\int \hat{f}(x,h) f(x) dx + \int f(x)^2 dx, \end{aligned}$$

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

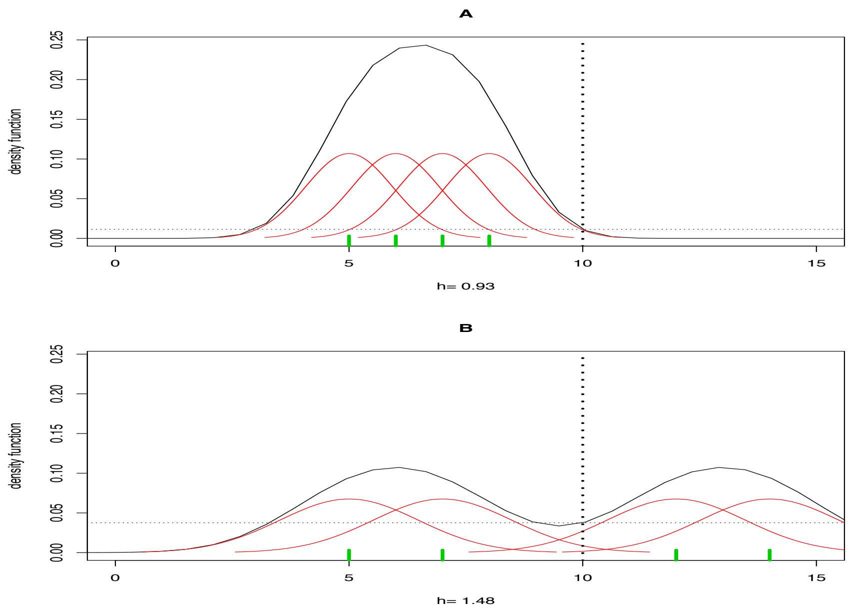
$MISE(h)$ can be evaluated and minimized without knowing explicitly $f(x)$ by using a bootstrap method (Taylor, 1989) as described in Section B of the appendix.

The dispersion of the observed sample of events is a feature of the underlying density, so minimising the $MISE(h)$ leads to a larger optimal h for samples with more dispersion. The smoothing parameter is indeed an increasing function of the sample variance.[14] This is illustrated

[14] In the particular case of the underlying pdf being normally distributed, one can show that h_{opt} is actually

in Figure 5 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 location x should be more at risk in B than A. The kernel density estimation is able to distinguish these two cases when estimating them as two separate processes.

Figure 5: Fixed KDE and Sample Variance in Separate Processes



3.2 Adaptive KDE

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

This method combines features of kernel density estimation and nearest neighbour 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.

proportional to sample variance Silverman (1986)

An observation in a low intensity area will therefore have its mass spread out over a wider 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 $\tilde{f}(x) = \frac{1}{nh_p}\sum_{i=1}^{n} k\Big(\frac{x-x_i}{h_p}\Big)$, 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 $\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n}\Big(\frac{1}{h\lambda_i}k(\frac{x-x_i}{h\lambda_i})\Big)$

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 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 fixed bandwidth method while $\alpha = 1$ coincides with the nearest method approach. $\alpha = 1/2$ is the standard choice in the statistics literature (see Terrell and Scott (1992)).

3.3 Generalisation to more than One Dimension

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

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

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

To estimate conflict risk, we need to consider at least 3 dimensions: latitude, longitude and time. The matrix H can be parametrized as follows:[15]

[15] In the main specification K is a restricted trivariate function in which events that happen beyond 200 Km or

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

The integral of the estimated density of the underlying violence process gives an estimate of the probability of occurrence of an event in a given space time window. This is used as risk measure in the rest of the paper.

4 Identification Strategy

The impact of conflict risk on infant mortality is investigated using a Difference-in-Differences identification strategy. Treatment and control groups are defined at enumeration area level (household cluster) and all of the variation in childhood exposure to treatment across enumeration areas and birth cohorts is exploited. I first estimate the following equation using ordinary least squares.

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

where i denotes an individual 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 violence related stress that child i has been exposed to, 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, respectively, 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). 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 enumeration area level.

In the most basic version of the specification shown in equation (1), 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. The full version of the main

after a period t have zero contribution to the density at t. Most of the findings are also robust if these restrictions are ignored.

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 constant all the other relevant characteristics. 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 absence of conflict.

The choice of infant mortality as main outcome variable is due to three main reasons. First, infant death is one of Africa's largest 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 methodological advantages: it is available for all the children in retrospective fertility surveys, and the relevant period of potential exposure to conflict is relatively short (in utero or during first year of life) decreasing therefore the likelihood that the estimated impact is driven by other confounding factors.

Interpretation of Coefficient

The coefficient γ does not represent the national impact of conflict on infant mortality but the average effect with respect to local averages, cohort averages and purged of region specific flexible trends. The enumeration area fixed effects are also eliminating some of the valuable cross-sectional variation in conflict exposure.

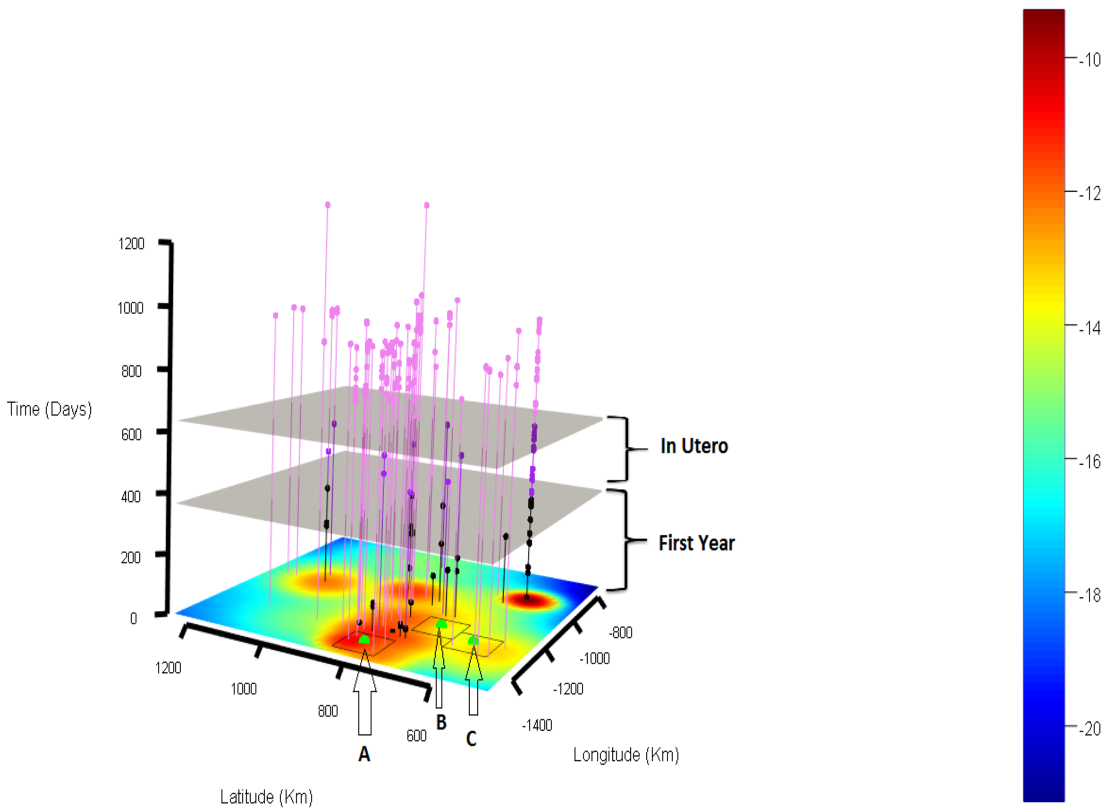
5 Empirical Results

5.1 Estimated Conflict Risk

The adaptive kernel density estimation method described above is performed on conflict data for Ivory Coast and Uganda.[16] 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 6 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

[16] Average estimated spatial smoothing parameters (h_s) are 34 and 28 Km for Ivory Coast and Uganda respectively. The temporal ones (h_t) are 508 and 207 days respectively.

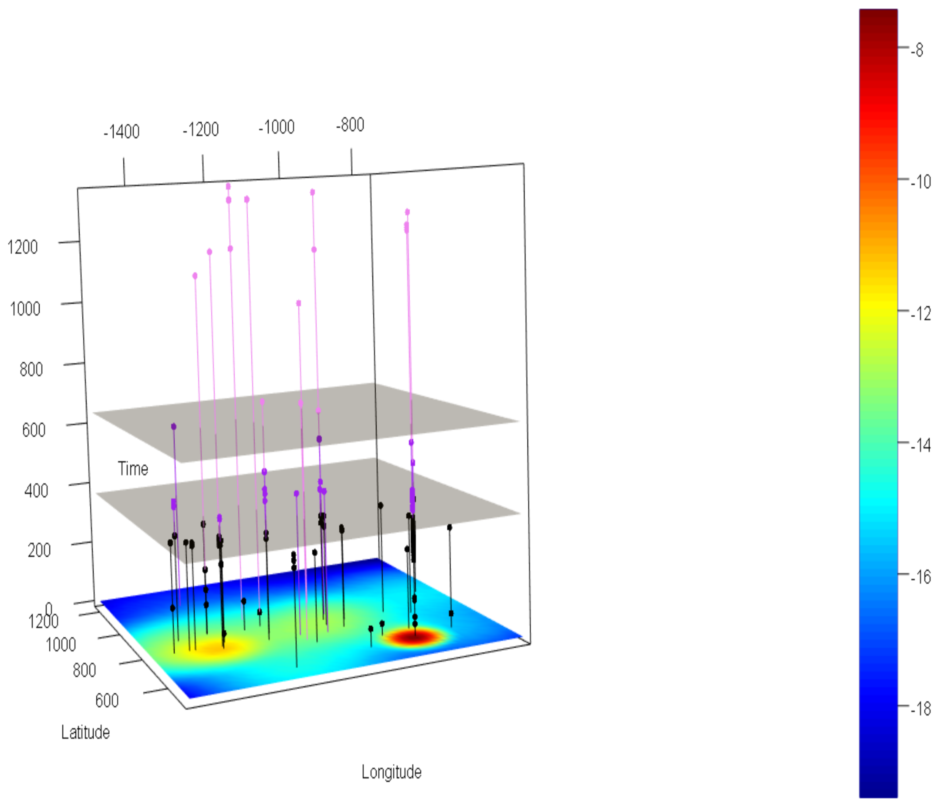
Figure 6: Risk for children conceived in September 2003 - Log Scale



conceived in September 2003 in Ivory Coast. Gray planes delimit the period in utero. Events in purple vertical bars occured in utero, events in black vertical bars occured during 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 log scale. For household clusters A, B and C for instance, there was no event happening in the relevant time window (conception to year 1) within 100 Km but the risk of an event was high. Cluster A has experienced many events just before conception and also during the relevant time window but beyond the 100 Km radius. High risk in cluster B is however only driven by events that occured beyond the 100 Km radius while risk in Cluster B is driven by events that happened before the relevant time window. These are examples of situations in which the new approach captures high risk but not the standard approach of counting events or casualties in a given space-time window. I show below that indeed children born in clusters like A, B and C also suffer major health setbacks.

Figure 7 shows a similar graph for children conceived in April 2010.

Figure 7: Risk for children conceived in April 2010 - Log Scale



5.1.1 Preliminary Observations

Before investigating the impact of violence risk on infant mortality, it's important to discuss the (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 in four quartile groups.

There is some correlation between the proposed measure of violence risk and the standard metrics used in the literature, but the two metrics also differ substantiallly. There was no event happening within 50 km around the place of birth of almost 90% of 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. 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 room for refining the treatment status for observations that the standard measures of conflict exposure cannot distinguish.

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. It 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.

5.1.2 Source of Variation in the Risk Measure

Table 2 shows the source of the variation that generates the children exposed to high risk of violence but not experiencing any event within 50 km during the relevant period of time (yellow cells in Table 1). It show that 22 % of these observations experienced an event within 50 km the year before their conception or the year after their first year of anniversary (time lags and forwards). By extending the size of the area considered to 150 km and keeping the 1 year time lag before and after the relevant period of time, we cover 90% of these observation. However, occurrence of events in space and time are correlated in such a way that most of these children experience at least one event in spatial lag and one event in temporal lag (75 % overlap).

Table 2: Source of Variation in the Risk Measure

	Share of observations with events:			
Area radius (Km)	only in space	only in time	in space and time	Total
50	-	21.51	-	21.51
100	9.53	23.92	37.36	70.81
150	5.62	12.28	74.22	92.12

Table 3 shows the distribution of my sample in Uganda 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. The probability of being exposed to an event is grouped in four quartile groups.

Table 3 shows some correlation between the proposed violence risk measure and the standard metrics used in the literature, but it also shows some substantial variations. 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.

Table 3: 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]	[4 ; 12]	13 +	Total
Q1	1,192	0	0	0	0	1,192
Q2	1,227	20	8	0	0	1,255
Q3	1,075	69	51	6	0	1,201
Q4	685	126	156	100	154	1,221
Total	4,179	215	215	106	154	4,869

Rows represent the probability of exposure to at least one event in utero or during the first year of life. It 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: Main Results and Robustness

Table 4 shows the estimated effects of being exposed to high risk of violence on the likelihood of dying within the first 12 months of life in Ivory Coast. Column (1) shows the estimated coefficients for the basic specification from equation (1) in which I control only for enumeration area fixed effects and cohort fixed effects. The variable of interest is the standardized estimated level of risk of exposure to an event in utero or during the first year of life. The estimated γ coefficient is positive, significant. This coefficient increases 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) suggest that a standard deviation increase in violence risk increases the likelihood of dying by 1 percentage point. Column (4) controls for number of events that happen within 25, 50, 100 and 150 Km and the estimated γ remains stable and significant.

Column (5) splits the observations into 4 groups to test some of the implications of the risk model. The control group are the 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 setback. Those 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). The relevant treatment metrics is therefore in line with the risk model and avoids false positives that come from isolated events that do not generate any fear and true negatives that come from cohorts not exposed to direct violence but born under high risk.

The magnitude of the estimated effect is substantial. The gap in infant mortality rate between children in top and bottom quartets of risk distribution is of 6 percentage points, which represent more than 50% of average infant mortality rate.

Table 5 shows some robustness of the baseline specification. Column (1) includes region specific time trends, column (2) clusters the standard errors at 50x 50 Km PRIO-GRID cell level, column (3) uses older cohorts (born before 1995). Column (4) restricts the sample to observation that did not experience any event within 50 Km. The magnitude of the estimated coefficient is stable but standard errors are incresed. Column (5) uses risk measure in log scale. The estimated coefficient suggets that 1 % increase in risk measure increases infant mortality by 0.4 %. The last column shows that the results do not hold for male sample.

Table 6 is the equivalent of Table 4 for Uganda. The qualitative results are pretty similar. A standard deviation increase in violence risk increases infant mortality by 0.8 percentage points

Table 4: Impact of violence risk on infant mortality in Ivory Coast

	Infant Mortality				
VARIABLES	(1)	(2)	(3)	(4)	(5)
Standardized violence risk	0.008*	0.010**	0.010**	0.010*	
	(0.005)	(0.005)	(0.005)	(0.005)	
Low violence risk with at least 1 event within 50 km					-0.005
					(0.025)
High violence risk with no event within 50 km					0.053**
					(0.021)
High violence risk with at least 1 event within 50 km					0.069***
					(0.023)
Observations	4,963	4,963	4,944	4,944	4,944
R-squared	0.138	0.182	0.184	0.186	0.186
Cohort FE	YES	YES	YES	YES	YES
Enumeration Area FE	YES	YES	YES	YES	YES
Family characteristics	NO	NO	YES	YES	YES
Child characteristics	NO	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. Full set of controls includes mother's height, education, gender and age of household head, household wealth index, 12 months rainfalls (for the each of the two years preceding the birth of the child and during her first year of life), birth order, time gap between conception and the previous and following pregnancies. Robust standard errors in parentheses are clustered at enumeration area level. *** p<0.01, ** p<0.05, * p<0.1.

in Uganda. Children exposed to high risk of violence suffer major health setbacks even when the risk does not realize into actual event. Table 7 is the equivalent of Table 5 for Uganda.

Table 5: Robustness Ivory Coast

	Girls					Boys
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Standardized violence risk	0.010**	0.010*	0.008*	0.010		0.001
	(0.005)	(0.005)	(0.004)	(0.092)		(0.006)
log of violence risk					0.004**	
					(0.002)	
Observations	4,944	4,944	5,239	3,155	4,944	5,086
R-squared	0.197	0.184	0.179	0.235	0.185	0.195
Cohort FE	YES	YES	YES	YES	YES	YES
Enumeration Area FE	YES	YES	YES	YES	YES	YES
Region specific time trend	YES	NO	NO	NO	NO	NO
Family characteristics	YES	YES	YES	YES	YES	YES
Child characteristics	YES	YES	YES	YES	YES	YES

Full set of controls includes mother's height, education, gender and age of household head, household wealth index, 12 months rainfalls (for the each of the two years preceding the birth of the child and during her first year of life), birth order, time gap between conception and the previous and following pregnancies. Robust standard errors in parentheses are clustered at enumeration area level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Impact of violence risk on infant mortality in Uganda

	Infant Mortality				
VARIABLES	(1)	(2)	(3)	(4)	(5)
Standardized violence risk	0.011***	0.009**	0.008**	0.008**	
	(0.004)	(0.004)	(0.004)	(0.004)	
High risk with no event within 50 km					0.018**
					(0.008)
High risk with at least one event within 50 km					0.024*
					(0.014)
Observations	4,869	4,869	4,868	4,868	4,868
R-squared	0.109	0.155	0.160	0.161	0.160
Cohort FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Child characteristics	NO	YES	YES	YES	YES
Family characteristics	NO	NO	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. Full set of controls includes mother's height, education, gender and age of household head, household wealth index, 12 months rainfalls (for the each of the two years preceding the birth of the child and during her first year of life), birth order, time gap between conception and the previous and following pregnancies. Robust standard errors in parentheses are clustered at enumeration area level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Robustness Uganda

	Girls					Boys
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Standardized violence risk	0.008**	0.008**	0.009*	0.011		0.001
	(0.004)	(0.004)	(0.005)	(0.049)		(0.003)
log of violence risk					0.002	
					(0.002)	
Observations	4,868	4,868	2,463	4,178	4,868	5,060
R-squared	0.161	0.160	0.202	0.171	0.160	0.188
Cohort FE	YES	YES	YES	YES	YES	YES
Enumeration Area FE	YES	YES	YES	YES	YES	YES
Region specific time trend	YES	NO	NO	NO	NO	NO
Family characteristics	YES	YES	YES	YES	YES	YES
Child characteristics	YES	YES	YES	YES	YES	YES

Full set of controls includes mother's height, education, gender and age of household head, household wealth index, 12 months rainfalls (for the each of the two years preceding the birth of the child and during her first year of life), birth order, time gap between conception and the previous and following pregnancies. Robust standard errors in parentheses are clustered at enumeration area level. *** p<0.01, ** p<0.05, * p<0.1.

5.3 Placebo Test

Table 8 shows some placebo that test whether the results are driven by pre-existing trends. In column (1) and (3), I randomly assign risk values within each enumeration area for Ivory Coast and Uganda respectively. The estimated coefficients are close to zero and statistically insignificant. In column (2), 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.[17] column (4) does a similar exercise for Uganda using children born between 2006 and 2011 as fake war cohorts.[18] Results confirm that there is no pre-existing trend difference between areas with high and low violence risk.

Table 8: Placebo test and alternative spefications

	Ivory Coast		Uganda	
VARIABLES	(1)	(2)	(3)	(4)
Standardized violence risk with random values	0.001		0.004	
	(0.004)		(0.004)	
Maximum standardized violence risk		0.000		
X 1995-1996 cohorts		(0.011)		
Maximum standardized violence risk				-0.004
X 2011-2016 cohorts				(0.003)
Observations	4,944	1,621	4,868	3,739
R-squared	0.189	0.324	0.160	0.163
Cohort FE	YES	YES	YES	YES
Enumeration Area FE	YES	YES	YES	YES
Family characteristics	YES	YES	YES	YES
Child characteristics	YES	YES	YES	YES

Full set of controls includes mother's height, education, gender and age of household head, household wealth index, 12 months rainfalls (for the each of the two years preceding the birth of the child and during her first year of life), birth order, time gap between conception and the previous and following pregnancies. Robust standard errors in parentheses are clustered at enumeration area level. *** p<0.01, ** p<0.05, * p<0.1.

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

[17] Children born before 1995 are the non exposed cohorts in column (2) of Table 8.

[18] Children born after 2011 are the non exposed cohorts in column (4) of Table 8.

are, if anything, lower bounds of the true impact of conflict risk on infant mortality.

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, so that contemporary changes in omitted determinants of health are less likely to be driving the estimated coefficients.[19]

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 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 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 mostly 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 the policy against internal insurgency that occurred in 2001, after the September 11 terrorist attack. Violence in Uganda between 2002 and 2005 happened as a consequence of this exogenous shock and led to the ending of any significant activity from the rebel groups that were active in the country.

Migration

Conflict induced displacements could bias 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, land is the most valuable asset and the absence of property right makes it risky for farmers to leave their lands unused for too long or to try to establish themselves in another locality. IDMC (Internal Displacement Monitoring Center) estimated that, as of February 2015, over 80 % of the 2.3 million people

[19] The variations in violence intensity are even more drastic at local level. The space and time variation in violence intensity also helps in the identification strategy. Treatment (being exposed to 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.

displaced by violence since 2002 in Ivory Coast had managed to return to their homes. 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.

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.[20] 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 the case of Ivory Coast for instance, the empirical evidence suggests that households who had at least one child exposed to violence in utero or during their first year of life are similar to the other households living in conflict affected areas as shown in Appendix Table A2.[21]

Many factors could explain the fact that it is unlikely to observe selective fertility behaviors with respect to violence in countries affected by low intensity conflicts. In general, developing countries in Sub-Saharan Africa are facing high infant and child mortality rates. This high probability of loosing a child combined with the low cost of having an extra one and deeply rooted pro-natalist religious and cultural beliefs have led to high birth rates and a somehow fatalistic view over the survival of children.

5.5 Comparison with Existing Measures of Exposure to Violence

In theory, one of the benefit 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 level of (non) exposure to observed events. This section shows

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

[21] I examined characteristics like mother's education, number of births, height, as well as household head's age and gender. The only significant difference in balance Appendix Table A2 is the number of children born in treated versus non-treated households in rural areas. The treated families 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.

that this benefit is also empirically relevant.

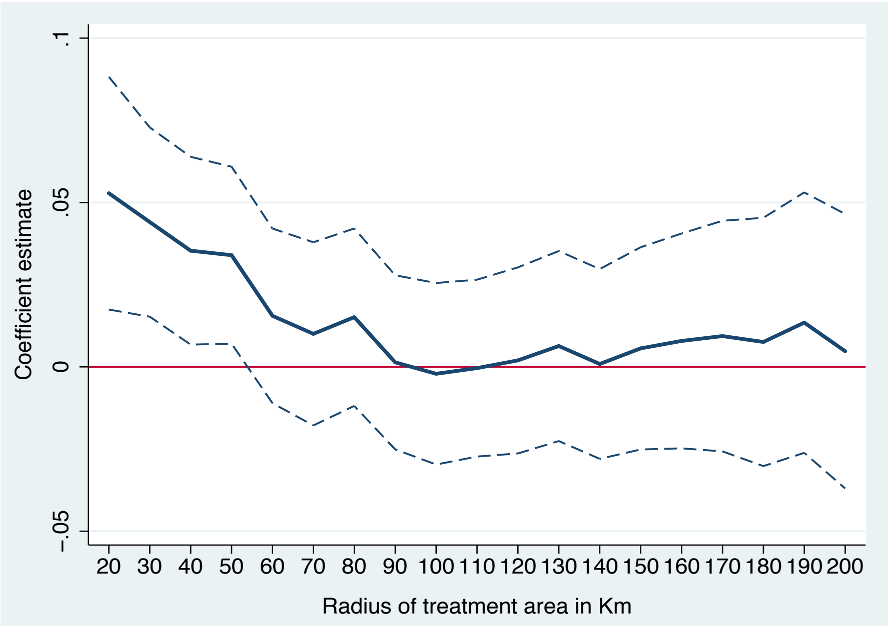
First, I show the estimated impact of conflict on infant mortality using the standard metrics in the literature. Figure 8 plots several values of the coefficient γ estimated from the main specification in equation (1) for Ivory Coast. The conflict variable is defined as a dummy equal 1 if there was at least one event that happened within a certain radius r from the place of birth of a given child. A new regression is ran 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 of radius around the household location (large enough to encompass a city).[22] Around 20% of the observations are classified as treated and their likelihood of dying before turning one year old increases by 5 percentage points. The point estimate is significant and quite substantial. It represents a 50% increase in the average infant mortality rate. As the radius increases, we are moving more observations from the control to the treatment group and the magnitude of the coefficient declines towards zero. It is however still substantial and significant up to 50 km (big enough to encompass a department - 2nd/3rd administrative level). Beyond this size, the coefficient is small and not significant meaning that we start putting in the treatment group observations that are not treated and these observations bring the estimated difference down to zero.

This sensitivity of the magnitude of the estimated impact to the size of the area considered is well documented in the literature. Researchers usually settle for the specification with the smallest standard errors and show some robustness to increasing or decreasing this size.

Figure 9 shows the estimated impact of conflict using the proposed risk measure 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 metrics used in the literature and the question here is whether the proposed risk measure is relevant enough to capture significant variations in the risk of exposure to violence within this sample. Small values of r mean more observations to split between treatment and control. The main specification is the regression that considers observations with no event within 50 km (first column of Table 1). The estimated

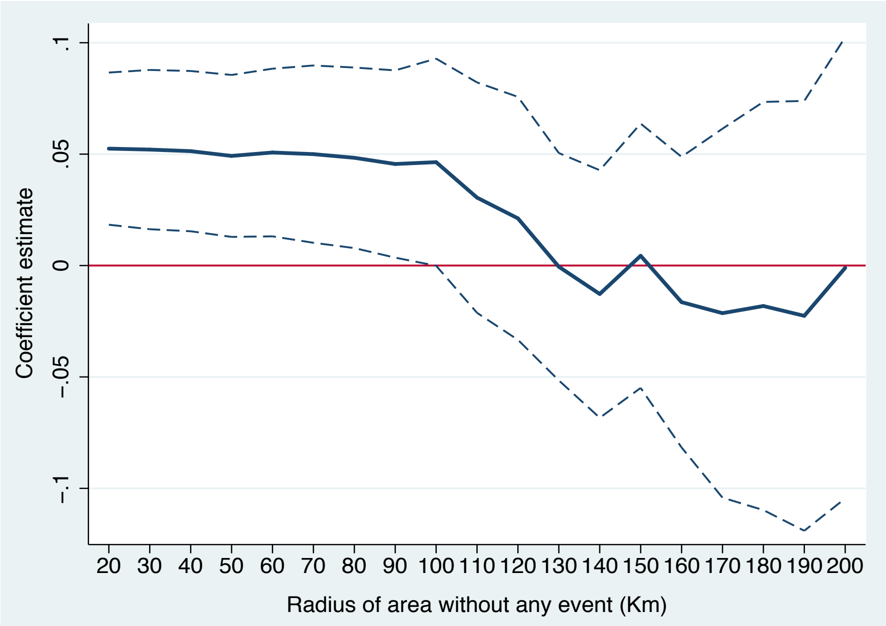
[22]In DHS data, some noise is introduced in the GPS coordinates of the enumeration areas that are surveyed for privacy reasons. They are displaced by up to 2 km in urban areas and 10 km in rural ones. For this reason, I use at least 20 km to define geographic areas that contain for sure the surveyed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

Figure 8: Impact of conflict on infant mortality using observed violence



Notes: Estimated impact of conflict on infant mortality using the main specification in equation (1). 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 first year of life). A new regression is ran 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 enumeration area level. The first regression considers a treatment area of 20 km of radius around the household location, the second 30 km, etc.

Figure 9: Impact of violence risk on infant mortality: sub-sample of children with no event within r km



Notes: Estimated impact of violence risk on infant mortality when restricting the sample to non treated observations according to standard metrics in literature. 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). 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 first year of life). A new regression is ran 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 enumeration area level. The first regression considers a treatment area of 20 km of radius around the household location, the second 30 km, etc.

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 is too small because we are looking at cohorts with no event within more than 150 km around their area of birth. The differences in the risk measure are just noisy in this sub-sample because they are all barely affected by the violence risk. This also explains the large confidence bands after 150 km in the graph.

Results in Figure 9 imply that the risk measure proposed in this paper is able to split an otherwise homogeneous control group (according to the classic methods used in the literature) into treatment and control group in such a relevant way that the magnitude and significance of the estimated effect is similar to comparing cohorts with observed events happening in their neighborhoods to the others.

5.6 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 timing of violence escalation and DHS survey years in Uganda allows me to partially investigate these channels. The DHS surveys provide indeed a rich set of information on the use of health services, 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 affected key health inputs and outcomes.

Column (1) of Table 9 shows first that exposure to high risk of violence in utero increases significantly infant mortality. Column (2) and (3) suggest that violence risk decreases 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 (4)), delivering in a health center (column (5)) or having access to a C-section (column (6)). Women exposed to high risk of violence during a specific pregnancy also have longer duration of postpartum amenorrhea which is evidence of maternal stress and insufficient nutrition.

These results suggest that conflict in Uganda affected the quality of health services and their use by citizens during crucial times. It also induced maternal stress and short term malnutrition.

Table 9: Channels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Infant Mortality	BW<=2.5 Kg	Small at birth	Q1 Prenatal care	home delivery	C section	Duration Amenorrhea
Standardized violence risk in utero	0.008**	0.016*	0.008	-0.010**	0.014**	-0.015***	
	(0.004)	(0.009)	(0.009)	(0.005)	(0.007)	(0.005)	
Standardized violence risk in utero and during 1st year							0.181**
							(0.077)
Mean depedent variable	0.044	0.096	0.239	0.158	0.376	0.087	8.166
Quatification: Gap Q4-Q1	0.030*	0.020	0.036*	-0.032	0.054*	-0.025	0.737*
	(0.015)	(0.014)	(0.020)	(0.021)	(0.028)	(0.026)	(0.430)
Observations	4,868	2,673	4,785	4,868	4,868	3,025	4,838
R-squared	0.160	0.123	0.085	0.195	0.259	0.128	0.264
Cohort FE	YES	YES	YES	YES	YES	YES	YES
Enumeration Area FE	YES	YES	YES	YES	YES	YES	YES
Family characteristics	YES	YES	YES	YES	YES	YES	YES
Child characteristics	YES	YES	YES	YES	YES	YES	YES

Full set of controls includes mother's height, education, gender and age of household head, household wealth index, 12 months rainfalls (for the each of the two years preceding the birth of the child), birth order, time gap between conception and the previous and following pregnancies. Robust standard errors in parentheses are clustered at enumeration area level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

6 Conclusion

This paper analyzed the impact of violence risk on child health using data from Ivory Coast and Uganda. 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 affect households. A new metric that captures perceived violence risk on the ground is therefore proposed in the paper and used to evaluate the impact of violence risk on child health in a Difference-in-Differences setting. 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, it 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 behaviors. An investigation into the potential channels through which this effect operates suggests that we cannot rule out factors like maternal stress, malnutrition and deterioration of quality/decrease in use of health services.

This paper has important policy implications for different stages of violent conflicts. First, We should focus even more on conflict prevention efforts to avoid the huge humanitarian and economic cost that will arise if violence breaks out. Second, during conflict, governments and NGOs should address fears/expectations of economic agents and prevent disruptions in 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.

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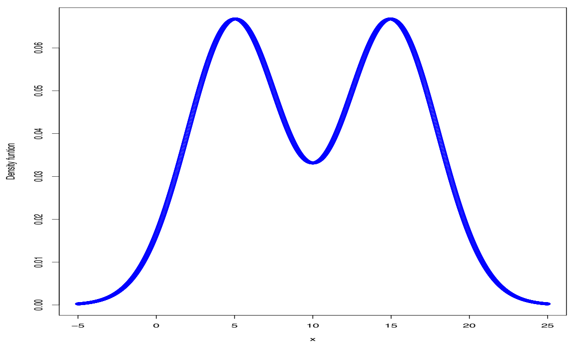
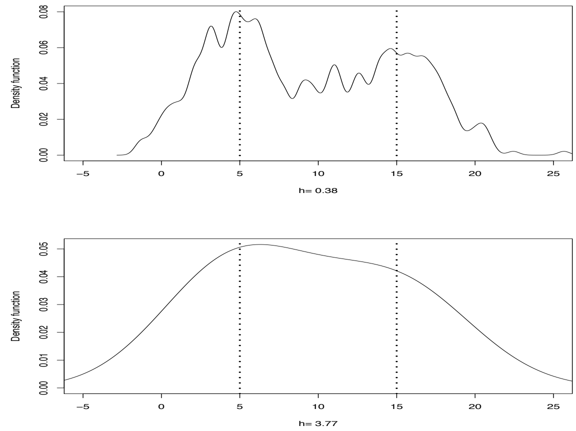
Appendix

Figure A1: Partition of Ivory Coast during Conflict

Figure A2: The role of the smoothing parameter



(a) Underlying density



(b) KDE with small and large bandwidth

A 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 standard deviation 3. The underlying distribution is shown in panel (a) of Figure A2. 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.

B Bootstrap

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 minimises 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 minimise 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 untill it converges

Table A1: Household characteristics in Ivory Coast by enumeration area (EA).

	URBAN			RURAL		
	Non war EA (1)	War EA (2)	Difference (1) - (2)	Non war EA (1)	War EA (2)	Difference (1) - (2)
Number of children born in household	3.041	2.813	0.228	3.568	3.480	0.088
	(0.208)	(0.078)	(0.218)	(0.127)	(0.078)	(0.148)
Wealth index	3.859	4.181	-0.322***	2.267	2.059	0.208*
	(0.129)	(0.048)	(0.135)	(0.097)	(0.053)	(0.110)
Mother's height (centimeters)	158.334	159.775	-1.441***	158.097	158.413	-0.316
	(0.656)	(0.243)	(0.686)	(0.337)	(0.318)	(0.461)
Mother's years of education	2.023	2.990	-0.967***	0.774	1.381	-0.607***
	(0.396)	(0.182)	(0.428)	(0.136)	(0.116)	(0.178)
Age of household head	44.050	45.872	-1.822	45.436	46.156	-0.720
	(2.075)	(0.649)	(2.131)	(0.700)	(0.599)	(0.917)
Female household head	0.186	0.204	-0.017	0.080	0.150	-0.070***
	(0.040)	(0.018)	(0.043)	(0.016)	(0.017)	(0.023)
Number of observations	220	1385	1605	979	2379	3358

War EA are enumeration areas with at least 1 conflict event within a 50 km radius between 1997 and 2012. Robust standard errors in parentheses, clustered at the enumeration area (EA) level. * significant at 10%, ** significant at 5%, and *** significant at 1%.

Table A2: Household characteristics in Ivory Coast by treatment status in war affected enumeration areas (EA)

	URBAN			RURAL		
	Never treated HH (1)	Treated HH (2)	Difference (1) - (2)	Never treated HH (1)	Treated HH (2)	Difference (1) - (2)
Number of children born in household	2.752	2.832	-0.080	3.296	3.590	-0.293***
	(0.133)	(0.093)	(0.162)	(0.102)	(0.097)	(0.129)
Wealth index	4.224	4.168	0.056	2.047	2.066	-0.018
	(0.060)	(0.057)	(0.074)	(0.070)	(0.063)	(0.079)
Mother's height in centimeters	160.064	159.684	0.380	159.012	158.056	0.956
	(0.439)	(0.269)	(0.481)	(0.388)	(0.439)	(0.578)
Mother's years of education	3.224	2.917	0.307	1.323	1.416	-0.093
	(0.320)	(0.200)	(0.347)	(0.163)	(0.136)	(0.186)
Age of household head	45.245	46.071	-0.826	45.320	46.653	-1.332
	(1.465)	(0.682)	(1.564)	(0.718)	(0.804)	(1.022)
Female household head	0.233	0.194	0.038	0.142	0.155	-0.013
	(0.029)	(0.022)	(0.036)	(0.021)	(0.021)	(0.027)
Number of observations	331	1054	1385	888	1491	2379

War EA are enumeration areas with at least 1 conflict event within a 50 km radius between 1997 and 2012. Treated HH (households) are families who had at least 1 child exposed (in utero or during first year of life) to the violence when it happened in their area. Non treated families had all their children before conflict started or after conflict started but there was no violent event in their area of residence around the birth of all their children. Robust standard errors in parentheses, clustered at the enumeration area (EA) level. * significant at 10%, ** significant at 5%, and *** significant at 1%.