The Effect of Conflict on Children's Learning Outcomes: Evidence from Uganda *

Osaretin Olurotimi†

October 29, 2022

Abstract

I estimate the effect of conflict on learning and schooling outcomes for children living in Uganda between 2010-2015. Using a difference-in-differences approach, I find that the Lord's Resistance Army's (LRA) activities in a neighborhood reduced learning outcomes in both math and English for the cohort of children exposed to armed conflict. Surprisingly, I find that exposure to LRA did not significantly affect other schooling outcomes, such as the probability of dropping out and being at the right age for a grade. Further, I find that the effect of conflict is worse those who were babies or in-utero when exposed to conflict. In addition, I provide evidence that a mechanism through which conflicts affect learning outcomes is neither physical disability nor school infrastructure, but teacher absenteeism. Results from this paper imply the need to distinguish between schooling and learning when measuring the effect of shocks on children.

Keywords: Conflict, Learning outcomes, Children

JEL Codes: I25, J13, O12

*I am grateful to Jeremy Foltz, Paul Dower, Priya Mukherjee and seminar participants at the University of Wisconsin's Development Economics Workshop for useful feedback. This work is supported by the University of Wisconsin-Madison's Graduate School Fellowship. Support for this fellowship is provided by the Graduate School, part of the Office of the Vice Chancellor for Research and Graduate Education at the University of Wisconsin-Madison, with funding from the Wisconsin Alumni Research Foundation and the UW-Madison. All residual errors are mine.

†University of Wisconsin–Madison. olurotimi@wisc.edu

1 Introduction

Human capital has significant implications for individual economic pathways and national development paths, particularly in the augmented Solow model (Mankiw, Romer, & Weil, 1992) and in some endogenous growth theory models (Lucas, 1988). One implication is the association between more schooling and higher wages (Duflo, 2001). However, despite human capital's centrality to economic growth, Hanushek (2016) shows that adding more schooling without improving cognitive skills is ineffective in enhancing long-term growth. Similarly, cognitive skills have a distinct effect on wages that is separate from schooling Valerio, Sanchez Puerta, Tognatta, and Monroy-Taborda (2016), and the UN's Sustainable Development Goals for education include targets that distinguish between educational access, i.e., schooling (Targets 4.1, 4.2, and 4.3), and learning (Targets 4.5 and 4.6). Therefore, as many education scholars have recognized, distinguishing between schooling and learning is essential in measuring educational outcomes. Specifically, the same shock could have different effects on schooling and learning. To measure these effects in Uganda, a developing East African country, this paper separately evaluates how exposure to conflict affects children's educational and learning outcomes.

Many violent conflicts have erupted in the East African region in the past few decades, including genocide in Rwanda, civil war in Somalia, the Tigray conflict in Ethiopia, and Uganda's Lord Resistance Army (LRA) terrorist activities. According to a United States Agency for International Development (USAID) statement, this region "contains several fragile or weakly governed states that are susceptible to conflict over natural resources and vulnerable to the challenges of violent extremism." Exposure to violence is challenging for both developing and developed countries. However, no previous studies have estimated the impact of conflict on learning outcomes for school-aged children in the East African context. This paper fills that gap.

Conflict can affect children's educational outcomes, including educational access, quantity, and quality. First, conflict could reduce access to schools by making travel to school dangerous or impossible (Blattman & Annan, 2010) or by causing damage to educational infrastructure. Second, conflict could cause a negative income effect that makes education less affordable if the conflict disrupts parents' livelihoods (Velásquez, 2020). Third, conflict could change the calculus of parents about the relative benefits of education versus other alternatives, such as buffering household earnings with income from child labor, i.e., a substitution effect. Fourth, conflict could affect education by imposing feelings of fear and insecurity, which may pose a psychological burden directly on children or may affect learning indirectly, as parents pass these burdens to children through reduced assistance with schoolwork or worse parenting practices. I develop a theoretical model to show that exposure to conflict in childhood can affect children's human capital. In the model, parents make health and education investments for their children subject to an income constraint determined by exogenous wages and human capital.The main insight from the theoretical model is about the mechanisms through which conflict can affect a child's human capital. These include making education more costly, thereby limiting parental investments in health and education for their children; reducing schooling efficiency, through a parameter representing the quality of schooling infrastructure (physical and human); and inducing aggregate budget set shifts through changes in parental wages or social norms around the value of education.

Empirically, this research combines measures of exposure to armed conflict from the geo-located conflict data from the Armed Conflict Location and Event Data Project (ACLED) with individual children's learning and household-level data from the UWEZO East Africa citizen-led assessment.[1] I use a difference-in-differences approach to estimate the effects of conflict by comparing learning and other educational outcomes between children in neighborhoods closer to geo-measured conflict incidents and children who live farther away. Ad-

[1]The UWEZO dataset is unique because the tests are administered in the household setting; therefore, it includes data on children who attend school and those who do not.

ditionally, I distinguish between the impact of medium-term conflict and short-term conflict. Specifically, I examine the impacts of the LRA's attacks, which dominated the conflict records in Uganda before 2010, versus relatively less severe conflict incidents such as violence against civilians, riots, and protests, which made up the bulk of the conflict incidents between 2010 and 2015and occurred contemporaneously with surveys measuring learning outcomes between 2010 and 2015. Finally, I explore potential mechanisms through which conflict affects learning outcomes, such as physical disability and measures of school quality.

My main finding is that conflict negatively impacts learning outcomes. At the same time, there are no significant effects on traditional schooling measures, such as whether a child is at the right age-for-grade or the likelihood of being a dropout. Further, I find that the effect of conflict is worse for the cohort who were babies or in-utero when exposed to conflict. . The main findings in this paper are robust to a number of robustness checks, including different fixed effects and placebo checks using a non-affected cohort of children.

The main contributions in this paper are as follows. First, this paper contributes to the literature on the effects of shocks on children's human capital. I contribute to this literature by exploring the effect of conflict on children with varying schooling statuses, i.e., enrolled and out-of-school children. Almond, Currie, and Duque (2018) review past research in this strand and establish that exposure to negative shocks in childhood has statistically and economically significant adverse, albeit heterogeneous, impacts. In addition to exploring schooling heterogeneity, I also explore how conflict affects children differently depending on their age at exposure.

Second, this paper contributes to the literature that specifically explores the effect of conflict on children's human capital. There have been papers focused on either health or education outcomes or both within this literature. Within the health and conflict sub-literature, Akresh, Lucchetti, and Thirumurthy (2012) find that exposure to the Eritrea-Ethiopia war affected the health outcomes of children later. Mansour and Rees (2012) look

at the impact of the al-Aqsa Infatida on the birth weight of children who were in utero, whose mothers were living the West Bank and Gaza during the conflict. Minoiu and Shemyakina (2012) find that conflict in Ivory Coast hurt children's height. In a comprehensive study of the effects of conflict in Africa, (Bendavid et al., 2021), conflict is associated with increased child mortality from causes other than direct conflict-related violence . Although this paper focuses on learning outcomes, I use available health outcomes, including physical disability, as a proxy to determine whether health is a likely mechanism through which conflict affects educational outcomes.

There are also some papers devoted to the effect of conflict on educational outcomes. For instance, Shemyakina (2011) explores the effect of the war in Tajikistan on school enrollment and finds that school-aged children were more likely not to have attained the expected years of schooling by age 17 compared to a pre-war cohort. Similarly, Akbulut-Yuksel (2014) explores the long-term effect of World War II on educational, wellbeing, and labor market outcomes and finds that, even after many decades, children raised in places with wartime destruction attain fewer years of schooling, are shorter, and have worse labor outcomes, if they come from low socio-economic status families. In a different context, Peru, León-Ciliotta (2012) examines a violent conflict's short- and long-term effects. The author finds an adverse impact of this shock and finds that the effect is more persistent if it occurred before a child is of school-going age than if it happened after a child is of primary school-going age. Finally, in the same tradition as the others but using a different type of conflict, i.e., terrorist activity, Bertoni, Di Maio, Molini, and Nisticò (2019) examine the effect of a deadly terrorist group – Boko Haram, operating in Northeast Nigeria - on the educational outcomes of children. The authors find that exposure to armed conflict negatively affects the probability that a child is enrolled in school and school attainment. My work is similar to the conflict and education papers mentioned above bin that I define my treatment in a similar way, i.e., by using geo-proximity to a conflict incident. However, it differs in that I focus on exploring the effect of violent conflict on learning outcomes, which is arguably an output-based measure

of human capital. Further, I provide the first evidence of the impact of conflict on learning outcomes for children aged 5-15 who are still undergoing basic education.

To be sure, some papers have examined the effect of conflict on learning outcomes. For instance Brück, Di Maio, and Miaari (2019) find that exposure to conflict affects the likelihood of passing final exams and exam scores of high school students in Palestine. Also, Ang (2021) examines the effect of police officer killings on high-school students who live near the killings and attend public schools in Los Angeles in the United States. The paper finds a drop in attendance immediately after the event, a decline in academic performance (measured by the grade point average (GPA)) over several semesters, and an increased likelihood for affected children to be diagnosed with learning disabilities and depression. This work is related to my research because it shows that geographic exposure to violence has psychological costs that researchers can observe in the short and long term. I extend the external validity of this literature by studying the impact of both medium-term and contemporaneous conflict on children's learning outcomes in Uganda.

The rest of the paper is organized as follows. Section 2 outlines a simple theoretical model to help fix ideas about the impact of conflict, while Section 3 provides some background on conflict in Uganda. I then present the data and empirical strategy in Sections 4 and 5 respectively. Results and robustness checks are presented in Section 6. Finally, Section 7 concludes.

2 Theoretical Model

The setting of this model, which is influenced by the model of human capital outlined in Almond et al. (2018), is a developing country consisting of utility-maximizing households. A household consists of a single child and a parent who makes decisions on behalf of the child. The agents in this model all live for three periods $t = 0, 1, 2$. The first period is childhood, followed by productive adulthood, then retirement. Human capital is produced in childhood,

while the returns are realized in adulthood. There are no earnings in retirement. I assume that there is no savings mechanism or credit market.

Human Capital Production

Let h be human capital, let b be investments in healthcare and nutritious food for a child, and let e be investments in education, e.g., school fees and cost of books, cost of accessing school, or the opportunity cost of the time that a parent spends in developing a child's human capital. The opportunity cost could be time spent reading to a child and helping a child with homework. Note that, for simplicity, this departs from the literature that typically distinguishes between time and monetary investment in education. A is a regional efficiency parameter representing the quality of schooling and access roads, which augments education[2] inputs only. A child's human capital production function is a Constant Elasticity of Substitution (CES) [3] function depicted below:

$$h = \left[(b^{\rho} + [Ae]^{\rho})^{\frac{1}{\rho}} \right] \tag{1}$$

I denote $\rho \in (-\infty, 1]$ as the substitution parameter, which shows how much the human capital production function inputs are substitutes or complements. The human capital production function allows an uneducated child to accumulate human capital as a function of health investments b alone. Initially, parents have human capital $\bar{h}$, which was determined in their childhood.

Utility Maximization. I assume that parents make human capital investment decisions on behalf of their children. In this model, the initial parents live only for two periods - productive adulthood and retirement, when they earn no income. Let C_t be consumption

[2]One can imagine that school infrastructure also boosts health inputs via toilet infrastructure or access to clean drinking water at school. I abstract away from this to allow out-of-school children to accumulate human capital.

[3]The production function of choice is a Constant Elasticity of Substitution (CES) function chosen because, given particular values of the substitution parameter, this function can contain the linear, Cobb-Douglas and Leontief functions as special cases.

per period and let α_i be a cultural weight that adults attach to a child's human capital, which can vary by age and gender of the child or the educational status of the parents. Another way to think of α_i is as a measure of altruism that parents have toward their children. Initial parents maximize a utility function.

$$U = f(C_1, \alpha_i h, C_2) \tag{2}$$

Let p represent the prices of the respective goods, and let w be an exogenous wage in each period. In period 1, the parent's income is their wage multiplied by their human capital $w_1\bar{h}$ less a share (θ) of their present-day income given to their retired parents. The parameter θ is exogenous to the model and can be considered a cultural norm.[4]During their retirement, a parent's consumption is equal to a share of their child's expected wage $w_2 h$. I assume that θ is constant between periods 1 and 2.

The parent maximizes utility subject to non-negativity constraints on consumption, as well as the following budget constraints:

for t=1

$$P_1 C_1 + P_b b + P_e e \leq (1-\theta) w_1 \bar{h} \tag{3}$$

for t=2

$$P_2 C_2 \leq \theta w_2 h \tag{4}$$

I denote $\frac{w}{P_2}$ as $\tilde{w}$. Because a rational consumer will leave no consumption off the table, I rewrite equation 4 as

$$C_2 = \theta \tilde{w} h \tag{5}$$

Let us consider the case where $U = f(C_1, \alpha_i h, C_2) = log(C_1) + log(\alpha_i h) + log(C_2)$

[4]In his memoir, Born a Crime, Noah (2016) jokingly refers to these payments as "the African tax". Seriously, Wantchekon, Klašnja, and Novta (2014) show that there exists a "family tax" in Benin, where more educated people transfer resources to relatives

I can then substitute C_2 into the utility maximization and get the following Lagrange. Note that I abstract away from any time-discount factor between periods 1 and 2.

$$L_{(}\, max c_1, b, e) \; = log(C_1) + log(\alpha_i h) + log(\theta \tilde{w} h) + \gamma((1-\theta) w_1 \bar{h} - P_1 C_1 - P_b b - Pee) \quad (6)$$

which gives us the following first-order conditions:

$$\frac{\partial L}{\partial C_1} = \frac{1}{C_1} - \gamma P_1 = 0 \quad (7)$$

$$\frac{\partial L}{\partial b} = \frac{2}{\rho} \frac{\rho b^{\rho-1}}{b^{\rho} + (Ae)^{\rho}} - \gamma P_b = 0 \quad (8)$$

$$\frac{\partial L}{\partial e} = \frac{2}{\rho} \frac{A^{\rho} \rho e^{\rho-1}}{b^{\rho} + (Ae)^{\rho}} - \gamma P_e = 0 \quad (9)$$

$$\frac{\partial L}{\partial \gamma} = 1 - \theta w_1 \bar{h} - P_1 C_1 - P_b b - Pee = 0 \quad (10)$$

Solving the first-order conditions leads to the following relationships.

$$(\frac{b}{e})^{\rho-1} = A^{\rho} * \frac{P_b}{P_e} = (\frac{e}{b})^{1-\rho} \quad (11)$$

$$e = b(\frac{A^{\rho} P_b}{P_e})^{\frac{1}{1-\rho}} \quad (12)$$

$$C_1 = \frac{P_b}{P_1} \frac{b^{\rho} + (Ae)^{\rho}}{2b^{\rho-1}} \quad (13)$$

$$C_1 = \frac{P_e}{P_1}\frac{b^\rho + (Ae)^\rho}{2A^\rho e^{\rho-1}} \tag{14}$$

$$e = \frac{(1-\theta)w_1\bar{h}}{\frac{P_e}{2}(1 + (\frac{P_e}{AP_b})^{\frac{\rho}{1-\rho}} + P_b(\frac{P_e}{A^\rho P_b}^{\frac{1}{1-\rho}})) + P_e} \tag{15}$$

2.1 Testable Hypotheses

From this model, one can obtain the following testable hypothesis:

1. If one assumes that conflict increase the price of educational(e) inputs by making it more costly to access schooling inputs, then conflict causes a decrease in children's human capital(h). For instance, note that $\frac{\partial C_1}{\partial P_b} = \frac{b^\rho+(Ae)^\rho}{2P_1 b^{\rho-1}} > 0$ and $\frac{\partial C_1}{\partial P_e} = \frac{b^\rho+(Ae)^\rho}{2P_1 A^\rho e^{\rho-1}} > 0$. Given our budget constraint, this means that an increase in the price of education and health inputs decreases the amount of education and health investments directly via a price effect, i.e., the same money can buy fewer inputs, and via a substitution effect, i.e., parents consume more in period one.

2. If conflict causes a reduction in the efficiency parameter A, then conflict causes parental educational inputs and a child's human capital to decrease, ceteris paribus. This could happen if, for instance, schooling infrastructure is destroyed or teacher absenteeism increases. We know that $\frac{\partial e}{\partial A} = (\frac{P_b}{P_e})^{\frac{1}{1-\rho}} b * \frac{\rho}{1-\rho} A^{\frac{2\rho-1}{1-\rho}} > 0$. Therefore, a reduction in schooling efficiency will lead to a reduction in educational investment and in a child's human capital.

3. Holding schooling quality A constant, exogenous changes in wages, as well as changes in the values that parents place on education, can affect a child's human capital. As an example, exogenous changes in the budget set could limit the set of consumption and human capital inputs a family can afford. If we let $\frac{1}{\frac{P_e}{2}(1+(\frac{P_e}{AP_b})^{\frac{\rho}{1-\rho}}+P_b(\frac{P_e}{A^\rho P_b}^{\frac{1}{1-\rho}}))+P_e} = \lambda$, then we can denote $e = \lambda(1-\theta)w_i\bar{h}$. Then, we obtain the following comparative statics results: $\frac{\partial e}{\partial w_1} = \frac{1}{\lambda}(1-\theta)\bar{h} > 0, \frac{\partial e}{\partial \theta} = -\frac{w_1\bar{h}}{\lambda} < 0$. As in Shah and Steinberg

(2017), wages in each period can be related to shifts in aggregate productivity, while cultural norms may change θ[5].

In this paper, I directly test the hypothesis that conflict reduces a child's human capital as measured by learning outcomes. The main insight from the theoretical model is about the mechanisms through which an exogenous shock[6]such as conflict can affect a child's human capital. The potential mechanisms include making education more costly (as in hypothesis one), reducing schooling efficiency (as in hypothesis two) or inducing aggregate budget set shifts through parental wages or social norms around the value of education (as in hypothesis three). Although the fundamental analysis is agnostic about the exact mechanism at play in Uganda, I provide some analysis that refines the set of mechanisms at play.

[5]Given that culture is sticky in the short run, one can safely abstract away from this possibility
[6]This model can extend to include other shocks such as famines, pandemics, and weather shocks

3 Country Background

Conflict in Uganda. Uganda, located in East Africa, has witnessed several episodes of conflict since its independence from colonial rule in 1962. Some notable conflict incidents include the killing of citizens and expulsion of non-citizens that happened during the reign of terror by then-President Idi-Amin between 1971-1980, after the forceful removal of the previous leader. The Luweero Bush war in the 1980s followed Idi Amin's rule; this was a civil war characterized by rival factions of the country seeking political power. The Luweero war culminated in the coming to power of Uganda's longtime and current leader, President Museveni, in 1986. Other incidents of conflict include suicide bombings as recently as 2021 by the insurgency group Allied Democracy Forces (ADF), with some ties to the Islamic State (ISIS), and the election-related violence of 2021, which involved supporters of presidential candidate Bobi Wine and the state machinery of the incumbent president. However, the most pervasive source of conflict has come from the activities of a terrorist group known as the Lord's Resistance Army (LRA), which enforced a reign of terror, predominantly in the Northern part of Uganda, for about two decades, with peak activity around 2004-2006. See figure A4 for the yearly distribution of LRA attacks available in the conflict dataset used in this paper.

The LRA is led by Joseph Kony, the infamous subject of a viral video titled "Kony 2012", which sought to garner international support for curbing LRA activities and bringing the perpetrators to justice. A United Nations article reports that up to 25,000 children were abducted by the LRA and forcibly converted to child soldiers. Other impacts of LRA activities and the associated Ugandan military response include displacing over 1.5 million people from their homes, although resettlement has occurred as LRA activities ceased (Bayne, 2007).

Geographic Divisions of Uganda. Geographically, Uganda has the following spatial classifications in descending other: region, district, county, sub-county, parish, and village.

Our treatment variable – exposure to conflict – varies at the parish level. On average, there are about 4,000, 25,000, and 240,000 people who live in a parish, subcounty and district, respectively.

4 Data Sources

4.1 Household Data

I use the household-level data from the UWEZO East Africa citizen-led assessment, covering 2010 to 2015. A strength of the UWEZO assessment is that children are tested at home; thus, the dataset includes both children who attend school and those who do not. The data is a cross-section of children aged 6-16 assessed with English and math tests of grade 2-level curriculum and accompanying household surveys. On average, there are about 80,000 children surveyed each year. For all the relevant years, enumerators visited all census districts in each country, and 30 different villages within each district were sampled using probability proportional to size, with 20 households sampled in every village using systematic random sampling.

Some of the variables collected include the child's age, gender, and type of school attended. Household information collected includes parents' age and years of education completed, household size, number of children within a household, asset ownership, gender of household head, and whether a child receives extra tuition outside of regular schooling.

4.2 Conflict Data

Conflict data comes from the Armed Conflict Location and Event Data Project (ACLED), which collects data on violent events such as battles, explosions, remote violence, protests, and riots worldwide. Table A11 shows the definition of each type of conflict incident. I use unique parish, sub-county, and district names to match longitude and latitude information

for children in the UWEZO dataset at the parish level to the GPS location of conflict incidents. Mainly, the ACLED dataset records incidents of violence within a country and includes details such as the type of event, date and year, longitude and latitude of the event, and the number of fatalities. For Uganda, the data records violent events that occurred from 1997 to 2020. Figure A1 shows the distribution of conflict in Uganda by type of conflict, while figure A3 shows the geographical dispersion of conflict across Uganda. Battles and violence against civilians dominate the conflict records, especially before 2010. Since 2010, the main forms of conflict in Uganda have been riots and battles against civilians. To identify conflict perpetrated by the LRA, I use the actor name to identify conflict incidents where the LRA is either the main or secondary actor. LRA events make up about 60% of conflict incidents in the period that LRA is active in the ACLED dataset i.e 1997-2006. The other significant actors are the Military and Police Force of Uganda, who contribute about 20% of the remaining conflict incidents.

4.3 Main Variables

The main dependent variable is children's learning outcomes measured by their scores on math and English tests. The children are tested on progressive knowledge areas within the subjects and are assigned a numeric score that represents the last level they are able to successfully complete. In math, the progressive levels are nothing(1), counting(2),numbers(3), addition(4),subtraction(5), multiplication(6), and division(7); while, for English, the progressive levels used are nothing(1), letter(2), word(3), paragraph(4), and story(5).

Additionally, to capture a higher cognitive level, I examine children's ability to correctly answer English comprehension questions. The English comprehension variable tests a child's ability to answer four comprehension questions correctly based on two stories. The raw scores range from 0 to four(4) depednding on the number of questions a child answers correctly. .

For comparability, the test scores in math, English, and English comprehension are standardized by age to have a mean of 0 and a standard deviation of one.

I also explore other educational outcomes, such as the probability of dropping out and whether a child is at the right age for a grade.

The main explanatory variable is geo-measured proximity to a conflict event. I define a child as being exposed to conflict if he or she was within 10 kilometres of a conflict incident. Child controls include age, grade and gender, while household controls include the educational attainment of parents, number of children within the household and asset ownership.

4.4 Descriptive Statistics of Children Data

Table 1 presents some descriptive statistics on children in the dataset.The average raw math score in the sample is 4.28 and the average English score is 2.8. This implies that, based on the knowledge domains described in the variable section above, the average child can add and read words. The average child in the sample is about 11 years old and is in the 4th grade. 89% of children are attending a school, while 2% are school dropouts.

5 Identification Strategy

To estimate the impact of conflict on children, I use a difference-in-differences approach. First, I created an unbalanced panel at the parish level by including only children who live in parishes that were visited more than once during the six survey years I have data. Subsequently, to evaluate the impact of LRA attacks on children's outcomes, I exploit the fact that LRA attacks were geographically contained. I categorize a child as being treated if they lived in a parish affected by LRA, i.e., within 10 kilometres of an LRA event, and

were alive or in utero during the LRA attacks. I then use a difference-in-differences equation which includes survey-year and parish fixed effects.

The treatment group includes children in the age cohort whose birth year is earlier than 2006 and who live in a parish that experienced LRA activity, while the comparison group is children in the same age cohort who live in different parishes. The fundamental identifying assumption is that parallel trends between treated and untreated parishes, i.e., learning and other educational outcomes, would have evolved in a similar pattern in both places in the absence of the conflict. To check that the parallel trends assumption holds, I check the pre-trends in educational outcomes using the educational attainment of the mothers of children in the sample who should have completed their schooling before the LRA attacks began. These checks suggest that educational outcomes were progressing similarly in all areas of Uganda before the attacks (please see the picture in figure A5).

There may be changes in educational policy and investments over time that are not captured by parish fixed effects. For this and other political trends, I include subcounty-birthyear time trends. The estimating equations are shown below.

5.1 Impacts of LRA attacks

To estimate the effect of the LRA attacks, I estimate the following equation:

$$Y_{iytd} = \alpha + \beta_1 LRAparish_d * LRAcohort_{it} + \beta_2 LRAcohort_{it} + \beta_3^{'} X_{iy} + \gamma_y + \theta_d + \eta_r * t + \epsilon_{iytd}$$

The outcome Y includes learning outcomes in math and English and other educational outcomes for a child i measured in survey year y born in year t, living in parish d. The independent variable of interest is $LRAparish_d * LRAcohort_{it}$, which indicates that a child lived in a parish that experienced LRA activity - $LRAparish_d$ (defined as being within 10kilometres of an LRA conflict incident) and a child was in-utero or alive during the LRA

attacks and is part of the $LRAcohort$. Parish and survey year fixed effects are represented by θ_d, andγ_y, respectively. η_{rt} are linear sub-county-birth-year linear trends. X includes a vector of child and household-level controls. Because the assignment to treatment is done at the parish level, the error term ϵ_{iytd} is clustered at the parish level. If the hypothesis that LRA negatively affects learning outcomes is true, I expect that β_1 will be negative and significant.

5.2 Impact of Contemporaneous Conflict

I estimate the impact of exposure to contemporaneous conflict, i.e., a conflict that occurs in the year a child was surveyed from all sources in the ACLED dataset. Because of challenges with the traditional two-way fixed effect estimates when the treatment is binary and staggered (see Goodman-Bacon (2021) and Callaway and Sant'Anna (2021)), I estimate group average treatment on the treated (ATT) effects using the Callaway and Sant'Anna difference-in-differences estimator for the repeated cross-section. The control group comprises children who live in parishes that were not yet affected by conflict. I implement this estimator with standard errors clustered at the parish level to allow for correlation between outcomes of children who live in the same parish. This estimator excludes children who were always treated, i.e., children who lived in parishes that were exposed to any conflict before the year that they were surveyed. The treatment year is the year that a child's parish was first exposed to conflict.

This estimator estimates ATT under the following assumptions: sampling in each year is independent and identically distributed (iid), there are conditional parallel trends between children who were treated later and were not yet treated, there is limited treatment expectation, there is irreversible treatment (i.e., the effects of being treated by conflict are permanent), and there is common support between treated and not yet treated groups, where

Y is the learning outcome for a group(g) of children who experienced conflict for the first time in the same year.

The group ATT is expressed as:

$$ATT_(gt) = E[Y_t(g) - Y_t(0)|G_g = 1] \tag{1}$$

6 Results

Below, I present the results of exposure to the LRA on children's learning and schooling outcomes, followed by an exploration of potential mechanisms and a discussion of heterogeneous effects by gender, cohort (i.e age at exposure to LRA), and schooling status. This section will conclude with results from the Callaway Sant'Anna estimator of the effect of contemporaneous conflict.

6.1 Effect of LRA Conflict

6.1.1 Learning outcomes

Table 2 presents results of the impact of LRA attacks on age-standardized math and English test scores of children using the baseline LRA specification.[7] It also includes results for English comprehension in column three. The results show that exposure to the LRA has a negative effect on learning outcomes in both math and English. Considering that the mean test scores in math and English are 4.3 and 2.8, respectively, the effect of the LRA on the children who were exposed is a reduction of about 2.5% and 4.8% in math and English, respectively. Also, exposure to the LRA results in children being less likely to be able to complete an English comprehension question

[7]Figure A7 and A6 show that the impact of LRA attacks on learning outcomes appear to attenuate with distance, especially for English test scores.

6.1.2 Schooling Outcomes

Table 3 provides the results of LRA attacks on other measures of educational achievement, including whether a child is at the right age for a grade (i.e., on track), the probability of being a dropout, and a child's self-reported school enrollment status. The results show that being exposed to LRA attacks has no significant impact on these measures. On the other hand, being exposed to the LRA has a significant and positive impact on the likelihood of a child being enrolled in school. Specifically, exposure to the LRA increases the probability of being enrolled, and reduces the probability of having never enrolled[8] in school by about 3 percentage points.

These results are noteworthy because they suggest that, even when conflict has no negative effect on schooling as proxied by enrollment status and the likelihood of being on track, conflict can still have negative effects on learning outcomes, as seen in our discussion of the results on learning outcomes from Table 2.

6.1.3 Alternate Conflict Measures.

I use two alternative[9] definitions of conflict exposure - the count of LRA conflict incidents and the sum of fatalities in the ACLED database in the total period that LRA was active, i.e., between 1997-2006 within 10 kilometers of a child's parish. Tables A1 and A2 present the results. I find that these measures of conflict have nil effect on learning outcomes. A likely explanation is that ACLED records the same "macro-conflict" attack on a community as multiple events if news stories are written about it multiple times hence these measures are not informative. Alternately, these nil results could simply mean that the extensive and non-intensive margins of conflict matter in this context.

[8] Of students who are not currently enrolled in school, some have never enrolled in any school.
[9] This follows the tradition of most papers in the conflict literature; for example, see Bertoni et al. (2019)).

6.1.4 Heterogeneous effects of Exposure to the LRA

Cohort. One concern with defining LRAcohort as those who were alive or born during LRA activities is that it may conflate the effect of a child actually experiencing LRA activities, whether they are in-utero or alive, with that of being born in a parish experiencing the after-effects of a LRA attack. To disentangle these treatments, I separate the LRAcohort into different age cohorts of children who lived in an LRAparish the first time LRA attacked that parish. Tables 4 and 5 show the results of LRA exposure by cohort. The results suggest that the effect of LRA on math test scores is notably worse if a child was a baby, was above five years, or was born after the LRA had already visited a parish. However, the only cohort whose learning outcomes in English were negatively affected is those who were babies when the LRA first visited their parish. Taken together, the results on math and English imply that exposure to the LRA was especially harmful to learning outcomes if a child was a baby or in utero when the LRA first visited their parish[10]

Schooling Status. Table 6 reports heterogeneous impacts by schooling status. The results suggest that the impacts of LRA on children's learning outcomes are significantly worse for out-of-school children in English literacy but not in math. However, as seen in table 7 exposure to the LRA is not significantly more harmful for children who have never-enrolled in school. The difference in results between Table 6 and 7 suggest that there might be a schooling-related mechanism that is at play for children who have at least had some schooling before becoming out-of-school children compared to those who have never attended school.

Gender. Table 8 shows the heterogeneous effects of exposure to LRA activities by gender. The coefficient on the triple interaction of $LRAparish_d * LRAcohort_{it}$ with the Female

[10]These results suggest there might be a maternal mechanism at play here; however, the data does not allow me to verify this.

variable shows that the effect of the LRA on learning outcomes is directionally but not significantly worse for females in math and English.

6.2 Mechanisms

Below, I discuss some suggestive evidence about the potential mechanisms by which conflict affects learning.

6.2.1 Health-related Outcomes

Table 9 presents the results of the LRA conflict on the health outcomes available in the data, including whether the child's left or right eye is ok and whether the child has any physical disability. The results show that, although exposure to the LRA has a negative coefficient in these regressions, they are not statistically significant. These results suggest that the channel through which the LRA affects learning outcomes is not via physical disability.

6.3 Village Schooling Infrastructure

Using village-level data collected between 2010-2015, I examine whether there are statistically significant differences in the availability of schooling infrastructure between villages in LRA-affected parishes and villages in parishes not affected by LRA.[11] The results of this comparison are shown in Table A7. On average, villages affected by LRA have significantly more secondary schools, while there are no significant differences in the number of primary schools and early childhood education schools. These findings suggest that any schooling infrastructure deficiency that may have been caused by LRA attacks no longer exists. Therefore, whatever deficiency in learning outcomes we observe is not attributed to less schooling infrastructure in LRA parishes. However, this result does not rule out other school-based

[11] Let Y be the outcome for village v in parish p in survey year y. α_s and δ_y are sub-county and survey year fixed effects, respectively. I estimate the following equation: $Y_{vpy} = \beta_4 LRAparish10k + \alpha_s + \delta_y + \epsilon_{vpy}$

mechanisms, including teacher quality, school quality, administrative quality, and teacher and student absenteeism rates.

6.4 Within School Infrastructure

One may argue that the number of schools in a village only indicates ease of access to school, but provide inadequate information on schooling infrastructure and quality. Therefore, I use school-level data to check whether there are any differences in within-school infrastructure between schools in parishes affected by the LRA and those that are not.[12]. I check whether schools in non-LRA parishes are more likely to have libraries, school nutrition programs, or connection to electricity. Table A8 shows these results. I note that there is no significant difference in these indicators of school-based infrastructure. In conjunction with the previous result on village-based infrastructure, these suggest that the mechanism at work may be different aspects of school quality, parental income, maternal health, or psychological channels.

6.5 Teacher Absenteeism

I examine whether there is an association between exposure to conflict and a dimension of school quality: teacher absenteeism. For this analysis, I use the accompanying school survey for 2013-2015, limiting my sample to the schools that are within 10 kilometers of a violent conflict (a conflict with at least one fatality) in the years in which they were surveyed. I then compare the proportion of teachers within schools who were present on a survey day that occurred during a conflict month with the proportion who were present on a survey day that did not occur during a conflict month. The results are shown in A9. Overall, the results suggest that teacher absenteeism is higher on school days that are within a month of a violent conflict.

[12]Let Y be the outcome for school t in parish p in survey year y. α_s and δ_y are sub-county and survey year fixed effects, respectively. I estimate the following equation $Y_{tpy} = \beta_5 LRAparish10k + \alpha_s + \delta_y + \epsilon_{vpy}$

6.5.1 Robustness Checks and Caveats

Below, I discuss some threats to identification in the LRA regressions and present robustness checks:

Household Selection. Household exposure to a conflict may be endogenous to neighborhoods. As a result, there may be systematic and unobserved differences between households exposed to conflict and those who are not. Parish fixed effects address some of these concerns if one assumes that there is not a lot of dispersion between households within parishes. To further ease concerns about this source of endogeneity, in addition to parish fixed effects, I include a rich set of controls for parental education, age, and assets.[13] Also, I re-estimate the baseline LRA regressions using household fixed effects. In this instance, the variation comes from households that have children who are in the LRA cohort and children who are not. Table A3 shows the results. I find that exposure to LRA still has a negative impact on English, although the impact on math is no longer significant. These estimates are not preferred because they do not include a panel element for the households, unlike the baseline regression, where I can include parish fixed effects.

Placebo Check. To be sure that the effects of the LRA were experienced only by the relevant cohort, I check the main regressions against the cohort that was not alive or in utero during the period when the LRA was active. I estimate equation 2 where $nonLRAcohort_{it}$ is defined as the cohort that was born after 2007, i.e, the year after LRA ceased to be active:

$$Y_{iytd} = \alpha + \beta_6 LRAactive_d * nonLRAcohort_{it} + \beta_7 nonLRAcohort_{it} + \beta_8^{'} X_{iy} + \gamma_y + \theta_d + \eta_r * t + \epsilon_{iytd} \tag{2}$$

[13] One concern with using assets as a control is that it is a "bad" control, i.e., one that is also influenced by exposure to conflict. I find that the results are largely robust to the exclusion of household assets.

The results are presented in table A4. I find that, for the cohort of children who presently live in LRA parishes, there is no impact on learning outcomes from living in a parish that previously experienced LRA activities.

Alternate Fixed Effects. The main results in the paper are robust to using birth-year fixed effects in place of controlling for age. Also, in a different specification, I estimate the LRA regressions on learning outcomes using parish-year fixed effects in place of parish and year fixed effects; I find that the results are robust to this specification (Tables are available upon request).

Other Conflicts Coinciding with LRA Although LRA is the dominant actor, i.e they are actors in about two-thirds of the conflict records in the period that I examine i.e 1997-2006, one may be concerned that any effect of LRA attacks that I observe may not be wholly due to LRA, but could be caused by the other actors who cause some of the other conflict incidents. I check whether exposure to all conflict incidents(LRA inclusive) has any effect on children's learning outcomes. Table A5 shows that for the children who were alive between 1997-2006, experiencing all other conflict incidents have no significant negative impact on test scores.

Likewise, I check the effect of other conflict actors asides from the LRA who are active between 1997-2006. I compare if children who live in parishes that experience this "Other conflict" have worse learning outcomes compared to children who do not experience any conflict. I do not find that exposure to these other conflict incidents adversely affect learning outcomes as shown in A6.

Migration. Migration may affect the composition of households present in a location during each survey year. For example, families who remain in a district may be less able or willing to move away from a conflict-prone area, perhaps due to a lack of outside geographic

options. Conversely, the current residents of the parishes may be substantially different from those who lived there during the attacks. In that case, any effect I see is likely attenuated. Unfortunately, the data available do not allow me to check migration trends.

6.6 Effect of Contemporaneous Conflict

In figure 2, I present the results of using the CSDID estimator to evaluate the impact of exposure to contemporaneous conflict on learning outcomes. The results show that exposure to conflict has a negative effect on math scores in the year that the conflict occurred. However, there appears to be no effect of contemporaneous conflict on English test scores. These results may be explained that less violent conflict make up the bulk of conflict incidents happening in Uganda between 2010-2015.

7 Conclusion

In this paper, I examine the effect of exposure to conflict on children's learning outcomes in Uganda. I combine data from the UWEZO East Africa citizen-led household survey of learning outcomes with conflict data from ACLED. In particular, I examine the effect of historical exposure to an insurgency group - The Lord's Resistance Army (LRA)- and exposure to conflict contemporaneously.

I find that exposure to the LRA reduced children's learning outcomes in math and English by about 2.5% and 4.8%, respectively, with children exposed to LRA as babies having worse outcomes. However, I find no impact of the LRA on traditional school-related educational measures, such as whether a child is at the right age-for-grade and the likelihood of being a school dropout. Also, exposure to the LRA has adverse effects on math, but not on English, for children who have never enrolled in school, compared to those who attend school. Methodologically, these findings suggest that only measuring school-related outcomes omits other impacts of conflict, including cognitive outcomes.

I also find that there are no significant impacts on learning outcomes when conflict is defined by fatality or incident counts. This finding suggests that, for learning outcomes, at least in this context, exposure to a conflict has a negative impact, regardless of the intensive margin of the conflict.

To situate the economic magnitude of the findings in this paper, I conduct back-of-the-envelope estimates to quantify the effect of poorer learning outcomes on children's future wage earnings in Uganda. First, I turn to the estimate in Valerio et al. (2016) from Ghana, where a one standard deviation (sd) increase in reading proficiency is associated with about a 19 percentage point increase in hourly wages, compared to a five percentage point increase in hourly wages for an additional year of schooling. Similarly, using an estimate for Kenya, the return to a year of education is seven percentage points, compared to 16 percentage points for a one standard deviation increase in reading proficiency. In my primary analysis,

exposure to the LRA reduces learning outcomes in English by about 0.1 sd., which amounts to about a two percentage point reduction in hourly wages. If this learning deficiency is not corrected, this could compound over the 45 years (assuming that the average child works from age 20 to age 65) that are spent productively in the labor force.

The implications of this paper for human capital policy include a need to measure and intervene in learning when children have been exposed to a conflict shock, regardless of the effect of the shock on schooling.

Table 1
Sample Means for Key Variables

	Full sample	LRA parish	Non-LRA Parish	Difference (3)-(2)
Child's age	10.51	10.57	10.49	-0.08***
Current Grade	3.56	3.57	3.55	-0.02*
Number of children in household	3.89	3.87	3.89	0.03**
Head of Household is female	0.32	0.37	0.31	-0.06***
Mother completed primary school	0.73	0.70	0.74	0.04***
Age of mother	37.53	37.47	37.56	0.10
Father completed primary school	0.88	0.91	0.88	-0.03***
Asset Index	2.31	2.19	2.34	0.15***
Child has a disability	0.07	0.09	0.06	-0.03***
Child is female	0.49	0.48	0.49	0.01**
Maths test score	4.28	4.23	4.29	0.06***
English test score	2.80	2.67	2.83	0.16***
Age-grade is at most 6	0.34	0.34	0.34	0.01***
Child has dropped out of school	0.02	0.02	0.02	0.00**
Child reports to be enrolled in school	0.89	0.89	0.89	-0.00
Observations	351015	66937	279011	345948

Notes: The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2
Effect of LRA on Children's Learning Outcomes

VARIABLES	(1) Math	(2) English	(3) English Comprehension
LRAparish10k*LRAcohort	-0.0424**	-0.0861***	-0.0596***
	(0.0184)	(0.0172)	(0.00927)
LRAcohort	0.134***	0.0343***	-0.2103***
	(0.00829)	(0.00788)	(0.00850)
Observations	153,007	152,423	152,423
R-squared	0.581	0.617	0.424
Controls	Yes	Yes	Yes
Parish FE	Yes	Yes	Yes
Survey YearFE	Yes	Yes	Yes

Notes: The learning outcomes presented here have been standardized. I control for a child's age and gender, subcounty-birthyear linear trends, parents' education, gender of household head, mother's age, number of children in the household, and household asset ownership. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3
Effect of LRA on other Educational Outcomes

VARIABLES	(1) Ontrack	(2) Dropout	(3) Child reports as enrolled	(4) Never enrolled
LRAparish10k*LRAcohort	0.0121	0.00224	0.0315***	-0.0338***
	(0.00848)	(0.00224)	(0.00984)	(0.00964)
LRAcohort	-0.150***	-0.0190***	0.0883***	-0.0693***
	(0.00396)	(0.00109)	(0.00392)	(0.00382)
Observations	163,666	179,998	179,998	179,998
R-squared	0.644	0.067	0.175	0.220
Controls	YES	YES	YES	YES
Parish FE	YES	YES	YES	YES
Survey YearFE	YES	YES	YES	YES

Notes: All variables used here are dummy variables coded 0 or 1. For instance, Ontrack=1 if a child is in the right grade for her age and 0 otherwise. I control for a child's age and gender, sub-county-birthyear linear trends, parents' education, gender of household head, mother's age, number of children in the household, and household asset ownership. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4
Effect of LRA on Math scores by Cohort

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Math
LRAcohort_baby	0.181***			
	(0.00528)			
LRAparish10k*baby	-0.0412***			
	(0.0133)			
LRAcohort_underfive		0.159***		
		(0.00656)		
LRAparish10k*underfive		0.0653***		
		(0.0122)		
LRAcohort_abovefive			0.123***	
			(0.00441)	
LRAparish10k*abovefive			-0.0669***	
			(0.0183)	
LRAcohort_beforebirth				0.222***
				(0.00617)
LRAparish10k*beforebirth				-0.0325**
				(0.0132)
Observations	155,390	155,390	155,390	155,390
R-squared	0.584	0.583	0.583	0.585
Child Controls	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES
Parish FE	YES	YES	YES	YES
Survey YearFE	YES	YES	YES	YES

Notes: Each cohort is defined by being in that age group when LRA was active within 10kilometre of a parish for the first time. For instance, $LRAparish10k * baby$ indicates that a child was born the first year that LRA was active within 10kilometres of her parish. The $LRAcohort - baby$ are those who share the same birth year as those within the LRA parishes. Similarly, $LRAparish10k * underfive$ and $LRAparish10k * abovefive$ shows that a child is both within the relevant cohort and lives in a parish where the first year of LRA activity occurred when the child is younger and older than five, respectively. $LRAparish10k * beforebirth$ implies that LRA visited a child's parish for the first time before a child was born, although the child was born during the period that LRA was active, i.e., before 2006.

Table 5
Effect of LRA on English scores by Cohort

VARIABLES	(1) English	(2) English	(3) English	(4) English
LRAcohort_baby	0.0676***			
	(0.00553)			
LRAparish10k*baby	-0.0415***			
	(0.0132)			
LRAcohort_underfive		0.00400		
		(0.00649)		
LRAparish10k*underfive		0.00163		
			(0.0127)	
LRAcohort_abovefive			0.0793***	
			(0.00463)	
LRAparish10k*abovefive			0.0347*	
			(0.0193)	
LRAcohort_beforebirth				0.0765***
				(0.00653)
LRAparish10k*beforebirth				0.0179
				(0.0127)
Observations	154,827	154,827	154,827	154,827
R-squared	0.618	0.618	0.617	0.618
Child Controls	YES	YES	YES	YES
Other Controls	Yes	Yes	YES	YES
Parish FE	YES	YES	YES	YES
Survey YearFE	YES	YES	YES	YES

Notes: Each cohort is defined by being in that age group when LRA was active within 10kilometre of a parish for the first time. For instance, $LRAparish10k * baby$ indicates that a child was born the first year that LRA was active within 10kilometres of her parish. The $LRAcohort - baby$ are those who share the same birth year as those within the LRA parishes. Similarly, $LRAparish10k * underfive$ and $LRAparish10k * abovefive$ shows that a child is both within the relevant cohort and lives in a parish where the first year of LRA activity occurred when the child is younger and older than five, respectively. $LRAparish10k * beforebirth$ implies that LRA visited a child's parish for the first time before a child was born, although the child was born during the period that LRA was active, i.e., before 2006.

Table 6
Effect of LRA on test scores on Out-of-School Children

VARIABLES	(1) Math	(2) English	(3) English Comprehension
LRAparish10k*LRAcohort*outofschool	-0.0764	-0.139**	-0.0827
	(0.0632)	(0.0671)	(0.0515)
LRAparish10k*LRAcohort	-0.0145	-0.0607***	-0.0265
	(0.0187)	(0.0177)	(0.0164)
LRAcohort	0.0648***	-0.0492***	-0.281***
	(0.00859)	(0.00819)	(0.00841)
Outofschool	-0.214***	-0.168***	-0.0350**
	(0.0183)	(0.0176)	(0.0163)
Outofschool*LRAcohort	-0.334***	-0.281***	-0.213***
	(0.0229)	(0.0228)	(0.0234)
Outofschool*LRAparish10k	-0.0218	0.0735*	0.0130
	(0.0408)	(0.0437)	(0.0338)
Observations	160,612	160,032	160,032
R-squared	0.500	0.508	0.329
Controls	YES	YES	YES
Parish FE	YES	YES	YES
Survey YearFE	YES	YES	YES

Notes: A child is defined as being out of school if they are not enrolled in a school as at the time of the survey. I control for the child's age and gender, subcounty-birthyear linear trends, parents' education, gender of household head, mother's age, number of children in the household, and household asset ownership. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7
Effect of LRA on test scores by School Enrolment Status

VARIABLES	(1) Math	(2) English	(3) English Comprehension
LRAparish10k*LRAcohort*neverenrolled	-0.0699	-0.124	-0.00646
	(0.0939)	(0.112)	(0.0682)
LRAparish10k*LRAcohort	-0.0143	-0.0595***	-0.0222
	(0.0189)	(0.0179)	(0.0165)
LRAcohort	0.0682***	-0.0493***	-0.289***
	(0.00865)	(0.00828)	(0.00844)
Neverenrolled	-0.217***	-0.167***	-0.0259
	(0.0186)	(0.0182)	(0.0167)
Neverenrolled*LRAcohort	-0.323***	-0.203***	0.00876
	(0.0269)	(0.0289)	(0.0237)
Neverenrolled*LRAparish10k	-0.0170	0.0741*	0.00692
	(0.0416)	(0.0447)	(0.0347)
Observations	160,612	160,032	160,032
R-squared	0.497	0.505	0.327
Controls	YES	YES	YES
Parish FE	YES	YES	YES
Survey YearFE	YES	YES	YES

Notes: A child who is never-enrolled is one who is reported to have never attended school. I control for child's age and gender, subcounty-birthyear linear trends, parents' education, gender of household head, mother's age, number of children in the household, and household asset ownership. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Effect of LRA on Learning Outcomes by Gender

VARIABLES	(1) Math	(2) English	(3) English Comprehension
LRAparish10k*LRAcohort*Female	-0.0343	-0.0366	-0.0317
	(0.0244)	(0.0227)	(0.0231)
LRAparish10k*LRAcohort	-0.0256	-0.0678***	-0.0438**
	(0.0218)	(0.0198)	(0.0189)
LRAcohort	0.144***	0.0367***	-0.209***
	(0.00976)	(0.00891)	(0.0103)
Female*LRAcohort	-0.0198*	-0.00528	-0.00337
	(0.0112)	(0.00987)	(0.0116)
Female*LRAparish10k	0.00342	-0.00919	-0.00902
	(0.0219)	(0.0206)	(0.0200)
Female	0.000533	0.0100	0.00405
	(0.0103)	(0.00915)	(0.0105)
Observations	153,007	152,423	152,423
R-squared	0.581	0.617	0.424
Controls	YES	YES	YES
Parish FE	YES	YES	YES
Survey YearFE	YES	YES	YES

Notes: I control for child's age and gender, sub-county-birth-year linear trends, parents' education, gender of household head, mother's age, number of children in the household, and household asset ownership. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9
Effect of LRA on Disability

VARIABLES	(1) Left Eye Ok	(2) Right Eye Ok	(3) Child has Disability
LRAparish10k*LRAcohort	-0.0100	-0.0053	-0.0123
	(0.0079)	(0.0077)	(0.0127)
LRAcohort	0.0088**	0.0043	0.0115
	(0.0039)	(0.0038)	(0.0074)
Observations	13,083	13,084	13,322
R-squared	0.2272	0.1754	0.1518
Controls	YES	YES	YES
Parish FE	YES	YES	YES
Survey YearFE	YES	YES	YES

Notes: I control for child's age and gender, sub-county-birth-year linear trends, parents' education, gender of household head, mother's age, number of children in the household, and household asset ownership. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure 1
Effect of Contemporaneous Conflict on math

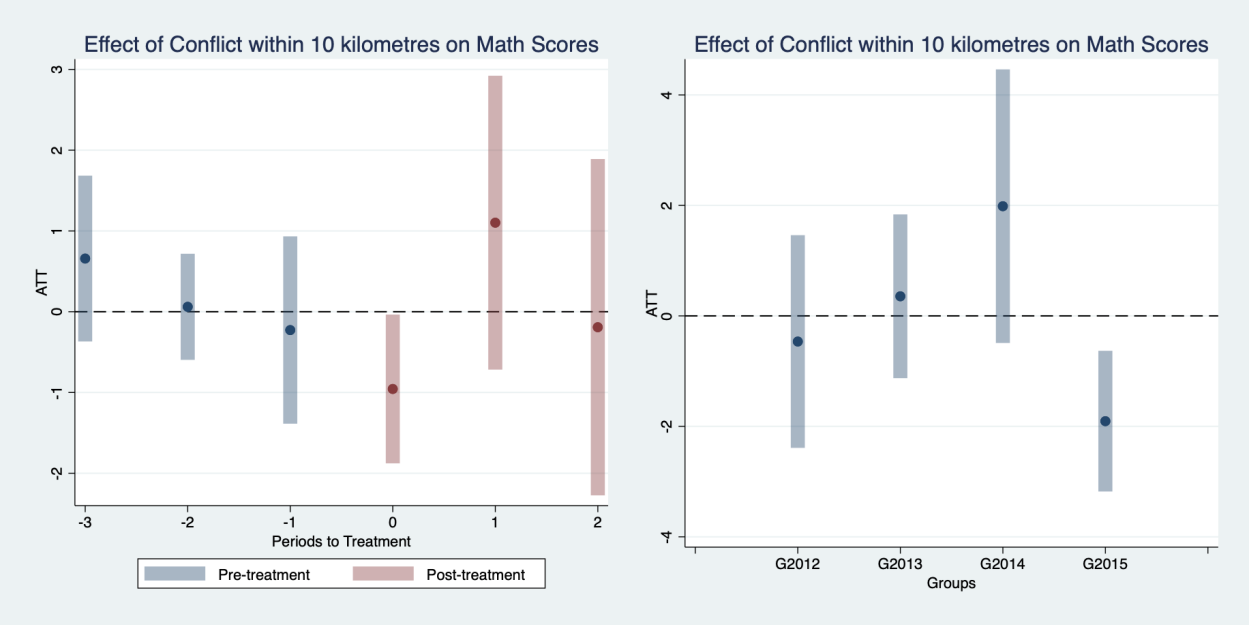


Figure 2
Effect of Contemporaneous Conflict on English

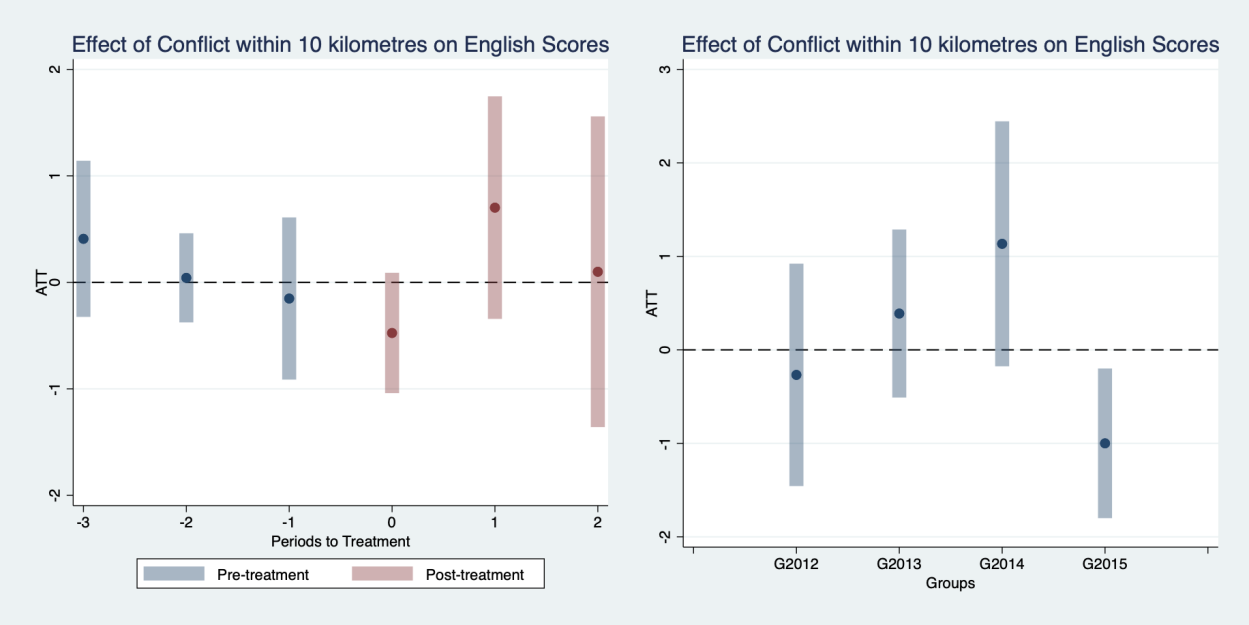
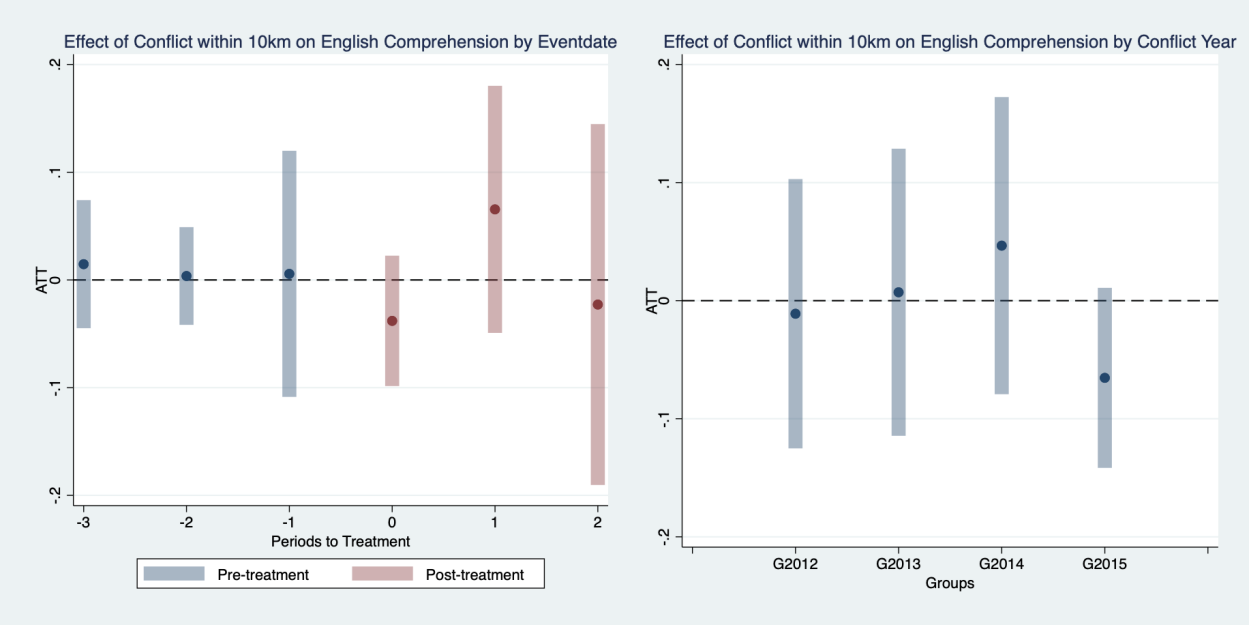


Figure 3
Effect of Contemporaneous Conflict on English Comprehension



References

Akbulut-Yuksel, M. (2014). Children of war: The long-run effects of large-scale physical destruction and warfare on children. *Journal of Human Resources*, *49*(3).

Akresh, R., Bhalotra, S., Leone, M., & Osili, U. (2021). First and second generation impacts of the biafran war. *Journal of Human Resources*. doi: 10.3368/jhr.58.4.0118-9272R1

Akresh, R., Lucchetti, L., & Thirumurthy, H. (2012). Wars and child health: Evidence from the eritrean–ethiopian conflict. *Journal of Development Economics*, *99*(2), 330-340.

Akresh, R., Verwimp, P., & Bundervoet, T. (2011). Civil war, crop failure, and child stunting in rwanda. *Economic Development and Cultural Change*, *59*(4), 777-810.

Almond, D., Currie, J., & Duque, V. (2018, December). Childhood circumstances and adult outcomes: Act ii. *Journal of Economic Literature*, *56*(4), 1360-1446.

Ang, D. (2021, February 2021). The effects of police violence on inner-city students. *Quarterly Journal of Economics*, *136*(1), 115–168.

Bayne, S. (2007). *Aid and conflict in uganda.*

Bendavid, E., Boerma, T., Akseer, N., Langer, A., Malembaka, E. B., Okiro, E. A., ... Wise, P. (2021). The effects of armed conflict on the health of women and children. *The Lancet*, *397*(10273), 522-532.

Bertoni, E., Di Maio, M., Molini, V., & Nisticò, R. (2019). Education is forbidden: The effect of the boko haram conflict on education in north-east nigeria. *Journal of Development Economics*, *141*, 102249.

Blattman, C., & Annan, J. (2010, 11). The Consequences of Child Soldiering. *The Review of Economics and Statistics*, *92*(4), 882-898.

Brück, T., Di Maio, M., & Miaari, S. H. (2019, oct). Learning The Hard Way: The Effect of Violent Conflict on Student Academic Achievement. *Journal of the European Economic Association*(5), 1502–1537. doi: 10.1093/jeea/jvy051

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time pe-

riods. *Journal of Econometrics*, *225*(2), 200-230. (Themed Issue: Treatment Effect 1)

Currie, J., & Walker, R. (2011, January). Traffic congestion and infant health: Evidence from e-zpass. *American Economic Journal: Applied Economics*, *3*(1), 65-90.

de Chaisemartin, C., & D'Haultfoeuille, X. (2021). *Difference-in-differences estimators of intertemporal treatment effects.*

Duflo, E. (2001, September). Schooling and labor market consequences of school construction in indonesia: Evidence from an unusual policy experiment. *American Economic Review*, *91*(4), 795-813.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254-277. (Themed Issue: Treatment Effect 1)

Hanushek, E. A. (2016, 10). Will more higher education improve economic growth? *Oxford Review of Economic Policy*, *32*(4), 538-552.

León-Ciliotta, G. (2012). Civil conflict and human capital accumulation: The long-term effects of political violence in perú. *Journal of Human Resources*, *47*(4).

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, *22*(1), 3-42.

Mankiw, N., Romer, D., & Weil, D. (1992). A contribution to the empirics of economic growth. *Quarterly Journal of Economics*, *107*(May), 407-437.

Mansour, H., & Rees, D. (2012). Armed conflict and birth weight: Evidence from the al-aqsa intifada. *Journal of Development Economics*, *99*(1), 190-199.

Minoiu, C., & Shemyakina, O. (2012, May). Child health and conflict in côte d'ivoire. *American Economic Review*, *102*(3), 294-99.

Noah, T. (2016). *Born a crime: Stories from a south african childhood.* New York: Spiegel Grau.

Quinn, J. R. (2021). *Thin sympathy: A strategy to thicken transitional justice.* University of Pennsylvania Press.

Raleigh, Clionadh, Andrew, L., Håvard, H., & Karlsen, J. (2010). Introducing acled-armed conflict location and event data. *Journal of Peace Research*, *47*(5), 651-660.

Rosales-Rueda, M. (2018). The impact of early life shocks on human capital formation: evidence from el niño floods in ecuador. *Journal of Health Economics*, *62*, 13-44.

Shah, M., & Steinberg, B. M. (2017). Drought of Opportunities: Contemporaneous and Long-Term Impacts of Rainfall Shocks on Human Capital. *Journal of Political Economy*, *125*(2), 527-561.

Shemyakina, O. (2011). The effect of armed conflict on accumulation of schooling: Results from tajikistan. *Journal of Development Economics*, *95*(2), 186-200.

Valerio, A., Sanchez Puerta, M. L., Tognatta, N., & Monroy-Taborda, S. (2016). Are there skills payoffs in low-and middle-income countries? empirical evidence using step data. *Empirical Evidence Using Step Data (November 3, 2016). World Bank Policy Research Working Paper*(7879).

Velásquez, A. (2020). The economic burden of crime: Evidence from mexico. *Journal of Human Resources*, *55*(4), 1287-1318.

Wantchekon, L., Klašnja, M., & Novta, N. (2014, 01). Education and Human Capital Externalities: Evidence from Colonial Benin *. *The Quarterly Journal of Economics*, *130*(2), 703-757.

Appendices

Appendix Table A1
Effect of LRA on Educational Outcomes: Conflict Fatalities

VARIABLES	(1) Maths	(2) English	(3) English Comprehension
LRAtreatment_fatalities10k	0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)
LRAcohort	0.127***	0.019***	-0.219***
	(0.008)	(0.007)	(0.008)
Observations	155,390	154,827	154,827
R-squared	0.581	0.617	0.425
Controls	YES	YES	YES
Parish FE	YES	YES	YES
Survey YearFE	YES	YES	YES

Notes: $Fatalities10k$ is the sum of fatalities between 1997-2005 where LRA is the main or secondary actor within 10 kilometers of the parish a child lives. The main dependent variable $LRAtreatmentfatalities10k$ is $Fatalities10k * LRACohort$, where LRAcohort is a dummy variable equal to 1 if a child's birth year is earlier than 2006. I control for child's age and gender, subcounty-birthyear linear trends, parents' education, gender of household head, mother's age, number of children in the household, and household asset ownership. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A2
Effect of LRA on Educational Outcomes: Conflict Count

VARIABLES	(1) Math	(2) English	(3) English Comprehension
LRAparish10k*LRAcohort	-0.000	-0.000	-0.001**
	(0.000)	(0.000)	(0.000)
LRAcohort	0.127***	0.019***	-0.219***
	(0.008)	(0.007)	(0.008)
Observations	155,390	154,827	158,827
R-squared	0.581	0.617	0.425
Controls	YES	YES	YES
Parish FE	YES	YES	YES
Survey YearFE	YES	YES	YES

Notes: $Conflictcount10k$ is the total count of conflict events between 1997-2005 where LRA is the main or secondary actor within 10 kilometers of the parish a child lives. The main dependent variable $LRAtreatmentcount10k$ is $Conflictcount10k * LRACohort$, where LRAcohort is a dummy variable equal to 1 if a child's birth year is earlier than 2006. I control for child's age and gender, subcounty-birthyear linear trends, parents' education, gender of household head, mother's age, number of children in the household, and household asset ownership. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A3
Effect of LRA on Learning Outcomes with Household Fixed Effects

VARIABLES	(1) Math	(2) English	(3) English Comprehension
LRAparish10k*LRAcohort	-0.0149	-0.0609***	-0.0760***
	(0.0194)	(0.0194)	(0.0215)
LRAcohort	0.0931***	0.0131	-0.1759***
	(0.0087)	(0.0087)	(0.0104)
Observations	245,470	245,072	245,072
R-squared	0.7733	0.7923	0.7645
Controls	YES	YES	YES
Household FE	YES	YES	YES
Survey YearFE	YES	YES	YES

Notes: I control for a child's age, grade, gender, and subcounty-birthyear linear trends. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A4
Effect of LRA on Children's Learning Outcomes with Non-LRA cohort

VARIABLES	(1) Math	(2) English	(3) English Comprehension
LRAparish10k*Child doesn't experience LRA	0.0939***	0.0917***	0.0612**
	(0.0363)	(0.0281)	(0.0283)
Child doesn't experience LRA	-0.112***	0.00253	0.0830***
	(0.0171)	(0.0143)	(0.0161)
Observations	197,220	196,855	196,855
R-squared	0.562	0.602	0.608
Controls	Yes	Yes	Yes
Parish FE	Yes	Yes	Yes
Survey YearFE	Yes	Yes	Yes

Notes: I control for child's age and gender, subcounty-birthyear linear trends, parents' education, gender of household head, mother's age, number of children in the household, and household asset ownership. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.Notes: I control for a child's age, grade, gender, and subcounty-birthyear linear trends. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A5
Effect of all conflict on Children's Learning Outcomes

VARIABLES	(1) Math	(2) English	(3) English Comprehension
All Conflict Parish*LRAcohort	-0.00716	0.0122	-0.0147
	(0.0146)	(0.0139)	(0.0146)
LRAcohort	0.130***	0.0131	-0.215***
	(0.00945)	(0.00876)	(0.00957)
Observations	155,390	154,827	154,827
R-squared	0.581	0.617	0.424
Controls	Yes	Yes	Yes
Parish FE	Yes	Yes	Yes
Survey YearFE	Yes	Yes	Yes

Notes: All conflict comprises of all the conflict incident that occurs in Uganda between 1997-2006. I control for child's age and gender, subcounty-birthyear linear trends, parents' education, gender of household head, mother's age, number of children in the household, and household asset ownership. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.Notes: I control for a child's age, grade, gender, and subcounty-birthyear linear trends. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A6
Effect of Non-LRA conflict on Children's Learning Outcomes

VARIABLES	(1) Maths	(2) English	(3) English Comprehension
Other Conflict Parish* Otherconflictcohort	0.0163	0.0694***	0.0110
	(0.0181)	(0.0175)	(0.0183)
Otherconflictcohort	0.131***	0.0127	-0.210***
	(0.00944)	(0.00884)	(0.00938)
Observations	126,801	126,269	126,269
R-squared	0.579	0.614	0.426
Controls	Yes	Yes	Yes
Parish FE	Yes	Yes	Yes
Survey YearFE	Yes	Yes	Yes

Notes: Non-LRA conflict comprises of all the conflict incident that occurs in Uganda between 1997-2006 that are not perpetrated by the LRA. The Otherconflict cohort excludes all children who are exposed to LRA in this period. I control for child's age and gender, subcounty-birthyear linear trends, parents' education, gender of household head, mother's age, number of children in the household, and household asset ownership. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.Notes: I control for a child's age, grade, gender, and subcounty-birthyear linear trends. Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A7
Association between LRA Conflict and Village School Facilities

VARIABLES	(1) Preschools	(2) Preschools	(3) Govt. Pry Schls	(4) Govt. Pry Schls	(5) Govt. Sec Schls	(6) Govt. Sec Schls
LRAparish10k	-0.141	-0.133	-0.042	-0.034	0.050*	0.045*
	(0.170)	(0.147)	(0.069)	(0.057)	(0.028)	(0.023)
Observations	2,374	2,899	5,524	6,905	3,349	4,053
R-squared	0.497	0.401	0.381	0.246	0.406	0.421
Subcounty-Year FE	Yes	No	Yes	No	Yes	No
Subcounty FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes

Notes: Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A8
Association between LRA Conflict and School-based Infrastructure

VARIABLES	(1) Library	(2) Library	(3) Schoolfeeding	(4) Schoolfeeding	(5) Sch_elec	(6) Sch_elec
LRAparish10k	0.104	0.099	0.054	0.014	0.026	0.017
	(0.074)	(0.070)	(0.044)	(0.043)	(0.037)	(0.031)
Observations	1,443	1,604	3,278	3,805	3,274	3,806
R-squared	0.452	0.386	0.532	0.340	0.549	0.462
Subcounty-Year FE	Yes	No	Yes	No	Yes	No
Subcounty FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes

Notes: Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A9
Association between LRA Conflict and Teacher Absenteeism

VARIABLES	(1) Proportion of Teachers Present	(2) Proportion of Teachers Present
School surveyed within Conflict Month	-0.025	-0.179***
	(0.028)	(0.047)
Observations	501	500
R-squared	0.004	0.793
Parish FE	No	Yes
Year FE	Yes	No

Notes: Robust standard errors are in parentheses and clustered at the parish level. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

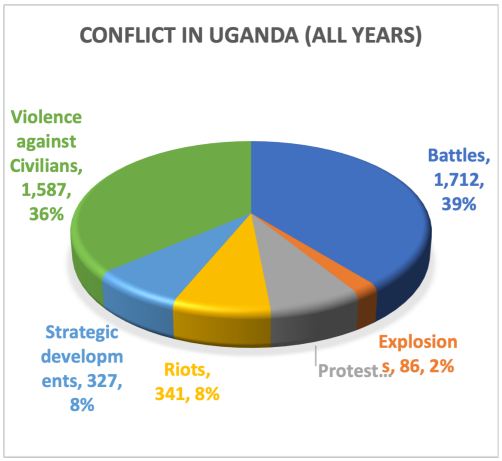
Appendix Table A10
Difference table by Contemporaneous Conflict

	Full sample mean	Contemporary Conflict mean	Unaffected Parish mean	Difference (3)-(2) b
Child's age	10.51	10.50	10.51	0.01
Current Grade	3.56	3.60	3.55	-0.05***
Number of children in household	3.89	4.08	3.86	-0.22***
Head of Household is female	0.32	0.28	0.33	0.05***
Mother completed primary school	0.73	0.78	0.73	-0.05***
Age of mother	37.53	37.46	37.54	0.07
Father completed primary school	0.88	0.90	0.88	-0.02***
Asset Index	2.31	2.43	2.30	-0.14***
Child has a disability	0.07	0.06	0.07	0.01
Child is female	0.49	0.49	0.49	-0.00
Maths test score	4.28	4.27	4.28	0.01
English test score	2.80	2.80	2.80	-0.00
Age-grade is at most 6	0.34	0.41	0.39	-0.02***
Child has dropped out of school	0.02	0.02	0.02	0.00***
Child reports to be enrolled in school	0.89	0.92	0.89	-0.03***
Observations	351012	43502	307510	351012

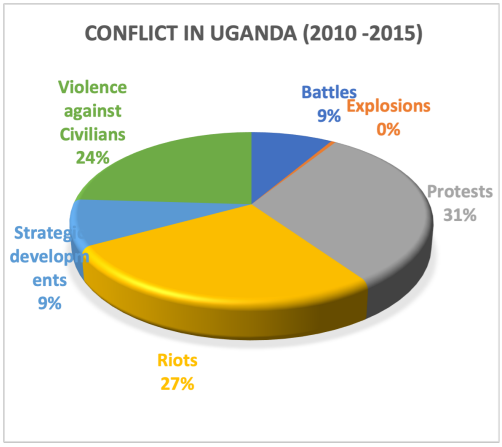
Appendix Table A11
Definition of Conflict Events by ACLED

Event Type	Definition
Battles	Violent clashes between two or more armed groups
Explosions/remote violence	Events involving the use of explosive devices
Violence against civilians	Attacks on civilians
Riots	Violent demonstrations, often spontaneous
Protests	Nonviolent demonstrations

Appendix Figure A1
Conflict Distribution in Uganda



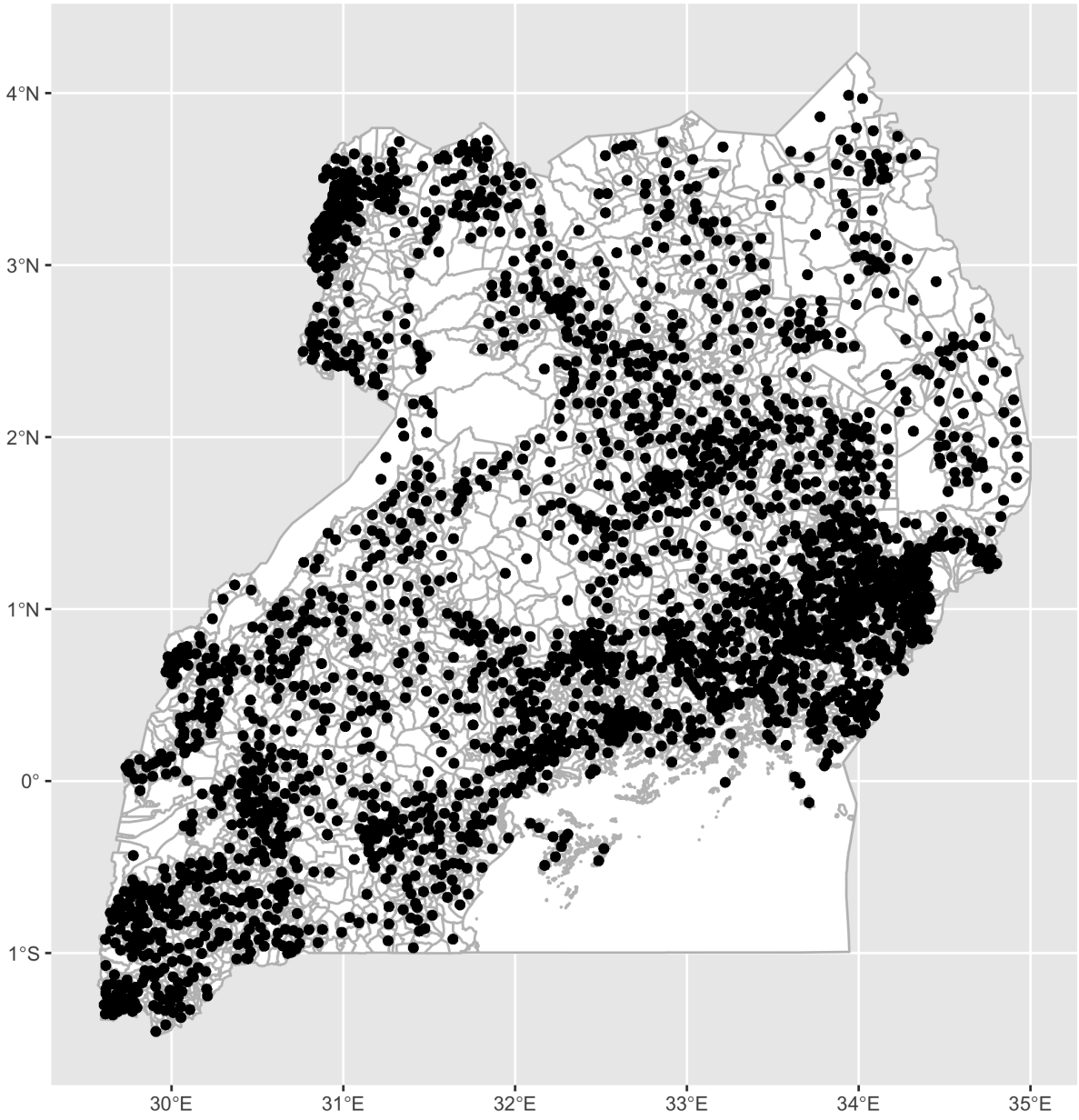
(a) ACLED Conflict (All years)



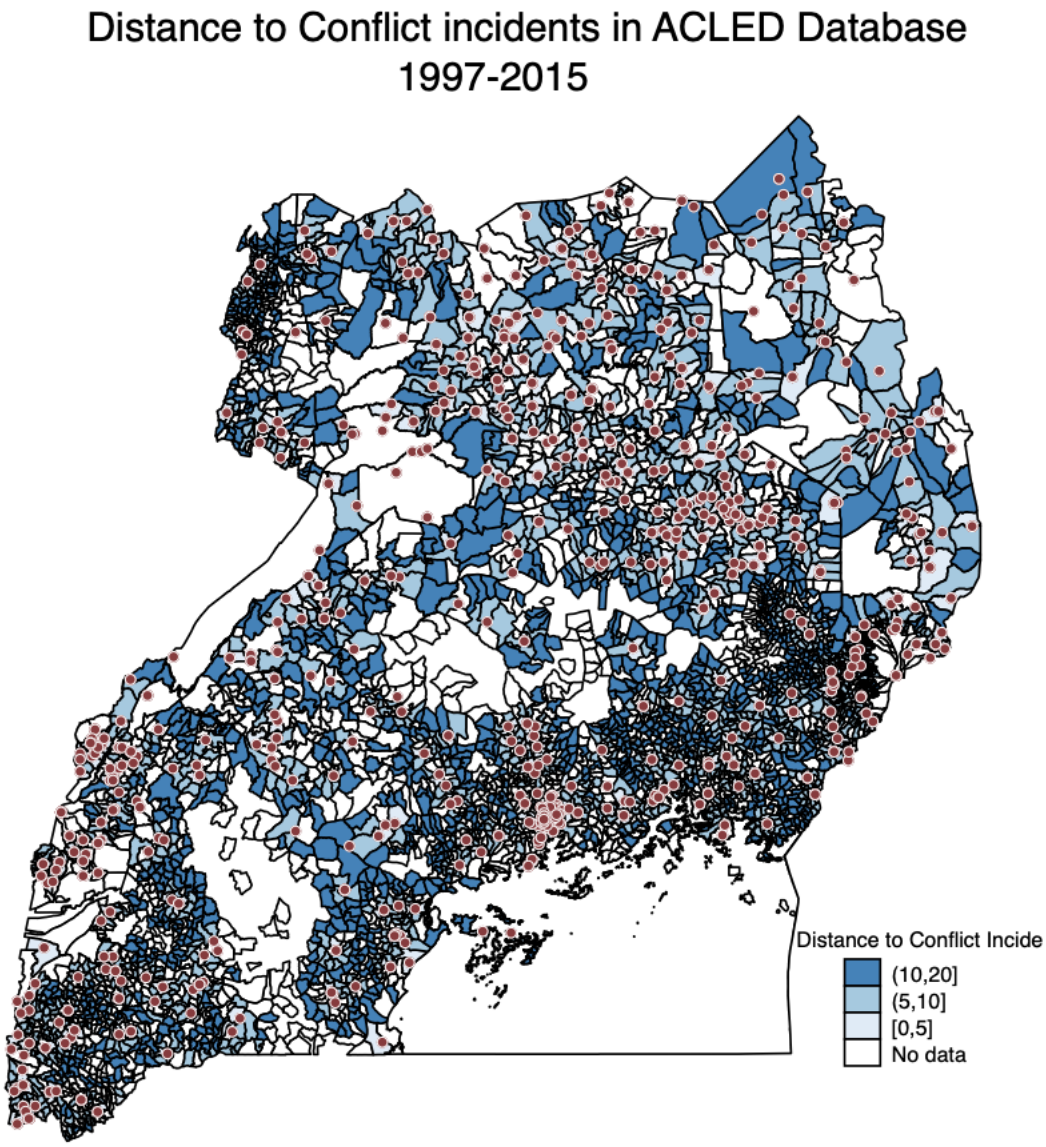
(b) ACLED Conflict (2010-2015)

Source: ACLED

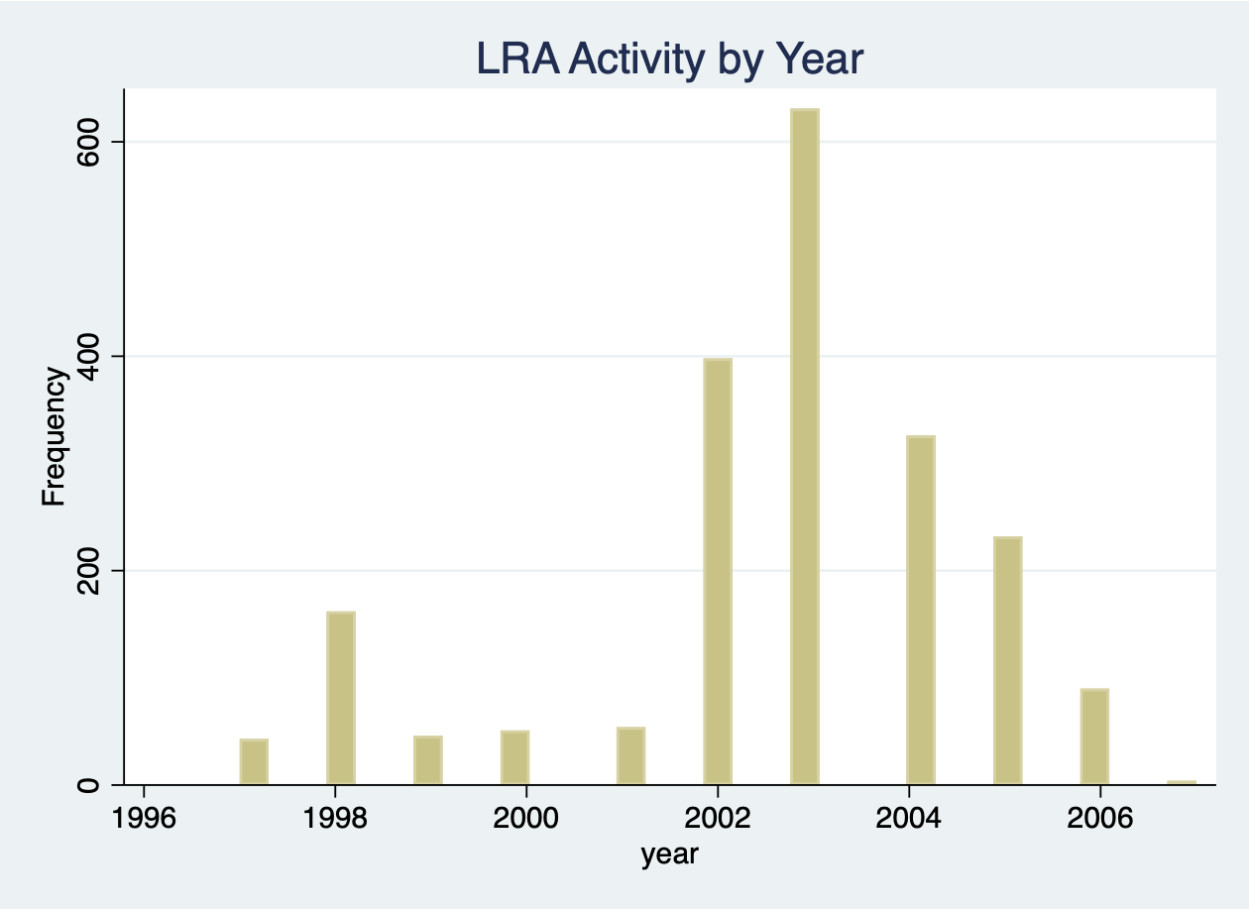
Appendix Figure A2
Parishes visited more than one year by UWEZO in Uganda



Appendix Figure A3
Geographical Dispersion of Conflict in Uganda

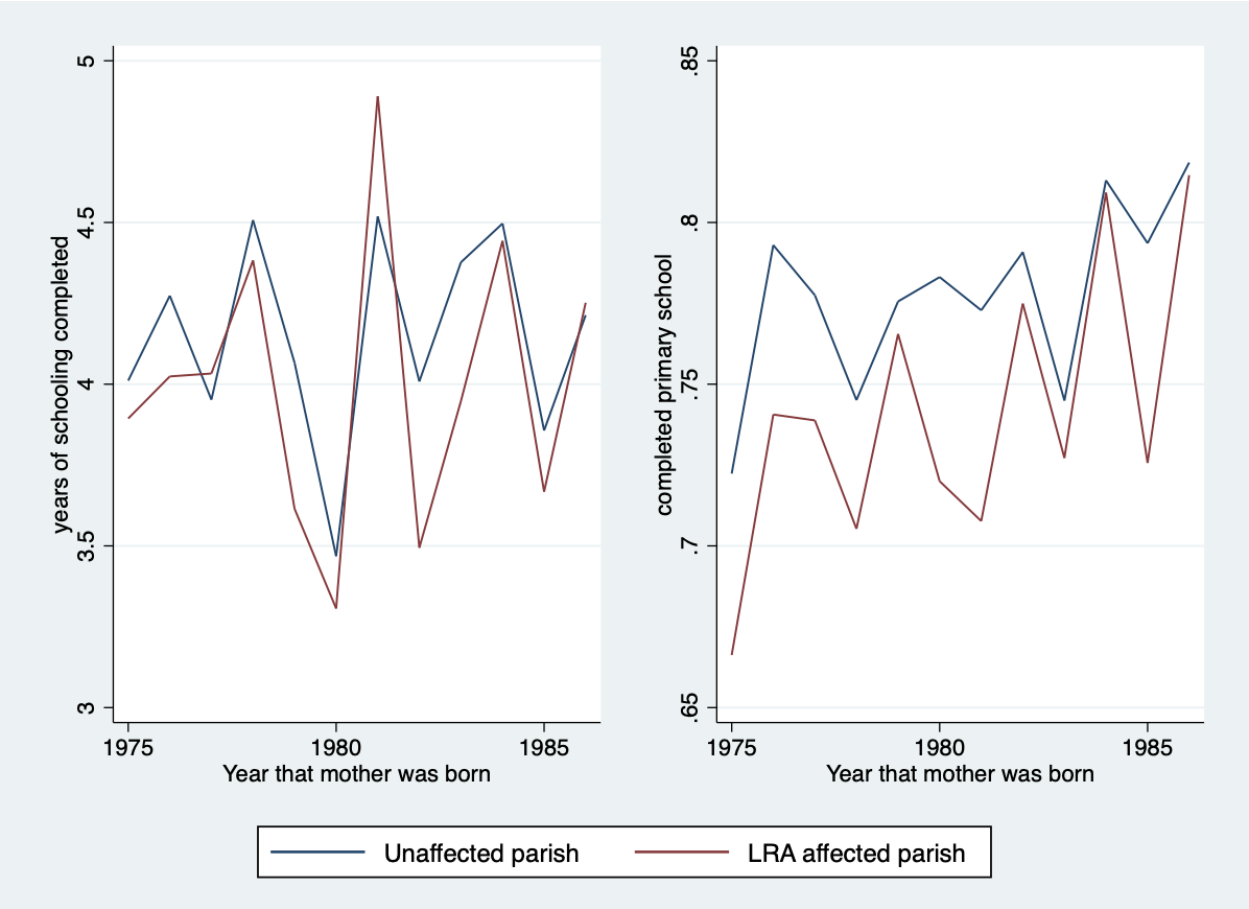


Appendix Figure A4
LRA Activity by year

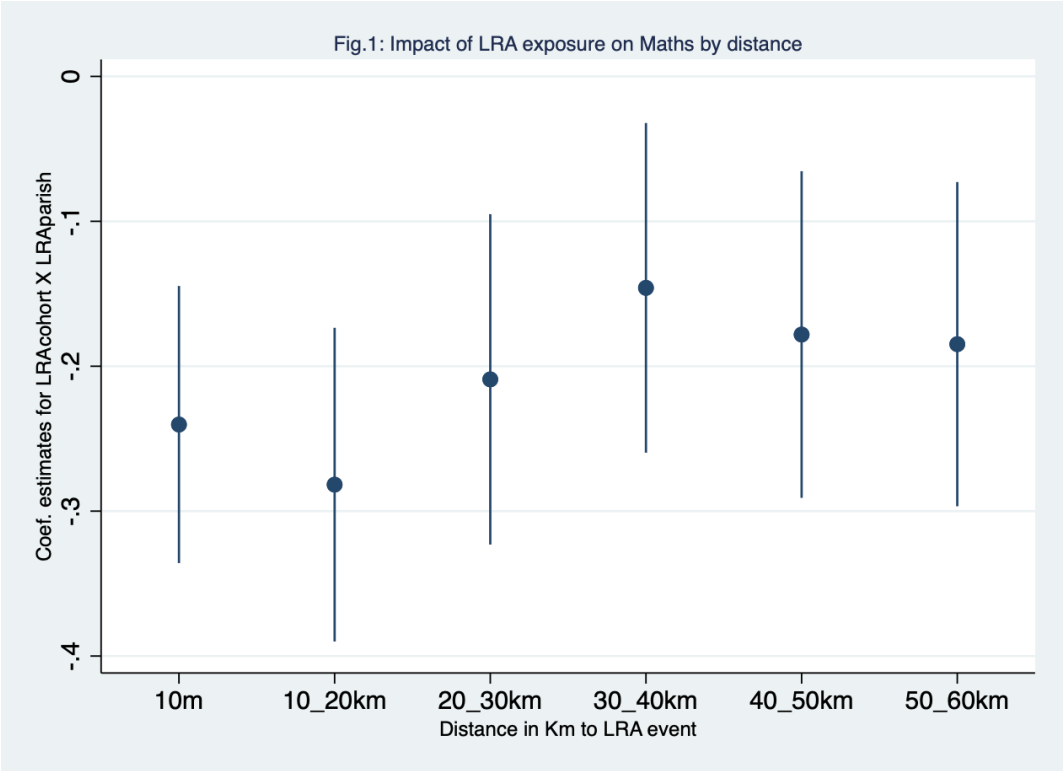


Source: ACLED

Appendix Figure A5
Parallel Trends in Pre-conflict Educational Outcomes



Appendix Figure A6
Impact of LRA exposure on Maths by distance



Appendix Figure A7
Impact of LRA exposure on English by distance