H i C N Households in Conflict Network
The Institute of Development Studies - at the University of Sussex - Falmer - Brighton - BN1 9RE
www.hicn.org

Estimating the Causal Effects of War on Education in Côte D'Ivoire

Andrew L. Dabalen* and Saumik Paul †

HiCN Working Paper 120

August 2012

Abstract: In this paper we estimate the causal effects of civil war on years of education in the context of a school-going age cohort who are exposed to armed conflict in Cote d'Ivoire. Using year and department of birth to identify an individual's exposure to war, the difference-in-difference outcomes indicate that the average years of education for a school-going age cohort is .94 years fewer compared to an older cohort in war-affected regions. To minimize the potential bias in the estimated outcome, we further use a set of victimization indicators to identify the true effect of war. The propensity score matching estimates do not alter the main findings. In addition, the outcomes of double-robust models minimize the specification errors in the model. Moreover, we find the outcomes are robust across alternative matching methods, estimation by using subsamples and other education outcome variables. Overall, the findings across different models suggest a drop in average years of education by a range of .2 to .9 fewer years.

Keywords: war, human capital, education, propensity score matching, evaluation, Africa

* The World Bank
† Osaka University
The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent. This study was financed by the generous support of the Trust Fund for Environmentally and Socially Sustainable Development (TFESSD) managed by the World Bank. The authors are responsible for any remaining errors.

I. Introduction

Conflict affects education in several ways. It destroys infrastructure (Abdi, 1998), displaces and most tragically results in the deaths of students and teachers (Buckland, 2005), causes problems in harmonizing school calendars across war-affected regions (UNICEF, 2005) while schools remain closed for an indefinite period of time (Bruck, 1997), and has a damaging and pernicious socio-psychological impact on students (Sany, 2010). A cross-country analysis by Lai and Thyne (2007) shows that countries experiencing civil war suffer a decline in school enrolment by 1.6 to 3.2 percentage points. Evidence is growing at the subnational level that the outcomes are similar. Merrouche (2006) documents that an exposure to landmines in Cambodia resulted in an average loss of .4 years of education. In a similar study, the mid-1990s genocide in Rwanda lowered the average level of educational attainment by .5 years (Akresh and de Walque, 2008). From the perspective of gender, Shemyakina (2006) finds that conflict makes no significant impact on male education rates in Tajikistan. However, females were 12.3 percentage points less likely to complete the mandatory secondary schooling compared to those who completed their education before the war broke out. A recent study, using household survey data between 2000 and 2008 from twenty-five conflict affected countries, finds that conflict leaves a legacy of fewer average years of education, decreased literacy rates and a smaller share of the population with formal schooling (UNESCO, 2010).

In this paper we estimate the average causal effect of civil war on education in Cote d'Ivoire. In particular, we measure the effect of Ivoirian conflict, which reached its peak between 2002 and 2004, on years of education for individuals who were exposed to it in their school-going age. The civil war in Cote d'Ivoire broke out in September 2002 as a result of growing ethnic tensions and a failed attempted military coup. It divided the country into two: the rebel-held North and the government-controlled South and caused more than 3,000 deaths (World Bank, 2010). The war internally displaced more than 700,000 people and as many as 500,000 children were out of school between 2002 and 2004 (UNICEF, 2004). According to the Ministry of Education in Cote d'Ivoire (2004), education in the North was affected more severely than education in the South. As per this report, almost 50 percent of the school-going aged children were out of school and only 20 percent of government-paid teachers stayed in their posts in the North since 2002. Moreover, the start of the 2005 school year was delayed in the North, and approximately 72,000 children were unable to write their examinations in the North (UNICEF, 2005).

A recent study by UNESCO (2010) uses 2006 Multiple Indicator Cluster Survey (MICS) to conduct a quantitative study on the relationship between education and war in Cote d'Ivoire. This study finds an increase in the uneducated proportion of male cohorts in war-affected areas. Looking separately at the educational attainments for males and females, it concludes that for both genders the average educational attainment has dropped since the conflict broke out. To our knowledge this is the only quantitative study so far that examined the impact of war on education in Cote d'Ivoire. However, this study does not draw any causal inference on the potential impact of war on education. In addition, the MICS survey was undertaken in 2006 just after conflict had reached its peak, and as a result it might not have demonstrated the full impact of war.

This study aims to bridge this knowledge gap. We calculate the average causal effect of civil war on education in Cote d'Ivoire using the Households Living Standards Survey (HLSS) data collected in 2008 and the data on local incidences of conflict is taken from the Armed Conflict Location and Event Database (ACLED). We employ a number of strategies to identify the causal effect of war on education for the school-going age-cohort. First, we use year and department of birth to determine an individual's exposure to war. The difference-in-difference outcomes indicate that the average years of education for individuals aged 10 to 22 is .94 years fewer compared to the individuals aged 23 to 32 in war-affected regions. However, the underlying assumptions for difference-in-difference estimation can possibly be violated in the present study by several factors - internal migration, heterogeneous selection into victimization within regions and varying intensity of conflict across regions. These could be potential sources of bias in the estimated causal effect.

The causal inferences on the impact of war can also be affected if education itself worked as a catalyzer of war. Moreover, there were reasons other than the conflict that could produce a detrimental effect on the educational performances (for example deaths of teachers from HIV/AIDS). The NGO-run primary and secondary schools, which stepped in to fill the education gap in the North during and after the war, might create a downward bias in the estimated impact of war on education. As a second identification strategy, we use a set of victimization indicators to measure the potential effect of war and estimate a counterfactual comparison group based on propensity scores matching. This, we expect, is likely to minimize the selection bias and confounding in the causal effect. The average causal effect of war identified by all the victimization categories indicates .2 to .9 fewer average years of education for war victims compared to the matched control group. The outcomes of double-robust models satisfactorily show less chances of misspecification in the estimated models. The outcomes are robust when we use a number of sensitivity analyses including alternative matching methods, estimating the North and the South subsamples separately.

The paper is structured as follows. In section II, we provide a brief outline of the nexus between education, politics and war in Cote d'Ivoire. Section III describes the data and provides some descriptive evidence. We discuss the empirical models, identification strategies and the empirical findings in section 4. This is followed by the outcomes of sensitivity analysis in section 5. We provide our concluding remarks at the end.

II. The Political Economy of War and Education

To decipher the impact of war on education in Cote d'Ivoire, it is important to understand the Ivoirian education system and how it was linked to the causes and consequences of armed conflict. First we provide a brief account of the war and education nexus in Cote d'Ivoire for the period until the war broke out. We then discuss it for the period 2002 to 2006, during and after the conflict peak.

2.1 The period until 2002: Education as a catalyzer

Since its independence in 1960, Côte d'Ivoire experienced unprecedented economic prosperity and this lasted with sound economic management, improved trade relationships with the Western world, effective development of the cocoa and coffee industries and an ethnically inclusive political system, until the 1980s. However, the worldwide recession and volatility in cocoa and coffee prices from the mid-1980s, followed by structural adjustment programs, prompted an economic stagnation following the declining state-run welfare system and rising unemployment. In the 1990s, the concept of *Ivoirite* became the major political discourse and in 1994 the new Electoral Code restricted the right to vote and presidential candidacy nominations to only Ivorian nationals with complete Ivoirian parenthood. This transformed the ethnic strife into a religious fault line between: firstly, the Muslim dominated North consisting of the majority of immigrants and descendants of the immigrants from neighboring countries (Burkina Faso, Niger and Mali); and secondly, the Christian dominated south.

Notwithstanding the economic and social upheavals, the perception has been that the education system was central to Ivoirian identity and politics. Cote d'Ivoire follows the centralized French education system, where the government plays a key role in curriculum development, coordination and allocation of resources and the organization of national examinations through the ministries of Education, Vocational Education and Higher Education. Prior to the civil war the education system was already struggling with a student-teacher ratio close to 40 (UNAIDS, 1998) while the net enrollment rate in primary education recorded around 60 percent (Cote d'Ivoire Ministry of Education, 2003). In 2000, following the Education for All (EFA) initiative - a worldwide plan to meet the learning outcomes of all children, youth, and adults by 2015 - a number of educational reforms were initiated by the newly elected President Laurent Gbagbo. The proposed agenda addressed areas that needed much attention including improvement of the status of teachers, enactment of the free public schooling through tenth grade and a nationwide preschool system. Perhaps because of this the net national enrollment rate in primary education slightly improved to 64.2 percent in 2001 (Cote d'Ivoire Ministry of Education, 2003).

While economic disparity between the North and the South and polarization of ethnicity and identity based on national origin were arguably the main causes of Ivoirian civil war, unequal access to education and uneven allocation of educational infrastructures between the North and the South also played a crucial role (Sany, 2010). Despite the improvement in country-wide net enrollment rates in the early 2000s, the enrollment rate in the Northern states of Korhogo and Odiene were below 40 percent. Overall, there was a marked disparity in enrollment rates between the Northern states (less than or equal to 50 percent) and the Southern states (close to 80 percent).

2.2 The period from 2002 to 2004: Education as a tactic of war

The first phase of armed conflict started in September, 2002 but lasted for only a few months. The national army (FANCI) was joined by the Young Patriots, a youth militia that supported then President Gbagbo. On the other side, the rebel groups - the *Movement for Justice and Peace* (MJP), the *Movement of the Ivory Coast of the Great West* (MPIGO) and supporters of Alessane Outarra (current President) - joined forces under the banner of the *Forces Nouvelles* (FN) led by Guillame Soro. The momentum of educational reform initiated in 2000 was soon arrested by the outbreak of civil war. As the conflict broke out, education moved to the bottom of the national priority list (Sany, 2010). A UNICEF estimation in 2005 accounted for as many as 700,000 children being out of school between 2002 and 2004. This figure included students from primary school to university level. In November 2004, riots against the French force in Abidjan destroyed infrastructure including numerous schools buildings there (UNICEF, 2005). In 2004, the Cote d'Ivoire Ministry of Education documented more than 50 percent of the students in the North did not have any access to school.

As argued by Sany (2010) education was used by both parties as a tactic of war. Due to war the organizational and institutional challenges in delivering the basic educational facilities were less in the government-held South compared to the rebel held-North. The Government side used this as a strategy to portray the inability of non-governmental forces in providing basic education and necessary infrastructure. Perhaps it paved a way for the government to legitimize its position, but it forced the non-governmental opposition to come up with an alternative strategy. An UNOCHA (2004) report found that there were more than 300,000 children in the North attending NGO-run primary and secondary schools from 2002 to 2004. The success of the NGOs in delivering education in the North indicates that the disparity in the provision of educational facility had more to do with the agendas of the political parties in conflict than to the fear of violence and lack of security (Sany, 2010). Validation of previous examination results in the rebel-held North and harmonization of the school calendars between the North and the South – later became part of the peace agreements signed by the parties in conflict.

In addition, since the early 1990s the teacher's struggle to regain their lost status due to Structural Adjustment Program became an alarming issue especially for the political parties in power. As Sany (2010) remarks the struggle within the education sector has also facilitated the escalation of the conflict from the university campus into the political sphere. During the conflict both sides actively sought to include university students on their side. The higher education institutes filled with active students' organizations and teachers' associations became the center stage of political movements. Many prominent political leaders including the former President Laurent Gbagbo and former Prime Minister Guillaume Soro emerged from the students' movements, reinforcing the Ivoirian sentiment that the education system has produced political leaders rather than business leaders (Sany, 2010).

III. Data and Descriptive Evidence

Figure 3.1 Incidence of Conflict in Cote d'Ivoire: 2001 to 2006

Source: Authors' calculation based on the ACLED database

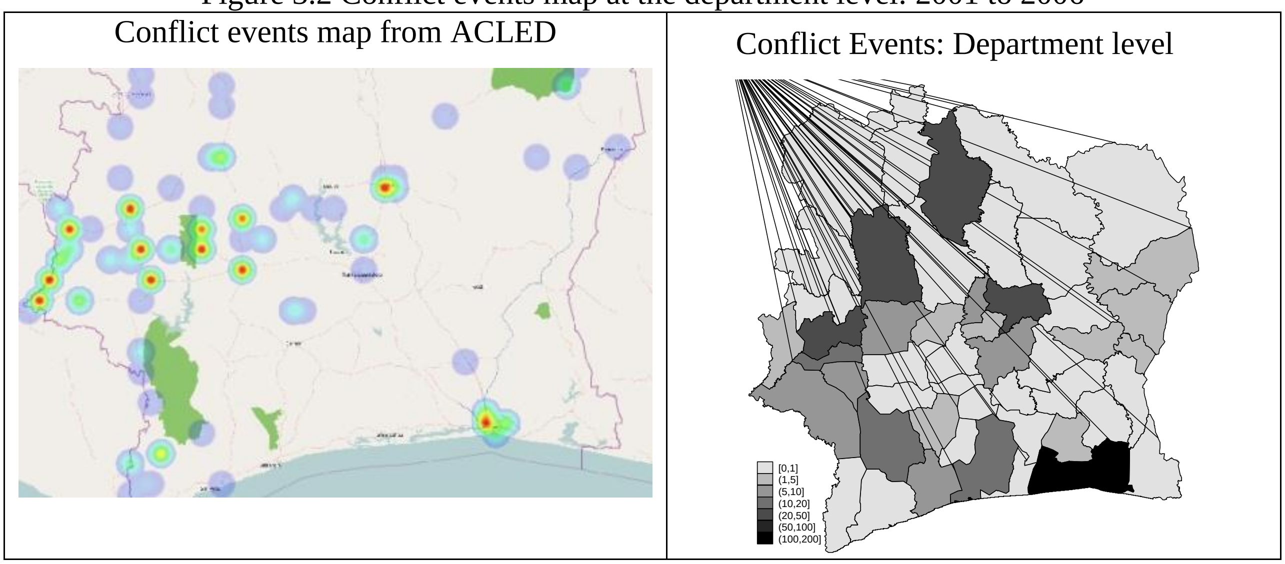
In this study we use two main data sources. The data on local incidences of conflict is taken from the Armed Conflict Location and Event Database (ACLED). The Armed Conflict Location and Event Database[1] (ACLED) (Raleigh, Hegre, and Carlson, 2009) compiles exact locations, dates, and additional characteristics of individual battle events in states affected by civil war. The conflict data for Cote d'Ivoire is available for the period from 1997 to 2010. The ACLED database on Cote d'Ivoire reports a total number of 965 conflict events between 1998 and 2008. It tracks rebel activity and distinguishes between territorial transfers of military control from governments to rebel groups and vice versa. The conflict events are disaggregated into six categories: (i) Battle - government regains territory, (ii) Battle - no change of territory, (iii)

[1]For more information go to the ACLED website at http://www.prio.no/CSCW/Datasets/Armed-Conflict/Armed-Conflict-Location-and-Event-Data/

Battles - rebels overtake territory, (iv) Non-violent activity by a conflict actor, (v) riots/protests, and (vi) Violence against civilians. In Figure 3.1, we show the total number of reported conflicts per year for the period starting from 2001 to 2006. The conflict intensity reached its peak between 2002 and 2004 with a total of 459 conflict events.

For empirical purposes, we disaggregate the conflict events into 50 departments, which are nested into 19 regions in Cote d'Ivoire. To decipher the causes and consequences of conflict at the local level, many studies have used smaller geographical regions or artificial geographic grid-cells (without pertaining to any meaningful sub-national border) as the unit of analysis. Some researchers prefer to follow the grid-cell approach because the unit of analysis does not change spatially (Buhaug and Rod, 2006). In comparison, when the unit of analysis is the sub-national regions, they are likely to vary in terms of area. In this study we map the exact locations of the conflict event provided by the ACLED database into 50 departments using spatial coordinates taken from the DIVA-GIS[2] website.

Figure 3.2 Conflict events map at the department level: 2001 to 2006



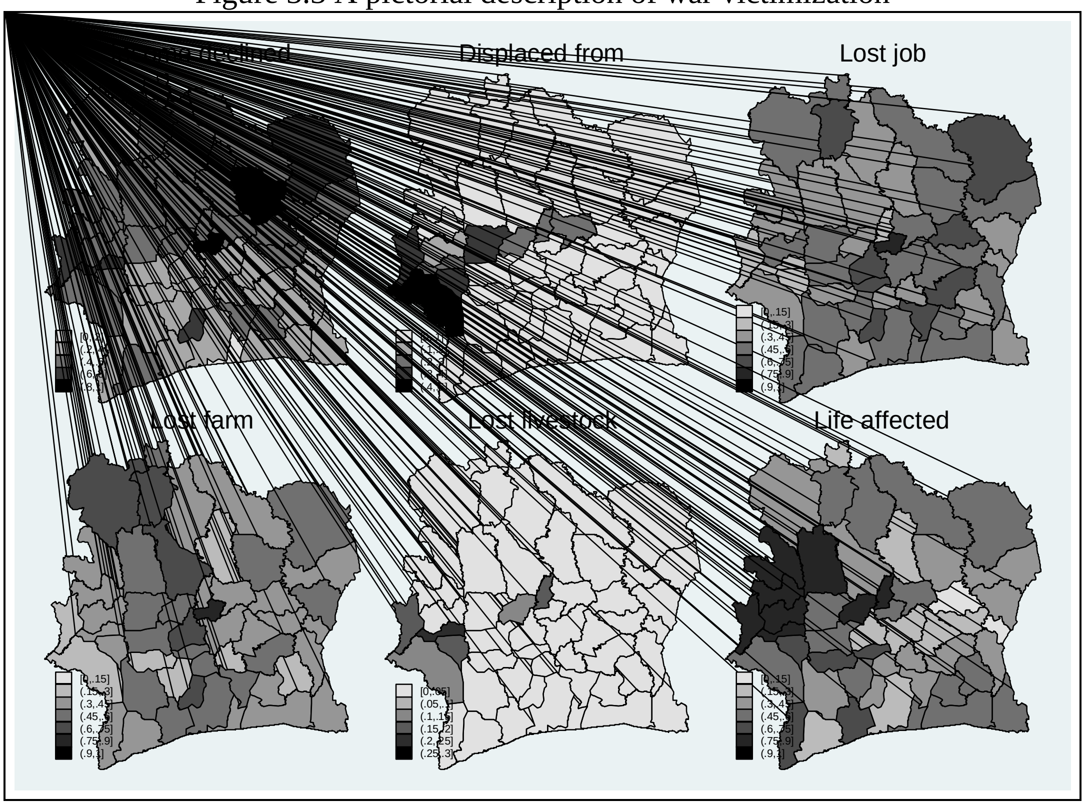
Source: ACLED and authors' own calculations

Figure 3.2 plots the total number of conflict events at the department level for the period 2002 to 2004. On the left hand panel of Figure 3.2, we show the conflict prevalence map taken

[2]DIVA-GIS website for Cote d'Ivoire http://www.diva-gis.org/datadown

from the ACLED website[3]. On the right hand panel, we plot the intensity of conflict across departments. The geographical areas marked with darker shades indicate departments that experienced more intense conflict. The incidences of civil conflict have been more frequent in the western and southern departments of Core d'Ivoire and in the neighborhood Abidjan. Between 2001 and 2006, the average number of conflict events per department recorded at 8.6. In 2003, only in Abidjan did the number of armed conflict events escalate to more than 150. Furthermore the conflict events occurred at a large number near the Line of Control administered by UN and French troops. About three-quarters (37 out of 50) of the departments experienced at least one conflict event during the period from 2002 to 2006.

Figure 3.3 A pictorial description of war victimization



Source: ACLED and authors' own calculations

Cote d'Ivoire has a rich history of detailed household surveys dating back to 1985. In this study we use the 2008 round of Households Living Standards Survey (HLSS) data, also known as *Enquete sur le Niveau de Vie de Menage* (ENV). These surveys were undertaken by the

[3]The following website http://www.acleddata.com/index.php/dynamic-maps provides conflict maps for a number of countries.

National Institute of Statistics in Cote D'Ivoire. The ENV-2008, jointly administered by the National Institute of Statistics - Cote d'Ivoire and UNICEF, was specifically designed to document the consequences of the civil war. A new section on the 'impact of the war' was added, which included a range of questions that are commonly used to evaluate the welfare impact of war on individuals and households. For example, household respondents were asked: "How did your income change over the years of crisis?" / "Has the current crisis affected your life?" In addition, the survey included a set of questions on the physical impact and casualty of the war, such as "Have you registered a death or illness linked to the crisis? / "Have you been displaced during the war?" / "Have you suffered any violence linked to the crisis?"

In Figure 3.3 we provide a pictorial view of the war victimization based on household responses. We plot the average responses at the department level; darker shades imply a higher average rate of victimization experience for the inhabitants in a department. It is evident that the civil war had an adverse effect on the livelihood of the entire population in Cote d'Ivoire; however the impact was more prevalent in the Middle and the Northwest of the country. Overall, between 30 to 50 percent of the respondents experienced declines in their income. The incidence of war victimization was more prominent in the departments located near the UN-peace keeping line and to the West where the civil war was more intense. Nearly 30 percent of the respondents had to hide during the war in the Northwestern departments. The conflict in the mid-West of the country is also marked by high levels of internal displacement. The adverse effect of the war on jobs and land is prevalent throughout the country. However, the people in the mid-West reported to have experienced loss of livestock and non-land assets.

Finally, we turn to the education system in Cote d'Ivoire. It mostly follows the centralized French education system, where the government plays a key role in curriculum development, coordination and allocation of resources and the organization of national examinations through the ministries of Education, Vocational Education and Higher Education. The *Certificat d'etude primaries elementaires* (CEPE) is awarded after completing six years of primary education, which is followed by seven years of secondary schooling. In the final year of secondary school students earn a baccalaureate degree. Universities, technical and vocational trainings are part of the higher education system in Cote d'Ivoire (Sany, 2010). As is evident from the ENV-2008 data, in the sub-population consisting of individuals aged 12 and above, about 35 percent earned a CEPE whereas only 10 percent completed the baccalaureate degree. However, almost 40 percent from the same group of people did not complete the CEPE. The average years of education stands a little above 7 years, which is one additional year of education after six years of primary education (CEPE). Based on this, we infer that the age-cohort of primary school goers are likely to be one of the potential victims of war. In this study, we use years of education as the main outcome variable to evaluate the causal effects of war on education in Cote d'Ivoire.

IV. Empirical Outcomes

4.1. Identification using department and year of birth: age-cohorts from ENV-2008

According to the ENV-2008 survey data, for more 90 percent of the individuals who earned the CEPE (completed six years of primary education), it took between 6 to 10 years. This suggests the majority of the students in the primary school are in the 6 to 16 age group with the plausible assumption that primary education normally starts at the age of six. To identify the potential victims of war, we construct a young cohort including all primary school goers who were exposed to the conflict between 2002 and 2006. Based on this, the individuals aged between 10 and 22 years constitute the young cohort in the ENV-2008 survey. Using ENV-2008, we compare average years of education for individuals in the young cohort against an older cohort, aged between 23 and 32. The individuals in the old cohort are likely to be over the age of primary school goers between 2002 and 2006. We use the year of birth and the department of birth to identify an individual's exposure to war. To begin with, a straight forward difference-in-difference of average years of education is calculated based on year and department of birth.

Table 4.1.1 Means of Years of Education by Cohort and War Prevalence

	Years of education		
	No War	War	Difference
Old Cohort (Aged 23 to 32 in 2008)	7.84	9.18	-1.34
	(0.14)	(0.08)	(0.18)
Young cohort (Aged 10 to 22 in 2008)	6.32	6.46	-0.14
	(0.06)	(0.04)	(0.07)
Difference	1.52	2.71	-1.20
	(0.13)	(0.08)	(0.16)

Note: Standard errors are in parenthesis, all estimated coefficients are statistically significant at 1 percent

Table 4.1.1 reports average years of education for both age-cohorts and a war prevalence dummy, which takes the value of one if a department (of birth) experienced at least one conflict event, zero otherwise. The war prevalence of a department reflects the total number of conflict events between 2002 and 2006. For both age-cohorts, the average years of education in conflict-affected departments is higher compared to the rest. However, the gap in average years of education is negligible for the young cohort. Two possible explanations can be offered. First, the war zones (departments that experienced conflict) traditionally had higher average years of education and this could be due to better educational facilities or better job prospects. Second, due to the pernicious effect of conflict throughout the country, the gap in average years of education between war and non-war zones became smaller for the young age-cohort. This is supported by the evidence that the gap in average years of education between older and younger cohort is twice as big in the war zones compared to the departments with no war event. Overall, the difference-in-difference outcome suggests that an individual aged between 10 and 22 experienced an average drop of 1.2 years of education if resided in a war affected department.

We generalize this identification strategy with a regression framework, shown as equation 1 (Duflo, 2001; Merrouche, 2011; Shemyakina, 2011). This estimates the average years of education as a function of birth fixed effects and household / individual specific controls. If exposure to conflict (i.e. residing in the departments that had at least one conflict event) is detrimental to years of schooling, then the estimated coefficient of average years of education will be negatively related to the intensity of war for the young age-cohort which is exposed to conflict.

(1) $$\boldsymbol{y_{ijk} = C_1 + Depart_{1j} + Birth_{1k} + (War_j \times Treat_i)\beta_1 + (X_i)\delta_1 + \varepsilon_{ijk}}$$

where y_{ijk} measures years of education for an individual *i* born in department *j* in year *k*. C_1 is a constant, $Depart_{1j}$ is a dummy variable indicating department of birth fixed effect, $Birth_{1k}$ is a dummy variable that measures cohort of birth fixed effect, $Treat_i$ is a dummy variable indicating whether the individual belongs to the young cohort, War_j is a variable measuring intensity of conflict and X_i is a vector of household specific controls.

Table 4.1.2 presents estimates of equation (1). The first two columns show the baseline regression outcomes when the war intensity variable is a dummy, takes a value of one if a department had at least one war event, zero otherwise. The baseline regression model without household controls yields a coefficient of -.94. This suggests average years of education for individuals aged 10 to 22 is .94 years fewer compared to the individuals aged 23 to 32 in departments that had at least one conflict event. The coefficient drops to -.5 when we include household level control variables (as shown in column 2). If there is significant variation in the conflict count across departments, the dummy conflict indicator may not adequately explain the variation in average years of education across departments. As a robustness check, the last two columns report the estimated coefficients of years of education when the war intensity variable is measured as the actual number of conflict events. The outcome suggests that an increase in the war intensity by one additional event of conflict lowers the average years of education for the young age-cohort (aged 10 to 22 years) by .01 years compared to old age-cohort (aged 23 to 32).

Table 4.1.2 Effect of War on Education using 2008 household survey data
(Dependent variable = Years of Education)

	War intensity = dummy (=1 if there was at least one war event)		**War intensity = actual number of conflict events**	
War intensity × Young Cohort	-0.940***	-0.499***	-0.011***	-0.008***
Control variables				
Birth fixed effects (department)	Yes	Yes	Yes	Yes
Birth fixed effects (Age Cohort)	Yes	Yes	Yes	Yes
Household controls	No	Yes	No	Yes
Constant	8.355***	4.677***	8.477***	4.651***
Observations	16,345	16,017	16,345	16,017
R squared	0.235	0.423	0.241	0.426

Notes: The household level controls include log per capita consumption expenditure, gender, gender of household head, average years of education in the household, ethnic groups and religious groups; *** implies significant at 1%, ** implies significant at 5% and * implies significant at 10%.

The estimated coefficients of the causal effect of war on education show an expected sign. However, underlying assumptions of the difference-in-difference model in the present context deserve more careful consideration. First, using department of birth as an identification strategy may not reveal the heterogeneous impact of war victimization on education for children from different socio-economic groups. In other words, there exists a possibility of selection into victimization across individuals which could be largely hidden by the total number of conflict events in a department. Second, the proximity to a war zone dummy variable may fail to identify the true impact of war on education because the intensity of war measured as the count of war events varies significantly across departments. Third, due to a large number of internally displaced people, it is often hard to track their movements between 2004 and 2008. If many school-going children were displaced from one department to another, then it is likely that it would produce an upward bias on the average education impact of war. It is also possible that the household control variables for the comparison group might have changed over time, especially if they migrate. As a result, we harbor on an alternative identification strategy to minimize the potential bias that might arise due to these factors.

4.2 Identification using victimization indicators from ENV-2008

As a next step, we use 11 victimization indicators as potential identifiers of true war victims. The victimization indicators are dummy variables, which takes the value of one for a household or individual being a victim, zero otherwise. It is possible that the self-reported victimization indicators may produce subjective bias related to a particular ethnic group or other identities. The simplest way to detect the extent of this bias is to estimate each victimization indicator as a function of the observable characteristics. The estimated outcome does not conform to any subjective bias generated by any particular variable (for reasons of space we do not show the outcome in the paper; it is available from the authors if requested).

We first estimate the standard linear OLS regression outcomes of years of education as a function of the victimization dummy and household and individual controls on a sample restricted to individuals aged between 10 and 22 (who are likely to be in the primary school during the conflict). In Table 4.3.1 we report the estimated coefficients for the eleven victimization categories (columns M1 through M11). The coefficients of all the victimization dummy variables are negative. The coefficients are statistically significant for victimized individuals or households when they registered deaths or injuries due to conflict , income dropped, lost job, lost livestock and experienced violence due to war. Overall, the estimated war outcomes on education are in line with previous findings, despite the fact that the impact of war is now identified by a set of victimization indicators based on the subjective evaluation of war impact by the survey respondents.

Table 4.3.1 OLS Regression outcomes on Average Years of Education

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11
Registered deaths	-0.128**										
Registered injury		-0.115*									
Displaced			-0.033								
Income dropped				-0.220***							
Lost ownership					-0.125						
Lost job						-1.602***					
Lost farm							-0.516				
Lost livestock								-0.682***			
Lost assets									-0.200		
Affected by the war										-0.058	
Experienced violence											-0.240***
Control variables											
Birth fixed effects (department)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth fixed effects (Age Cohort)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	6.152***	6.076***	6.185***	6.213***	6.181***	6.115***	6.192***	6.168***	6.190***	6.235***	6.172***
Observations	10,552	10,331	10,492	10,625	10,625	10,625	10,625	10,625	10,625	10,625	10,625
R squared	0.455	0.457	0.456	0.457	0.456	0.457	0.456	0.456	0.456	0.456	0.456

Notes: The household level controls include log per capita consumption expenditure, gender, gender of household head, average years of education in the household, ethnic groups and religious groups; *** implies significant at 1%, ** implies significant at 5% and * implies significant at 10%.

The identification strategies used so far assume that the war victims (as identified above) and control groups are exchangeable, such that they have identical distributions of variables. This can be confirmed by data using a randomized controlled trial; however, drawing causal inference using survey data requires a more careful analysis because selection biases and confounding invalidates the exchangeability assumption. In such cases the estimated causal effects are likely to be biased. Here we discuss a number of events that could be potential sources of bias in the estimated causal effect. First, education could be seen as a catalyzer of war in Cote d'Ivoire. The distribution of educational facilities was unequal between the rebel-held North and the government-controlled South. This might produce an upward bias in the causal effect of war on education. Second, there were reasons other than the conflict that had a negative impact on attainment of education. This includes the large number of deaths of teachers as a result of HIV/AIDS (Sany, 2010). Third, NGO-run primary and secondary schools stepped in to fill the education gap in the North in 2004. This could also produce a downward bias in impact of war on education.

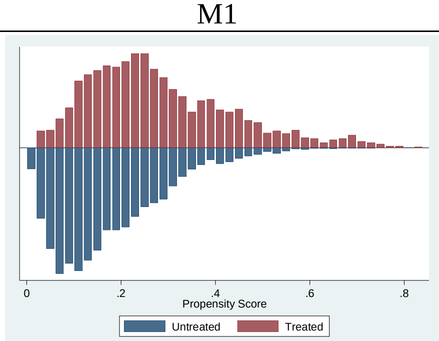
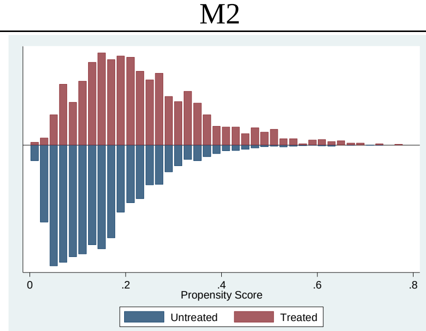
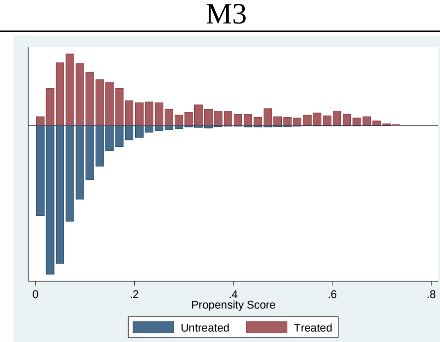
All these factors could potentially generate selection bias and confounding errors, thus invalidating the exchangeability assumption. In the presence of these possibilities, it is unrealistic to assume that the incidence of war is randomly assigned and the confounding factors may generate bias in the causal effect of war on education. Since a direct comparison of two groups of individuals may not overcome the problem of identification, we go one step further and employ propensity score matching (Rosenbaum and Rubin, 1983). This means pairing individuals who are identical based on all observable characteristics (including department of birth, other households characteristics and the relevant socio-economic factors) that the rich ENV-2008 survey data offers, except variables that measure war victimization. We discuss it more formally below. Let us denote the binary victimization indicator W_i equals to one if individual *i* is a war victim and zero otherwise. We are particularly interested in estimating the average treatment effect on the treated (ATT). This can be written as equation (2) below:

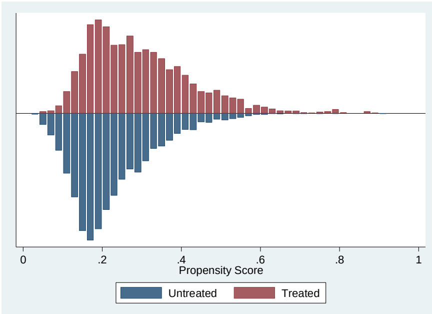
$$\textbf{(2)}\quad \tau_{ATT} = Educ(\tau|W = 1) = E\ [Educ(1)|W = 1)] - E\ [Educ(0)|W = 1)]$$

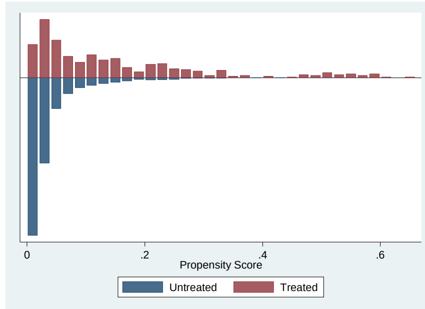
where $Educ_i(W_i)$ denotes the potential education outcome (years of education in our case) for each individual i. As the average education level of the counterfactual comparison group - $E\ [Educ(0)|W = 1)$ - is not observed, we generate propensity scores to choose a proper substitute from the matched pairs based on propensity scores. Propensity scores are generated by simple probit regression. Individuals are paired chosen from the war victims (treatment group) and the rest (control group) based on the similar propensity scores and then we calculate the average difference in years of schooling across them. There exists a range of possibilities for matching algorithms; however, the performance of different matching estimators depends largely on the data structure (Zhao, 2000). For our purpose, we use the straightforward nearest neighbor matching as a baseline strategy. This method first categorized both the treatment and the control group records according to the estimated propensity score and then searches backward and forward for the closest control units for a particular treatment value.

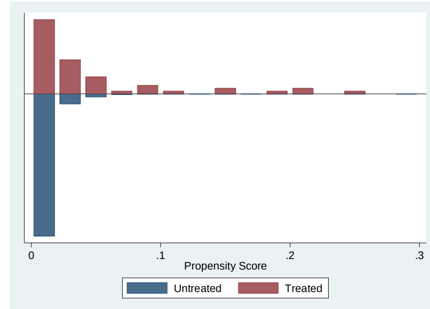
Figure 4.3.2 provides a visual description of the comparison of propensity score distributions between the direct civil war victims (treated) and the matched comparison groups (untreated). The visual analysis of the density distribution of propensity scores is the most straight forward way to check the overlap and the region of common support between the treatment and comparison group (Caliendo and Kopeinig, 2005). To determine the average treatment effect on the treated (ATT), it is sufficient to ensure the existence of potential matches in the control group (Bryson, Dorsett and Purdon, 2002). In our case, except M5, M6, M7 and M8, the rest of the models show a satisfactory match just by visual observations. Overall, most of our empirical models do not encounter any common support problem. We discuss this in further detail in the next section.

Figure 4.3.2 The common support between the war victims and the comparison groups

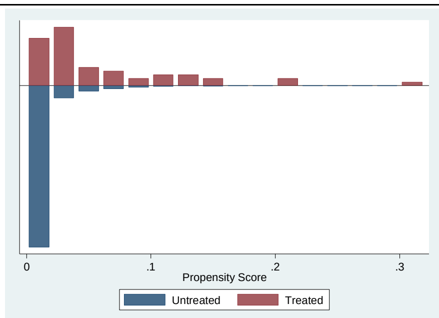
M1	M2	M3
		
M4	M5	M6

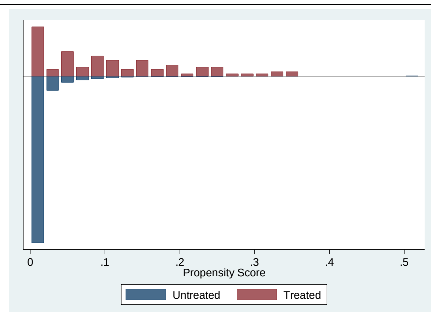


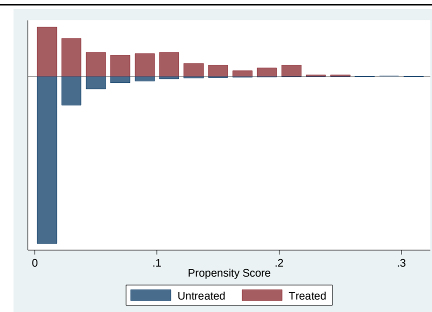




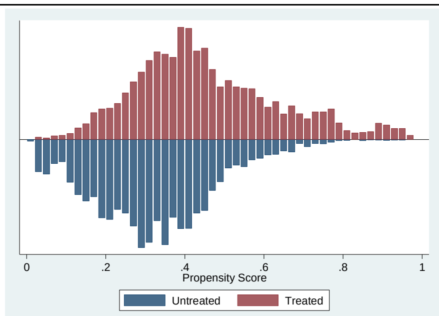
M7 | M8 | M9







M10 | M11



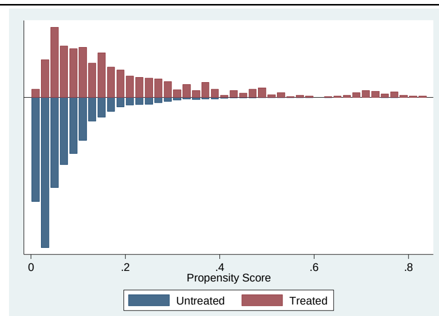


Table 4.3.2 summarizes the estimated effect of war on educational outcomes for each of the 11 models. The propensity score matching method yields a negative impact of conflict on years of education in the sample restricted to individuals aged between 10 and 22. The average treatment effect on the treated (ATT) indicates that irrespective of the type of war victimization, war victims in comparison with the matched control group indicate a lower average years of education. The mean difference is significant particularly when the war victims registered for deaths due to the war, their income dropped, they lost jobs and they reported being affected by the war.

Table 4.3.2 Estimated effects of war on years of education using propensity score matching (Matching method: nearest neighbor)

	Model	Observations	Treatment	Controls	ATT
M1	Registered deaths	10496	6.368	6.561	-0.193*
M2	Registered injury	10249	6.490	6.590	-0.100

M3	Displaced	10888	6.425	6.564	-0.139
M4	Income dropped	10625	6.409	6.686	-0.277**
M5	Lost ownership	10070	6.217	6.530	-0.313
M6	Lost job	6541	5.182	6.364	-1.182*
M7	Lost farm	4870	5.392	5.804	-0.412
M8	Lost livestock	5335	5.589	5.900	-0.311
M9	Lost assets	7305	6.811	7.232	-0.421
M10	Affected by the war	10625	6.535	6.761	-0.226**
M11	Experienced violence	10167	6.468	6.625	-0.158

*** implies significant at 1%, ** implies significant at 5% and * implies significant at 10%.
(ATT: the average treatment effect on the treated)

V. Sensitivity analysis

5.1. Combining matching and regression: double-robust estimation

Any method that uses propensity score matching requires that the model is specified correctly with all relevant confounders included in the model (Emsley et al, 2008). In reality it is hard to ascertain that the empirical models we estimate are correctly specified. However, as a robustness check one can use the concept of double-robust estimators (Robins, 2000; Bang and Robins, 2005). The double-robust estimation method requires a model for estimating the propensity scores and the outcome model (OLS in our case) in the same estimator. Ideally, this method selects only those observations which are on common support and discards the rest of the data. In the context of the present study, by using this method we prune from the data all the observations that are not similar to the propensity scores of war victims, and then run a simple linear OLS regression on the observations that are left in the data set. Additionally this retains the weights from matching, thus indicating how many times each control case will be used in the regression. The double-robust estimators provide unbiased estimates of the treatment effect when either or both of these models are correctly specified. In a sense, it provides more protection against the misspecification (Uysal, 2011).

Table 5.1 Comparison of estimated effects of war on years of education: OLS, propensity score matching and doubly robust model

Model		OLS model (coefficients)	Propensity score matching model (ATT)	Double-robust model (coefficients)
M1	Registered deaths	-0.128**	-0.193*	-0.156**
M2	Registered injury	-0.115*	-0.100	-0.100
M3	Displaced	-0.033	-0.139	-0.131
M4	Income dropped	-0.220***	-0.277**	-0.287***
M5	Lost ownership	-0.125	-0.313	-0.102
M6	Lost job	-1.602***	-1.182*	-1.665***
M7	Lost farm	-0.516	-0.412	-0.077
M8	Lost livestock	-0.682***	-0.311	-0.128
M9	Lost assets	-0.200	-0.421	-0.153
M10	Affected by the war	-0.058	-0.226**	-0.106*
M11	Experienced violence	-0.240***	-0.158	-0.021

** implies significant at 5% and * implies significant at 10%.

In Table 5.1, we compare the estimates of the linear OLS model, propensity score matching and double-robust model for 11 victimization categories, M1 to M11. We use this table as a sensitivity analysis to assess the specification of the OLS and propensity score matching models. If these models are correctly specified then ideally the double-robust estimates would produce a similar effect. As is shown in Table 5.1.1, M2, M3 and M4 are correctly specified in the propensity score matching. However, M5 and M6 are correctly specified when estimated in the OLS model. We conclude this as they closely match with the double-robust estimated coefficient of the causal effect of war on years of education. The outcomes from the rest of the models do not conform to the double-robust estimates closely. Overall, the support is mixed, and there exists a trade-off in the estimation model choice between the OLS and propensity scores matching.

5.2. Implementing alternative matching criteria

So far, we used the *nearest neighborhood with replacement* as a baseline matching criterion. A number of alternative matching criteria do exist and it is argued that in large samples all of these propensity score matching estimators should yield the same results asymptotically (Smith, 2000). However, choosing an appropriate matching criterion becomes a concern when we are left with small samples (Heckman, Ichimura and Todd, 1997). In our study models such as M6, M7, M8 and M9 have a relatively smaller sample size. As a robustness check we estimate the causal effect of war on education using three additional matching criteria for each of the models. Since performance of different matching criteria depends largely on the data structure and varies case-by-case (Zhao, 2000), we compare the average treatment effect on the treated (victims) from different matching estimators side by side (Table 5.2).

Table 5.2 Comparison of estimated effects of war on years of education: ATT based on alternative matching criteria

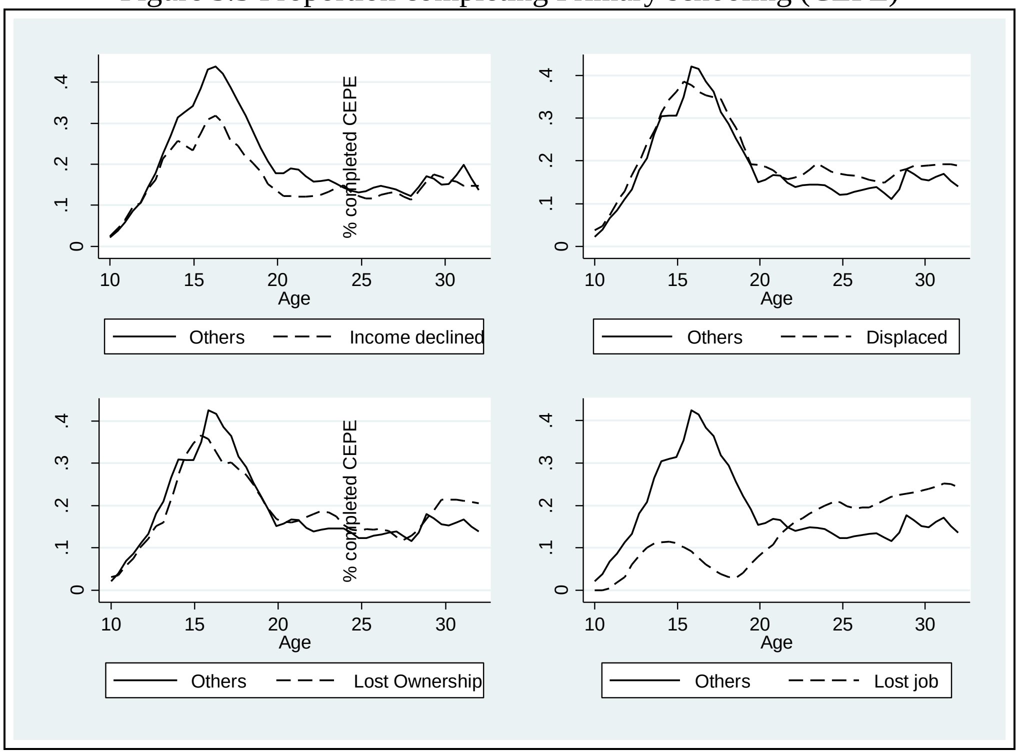
Model		ATT (Nearest Neighbor) Baseline	ATT (Nearest Neighbor no replacement)	ATT (Caliper matching .007)	ATT (Kernel matching)
M1	Registered deaths	-0.193*	-0.172*	-0.186	-0.159*
M2	Registered injury	-0.100	-0.151	-0.096	-0.129
M3	Displaced	-0.139	-0.040	-0.147	-0.002
M4	Income dropped	-0.277**	-0.172*	-0.275**	-0.199**
M5	Lost ownership	-0.313	-0.248	-0.253	-0.225
M6	Lost job	-1.182*	-1.036*	-1.182*	-1.427***
M7	Lost farm	-0.412	-0.294	-0.104	-0.876*
M8	Lost livestock	-0.311	-0.400	-0.253	-0.767**
M9	Lost assets	-0.421	-0.384	-0.409	-0.052
M10	Affected by the war	-0.226**	-0.178**	-0.216**	-0.173**
M11	Experienced violence	-0.158	-0.319**	-0.214	-0.219*

A quick observation of Table 5.2 reveals that the causal effect of war on education is negative throughout and this outcome is independent of any matching criterion. If we compare the outcomes from the *nearest neighbor matching with replacement* (baseline) and the *nearest neighbor matching without replacement*, the average war effect on education is largely across the models with a few exceptions. We modify the nearest neighbor matching by imposing a caliper of .007, which in this case is the maximum propensity score distance for matching. This filters the bad matches which are outside the caliper tolerance level. The estimation based on the *caliper matching* yields similar outcomes to baseline models. Finally, we use a non-parametric matching estimator, the *kernel matching*, which uses weighted averages of all entries in the control group to construct the counterfactual outcome. According to Smith and Todd (2005), kernel matching can be seen as a weighted regression of the counterfactual outcome on an intercept with weights given by the kernel weights. The outcome is similar to the baseline model;

however, in most of the models, the estimated effect of war on education is significant using the kernel method. This could possibly be because kernel matching includes observations that are bad matches. Overall, we find robust support for the baseline findings.

5.3. Alternative measures of educational outcomes

Figure 5.3 Proportion completing Primary schooling (CEPE)



In the previous analysis we used only total years of education as an educational outcome variable. As a sensitivity analysis, we propose to look at another potential outcome variable that measures the percentage of population that completed CEPE (six years of primary education). This is justified by the fact that the average years of education based on the ENV-2008 data is recorded as being little over 7 years and almost 40 percent of the population fail to complete the CEPE. Thus, percent completed CEPE will be a good indicator the status of education in Cote d'Ivoire. We estimate nonparametric kernel-weighted local polynomial regressions of percent ever completing six years of primary education against age using Epanechnikov kernel.We ran the regressions separately for the war victims and the rest of the sample as identified by the victimization indicators. Figure 5.3 provides the outcomes of non-parametric estimation for four victimization categories. Of the victimized groups, individuals whose family members suffered from income loss or job loss are less likely to complete CEPE. This is evident particularly in the age-cohort with individuals aged between 10 and 22. The internally displaced individuals do not show a different trend in the successful completion of CEPE. Households that suffered from ownership loss, individuals in the aged between 10 and 22, do indicate a drop in the rate of successful completion of six years of primary education.

5.4. Estimating impact of war on sub-samples: The North versus the South

As the final robustness check, we compare empirical outcomes from sub-samples: the North and the South. Table 5.4.1 reports the simple difference-in-difference outcome of average years of education on age-cohorts between the North and the South sub-populations. Out of a total of 50 departments the North has 16 which were located to the north of the United Nations peace-keeping line (also known as the fault line). The rest of the departments are classified as being in the South. As is evident from Table 5.4.1, for both the old and the young cohort, the average years of education is lower in the North. However, the difference is twice as big as for the old cohort (aged between 23 and 32 years) compared to the younger one (aged between 10 and 22 years). As a result the difference-in-difference outcome for years of education is .72 years. This implies individuals in the young-age cohort have on average .72 more years of education compared to the old cohort in the North. This is also supported by the fact that the difference in average years of education between the young and the old cohort is larger in the South compared to the North. These findings contradict those of many studies documenting that the impact of war on education was more severe in the North. Rather it suggests that despite the historically lower educational outcome in the North, the impact of war on education fell most heavily on the school going age-cohort that was exposed to the war.

Table 5.4.1 Means of Years of Education by Cohort and region

	Years of education		
	South	North	Difference
Old Cohort (Aged 23 to 32 in 2008)	9.13 (0.08)	7.81 (0.15)	1.33 (0.16)
Young cohort (Aged 10 to 22 in 2008)	6.56 (0.04)	5.96 (0.06)	0.61 (0.07)
Difference	2.58 (0.08)	1.85 (0.14)	0.72 (0.17)

Note: Standard errors are in parenthesis, all estimated coefficients are statistically significant at 1 percent

To obtain a generalized picture, we run OLS regression outcomes for the impact of war on the average years of education by region as identified by the victimization indicators. Table 5.4.2 compares the outcomes between the full sample, i.e. the North and the South sample. For the displaced household members and households that registered death due to war, the effect of war is negative and significant only in the North. However, when we compare educational outcomes of households where members lost their jobs or reported declines in income, we find that war had a similar negative effect. Overall, the similarities and dissimilarities in these findings might have a lot to do with the subjective bias in responses and selection bias into victimization between the North and the South sub-populations. Nevertheless, we do not find any clear evidence in support of the North being the worst war-affected region in terms of education outcomes.

Table 5.4.2 Comparison of OLS estimates of war on years of education: Full sample, the North sample and the South sample

	Full sample	North sample	South sample
Registered deaths	-0.128**	-0.420***	-0.049
Registered injury	-0.115*	-0.163	-0.102
Displaced	-0.033	-0.389***	0.081
Income dropped	-0.220***	-0.257**	-0.211***
Lost ownership	-0.125	-0.325	-0.062
Lost job	-1.602***	-1.092*	-1.701***
Lost farm	-0.516	-0.659	-0.332
Lost livestock	-0.682***	-0.036	-1.066***
Lost assets	-0.200	0.049	-0.273

Affected by the war	-0.058	-0.168	-0.035
Experienced violence	-0.240***	-0.078	-0.292***

Notes: The household level controls include log per capita consumption expenditure, gender, gender of household head, average years of education in the household, ethnic groups and religious groups; *** implies significant at 1%, ** implies significant at 5% and * implies significant at 10%.

VI. Conclusion

The relationship between education and war in Cote d'Ivoire is complex. While anecdotal evidence from various reports and studies suggest that education has been a clear victim of war, a closer look at the history of the political economy of the Ivoirian war reveals a somewhat different picture. To some extent education catalyzed the war due to the politically masterminded unequal provision of educational facilities between the North and the South. The education system in the North has been a victim of Ivoirian politics since the early 1990s and the North-South divide following the civil war only exacerbated that ongoing crisis. This makes the task of finding a causal inference of the war on education particularly challenging. In this paper we estimate the causal effect of civil war on years of education for individuals who were exposed to conflict between 2002 and 2006 in their school-going age. We use the Households Living Standards Survey (HLSS) data collected in 2008 (ENV-2008) and the data on local incidences of conflict is taken from the Armed Conflict Location and Event Database (ACLED) for the empirical analysis.

We employed several strategies to identify the true impact of war and to decipher its causal effect on education for the school-going age cohort. We use the year of birth and the department of birth to determine an individual's exposure to war. The difference-in-difference outcomes indicate that the average years of education for individuals aged 10 to 22 is .94 years fewer compared to the individuals aged 23 to 32 in war-affected regions. The validity of the finding is tested by a number of factors such as internal displacement due to war, heterogeneous selection into victimization both across and within a region and varying intensity of conflict across regions. These are potential sources of bias in the estimated causal effect and furthermore, conflict affects education in several ways. The direct impacts include destruction of infrastructure, displacement and most tragically deaths of students and teachers, problems in harmonization of school calendars across the war-affected regions and closure of schools for an indefinite period. Other effects such as loss of jobs and farm, decrease in income and experiencing violence could also affect the education of children in the same household. To realize the full potential impact of war, as a second strategy we used a set of victimization indicators to identify the true impact of the war.

When education works as a catalyst for the war, the causal inferences on the impact of war suffer from endogeneity problems. Also the activities of NGO-run primary and secondary schools, which stepped in to fill the education gap in the North, might create a downward bias in the impact of war on education. Both of these factors are likely to violate the assumption that the war victims and the comparison group are exchangeable in order to make a causal inference of the impact of war on average education. As a final step, we used propensity scores matching to minimize the selection bias and confounding in the causal effect. The average effect of war as identified by the victimization categories reports a .2 to .9 fewer average years of education for the war victims in comparison to the matched control group. The moderately satisfactory outcomes of double-robust models lower chances of misspecification in the estimated models. The outcomes are also robust when we use a number of sensitivity analyses including alternative matching methods, using different educational outcome variables and estimating the North and the South subsamples separately.

Understanding the mechanism though which war affects education is critical in order to disentangle the causal effects of war on education. The education and war nexus in Cote d'Ivoire provides a complex picture and in this paper we attempted to explore the channels through which war could possibly affect education. Nevertheless, some caveats apply. The role of third parties, such as NGOs in promoting primary and secondary education in the North is difficult to measure in the estimated causal effect. However, in the presence of NGO activities the estimated coefficients can be considered as a lower bound of the causal effect that war has on education. It is also possible that the existence of internally displaced populations and the timing of the survey could downplay the estimated causal effect. Overall, the empirical evidence derived from our study on Cote d'Ivoire provides robust support to the existing studies on how war has a detrimental impact on education.

References

Abdi, Ali A. 1998. Education in Somalia: history, destruction, and calls for reconstruction. *Comparative Education* 34, no. 3 (November): 327-340.

Akresh, Richard, and Damien de Walque. 2008. *Armed conflict and schooling: Evidence from the 1994 Rwandan genocide*. Policy Research Working Paper 4606. Washington: World Bank.

Bang, H., and J. M. Robins. 2005. Doubly robust estimation in missing data and causal inference models. *Biometrics* 61: 962–973.

Brück, Tilman. 1997. *Macroeconomic effects of the war in Mozambique*. QEH Working Paper Series. Queen Elizabeth House: University of Oxford International Development Centre, December.

Bryson, A., R. Dorsett, and S. Purdon. 2002. The Use of Propensity Score Matching in the Evaluation of Labour Market Policies," Working Paper No. 4, Department for Work and Pensions.

Buckland, Peter. 2005. *Reshaping the future: Education and post-conflict reconstruction*. Washington: World Bank.

Caliendo, Marco & Sabine Kopeinig, 2008. "Some Practical Guidance For The Implementation Of Propensity Score Matching," *Journal of Economic Surveys*, Wiley Blackwell, vol. 22(1), pages 31-72, 02

Emsley, R. A. 2007. Statistical Models of Selection and Causation. PhD thesis, University of Manchester, UK.

ENV-2008, "Enquête sur le Niveau de Vie des Ménages de Côte d'Ivoire," National Statistical Institute and Ministry of Planning and Development of Côte d'Ivoire.

Heckman, J., H. Ichimura, and P. Todd. 1997. Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme," *Review of Economic Studies*, 64, 605-654.

Lai, Brian, and Clayton Thyne. 2007. The effect of civil war on education, 1980-97. *Journal of Peace Research* 44, no. 3 (May): 277-292.

Merrouche, Ouarda. 2006. The human capital cost of landmine contamination in Cambodia. *Households in Conflict Network*, no. 25. Working Paper (December).

Robins, J. M. 2000. Robust estimation in sequentially ignorable missing data and causal inference models. In *Proceedings of the American Statistical Association Section on Bayesian Statistical Science 1999*, 6–10. Alexandria, VA: American Statistical Association.

Rosenbaum, P. R., and D. B. Rubin. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70: 41–55.

Shemyakina, Olga. 2006. *The effect of armed conflict on accumulation of schooling: Results from Tajikistan*. HiCN Working Paper 12. Falmer: University of Sussex, November.

Sany, J., 2010, "USIP Special Report," United States Institute of Peace. Available on: http://www.usip.org/files/resources/SR235Sany_final_lowres-1.pdf

UCDP/PRIO, 2009. *UCDP/PRIO Armed Conflict Dataset Codebook Version 4-2009.* Uppsala and Oslo: Uppsala Conflict Data Program (UCDP) and International Peace Research Institute (PRIO). Available on: http://www.prio.no/CSCW/Datasets/Armed-Conflict/Battle-Deaths/

UNESCO 2010 *Education for All: Global Monitoring Report*, the Quantitative Impact of Armed Conflict on Education

UNICEF, 2003, "Côte d'Ivoire sub-Regional Crisis Donor Update," 15 September, available on http://reliefweb.int/node/117935

UNOCHA, 2003a, "Fighting Near the Liberian Capital Drives Thousands into Bush," February 8, available on http://reliefweb.int/node/119067

UNOCHA, 2004, "Fighting in Côte d'Ivoire Jeopardizes Humanitarian Aid," November 4, available on http://reliefweb.int/node/157760

UNOCHA, 2006a, "Côte d'Ivoire: Five Dead in Clashes with UN Peacekeepers in *Wild West*," January 18, available on www.irinnews.org/report.asp?ReportID=51196

UNOCHA, 2006b, "Côte d'Ivoire: UN Staff Being Evacuated as Sanctions Loom," January 27, available on http://www.irinnews.org/printreport.aspx?reportid=57960

World Bank 2010. Country brief: Côte d'Ivoire. World Bank, January 20. http://go.worldbank.org/SN2JJ08PI0

Zhao, Z. 2000. Data Issues of Using Matching Methods to Estimate Treatment Effects: An Illustration with NSW Data Set," Working Paper, China Centre for Economic Research.