The Effects of Armed Conflict on Educational Attainment and Inequality

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Abstract
We use the variation in the timing of conflict between countries using a difference-in-differences matching strategy to identify the impacts of armed conflict on years of schooling and educational inequality. We draw upon data from the Uppsala Conflict Data Program and the Ethnic Power Relations databases, which enable us to distinguish between ethnic and non-ethnic conflicts. Further, we are able to identify the effect of conflict onset as well as the incidence of conflict in years following onset. Our results provide evidence that the introduction of any conflict worsens educational attainment and exacerbates pre-existing inequalities thereof. This paper also shows that conflict effects are more pronounced when ethnic in nature and that attainment and inequality outcomes worsen as conflicts persist over time. Our results are robust to different regression specifications and propensity score matching algorithms.

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1 Introduction

This paper is part of a research project commissioned by the UNICEF Peacebuilding, Education, and Advocacy (PBEA) Programme and funded by the Government of the Netherlands to better understand the relationship between conflict and educational inequality. It builds on an earlier work by the same team of the FHI 360 Education Policy and Data Center, which found that the risk of conflict is substantially higher at higher levels of education inequality between groups, all other known predictors of conflict held equal (Omoeva & Buckner, 2015).

The current study investigates the reverse relationship, examining what the consequences of conflict are for the distribution and equity of educational opportunity. Existing literature strongly suggests that conflict erodes educational progress, yet little research analyzes how conflict reshapes inequality in education, a gap this study seeks to fill. The limited quantitative literature provides some evidence of the adverse effects of conflict on educational outcomes but not on inequality. For instance, previous quantitative research studies that have employed cross-national analyses find that conflict slows school access during periods of conflict (Lai & Thyne, 2007; Shields & Paulson, 2015; Stewart, Huang, & Wang, 2000).

Akresh and De Walque (2008) investigate the impacts of the 1994 Rwandan genocide and find that education levels among non-poor boys have declined relative to poor boys, thus lowering the inequality between poor and non-poor groups. This disparity is explained as being likely due to conflict affecting resources among the non-poor disproportionately leading to lower education enrollment and attainment. Valente (2011) who examines the impacts of civil war in Nepal between 1996 and 2006 argues that the conflict leads to higher migration rates among the most educated and affluent groups, whereas the poorest are more likely to remain. As a result, overall educational attainment declines, however the gaps between the most and least educated are narrower. On the other hand, several studies argue and provide some evidence that conflict exacerbates inequalities in education at the subnational level (Kibris, 2015; Shemyakina, 2011; and Aguero and Majid, 2014), between gender groups (Justino, 2010), and between ethnic groups (Østby and Urdal, 2014).

As a result, theoretical predictions of the effect of conflict on education inequality, based on the literature, are ambiguous. In this study, we disambiguate the effect of conflict on educational attainment and inequality by estimating the net causal effect by employing a quasi-experimental research design to identify the causal effect of violent conflict on the distribution of educational attainment.[1] Specifically, we employ a matching difference-in-differences (DD) approach to identify the causal effect of armed conflict on education using

[1] For the remainder of the paper, we define educational attainment as (mean) years of schooling completed.

a comprehensive panel dataset including 100 countries spanning over 50 years from 1960 to 2010. by comparing the pre- and post-conflict outcomes between similar country-year observations who differ only in terms of their conflict experience. We disaggregate the effects of conflict by nature of the conflict (ethnic and non-ethnic), intensity of the conflict (minor and major), by duration of the conflict, and by level of fragility of the observations experiencing conflict.

Our empirical results demonstrate that conflict undermines educational opportunity for some more than others, but that effects are considerably nuanced and context-dependent, at times even contradictory when viewed across the universe of conflicts, with impacts borne disproportionately by poorer or wealthier families, girls or boys, or particular ethnic or religious groups depending on the setting. In terms of educational attainment, our findings show robust evidence that years of schooling decrease with conflict. More interesting are the results from ascertaining the distribution of education attainment in the event of armed conflict. To that end, we find that the incidence of armed conflict, on average, worsens disparities in education between wealth groups, gender groups, and overall inequality at the national level. The disaggregated results show that the conflict effect is most prominent among ethnic conflicts that last at least six years and worsens over time. In addition, we find that countries whose observable demographic, economic, and political characteristics predict a high likelihood of conflict are affected most by the incidence of such events.

The remainder of the paper is structured as follows: Section 2 presents a brief literature review; Section 3 discusses the methodological approach that we employ for our analysis; Section 4 discusses the dataset construction and the descriptive characteristics of our data; Section 5 presents the findings of the regression analysis; and Section 6 concludes the paper and offers a discussion for policy considerations.

2 Literature Review

The theoretical links between violent conflict and education are numerous and complex, resulting from constraints in the supply of and/or demand for education. They include resource reductions, recruitment into armed groups, safety threats in and on the way to school, and the consequences of poverty and food insecurity (Justino, 2016). For example, conflict can impede educational access and quality through resource reductions caused by the destruction or occupation of schools, decreased funding for education, or a diminished teaching force as staff stop attending due to perceived risks. Attendance wanes where students become combatants or avoid schools deemed unsafe, especially where schools are targets of violent attacks, sites of rebel recruitment, or travel to school leaves children vulnerable to kidnapping or sexual assault. Furthermore, attendance and learning may be indirectly influenced when conflict results in increased poverty or food insecurity. In these situations, households may struggle with the cost (or opportunity cost) of sending a child to school and children may suffer malnutrition, which limits cognitive abilities in the short-term and long-term, especially when experienced in early childhood.

Research supports the relationship of conflict and reduced educational outcomes. Cross-national analyses find that conflict slows school access during periods of conflict (Lai & Thyne, 2007; Shields & Paulson, 2015; Stewart, Huang, & Wang, 2000), which can diminish human capital stocks in the long-term. Case study research strongly confirms these findings, with evidence from Bosnia (Swee, 2009), Tajikistan (Shemyakina, 2011), Rwanda (Agüero & Majid, 2014; Akresh & De Walque, 2008), Cote d'Ivoire (Dabalen & Paul, 2012), and Colombia (Rodriguez & Sanchez, 2012) for drops in educational attainment among conflict-affected populations. While drops in education during conflict are well-documented, research acknowledges that broader factors of instability, rather than conflict per se, may induce these declines (Shields & Paulson, 2015; UNESCO, 2011).

Although research clearly points to the tendency of conflict to undermine educational attainment, the consequences for educational inequality are less clear, explored mostly through case studies with differing results. Inequality will rise when educational declines during conflict are borne disproportionately by disadvantaged groups. Several of the mechanisms through which conflict threatens education, in theory, leave less-privileged households or individuals more vulnerable to educational challenges. For example, when conflict leads to economic declines or food shortages, as is often the case (Collier et al., 2003; Gates et al., 2012), poor families may be less able to fund their children's education or to provide the nutritional staples that underpin strong cognitive development. In an example of rising gender inequality, Shemyakina (2011) shows that educational attainment among women, particularly poor women, suffered more than that of men during civil war, reinforcing preexisting gender gaps in education in Tajikistan.

Elsewhere, conflict may reduce inequality but for the perverse reason that educational drops are larger among the elite. This situation may arise where education is affected for all, but where disadvantaged groups have low initial levels of education so that a floor effect limits the extent of their declines. For instance, in Rwanda, Akresh and De Walque (2008) find education levels among men and the non-poor were most reduced during the genocide and suggest this may be because they had more to lose since education among women and the poor was already low at the outset of the genocide. Furthermore, violence may also target elites, as with Rwandan and Cambodian genocides (de Walque, 2006; Justino, 2016), leading to lower inequality.

As discussed above, conflict tends to harm education. In certain cases, however, education levels may actually improve during conflict, such as when low-level conflict does not impede the supply of education (de Groot & Göksel, 2011) or when displacement to camps or new communities means better educational opportunities relative to limited (or unavailable) schooling options at home (Ferris & Winthrop, 2010). Another consideration is that negative impacts on education may manifest as weaker educational growth rather than absolute declines given the strong global trend of educational expansion (Shields & Paulson, 2015). These situations may also restructure inequality in divergent ways. For example, average years of schooling rose during Guatemala's 36-year civil war, but educational gains were shallower for rural Mayan youth (a relatively disadvantaged group) in regions more affected by conflict, intensifying preexisting disparities (Chamarbagwala & Morán, 2011). Conversely, gender inequality narrowed in Nepal, with women in conflict-affected regions experiencing educational gains, possibly because reduced inequality for women and other disadvantaged groups was a rebel goal (Valente, 2011).

In sum, existing evidence, comprised largely of case studies, shows that conflict tends to impact some more than others, with rising or falling inequality a result. We build on this case study literature by examining this hypothesis using a quantitative empirical strategy, examining the effect of conflict incidence on several dimensions of educational inequality.

3 Methodology

3.1 Conceptual Framework

For this study, we define educational inequality along four main dimensions: national (across all individuals, or *vertical* inequality), wealth, ethnic/religious, and gender. It is clear that the advent of conflict is expected to lower overall educational attainment for a given country. We argue that the effects of conflict are not uniform across the affected population but rather have a disproportionately adverse effect on different subgroups within the population. Two possible effects of conflict could lead to different levels of inequality in response to exposure to conflict. The first is such that the advent of armed conflict could worsen preexisting inequalities between different groups within a country. It is likely that the least wealthy in any given economy are those who are most reliant on public resources for education. In times of war, these resources become relatively scarce for the poorest groups and as a result have fewer educational opportunities than they would have in times of peace. In this case, conflict would exacerbate educational inequality as the less advantaged groups exhibit larger declines in their educational attainment relative to the advantaged groups.

Alternatively, in countries where education is concentrated among the advantaged groups conflict can only lower their educational attainment whereas the educational attainment of the least educated is less likely to change as dramatically. Violent conflict in some cases may target the most advantaged, disproportionately reducing the educational outcomes of the most affluent relative to the rest of the country. In such cases, the educational attainment of the high education group converges toward that of the low education group, resulting in lower educational inequality. In a similar vein, if conflicts are driven by inter-group differences in resources or even sociopolitical differences, then we may see disproportionately adverse educational effects on the losing side of the conflict. This would also lead to potentially opposing effects on inequality in education depending on the level of education of the winning and losing sides.

It is possible that different mechanisms by which violent conflict influences educational outcomes occur simultaneously, making it difficult to unpack the exact mechanisms behind the effects of conflict. As such, we are only able to observe and identify the net effect of armed conflict on educational attainment and inequality given the cross-national nature of our analytic dataset. However, we are able to make predictions regarding the consequences of conflict, ascertain the types of conflicts that are most impactful, the macroeconomic and political traits that are conducive to conflict, and identify the subgroups within society that are most at-risk.

3.2 Identification Strategy

3.2.1 Difference-in-Differences

We exploit variation in the timing and duration of conflict between countries as the basis for our strategy to identify the effect of conflict on educational attainment and inequality, in essence, treating the incidence of conflict as a natural experiment. As such, we employ a difference-in-differences (DD) strategy to determine the effect of conflict on educational outcomes by comparing the change in outcomes in pre- and post-conflict periods between treatment and control countries. In this case, countries who have ever experienced conflict are assigned to the treatment group and countries who have never experienced conflict are assigned to the control group.[2] Formally, we write the DD regression equation as follows.

$$y_{ct} = \gamma_c + \lambda_t + \phi f(p_t) + \delta(T_c.Post_t) + X\beta + \varepsilon_{ct} \quad [1]$$

where Y_{ct} represents mean years of schooling among youths aged 15-24 years old or inequality in education in country c observed in year t. We measure educational inequality using the Gini coefficient evaluated at the national (within-country) level, between-ethnic/religious groups, and between-wealth decile groups. Additionally, we measure educational inequality between gender groups using the gender parity index. γ_c and λ_t represent country and year fixed effects, respectively. T_c is a dummy variable that denotes the treatment group and takes on a value of one if country c has experienced armed conflict at least once since 1946, zero otherwise. $Post_t$ is a dummy variable that denotes the incidence of conflict in year t. Therefore, variation in the interaction of T_c and $Post_t$ identifies the treatment effect of armed conflict on the outcome y_{ct}, δ.

[2] Countries are determined to have 'ever' participated in an armed conflict starting in 1946.

X denotes a matrix of observable time-varying country-level characteristics, lagged by five years, that are known correlates of educational attainment and inequality.[3] Specifically, we include variables that account for the level of economic activity (real GDP per capita), oil production per capita, total population, youths aged 15-24 as a proportion of total population, indicator variables for whether countries are considered a democracy, anocracy, or autocracy, and the number of ethnic/religious groups present in each country. Omoeva and Buckner (2015) show that countries with lower levels of economic development are more likely to experience conflict and tend to have lower levels of educational attainment.[4] Similarly, democratic political structures are positively correlated with educational attainment and negatively correlated with conflict (Persson, 2014). Fearon and Laitin (2003) show that the number of ethnic groups, in other words the degree of ethnic fractionalization, are a significant predictor of conflict.[5] As such, these covariates are included in the analysis to mitigate omitted variable biases when estimating δ. Finally, $f(p_t)$ is a quadratic time trend during peacetime that enables us to control for pre-conflict onset time trends in mean years of schooling and inequality in educational attainment.

In addition to the basic DD setup described in equation [1] that estimates the average effect of conflict on mean years of schooling and educational inequality, we test for heterogeneity in the treatment effect. First, we test whether the effect of conflict varies by nature of the conflict, ethnic or non-ethnic. Equation [1] becomes:

$$y_{ct} = \gamma_c + \lambda_t + \phi f(p_t) + \sum_{j=1}^{2} \delta_j \left(T_c^j . Post_t\right) + X\beta + \varepsilon_{ct} \qquad [2]$$

In this case, T_c^1 represents a non-ethnic conflict in country c in year t, while T_c^2 represents an ethnic conflict for the same country-year observation. The parameters of interest are δ_1 and δ_2 that denote the average treatment effect of non-ethnic and ethnic conflicts, respectively, as identified in the DD framework. We augment this model by further disaggregating the treatment effect by the intensity of the conflict. We define two levels of intensity, minor ($25 \leq b.r.d. < 1{,}000$) and major ($b.r.d. \geq 1{,}000$).[6] As a result, equation [2] becomes:

$$y_{ct} = \gamma_c + \lambda_t + \phi f(p_t) + \sum_{i}^{2} \sum_{j=1}^{2} \delta_{ij} \left(T_c^j . Post_t\right) . I_j + X\beta + \varepsilon_{ct} \qquad [3]$$

[3] Covariates are lagged by five years to mitigate potential simultaneity between the treatment and the covariates as well as the covariates and the outcome variables.

[4] See Lucas (1988) and Mankiw, Romer, and Weil (1992) for theoretical discussion of educational attainment and economic development and growth.

[5] See Fearon (2003) for a detailed discussion of ethnic fractionalization and its definition.

[6] *b.r.d.* is an acronym for battle related deaths. Intensity levels, minor and major, are defined based on UCDP/PRIO's own definitions of what constitutes a conflict (Gleditsch et al., 2002). Colombia's Bojaya massacre is an example of a minor conflict that resulted in 119 battle-related deaths and Sri Lankan civil conflict in 2009 between the state and the Liberation Tigers of Tamil Eelam is an example of a major conflict that resulted in over 10,000 deaths.

I_1 is an indicator function that takes on a value of one if the number of battle related deaths is larger than or equal to 1,000, zero otherwise, while I_2 indicates whether the number of battle related deaths is between 25 and 999. The interaction between the intensity indicators and the term $\left(T_c^j . Post_t\right)$ yields four distinct treatment effects that vary by type of conflict and by intensity of the conflict.

Collier, Hoeffler, and Soderbom (2004) examine the duration of civil wars and show that certain economic and political factors and inequalities therein increase the likelihood of lengthening these conflicts. As a result, it is reasonable to assume that the effect of conflict may vary with the duration of the conflict. As such, we allow the average treatment effect, as identified in equation [2], to vary over the duration of the conflict spell. This enables us to test for the heterogeneity of the treatment effect over time and determine whether conflict creates a shock on the educational system that attenuates over time or is permanent. In addition to the estimating the treatment effect of conflict over time, we estimate the effect on educational outcomes following the conclusion of said conflict. Formally, we estimate the following DD regression equation:

$$y_{ct} = \gamma_c + \lambda_t + \phi f(p_t) + \sum_{j=1}^{2} \delta_j \left(T_c^j . Post_t . f(w_t)\right) + X\beta + \varepsilon_{ct} \qquad [4]$$

To estimate the conflict effect over the duration of the conflict, we interact the term $T_c^j . Post_t$ with a parametric function $f(w_t)$, where w_t represents the number of years of the conflict as of year t. Therefore, δ_j becomes the slope of the change in educational outcomes over time for conflict countries relative to non-conflict countries.

In addition to satisfying OLS assumptions, the DD strategy requires that pre-conflict trends in schooling attainment and inequality to be parallel for both the treatment and control groups in order to produce causal effects.[7] We address the "parallel" trends assumptions in our basic specification that includes a quadratic time trend during peacetime (pre-conflict). However, it is still likely that our estimates of δ may not yield causal estimates due to a systematic mismatch in both observed and unobserved time-varying country characteristics, since assignment of conflict is non-random. As such, we pursue a strategy that combines the advantages of the DD technique with matching to correct for potential selection bias.

3.2.2 Propensity Score Matching

We follow the methods proposed by Heckman, Ichimura, and Todd (1997, 1998) to match treatment and control countries based on their pre-conflict attributes. Moreover, we implement several variants of propensity score matching and weighting schemes to construct a synthetic control group that best resembles the treatment sample in pre-conflict

[7] For a discussion on the use and assumptions of difference-in-differences methods, refers to Ashenfelter (1978), Abadie (2005), Imbens and Wooldridge (2009), and Angrist and Pischke (2009).

onset periods. We model the assignment of the treatment, conflict, by estimating the propensity score for each country-year observation using a logit model of the probability of experiencing conflict as a function of quadratic peace years, $f(p_t)$, and time varying country-level observable characteristics, X. Since we are concerned with selecting the control group based on pre-conflict characteristics, we estimate propensity scores using as follows.

$$\ln\left(\frac{P(w_{ct})}{1-P(w_{ct})}\right) = \gamma_c + \lambda_t + \phi f(p_t) + X\beta + \upsilon_{ct} \tag{5}$$

where $P(w_{ct})$ denotes the probability that country c in year t experiences conflict and $w_{ct} = T_c.Post_t$. As a result, equation [5] yields estimates of the propensity score, which will be the basis for our propensity score matching strategy. Propensity scores are therefore nothing other than the predicted value of $P(w_{ct})$. For simplicity, we will denote the propensity score as $\hat{p}_{ct} = \hat{P}(w_{ct})$. Keeping in line with Heckman, Ichimura, and Todd (1997, 1998), we compute the DD matching estimator using a kernel/local linear weighting matching algorithm. The counterfactual outcome is constructed as the kernel-weighted average of the outcome of all country-year observations in the control group. To mitigate the concern that 'bad' matches may be used, we enforce the common support condition by trimming the propensity score distribution between the treatment and control groups. The DD matching estimator under kernel based weighting is computed as follows:

$$\hat{\delta}^k = E[w_{ct}(y_{ct} - y_{ct'}) - (1 - w_{ct})W(\hat{p})(y_{ct} - y_{ct'})] \tag{6}$$

where $W(\hat{p})$ denotes kernel weights according to the following

$$W(\hat{p}) = \frac{K\left(\frac{\hat{p}_j - \hat{p}_i}{h_n}\right)}{\sum_j^{n_c} K\left(\frac{\hat{p}_j - \hat{p}_i}{h_n}\right)} \tag{6a}$$

K is a kernel function, h_n is a bandwidth parameter, j is an index for countries in the control group and n_c is the total number of observations in the control group.

We also estimate the average treatment effect, or the average effect of conflict, on mean years of schooling and/or inequality in educational attainment using propensity scores as inverse probability weights (IPW) as follows:

$$\hat{\delta}_{ATE}^{ipw} = E\left[\frac{w_{ct}}{\hat{p}}(y_{ct} - y_{ct'}) - \frac{(1-w_{ct})}{1-\hat{p}}(y_{ct} - y_{ct'})\right] \tag{7}$$

Using the same IPW matching algorithm, the average treatment effect on the treated, or the average effect of conflict on conflict-affected countries, is estimated as:

$$\hat{\delta}_{ATT}^{ipw} = E\left[w_{ct}(y_{ct} - y_{ct'}) - \frac{\hat{p}}{1-\hat{p}}(1 - w_{ct})(y_{ct} - y_{ct'})\right] \tag{8}$$

The DD matching estimator, similar to the simple DD estimator, requires that the parallel trends condition hold in pre-treatment periods for the treatment and control groups to produce causal estimates. The second condition for the DD matching estimator to produce causal estimates of δ, is that the propensity of receiving the treatment, or experiencing conflict, be strictly between 0 and 1. The third condition requires that the treatment and control samples be balanced along their covariates. Finally, it is important that the propensity score distributions for the treatment and control groups overlap, or fall under a common support. Heckman, Ichimura, and Todd (1997, 1998) show that a violation of common support, or comparing observations that are incomparable, can lead to biased estimates of δ.

4 Data and Descriptive Analysis

We construct the analytic dataset for this paper by combining aggregate country-level data as well as micro-level data that we aggregated to the country-level from various publically available sources. The remainder of this section will describe the dataset construction by outcome variables, conflict (treatment assignment) variables, and control variables. Finally, we compare the mean values for treatment and control observations and test for statistical significance of the mean differences. Comparing outcomes by treatment status denotes simple difference in means between conflict and non-conflict observations. However, comparing mean differences in the covariates serves as our test for sample balance prior to propensity score matching via inverse probability weights.

4.1 Educational Attainment and Inequality

4.1.1 Dataset Construction

We draw educational attainment data from public-use household survey data through three data programs: Multiple Indicator Cluster Survey (MICS) administered by UNICEF, the Demographic and Health Surveys (DHS) program funded by USAID and administered by ICF international, and the Integrated Public-Use Microdata Series-International (IPUMS-I) as collected and maintained by the Minnesota Population Center at the University of Minnesota. From these household survey/census data, we compute the mean years of schooling for all individuals aged 15 years or older in 10-year increments and compute aggregates at the national, ethnic/religious, gender, and wealth decile levels. In addition, we compute education Gini coefficient, Theil index, and coefficient of variation across these same dimensions for all available country-year observations.[8]

We follow a method similar to Barro and Lee (2010) to fill in missing country-year observations using a logical backward projection technique in 10-year increments. We stratify our projections by age group, gender, and by 5-year schooling bins. However, unlike Barro and Lee (2013), we empirically measure the amount of additional schooling

[8] Ethnic or religious identity groups comprising less than five percent of the total population were reclassified into an "other" category.

accumulated by individuals over 25 years after the age of 25. In essence, we find that individuals with fewer than 5 years of schooling accumulate approximately zero additional years of schooling after age 25 years. Conversely, men and women with more than 10 years of schooling accumulate between 0.3 and 0.7 years of schooling after age 25 years. In addition to computing the amount of schooling gained after 25 years of age, we adjust for the national mortality rate by age group and gender. As a result, we are able to extrapolate backwards the mean value of years of schooling for all age cohorts as far back as four decades prior to the administration of each household survey. Additionally, we create back-projections for specific ethnic, religious, wealth, and gender subgroups of each country that enables us to accurately estimate inequality measures where data were originally missing.

The final step in completing the construction of our educational attainment and inequality dataset, we fill in all missing country-year observations by interpolating between observed and/or backward extrapolated data points, separately for each country. In this case, we use simple linear interpolation to determine an approximate value for the missing years of schooling. Finally, the educational attainment and inequality dataset yields 4,650 country-year observations, which covers 95 countries over 68 years (1946-2013). However due to small sample sizes among the oldest and newest years, we restrict the final analytic sample to data points prior to (and including) 2010.

4.1.2 Inequality Measurement

The measurement of inequality is highly contested in the literature as different measures pose some comparative advantages over others.[9] To measure inequality in attainment between ethnic/religious groups, wealth groups, or nationally, we use the Gini coefficient due to its popular use in research and the gender parity index to convey disparities between males and females. We do not assert the use of any particular measure over another as the superior metric. However, to ensure the robustness of our findings we employ alternative measures of educational inequality, the Theil index and the coefficient of variation. We define the educational outcome variables of interest as follows.

Mean years of schooling, by country,

$$\bar{y}_{ct} = \frac{\sum_{i=1}^{n} y_{ict}}{n} \quad [9a]$$

overall (within-country) Gini coefficient,

$$g_{ct} = \frac{1}{2n^2 \bar{y}_{ct}} \sum_{i=1}^{n} \sum_{j=1}^{n} |y_{ict} - y_{jct}|; \quad [9b]$$

[9] Inequality measurement in economics whether it concerns income, health, or educational inequality has been debated for more three decades. For reference see Cowell and Kuga (1981), Yaari (1988), Silber (1999), Cowell and Flachaire (2007), and Ferreira and Gignoux (2011) among many others.

between-group Gini coefficient for each country,

$$gg_{ct} = \frac{1}{2\bar{y}_{ct}} \sum_{r=1}^{R} \sum_{s=1}^{S} p_r p_s |\bar{y}_{rct} - \bar{y}_{sct}|; \quad [9c]$$

within-country gender parity index in mean years of schooling:

$$gpi_{ct} = \frac{\bar{y}_{ct}^{f}}{\bar{y}_{ct}^{m}}; \quad [9d]$$

Finally, as a robustness check for the use of the Gini coefficient, we also compute the within-country Theil index and between-group Theil index,

$$t_{ct} = \frac{1}{n} \sum_{i=1}^{n} \frac{y_{ict}}{\bar{y}_{ct}} \ln\left(\frac{y_{ict}}{\bar{y}_{ct}}\right) \text{ and } gt_{ct} = \sum_{r}^{R} p_r \frac{\bar{y}_{rct}}{\bar{y}_{ct}} \ln\left(\frac{\bar{y}_{rct}}{\bar{y}_{ct}}\right); \quad [9e]$$

and the coefficient of variation for within-country and between-group:

$$cov_{ct} = \frac{\sigma_{y_{ct}}}{\bar{y}_{ct}} \text{ and } gcov_{ct} = \frac{\sigma_{\bar{y}_{r}ct}}{\bar{y}_{ct}} \quad [9f]$$

4.1.3 Sample Statistics and Trends

Table 1 presents the mean and sample size for years of schooling, gender parity ratio for years of schooling[10], Gini coefficient, Theil index, and the coefficient of variation computed at the national, ethnic/religious group, and wealth decile group levels. The sample distributions are further stratified by geographic region. The table shows that our overall sample size varies between 3,956 and 4,579 country-year observations across all educational outcomes except for inequality at the national level.[11] The sample mean years of schooling for the 95 countries, over the past 50 years is 5.73 years with a mean gender parity ratio of 0.74, and a mean within-country Gini coefficient of 0.43 (out of 1). In contrast, average educational inequality between ethnic/religious group yields a group Gini of 0.11, while the group Gini between wealth deciles is 0.23, on average. This means that, wealth inequality in our sample is more prominent relative to the inequality based on ethnic or religious affiliation.

Educational attainment, in terms of mean years of schooling, has more than doubled, globally, over the past half century (Barro and Lee, 2013). This trend holds true for developing and emerging economies (Figure 1). The same figure also plots trends in education inequality as defined by ethnic/religious groups, wealth decile, and nationally.[12]

[10] Value of years of schooling for females as a proportion of the value of years of schooling for males.

[11] We are unable to construct a similarly sized sample for our national inequality measures because we are unable to create backwards extrapolations of individual-level data. As a result, we are constrained to only having national inequality data points between observed values, rather than projected values.

[12] Wealth deciles are determined by computing a wealth index, which is comprised of certain household possessions and divided into 10 groups of equal size, for each household in each country-year observation.

We can see that, although trends in years of schooling have been steadily increasing, the progress made in terms of inequality is not as evident. The national education Gini coefficient has remained stable over the past 50 years hovering around 0.4 (out of 1), whereas the ethnic/religious and wealth decile group Gini coefficients have only declined by 0.07 and 0.13 points over the same time period, respectively.

Finally, Figure 2 plots mean inequality across all countries in our sample and across gender, ethnic/religious, wealth decile, and national dimensions of inequality. We can also see, from the figure, that all four inequality measures are correlated with each other where countries with high levels of inequality in one measure also have high levels of inequality on all other measures.[13] Countries with high inequality or gaps in education on one dimension tends to have high inequality on all other dimensions as well. The figure also confirms the notion that educational inequality between wealth groups explains a larger portion of total national inequality than between ethnic/religious groups. Moreover, the mean vertical Gini coefficient across all countries is about .43, while the mean wealth decile group Gini coefficient is about .23 and the mean ethnic/religious group Gini coefficient is approximately .11. Across all countries we find that the group Gini between wealth groups is consistently larger in magnitude than between ethnic/religious groups. Lastly, disparities between females and males is highest in countries exhibiting high levels of education inequality nationally, between ethnic/religious groups, and between wealth deciles.[14]

4.2 Incidence of Conflict

Following the end of the Second World War (WWII), over half the world's countries have participated in at least one conflict that resulted in a minimum of 25 battle related deaths, and about 88 percent have been civil conflicts (intra-state), half of which are ethnic in nature (Gleditsch et al., 2002; Pettersson and Wallensteen, 2015; Wimmer, Cederman, and Min, 2009).[15] Moreover, almost 32 percent of all internal conflicts were considered *wars* (major conflict) according to UCDP/PRIO definitions, i.e. conflicts that result in over 1,000 battle related deaths.

Table 2 displays the breakdown in the incidence of armed conflict by type, intensity, and decade. From our sample of 4,076 country-year observations, about 21 percent are in a state of armed conflict (ethnic or non-ethnic), half of which is ethnic in nature, and about three quarters of these (or of total) are considered minor ($25 \leq deaths \leq 1{,}000$). Over time, we can see that incidences of state-related armed conflicts peeked in the 1980s and 1990s

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[13] Simple correlations between the different measure show a high level of association between .68 and .94.
[14] The correlation coefficient between the vertical Gini and the gender parity index is -.84.
[15] Definitions and estimates of the incidences of conflict and civil conflicts are based on the Uppsala Conflict Data Program (UCDP) and the Peace Research Institute Oslo (PRIO) armed conflict database that were created by Gleditsch et al. (2002) and updated by Pettersson and Wallensteen (2015). Wimmer, Cederman, and Min (2009) identify conflicts as ethnic or non-ethnic.

where about a quarter of the sample was in a state of conflict. However, conflicts that are ethnic in nature are highest in the most recent two decades in the 1990s and 2000s. Between 12.5 and 13.7 of all observations in our sample were experiencing ethnic conflict. Finally, conflicts, both ethnic and non-ethnic, had the highest intensity in the 1980s.

Although the majority of countries have experienced some conflict at any given time in the past century, the timing of the occurrence of conflict varies between countries. This variation in the timing of armed conflict serves as the basis for our DD estimation strategy. For instance, in any given year since 1960, at least 10 countries experienced a state-related conflict and at least one country experienced a state-related conflict that is ethnic in nature (Figure 3). The incidence of ethnic and non-ethnic conflicts attained its peak in early 1990s with over 31 countries worldwide involved in ethnic or non-ethnic armed conflict. Figure 4 plots the proportion of all conflict-affected countries by the number of years of ethnic and non-ethnic conflict showing that different countries experience spells of armed conflict over varying durations, some for as long as 50 years.

4.3 Control Variables

The final phase of the analytic dataset construction is link educational outcomes and conflict incidence data with country-year level economic, demographic, and political characteristics. First, we draw upon data from the Penn World Tables (PWT) to determine real GDP per capita and from Ross and Mahdavi (2015) to obtain oil and gas production per capita, both of which are coupled to proxy for the macroeconomic level of economic production. Second, total and youth population size data are extracted from the United Nations Population Division (UNPOP). Finally, we incorporate political climate indicators from the Polity IV database (Marshall, Gurr, and Jaggers, 2014). We use the country Polity IV index scores to determine whether a country is a democracy, anocracy, or autocracy as follows. A country is defined as an autocracy if $-10 \leq polity \leq -6$, anocracy if $-5 \leq polity \leq 5$, or a democracy if $6 \leq polity \leq 10$.

Table 3 presents the sample summary statistics for the control variables in our study, disaggregated by decade. The overall trends show that economic output in terms of GDP per capita has steadily grown over the past five decades, while oil production has remained relatively stable. Population sizes as well as the proportion of youths, on average, have grown steadily over time. Interestingly, the number of ethnic groups have also somewhat increased over the same period. Finally, we observe a clear increase in the percentage of countries that are democratic or anocratic and a drastic decline in the percentage that are considered autocratic.

4.4 Sample Balance

To support our propensity score matching strategy, we perform a simple test for sample balance between conflict and no conflict observations, our treatment and control groups.

Figure 5 plots the propensity score distribution for conflict and no conflict observations, under matching using kernel-based weighting and under matching using propensity scores as IPW.[16] It is clear that the propensity score distributions for conflict and no conflict countries are quite different. However, it is encouraging for our study that the range of common support includes almost all data points in our sample—less than one percent of the sample falls outside of the common support. Figure 5, also shows that using kernel-based weights is able to mimic the propensity score distribution of the treatment group more closely than the IPW matching algorithm.

Table 4, displays the mean value of all covariates used in determining the likelihood of conflict incidence as well as the mean difference between conflict and no conflict states twice, once under no matching, i.e. the original unweighted sample, and again using kernel-based weights. In the unmatched sample, we find that conflict and no conflict observations are systematically and statistically different along almost all of the observed characteristics included. Educational inequality across all dimensions are higher among conflict countries. Oil production and GDP per capita are lower, population sizes are larger, and the likelihood of being an anocracy is higher among conflict countries than non-conflict countries.

When applying propensity score kernel weighting to our treatment and control groups as well as restricting to observations within the common support of the propensity score distribution, we see that almost all statistically significant mean differences are much smaller in magnitude and statistically insignificant. The only variable that remains significantly different is the five-year lagged education Gini coefficient across ethnic/religious groups. Although the difference is statistically significant, we argue that the magnitude of the difference is relatively small at 1.2 points (out of 100) and is unlikely to greatly impact our subsequent estimates of the effect of conflict on educational attainment and inequality. Overall, the kernel-based matching algorithm appears to balance the treatment and control groups along observable country characteristics, successfully.

5 Findings and Robustness Checks

5.1 Empirical Results

5.1.1 Effect of Conflict

Table 5 displays the results from estimating equation [1] with log mean years of schooling-($\ln(\bar{y}_{ct})$), gender parity index (gpi_{ct}), national Gini coefficient (g_{ct}), ethnic/religious group Gini coefficient (gg_{ct}^{ethnic}), and wealth decile group Gini coefficient (gg_{ct}^{wealth}) as outcomes. Further, the table presents the regression results under three different matching algorithms.

[16] Propensity scores are calculated by estimating equation [5] with all covariates lagged by five years. Both ATT and ATE weights are plotted under IPW matching.

The first panel presents the results from the simple difference-in-differences (DD) estimator with no matching. The second panel presents the results from the DD matching estimator using kernel-based weights. The final panel presents the results from the DD matching estimator with propensity scores used as inverse probability weights. We note that all matching estimators use weighting schemes to identify average treatment effects on the treated (ATT). In other words, we apply propensity score weighting to determine the effects of conflict on conflict-affected countries, rather than the average effect of conflict on any given country, which would be the average treatment effect (ATE).

Table 5 shows that, generally, the simple DD estimator understates the effect of conflict on mean years of schooling and educational inequality and that estimates are somewhat less precise in comparison to either of the DD matching estimates. As such, even when employing a DD strategy, we show that selection into the treatment group is still a valid source of bias when estimating the treatment effect. The estimates of $\hat{\delta}^{K}$ and $\hat{\delta}^{IPW}$, the average effect of conflict on conflict-affected countries under both matching techniques, are fairly similar across all outcomes. This indicates that the estimates of the conflict effect is robust to the matching algorithm. We find that mean years of schooling are only moderately negatively affected by conflict, on average, and that the estimated effects are not statistically significant. We estimate that conflict lowers mean years of schooling by 0.6 to 1.5 percent for countries that have ever experienced conflict. Relative to the mean years of schooling among conflict affected countries, the incidence of conflict lowers attainment by between 3 percent and 7.6 percent of a year of schooling.

However, in terms of the effect of conflict on various dimensions of educational inequality, we find that the GPI, the national Gini coefficient, and the wealth decile group Gini coefficient increase following the incidence of conflict. Therefore, conflict, on average, lowers GPI by 3.3 to 3.5 points (out of 100). Relative to a mean GPI for countries that have ever experienced conflict of 69.6 points, conflict lowers the GPI by approximately 5 percent. Similarly, we find that the incidence of conflict leads to higher education inequality at the national level, where, on average, conflict increases the national education Gini coefficient by 0.7 to 0.9 points (out of 100). This estimate translates to a 2 percent increase in inequality as measured by the Gini coefficient, relative to an average national Gini of 45.4 points.

The effects on education inequality are further corroborated when examining the impacts of conflict on education inequality between wealth deciles. We estimate that conflict increases the education inequality between wealth groups by 1.1 to 1.3 points (out of 100). Relative to the average wealth group Gini coefficient of 24 points, this effect translates to a 5.4 percent increase in education inequality between wealth deciles. Finally, when we examine the effects of conflict on education inequality between ethnic/religious groups, we find similar effects that are not statistically significant at the conventional levels. Nevertheless, we find that conflict (regardless of type) increases education inequality between ethnic/religious groups by 0.4 to 0.5 points (out of 100). However, relative to the average group Gini at the ethnic/religious group level, this effect translates to a 3.9 percent increase in inequality.

5.1.2 Effect of Conflict, by Type (Ethnic and Non-Ethnic)

In the following analysis, we disaggregate the effect of conflict to determine whether conflicts have differential effects on educational outcomes in terms of ethnic and non-ethnic armed conflicts. Table 6 presents the results from estimating equation [2] on mean years of schooling and inequality in education, nationally, by gender groups, by ethnic/religious groups, and by wealth deciles. Similar to Table 5, we also present the estimation results under different matching algorithms. Across all specifications, we consistently find that the effects of conflicts are more pronounced when the conflict is ethnic in nature than when it is not. Additionally, we find that the simple DD estimator produces smaller effect sizes relative to the DD matching estimators, which means that it is likely that the DD estimator is comparing countries that are incomparable to identify the effect of conflict.

The first column of Table 6 shows that non-ethnic conflicts have little to no effect on mean years of schooling, while ethnic conflicts lower mean years of schooling by 2.2 to 2.7 percent. Although these estimates are marginally insignificant statistically, the magnitude of the effect is not negligible. Relative to 5.078 years, a 2.7 percent decrease in mean years of schooling among conflict-affected countries is the equivalent of a decrease by 14 percent of one year of schooling. The pattern is duplicated when examining the effects on education inequality along gender groups. Ethnic conflicts lower GPI by 5.3 to 5.5 points, which relative to the average GPI of 69.6 points is an 8 percent decrease in gender parity. On the other hand, non-ethnic conflicts have a relatively smaller and statistically insignificant effect on GPI by between 1.7 and 1.9 points (2.7 percent decrease).

The third column of Table 6 shows that overall inequality is higher during the incidence of conflict and more so when the conflict is ethnic by nature. We estimate that the overall Gini coefficient for education inequality increases by 1.2 to 1.7 points (2.7 to 3.8 percent) during ethnic conflicts and only increases by 0.4 to 0.5 points during non-ethnic conflicts (1 to 1.1 percent). However, we note that these estimates are not statistically significant at the conventional levels. When examining the effect of conflict on education inequality along wealth decile groups, we again find that non-ethnic conflicts have a small and insignificant effect on inequality while ethnic conflicts have a larger and statistically significant effect on inequality. Moreover, we estimate that ethnic conflicts increase inequality in education between wealth groups by 2.2 to 2.3 points. Relative to a mean group Gini coefficient of 24 points, ethnic conflict increases inequality using this measure by 9.2 to 9.6 percent.

Surprisingly, when estimating the heterogeneous impact of conflict, by type, on ethnic/religious inequality in education, we find that non-ethnic conflicts tend to exacerbate inequality along ethnic/religious lines while ethnic conflicts have almost no effect. Specifically, we estimate that the ethnic/religious group Gini coefficient for educational attainment is increased during non-ethnic conflicts by 0.9 points. This effect size translates to a 7 percent increase in the ethnic/religious group Gini coefficient relative to an average group Gini coefficient of 12.7 points.

5.1.3 Effect of Conflict, by Type and Intensity

The results from estimating equation [3] are presented in Table 7, which follows the same format as Tables 5 and 6. However, the effect of conflict is stratified by type (ethnic and non-ethnic) and conflict intensity (minor and major). Similar to the results in Table 6, we find that ethnic conflicts have a relatively larger effect, in absolute value, than non-ethnic conflicts. However, the results show that major conflicts are more impactful among non-ethnic conflicts, whereas minor conflicts are more pronounced among ethnic conflicts. This result holds true across all DD matching and non-matching estimators, although the estimates from the DD matching results are more precisely measured.

We estimate that non-ethnic conflicts, minor and major, have a small and statistically insignificant effect on mean years of schooling, the gender parity index, the overall within-country education Gini coefficient, and the between-wealth group Gini coefficient. However, we find that non-ethnic major conflicts increase the probability of the between-ethnic/religious group Gini coefficient by 1.2 points, on average. This means that the incidence of a major non-ethnic conflict increases between-ethnic/religious group inequality by approximately 9.5 percent, relative to a mean group Gini coefficient of 12.7 points.

Among conflicts that are ethnic in nature, we find that minor conflicts are associated with a 2.8 to 3.3 percent decrease in mean years of schooling, whereas major conflicts lower mean years of schooling by 0.3 to 0.8 percent. Although these estimates are not statistically significant, the magnitude of the effect of minor ethnic conflicts on years of schooling is not negligible, as mean years of schooling is lower by almost 0.14 to 0.17 years. Minor ethnic conflicts lead to a decline in the gender parity index by about 6.3 to 6.5 points, while major ethnic conflicts lead to a relatively smaller decline in GPI of 2.4 to 2.6 points, out of 100. Relative to the mean GPI for countries in the treatment group, major ethnic conflicts lower GPI by about 9.1to 9.3 percent, while minor ethnic conflicts lower GPI only by about 3.4 to 3.7 percent.

The effects of ethnic conflicts on education inequality using the national level Gini, ethnic/religious group Gini, and the wealth decile group Gini are somewhat mixed. Major ethnic conflicts increase the national education Gini by 1.6 to 2.4 points, while minor ethnic conflicts increase the same measure by 1.2 to 1.6 points. In this case, only the estimate for major ethnic conflicts from using propensity scores as inverse probability weights is statistically significant. It is therefore difficult to gauge statistically whether major conflicts are more impactful than minor ones. Further, the effect on ethnic/religious group Gini are all small and statistically insignificant.

When examining the impacts of ethnic conflicts on the between wealth group Gini coefficient, we find that minor conflicts increase the Gini coefficient by 2.5 to 2.7 points, while major conflicts increase the Gini coefficient by 1.1 to 1.2 points only. This translates to about a 10.4 to 11.3 percent increase in the between-wealth group Gini coefficient, relative to a mean group Gini of 24 points. On the other hand, major ethnic conflicts increase the between-wealth group Gini coefficient by 4.6 to 5 percent and the increase is not statistically significant.

5.1.4 Effect of Conflict, by Type and Duration

Table 8 displays the results from estimating equation [4], where we estimate the heterogeneous effect of conflict by type and by the duration of conflict. Again, we find that non-ethnic conflicts exhibit smaller effects relative to ethnic conflicts across all education outcomes except for ethnic/religious group inequality in education. However, among ethnic conflicts, we find that the effect on mean years of schooling and inequality along gender groups, wealth groups, and nationally increase, in absolute value, as the duration of the conflict persists. However, following the conclusion of the ethnic conflict we see that mean years of schooling and inequality are somewhat ameliorated for a period before reaching a plateau. Figure 6 plots the marginal effects of ethnic conflict over time prior to the onset of, during, and following the conclusion of conflict.

Non-ethnic conflicts are largely statistically insignificant with the exception of the effect on between-ethnic/religious group inequality. We estimate that non-ethnic conflicts have no effect on education inequality of all types in the first five years. However, in the following five years (6-10 years), non-ethnic conflict exacerbates ethnic inequality in education by 1.6 points, by 1.4 points in the five years after that (11-15 years), and by 2.9 points when the duration of the conflict exceeds 16 years. In terms of percentage change in ethnic/religious group Gini, we estimate that the Gini coefficient increases by 12.6 percent in years 6 through 10, by 11 percent in years 11 through 15, and by 22.8 percent in years 16 and onward.

On all education outcomes other than between-ethnic/religious group inequality, ethnic conflicts exhibit a larger magnitude effect that increases with the duration of conflict. Moreover, we find that mean years of schooling increase by 2 percent during the first five years of ethnic conflict, but decrease in all periods afterward before dropping significantly after at least 16 years of conflict. The effect of ethnic conflict between years 6 and 10 of the conflict is virtually zero, but decreases by 2.2 percent in years 11 through 16 of the conflict. More noticeable, is the effect of ethnic conflict on mean years of schooling after at least 16 years of conflict, where we estimate an 18.2 to 18.7 percent decrease in mean years of schooling. Relative to a mean of 5.1 years, this effect translates to about 0.95 years of schooling among countries that have ever experienced conflict.

In terms of gender inequality, ethnic conflicts tend to have a substantial impact relatively early on. We find that GPI decreases by about one point in the first five years, by 7.3 to 7.4

points in years 6 through 10, by 10.5 points in years 11 through 15, and by 9.3 points in the years that follow. Relative to the mean GPI, this translates to a gender parity discrepancy in attainment by 1.4 percent in the first five years, by 10.6 percent in the second five years, by 15.1 percent in the eleventh through fifteenth year of the conflict, and by 13.5 percent after at least 16 years of ethnic conflict.

For overall inequality, we find a similar pattern, however, the effect sizes are relatively small. We estimate that the within-country Gini coefficient for education increases by 1 point in the first 10 years of ethnic conflict, by 1.2 points in the five years that follow, and by 2.2 points after at least 16 years. Relative to the mean national Gini of 69.6 points, these effects are equivalent to an increase of 2.2 percent in the first 10 years, 2.6 percent in years 11 through 15 of the conflict, and by 4.8 percent after 16 years or more of ethnic conflict. However, we find mostly small and statistically insignificant results in terms of the Gini coefficient between ethnic/religious groups.

Finally, we find that ethnic conflict does not affect inequality between wealth decile groups within the first five years of the conflict. We argue that it is likely due to our choice of using attainment as the measure of educational outcomes, where certain portions of the population will be unaffected by conflict if their education is already complete. On the other hand, children who are in school at the time of the incidence of conflict are those who would be affected by the time they are 15-24 years old. As such, we find that ethnic conflict exacerbates pre-existing education inequality between wealth groups by 2.3 points in years 6 through 10 of the conflict, by 3.7 points in years 11 through 15, and by 5.3 points in the years following the fifteenth year of the conflict. This is equivalent to an increase in the between-wealth group Gini coefficient by 9.6 percent in years 6 through 10 of the conflict, by 15.4 percent in years 11 through 15, and by 22 percent after at least 16 years of ethnic conflict.

5.1.5 Effect of Conflict, by Type and Propensity Score Subclassification

The analysis that follows investigates another potential source of heterogeneity in the effect of conflict on education attainment and inequality, propensity score subclassification. This strand of analysis shows that countries whose observable characteristics predict a high likelihood of conflict exhibit more negative reactions in their education outcomes relative to those countries whose predicted probability of conflict was lower. This result also provides some insight into the potential mechanism by which conflict affects the education system where countries whose macroeconomic and political environment enable the occurrence of conflict are those who are more fragile and susceptible to the effects of conflict.

Figure 5 displays the propensity score distribution for both the treatment and control groups and shows. The propensity score distribution for the treatment group appears to be bimodal with local maxima near the .1 and .5 marks. The median propensity score is .46, which is the threshold we use to stratify the treatment group. As a result, the treatment group is divided into equal groups where the first group has a mean propensity score of .24 and the second has a .59 mean propensity score. This means that the first group of treatment countries were those countries whose observable characteristics would predict a low probability of conflict, while the second are those countries whose characteristics are determinants of high likelihood of conflict.

Table 9 displays the results of stratifying the conflict effect by ethnic and non-ethnic conflicts, and by propensity subclassification. Across all specifications, we show that ethnic conflicts have a larger absolute value impact on education attainment and inequality. Additionally, we show that the treatment effect in the high likelihood of conflict group exhibit more pronounced effects on education attainment and inequality relative to those in the low likelihood group. The results from both the kernel and IPW matching estimators show that the incidence of ethnic conflict among countries that are highly predicted to experience conflict lowers mean years of schooling by 7.4 to 8 percent. Relative to the mean years of schooling for the treatment sample, this translates to about a 0.4-year decrease in schooling, on average.

In terms of gender education parity, treatment countries with a low propensity score experience a 2.7 to 3.1 point lower GPI, while treatment countries with high propensity scores experience a 7.9 to 8.2 point lower GPI, during ethnic conflict than during peacetime. This is equivalent to a 3.9 to 4.5 percent increase in the gender education gap among low conflict propensity countries, and an 11.4 to 11.8 percent increase in the gender gap among high conflict propensity countries. Overall education inequality as captured by the within-country Gini coefficient increases by the same rate among both treatment groups by between 1 and 1.2 points (out of 100), although only the effect for the high propensity group is statistically significant. This translates to an increase in the national Gini coefficient by between 2.2 and 2.6 percent, relative to the mean Gini for the treatment group.

The between-ethnic/religious group Gini coefficient does not appear to show a strong association with ethnic conflicts. However, non-ethnic conflicts tend to increase the group Gini by about 1.1 points (out of 100) among high propensity countries, which is equivalent to an 8.7 percent increase in the education inequality between ethnic/religious groups. The effect on the low propensity countries, in this case, is somewhat smaller at 0.8 points, which is equivalent to a 6.2 percent increase in the group Gini coefficient. Finally, in terms of between-wealth group inequality, we find that the incidence of ethnic conflict increases the group Gini by 3.8 to 4 points for the high propensity group, which translates to a 15.8 to 16.7 percent increase in educational inequality between wealth deciles.

5.2 Robustness Checks

In the following subsection of the analysis, we perform a number of robustness checks to test for potential misspecification in our regression models and, consequently, in the results reported in the previous sections. We first test for the validity of the DD common trends assumption prior to the incidence of conflict (the treatment). Second, we perform a placebo test using only pre-treatment data with a randomly assigned treatment date for countries who have ever experienced armed conflict between 1946 and 2010. Since the first two checks test for the validity of the DD identification strategy, we run the same analysis as reported in Table 5 using alternative measures of inequality nationally, and along gender, ethnic/religious, and wealth decile groups.

5.2.1 Common pre-treatment trends

To test for parallel trends during pre-treatment periods for both the treatment and control groups, we estimate a variant of equation [1] whereby we include country-specific quadratic peace year trends. Additionally, we replicate the analysis under the new specification and under no matching, kernel matching, and propensity scores as inverse probability weights. This strategy will enable us to test whether differences in pre-treatment trends exist and confirm whether the DD common trends assumption holds. As such, if the estimated treatment effects alter significantly when using country trends, then we would reject the null hypothesis that the treatment and control groups share parallel or common pre-conflict trends. Our objective in this analysis is to ascertain the validity of the DD approach and that the treatment and control groups did in fact follow similar trends prior to the incidence of conflict.[17] In essence, this approach tests whether identification of the treatment effect is via within-country changes in conflict incidence rather than a function of diverging trends in educational outcomes.

Table 10 presents the estimation results for the specification including country trends. We can see that the estimated effect of any conflict are largely the same as those presented in Table 5, where the specification did not include country trends. This result holds true under no matching, kernel matching, and propensity scores as inverse probability weights. Across all specifications and matching algorithms, the magnitude, direction, and statistical significance are unaltered between results from Table 5 and Table 10. Although, the estimated effects from including country trends are slightly smaller, although the differences are not statistically significant. As a result, we can reject the hypothesis that countries in the treatment and control groups had pre-conflict trends that were different which supports the validity of the DD estimates.

5.2.2 Falsification test

We perform an additional check to the robustness of the DD estimates using a falsification test. Using only data from pre-conflict years for the treatment group and maintaining all data from control group, we randomly assign a false conflict onset date for the treated countries

[17] See Besley and Burgess (2004), Wolfers (2006), and Angrist and Pischke (2009) for a discussion of DD identification and including country/state trends to test for common pre-treatment trends.

and extend the post-treatment period to every year following the false onset year. This enables us to run the DD strategy and test whether pre-conflict trends between the treatment and control countries diverged, thus violating the common trends assumption. Additionally, the false onset year doubles as a placebo test as countries assigned to the false conflict should not be affected. Therefore, if the test shows that the false DD effect is statistically significant then the DD strategy suffers from pre-treatment trends that are not parallel as well as potentially spurious correlations between conflict and education attainment and inequality.

The results of the falsification test are presented in Table 11 where we estimate the DD equation [1] using only pre-conflict data on mean years of schooling, the gender parity index, national Gini, ethnic/religious group Gini, and wealth group Gini. Across all outcome variables, we find no statistically significant estimates of the false conflict. Additionally, the direction of the DD estimate for each educational outcome runs counter to the actual DD estimates. If the DD estimates presented in Tables 5 through 9 were biased, the bias would be positive for mean years of schooling and gender parity index, and negative for all Gini outcomes. This means that, at worst, the DD strategy underestimates the true effect of conflict, and represents a lower bound to the effect of conflict. Given the results of the falsification test, we reject the hypotheses that the treatment and control groups do not have common pre-treatment trends, and that the DD estimates are spurious.

5.2.3 Alternative inequality measures

The final robustness check that we perform has to do with the choice of the gender parity index and Gini coefficient as the main measures of educational inequality nationally and between groups. To check for the sensitivity of the gender parity results we run the same analysis as presented in Table 5 but using gender attainment gap (measured in years) as the inequality measure. To test the sensitivity of our results for the Gini coefficient, we replicate the analysis using the Theil index and coefficient of variation as the measures of within-country and between-group inequality.

The results of the replication analysis with alternate inequality measures are presented in Table 12 under no matching, kernel matching, and propensity scores as inverse probability weights. The estimated DD effects under the different matching algorithm mirror the findings from the original inequality measures in terms of direction and statistical significance. Specifically, we find that the gender education gap and the within-country inequality in education increases in response to the incidence of conflict. Further, we find almost no effect on ethnic/religious group inequality via the Theil index or the coefficient of variation. We also find that between-wealth group inequality increases when using the coefficient of variation. However, the estimated effect of conflict is less precise using the group coefficient of variation, whereas the group Gini coefficient appears to produce smaller standard errors.

6 Conclusion and Policy Implications

The objective of this paper is to investigate and ascertain the links between the incidence of violent conflict and inequality in education, building empirical support for the relationship that has so far had theoretical grounding, but limited empirical evidence. We employ a research design that treats conflict as a natural experiment whereby we exploit variation in the timing and location of conflict to identify its causal effects on educational outcomes. We find that conflict, in general, lowers mean attainment by about 7.6 percent of a year of schooling, increases inequality at the national level where the Gini coefficient increases by approximately 2 percent, lowers the gender parity ratio by 5 percent, and increases the educational inequality between wealth decile groups by 5.4 percent as measured by the between-group Gini coefficient.

Furthermore, we take a more nuanced investigation of the effects of conflict on educational outcomes by disaggregating the conflict effect by type (ethnic and non-ethnic), by type and intensity, by type and duration, and by level of fragility (using propensity score subclassification). Across all levels of stratification presented in this paper, we find that ethnic conflicts are more harmful than non-ethnic ones, and chronic ethnic conflicts are more harmful than temporary conflicts of any sort. Finally, we find that the effects of ethnic conflicts on education inequality in fragile countries are more damaging than in countries with a better economic, political, and demographic infrastructure. More importantly, in modeling the trends of education inequality prior to, during, and post-conflict, we find that while education inequality declines in post-conflict years of peace, its levels tend to plateau or decline slowly, and potentially never reaching pre-conflict values.

On average, ethnic conflict lowers mean years of schooling by 0.14 years, widens the gap between boys and girls by about 8 percent, increases the national Gini coefficient for education by 3.8 percent, and increases the Gini coefficient between wealth groups by 9.6 percent. Ethnic conflicts that last longer than 16 years lower mean years of schooling almost by a full year (0.95 years), increases the gender gap by 13.5 percent, increases overall inequality at the individual level by 4.8 percent, and widens the education gap between wealth deciles by 22 percent on the group Gini coefficient. In assessing the impact of ethnic conflicts on education among highly fragile countries, we find that mean years of schooling are lower by 0.4 years, the gender gap is exacerbated by 13.5 percent, the overall Gini coefficient rises by about 3 percent, and the between-wealth group Gini coefficient inflates by almost 17 percent.

The findings in the study are consistent with the hypothesis that conflict exacerbates pre-existing levels of education inequality between groups, as well as inequality across all individuals in a given country. It is important to note that potential inequality reducing effects may still exist at the individual country level – as our literature review indicates. However, this study shows that by and large, the impact of conflict is detrimental, and the levels of inequality in education cannot be expected to return to pre-conflict levels on their own.

These findings provide additional support to the argument that education in conflict and post-conflict contexts does not merely remain the same or worsen for all groups, and that cycles of inequality may deepen, thereby creating the conditions for increased conflict risk, and potentially setting off a vicious cycle. This provides an impetus for greater attention to equity in education, particularly in conflict-affected and fragile settings – with expanding the metrics beyond outcome proxies (such as schooling completed or learning outcomes) to measures of inequality in education resource allocation. Programming and policy in education should also refer to this study as additional support for decisions that favor an equitable – though not always equal – resource distribution in education, particularly in favor of females and groups at the lower end of the socioeconomic spectrum.

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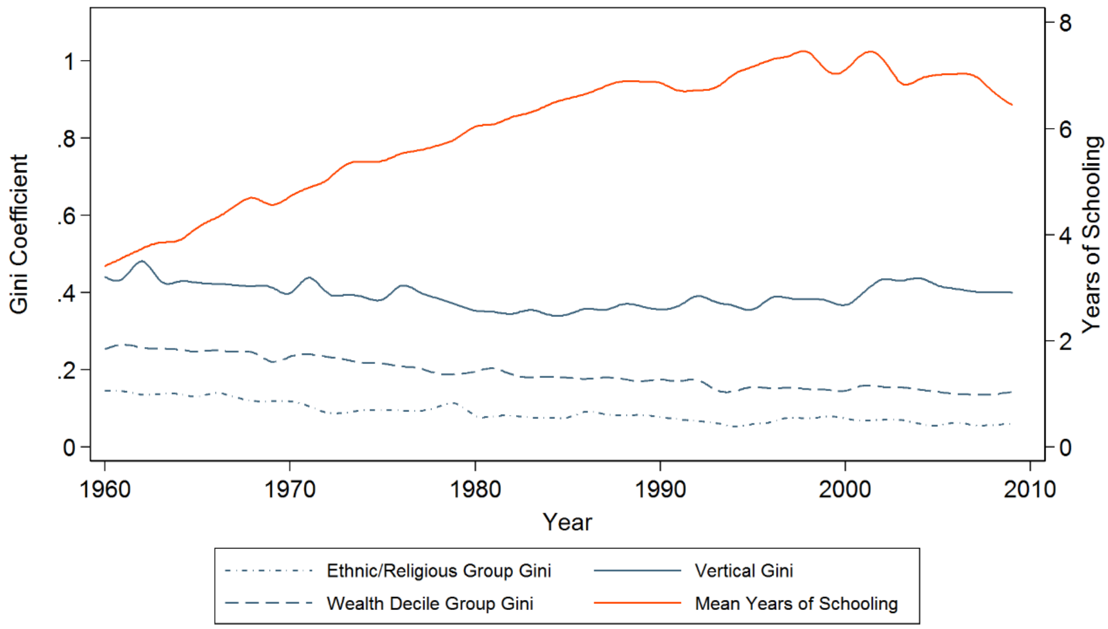
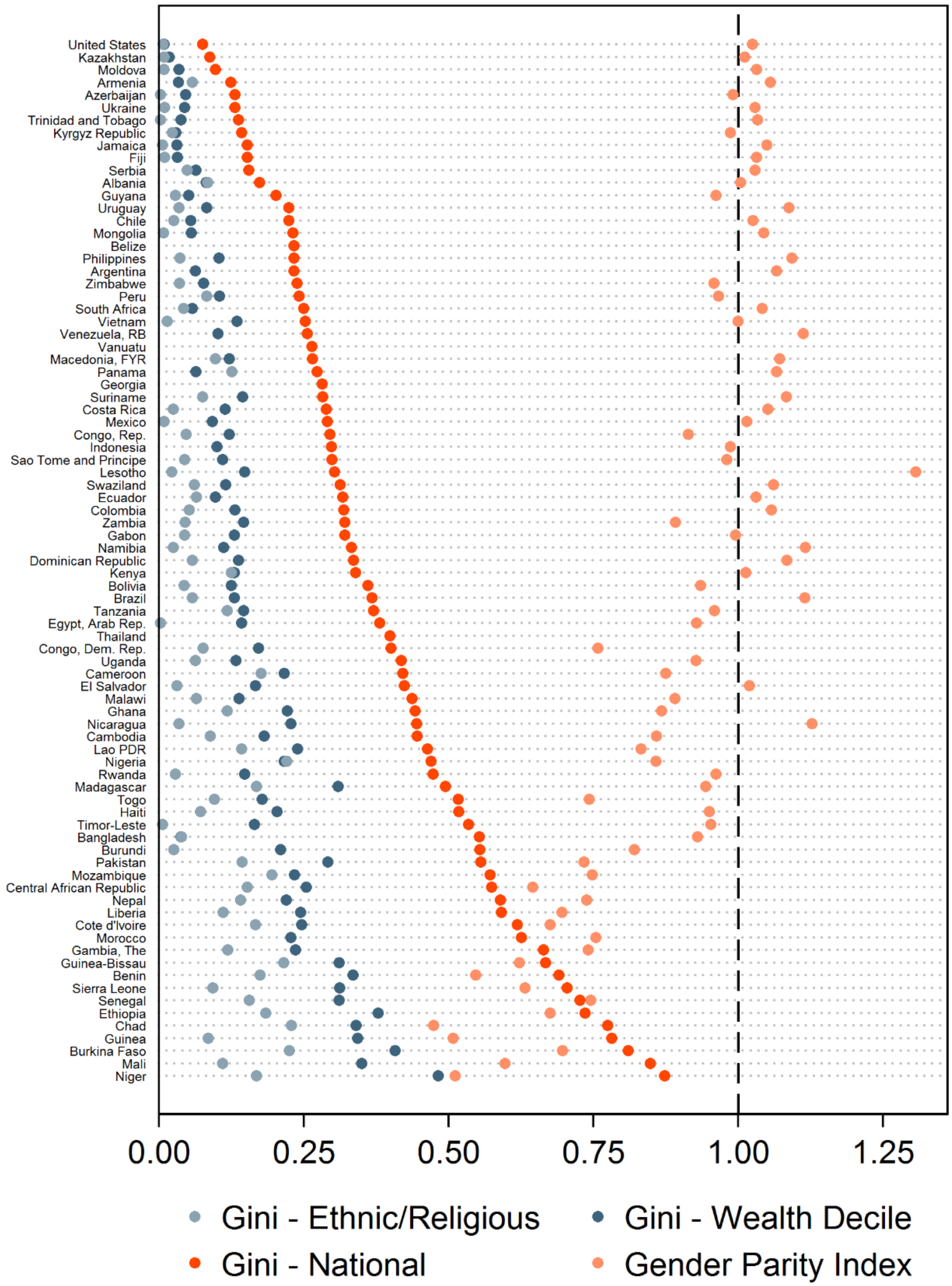
Figures

Figure 1. Trends in Education Attainment and Inequality



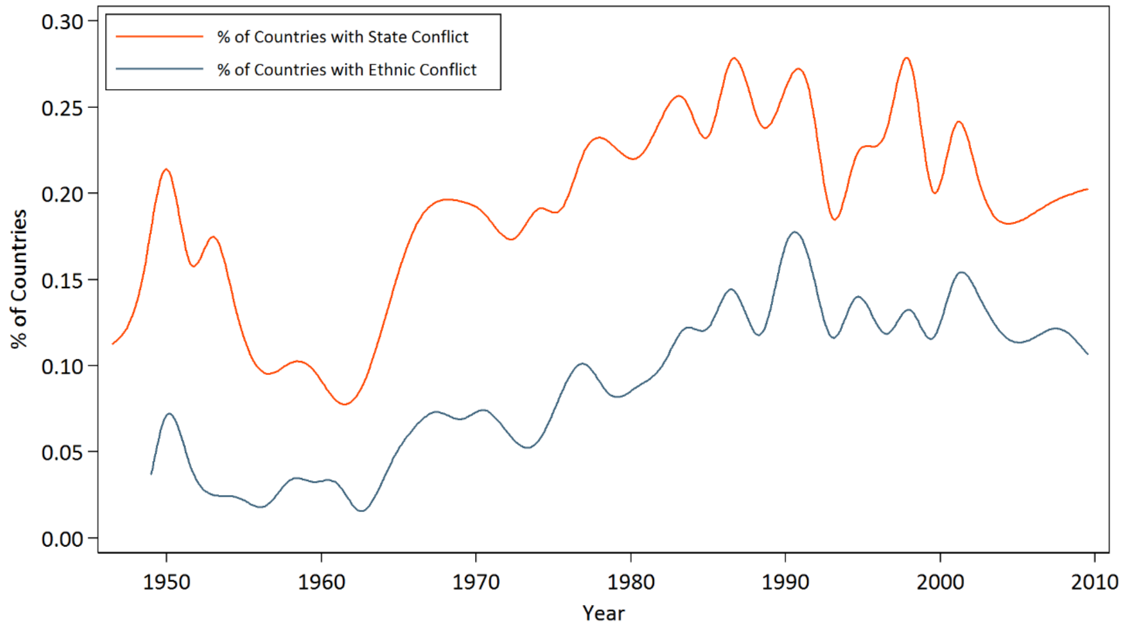
Source: Authors' calculations and EPDC, FHI 360 (2016)

Figure 2. Cross-Country Trends in Education Inequality



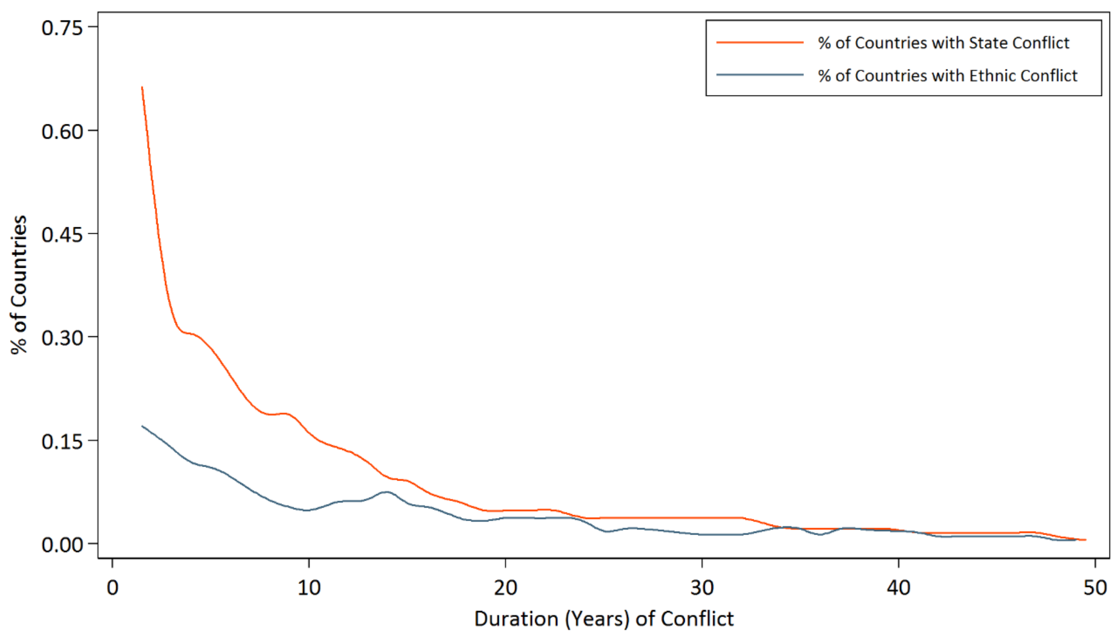
Source: Authors' calculations and EPDC, FHI 360 (2016)

Figure 3. Proportion of Countries Experiencing State and Ethnic Conflict



Source: UCDP/PRIO armed conflict database (2015)

Figure 4. Distribution of State and Ethnic Conflict Duration



Source: UCDP/PRIO armed conflict database (2015)

Figure 5. Propensity Score Distribution, Before and After Matching

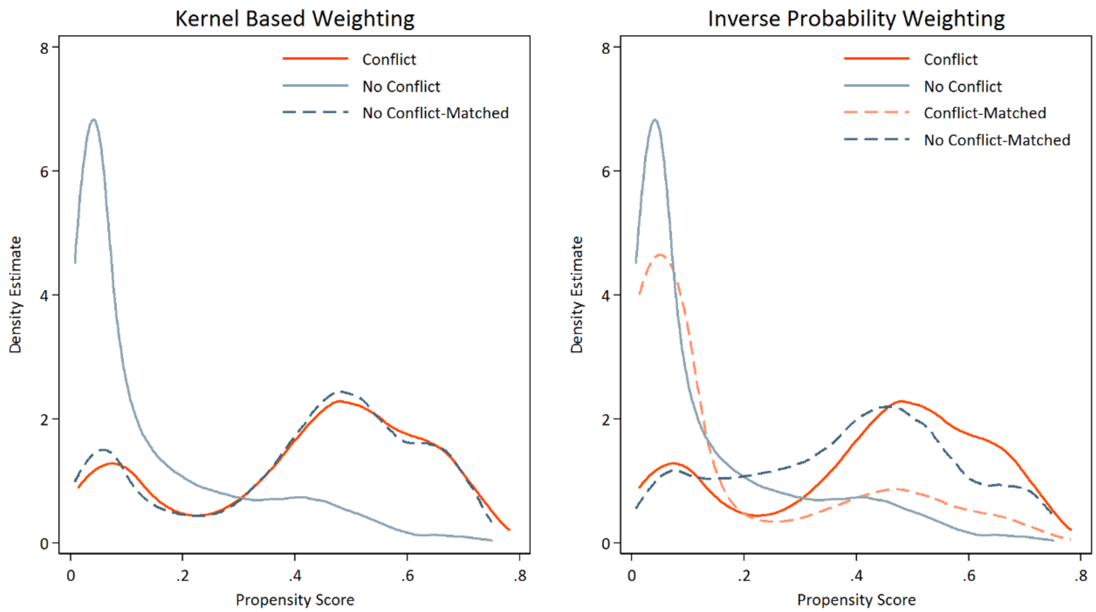
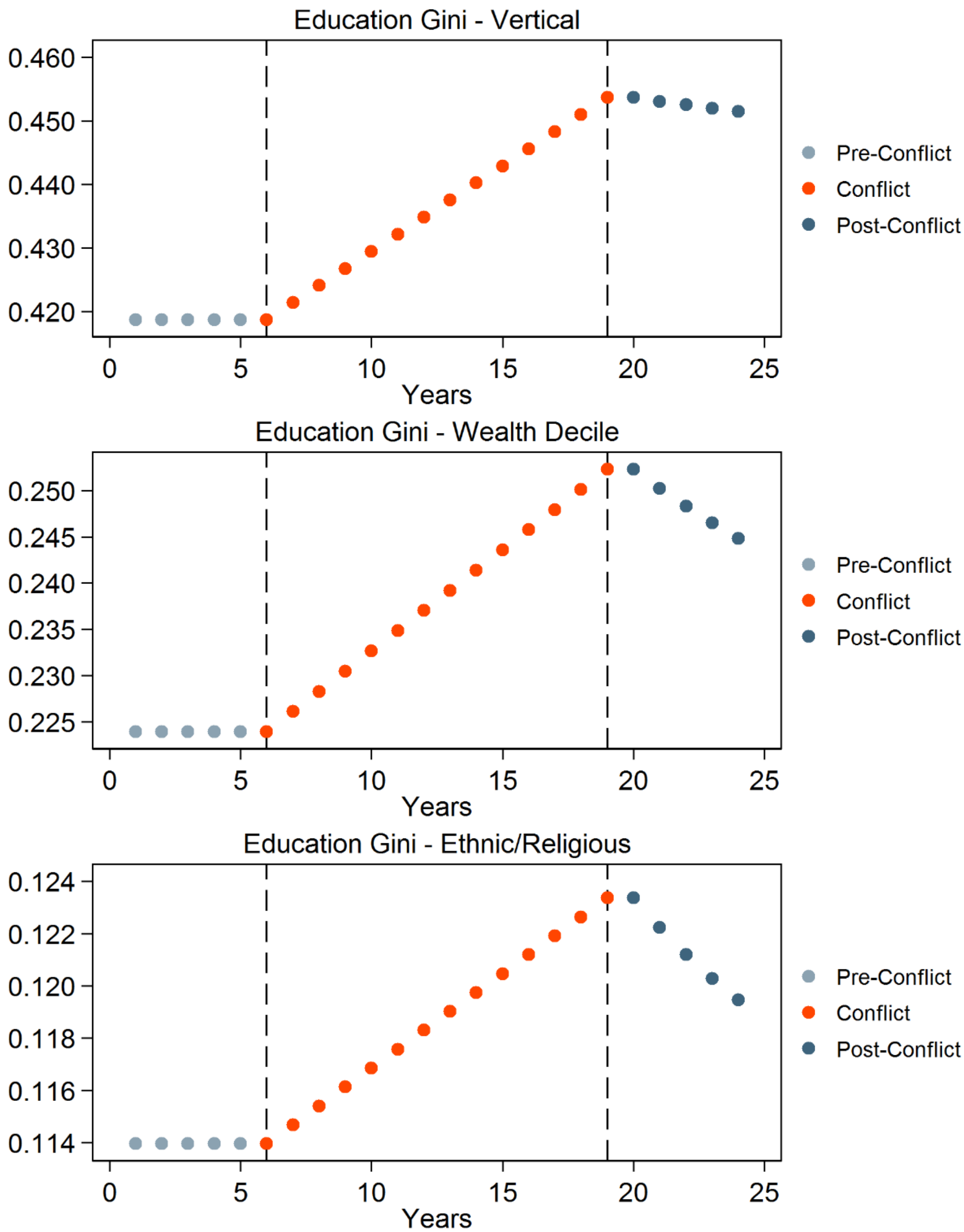


Figure 6. Predicted Inequality Pre-, During, and Post-Ethnic Conflict



Source: Marginal effects calculated using results from equation [4] with continuous duration variables

Tables

Table 1. Summary Statistics – Education Attainment and Inequality

	National					Ethnic/Religious Groups			Wealth Decile Groups		
	$\bar{y}$	gpi	g	t	cov	gg	gt	$gcov$	gg	gt	$gcov$
East Asia & Pacific	6.27	0.84	0.31	0.22	0.58	0.08	0.02	0.22	0.16	0.06	0.32
	(443)	(440)	(177)	(177)	(177)	(430)	(430)	(386)	(440)	(440)	(440)
Europe & Central Asia	10.23	0.96	0.15	0.06	0.29	0.04	0.01	0.10	0.07	0.01	0.14
	(473)	(470)	(56)	(56)	(56)	(491)	(491)	(431)	(470)	(470)	(470)
Latin America & Caribbean	7.46	0.96	0.38	0.31	0.70	0.09	0.03	0.22	0.17	0.06	0.33
	(978)	(950)	(616)	(616)	(616)	(858)	(858)	(836)	(931)	(931)	(917)
Middle East & North Africa	5.74	0.74	0.45	0.55	0.90	0.05	0.01	0.12	0.21	0.11	0.41
	(160)	(160)	(49)	(49)	(49)	(77)	(77)	(77)	(160)	(160)	(160)
North America	11.68	1.02	0.12	0.04	0.24	0.01	0.00	0.03	0.02	0.00	0.05
	(51)	(51)	(51)	(51)	(51)	(51)	(51)	(51)	(41)	(41)	(41)
South Asia	3.72	0.43	0.60	0.76	1.14	0.17	0.06	0.39	0.30	0.18	0.64
	(216)	(187)	(42)	(42)	(42)	(215)	(215)	(215)	(215)	(215)	(215)
Sub-Saharan Africa	4.19	0.60	0.56	0.79	1.22	0.14	0.05	0.32	0.29	0.19	0.64
	(1,732)	(1,725)	(521)	(521)	(521)	(1,692)	(1,692)	(1,588)	(1,732)	(1,732)	(1,675)
Total	**6.04**	**0.76**	**0.43**	**0.47**	**0.85**	**0.11**	**0.04**	**0.25**	**0.22**	**0.12**	**0.46**
	(4,053)	**(3,983)**	**(1,512)**	**(1,512)**	**(1,512)**	**(3,814)**	**(3,814)**	**(3,584)**	**(3,989)**	**(3,989)**	**(3,918)**

Notes: Numbers in cells represent mean values for mean years of schooling ($\bar{y}$), gender parity index (gpi), Gini coefficient (g), Theil index (t), coefficient of variation (cov), between-group Gini (gg), between-group Theil (gt), and between-group coefficient of variation ($gcov$). Numbers in parentheses represent the number of country-year observations in each cell. Top column headings denote group-level dimensions.

Table 2. Incidence of conflict, by Decade

		Incidence of State Conflict			Incidence of Ethnic Conflict		
	N	Total (%)	Minor (%)	Major (%)	Total (%)	Minor (%)	Major (%)
1960s	718	0.146	0.121	0.025	0.049	0.042	0.007
1970s	887	0.198	0.142	0.056	0.076	0.059	0.017
1980s	898	0.246	0.158	0.088	0.117	0.067	0.050
1990s	853	0.237	0.179	0.057	0.137	0.096	0.041
2000s	720	0.200	0.153	0.047	0.125	0.104	0.021
Total	**4,076**	**0.208**	**0.152**	**0.056**	**0.102**	**0.073**	**0.028**

Notes: All percentages represented in this table are calculated as percentages of the total in each region. State conflict refers to all state conflicts including ethnic and non-ethnic conflicts. The sum of major and minor conflict percentages within state and ethnic conflict types add up to the total percentage.

Table 3. Sample Summary, by Decade

	1960s	1970s	1980s	1990s	2000s	Total
Economic Output						
Real GDP ($) per capita	2,751	3,239	3,594	3,849	4,246	3,562
	(2,944)	(3,752)	(4,289)	(4,631)	(5,888)	(4,459)
Oil production ($) per capita	600	635	520	564	534	569
	(2,542)	(2,390)	(1,616)	(1,964)	(1,510)	(2,016)
Demographics						
Total population	14,762	16,745	21,425	25,749	31,145	21,855
	(28,477)	(31,225)	(44,128)	(44,391)	(51,632)	(41,215)
Pct. 15-24 years	0.177	0.190	0.193	0.191	0.197	0.190
	(0.016)	(0.014)	(0.018)	(0.016)	(0.020)	(0.018)
No. of ethnic/rel. groups	3.06	3.48	4.05	3.95	4.08	4.22
	1.31	1.86	2.13	2.13	2.07	1.98
Political Climate						
Democracy	0.234	0.170	0.232	0.435	0.493	0.314
	(0.424)	(0.376)	(0.422)	(0.496)	(0.500)	(0.464)
Anocracy	0.271	0.222	0.203	0.358	0.425	0.295
	(0.445)	(0.416)	(0.402)	(0.480)	(0.495)	(0.456)
Autocracy	0.495	0.608	0.565	0.207	0.081	0.391
	(0.500)	(0.488)	(0.496)	(0.405)	(0.274)	(0.488)
Observations	**718**	**887**	**898**	**853**	**720**	**4,076**

Notes: Numbers in cells denote variable means. Numbers in parentheses represent standard deviations. The year 2010 is included in the 2000s decade.

Table 4. Treatment and Control Group Sample Balance, Before and After Matching

	Unmatched			Matched		
	Conflict	No Conflict	Difference	Conflict	No Conflict	Difference
Gini - ethnic/rel. groups	0.127	0.108	0.019*	0.111	0.099	0.012*
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)
Gini - wealth decile groups	0.240	0.223	0.017*	0.214	0.207	0.007
	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)	(0.006)
Gini - national	0.454	0.420	0.034*	0.398	0.422	-0.024
	(0.011)	(0.006)	(0.013)	(0.013)	(0.007)	(0.015)
ln(Oil production per capita)	2.136	2.263	-0.127	3.497	3.099	0.397
	(0.101)	(0.061)	(0.118)	(0.213)	(0.115)	(0.242)
ln(Real GDP per capita)	7.545	7.712	-0.167*	8.132	8.115	0.017
	(0.037)	(0.017)	(0.041)	(0.078)	(0.039)	(0.087)
ln(Total population)	9.615	8.662	0.953*	10.184	10.309	-0.125
	(0.045)	(0.025)	(0.051)	(0.091)	(0.050)	(0.104)
Pct. age 15-24 years	0.190	0.188	0.002*	0.194	0.194	0.001
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Democracy	0.270	0.280	-0.010	0.512	0.461	0.052
	(0.017)	(0.009)	(0.019)	(0.035)	(0.017)	(0.039)
Anocracy	0.348	0.299	0.048*	0.294	0.318	-0.025
	(0.018)	(0.009)	-0.020	(0.032)	(0.016)	-0.036
Observations	**584**	**2,282**	**2,866**	**579**	**2,282**	**2,861**

Notes: All covariates listed in this table are lagged by 5 years. Numbers in cells reflect simple mean values, while numbers under the heading "Difference" denote the difference between the mean for the conflict and no conflict groups ($\mu_c - \mu_{nc}$). Numbers in parentheses denote standard errors. Difference in means are tested for statistical significance using a simple t-test.
* denotes statistical significance at the 10% level.

Table 5. Average Effect of Conflict on Attainment and Inequality

	$ln(\bar{y}_{ct})$	gpi_{ct}	g_{ct}	gg_{ct}^{ethnic}	gg_{ct}^{wealth}
Mean Outcome - Treatment Group	*5.078*	*0.696*	*0.454*	*0.127*	*0.240*
DD - No Matching					
Conflict	-0.013	-0.023*	0.008	0.003	0.006
	(0.019)	(0.013)	(0.006)	(0.004)	(0.006)
Observations	2,866	2,866	1,371	2,517	2,866
DD Matching - Kernel					
Conflict	-0.006	-0.033**	0.007**	0.004	0.011*
	(0.013)	(0.013)	(0.003)	(0.004)	(0.006)
Observations	2,861	2,861	1,042	2,507	2,861
DD Matching - IPW					
Conflict	-0.015	-0.035***	0.009*	0.005	0.013**
	(0.015)	(0.013)	(0.005)	(0.004)	(0.006)
Observations	2,866	2,866	1,121	2,512	2,866

Notes: Under both propensity score matching algorithms, the analytic sample is restricted to be within the common support. Matching weights are applied to estimate the average treatment effect on the treated (ATT). Numbers in parentheses denote standard errors clustered at the country-treatment level. All regression specifications include the full list of covariates that are lagged by five years, quadratic peace years, country fixed effects, and year fixed effects. Asterisks denote statistical significance as follows.
*** p<0.01, ** p<0.05, and * p< 0.10

Table 6. Average Effect of Conflict on Attainment and Inequality, by Type

	$ln(\bar{y}_{ct})$	gpi_{ct}	g_{ct}	gg_{ct}^{ethnic}	gg_{ct}^{wealth}
Mean Outcome - Treatment Group	*5.078*	*0.696*	*0.454*	*0.127*	*0.240*
DD - No Matching					
Non-Ethnic Conflict	-0.003	-0.010	0.004	0.005	0.000
	(0.023)	(0.013)	(0.008)	(0.005)	(0.006)
Ethnic Conflict	-0.025	-0.040*	0.013	0.000	0.014
	(0.027)	(0.023)	(0.012)	(0.006)	(0.011)
Observations	2,866	2,866	1,371	2,517	2,866
DD Matching - Kernel					
Non-Ethnic Conflict	0.006	-0.017	0.004	0.009*	0.002
	(0.016)	(0.013)	(0.005)	(0.005)	(0.005)
Ethnic Conflict	-0.022	-0.053**	0.012	0.000	0.022**
	(0.018)	(0.022)	(0.010)	(0.005)	(0.010)
Observations	2,861	2,861	1,042	2,507	2,861
DD Matching - IPW					
Non-Ethnic Conflict	-0.006	-0.019	0.005	0.009**	0.005
	(0.019)	(0.012)	(0.006)	(0.005)	(0.005)
Ethnic Conflict	-0.027	-0.055**	0.017	-0.001	0.023**
	(0.019)	(0.023)	(0.012)	(0.005)	(0.010)
Observations	2,861	2,861	1,042	2,507	2,861

Notes: Under both propensity score matching algorithms, the analytic sample is restricted to be within the common support. Matching weights are applied to estimate the average treatment effect on the treated (ATT). Numbers in parentheses denote standard errors clustered at the country-treatment level. All regression specifications include the full list of covariates that are lagged by five years, quadratic peace years, country fixed effects, and year fixed effects. Asterisks denote statistical significance as follows.
*** $p<0.01$, ** $p<0.05$, and * $p< 0.10$

Table 7. Average Effect of Conflict on Attainment and Inequality, by Type and Intensity

	$ln(\bar{y}_{ct})$	gpi_{ct}	g_{ct}	gg_{ct}^{ethnic}	gg_{ct}^{wealth}
Mean Outcome - Treatment Group	*5.078*	*0.696*	*0.454*	*0.127*	*0.240*
DD - No Matching					
Non-Ethnic Conflict - Minor	0.003	-0.008	0.004	0.005	-0.002
	(0.022)	(0.014)	(0.009)	(0.005)	(0.006)
Non-Ethnic Conflict - Major	-0.023	-0.016	0.004	0.006	0.007
	(0.034)	(0.015)	(0.013)	(0.007)	(0.008)
Ethnic Conflict - Minor	-0.029	-0.050*	0.013	0.002	0.017
	(0.030)	(0.026)	(0.013)	(0.006)	(0.013)
Ethnic Conflict - Major	-0.016	-0.013	0.020	-0.007	0.008
	(0.028)	(0.016)	(0.015)	(0.007)	(0.008)
Observations	2,866	2,866	1,371	2,517	2,866
DD Matching - Kernel					
Non-Ethnic Conflict - Minor	0.010	-0.015	0.003	0.008	0.001
	(0.016)	(0.014)	(0.005)	(0.005)	(0.006)
Non-Ethnic Conflict - Major	-0.007	-0.020	0.007	0.012*	0.008
	(0.022)	(0.013)	(0.010)	(0.006)	(0.007)
Ethnic Conflict - Minor	-0.028	-0.063**	0.012	0.002	0.025**
	(0.020)	(0.024)	(0.010)	(0.005)	(0.012)
Ethnic Conflict - Major	-0.003	-0.024	0.016	-0.006	0.011
	(0.021)	(0.016)	(0.010)	(0.006)	(0.008)
Observations	2,861	2,861	1,042	2,507	2,861
DD Matching - IPW					
Non-Ethnic Conflict - Minor	-0.003	-0.018	0.006	0.009*	0.004
	(0.018)	(0.013)	(0.006)	(0.005)	(0.006)
Non-Ethnic Conflict - Major	-0.013	-0.021	-0.003	0.011*	0.010
	(0.025)	(0.013)	(0.011)	(0.006)	(0.007)
Ethnic Conflict - Minor	-0.033	-0.065**	0.016	0.001	0.027**
	(0.021)	(0.026)	(0.011)	(0.005)	(0.012)
Ethnic Conflict - Major	-0.008	-0.026	0.024*	-0.008	0.012
	(0.020)	(0.017)	(0.013)	(0.006)	(0.008)
Observations	2,861	2,861	1,042	2,507	2,861

Notes: Under both propensity score matching algorithms, the analytic sample is restricted to be within the common support. Matching weights are applied to estimate the average treatment effect on the treated (ATT). Numbers in parentheses denote standard errors clustered at the country-treatment level. All regression specifications include the full list of covariates that are lagged by five years, quadratic peace years, country fixed effects, and year fixed effects. Asterisks denote statistical significance as follows.
*** p<0.01, ** p<0.05, and * p< 0.10

Table 8a. Average Effect of Conflict, by Type and Duration (No Matching)

	$ln(\bar{y}_{ct})$	gpi_{ct}	g_{ct}	gg_{ct}^{ethnic}	gg_{ct}^{wealth}
Mean Outcome - Treatment Group	*5.078*	*0.696*	*0.454*	*0.127*	*0.240*
DD - No Matching					
Non-Ethnic Conflict:					
1-5 Years	0.019	0.006	-0.001	-0.001	-0.006
	(0.022)	(0.015)	(0.011)	(0.006)	(0.008)
6-10 Years	0.000	-0.025	-0.002	0.012	0.006
	(0.039)	(0.021)	(0.017)	(0.010)	(0.011)
11-15 Years	-0.007	0.011	0.012	0.002	-0.018
	(0.054)	(0.031)	(0.011)	(0.010)	(0.012)
16+ Years	-0.014	-0.004	0.003	0.021	-0.004
	(0.043)	(0.026)	(0.012)	(0.014)	(0.016)
Ethnic Conflict:					
1-5 Years	0.014	-0.004	0.012	-0.007	-0.003
	(0.028)	(0.017)	(0.012)	(0.006)	(0.009)
6-10 Years	-0.005	-0.071*	0.009	0.002	0.022
	(0.041)	(0.038)	(0.010)	(0.008)	(0.018)
11-15 Years	-0.030	-0.103*	0.001	0.004	0.037
	(0.038)	(0.057)	(0.014)	(0.006)	(0.025)
16+ Years	-0.181***	-0.079	0.025*	0.015	0.049*
	(0.066)	(0.062)	(0.015)	(0.015)	(0.025)
Observations	2,866	2,866	1,371	2,517	2,866

Table 8b. Average Effect of Conflict, by Type and Duration (Kernel Matching)

	$ln(\bar{y}_{ct})$	gpi_{ct}	g_{ct}	gg_{ct}^{ethnic}	gg_{ct}^{wealth}
Mean Outcome - Treatment Group	*5.078*	*0.696*	*0.454*	*0.127*	*0.240*
DD Matching - Kernel					
Non-Ethnic Conflict:					
1-5 Years	0.029	0.012	-0.007	-0.001	-0.007
	(0.024)	(0.016)	(0.009)	(0.006)	(0.007)
6-10 Years	0.016	-0.022	0.009	0.016*	0.002
	(0.020)	(0.017)	(0.012)	(0.009)	(0.009)
11-15 Years	-0.002	-0.006	0.019***	0.014	-0.010
	(0.043)	(0.027)	(0.007)	(0.009)	(0.010)
16+ Years	0.018	-0.034	0.009	0.029**	0.006
	(0.043)	(0.025)	(0.008)	(0.012)	(0.015)
Ethnic Conflict:					
1-5 Years	0.021	-0.009	0.009	-0.010*	0.004
	(0.023)	(0.016)	(0.009)	(0.006)	(0.008)
6-10 Years	-0.001	-0.073**	0.010	0.002	0.023*
	(0.030)	(0.029)	(0.007)	(0.007)	(0.014)
11-15 Years	-0.022	-0.102**	0.012*	0.007	0.037*
	(0.032)	(0.048)	(0.007)	(0.005)	(0.020)
16+ Years	-0.182**	-0.095*	0.022**	0.013	0.053**
	(0.078)	(0.049)	(0.011)	(0.013)	(0.024)
Observations	2,861	2,861	1,042	2,507	2,861

Table 8c. Average Effect of Conflict, by Type and Duration (Propensity Score IPW)

	$ln(\bar{y}_{ct})$	gpi_{ct}	g_{ct}	gg_{ct}^{ethnic}	gg_{ct}^{wealth}
Mean Outcome - Treatment Group	*5.078*	*0.696*	*0.454*	*0.127*	*0.240*
DD Matching - IPW					
Non-Ethnic Conflict:					
1-5 Years	0.028	0.012	-0.008	0.000	-0.008
	(0.025)	(0.016)	(0.010)	(0.006)	(0.007)
6-10 Years	0.001	-0.025	-0.002	0.017**	0.005
	(0.026)	(0.016)	(0.014)	(0.008)	(0.009)
11-15 Years	-0.007	-0.008	0.003	0.013	-0.009
	(0.045)	(0.026)	(0.009)	(0.009)	(0.010)
16+ Years	0.012	-0.033	-0.011	0.027**	0.006
	(0.045)	(0.026)	(0.013)	(0.012)	(0.015)
Ethnic Conflict:					
1-5 Years	0.023	-0.011	0.011	-0.010*	0.004
	(0.023)	(0.017)	(0.009)	(0.006)	(0.008)
6-10 Years	0.002	-0.074**	0.001	0.002	0.023
	(0.032)	(0.031)	(0.008)	(0.007)	(0.014)
11-15 Years	-0.021	-0.105**	-0.004	0.006	0.037*
	(0.033)	(0.049)	(0.012)	(0.006)	(0.020)
16+ Years	-0.187**	-0.093*	0.025	0.013	0.051**
	(0.077)	(0.052)	(0.018)	(0.014)	(0.024)
Observations	2,861	2,861	1,042	2,507	2,861

Notes: Under both propensity score matching algorithms, the analytic sample is restricted to be within the common support. Matching weights are applied to estimate the average treatment effect on the treated (ATT). Numbers in parentheses denote standard errors clustered at the country-treatment level. All regression specifications include the full list of covariates that are lagged by five years, quadratic peace years, country fixed effects, and year fixed effects. In addition to the regular specification, we include quadratic post-treatment trends to assess lingering post-conflict effects. Asterisks denote statistical significance as follows.
*** $p<0.01$, ** $p<0.05$, and * $p< 0.10$

Table 9. Average Effect of Conflict, by Conflict Subclassification

	$ln(\bar{y}_{ct})$	gpi_{ct}	g_{ct}	gg_{ct}^{ethnic}	gg_{ct}^{wealth}
Mean Outcome - Treatment Group	*5.078*	*0.696*	*0.454*	*0.127*	*0.240*
DD - No Matching					
Non-Ethnic Conflict - p\hat<.46	0.001	-0.013	-0.002	0.005	0.001
	(0.018)	(0.012)	(0.006)	(0.005)	(0.006)
Non-Ethnic Conflict - p\hat>.46	-0.032	-0.015	0.005	0.007	0.004
	(0.044)	(0.022)	(0.010)	(0.008)	(0.010)
Ethnic Conflict - p\hat<.46	0.023	-0.011	0.008	-0.005	-0.004
	(0.030)	(0.015)	(0.011)	(0.007)	(0.009)
Ethnic Conflict - p\hat>.46	-0.107**	-0.088**	0.020**	0.007	0.044**
	(0.043)	(0.035)	(0.008)	(0.007)	(0.017)
Observations	2,866	2,866	1,292	2,517	2,866
DD Matching - Kernel					
Non-Ethnic Conflict - p\hat<.46	0.015	-0.014	0.000	0.007	0.002
	(0.019)	(0.012)	(0.004)	(0.005)	(0.006)
Non-Ethnic Conflict - p\hat>.46	-0.000	-0.017	0.008	0.010	0.001
	(0.020)	(0.018)	(0.008)	(0.007)	(0.007)
Ethnic Conflict - p\hat<.46	0.030	-0.027*	0.012	-0.006	0.006
	(0.026)	(0.016)	(0.012)	(0.007)	(0.008)
Ethnic Conflict - p\hat>.46	-0.074**	-0.079***	0.010*	0.004	0.038**
	(0.029)	(0.030)	(0.006)	(0.004)	(0.015)
Observations	2,861	2,861	1,042	2,507	2,861
DD Matching - IPW					
Non-Ethnic Conflict - p\hat<.46	0.006	-0.016	0.001	0.008	0.004
	(0.020)	(0.013)	(0.005)	(0.005)	(0.006)
Non-Ethnic Conflict - p\hat>.46	-0.020	-0.021	0.007	0.011*	0.006
	(0.026)	(0.018)	(0.008)	(0.006)	(0.008)
Ethnic Conflict - p\hat<.46	0.023	-0.031*	0.012	-0.006	0.008
	(0.024)	(0.016)	(0.012)	(0.007)	(0.008)
Ethnic Conflict - p\hat>.46	-0.080***	-0.082**	0.010*	0.003	0.040***
	(0.029)	(0.031)	(0.006)	(0.005)	(0.015)
Observations	2,861	2,861	1,042	2,507	2,861

Notes: Under both propensity score matching algorithms, the analytic sample is restricted to be within the common support. Matching weights are applied to estimate the average treatment effect on the treated (ATT). Numbers in parentheses denote standard errors clustered at the country-treatment level. All regression specifications include the full list of covariates that are lagged by five years, quadratic peace years, country fixed effects, and year fixed effects. Asterisks denote statistical significance as follows.
*** p<0.01, ** p<0.05, and * p< 0.10

Table 10. Average Effect of Conflict with Country Pre-Treatment Trends

	$ln(\bar{y}_{ct})$	gpi_{ct}	g_{ct}	gg_{ct}^{ethnic}	gg_{ct}^{wealth}
Mean Outcome - Treatment Group	*5.078*	*0.696*	*0.454*	*0.127*	*0.240*
DD - No Matching					
Conflict	-0.020	-0.017*	0.007	0.000	0.008*
	(0.014)	(0.009)	(0.005)	(0.004)	(0.005)
Observations	2,866	2,866	1,371	2,517	2,866
DD Matching - Kernel					
Conflict	-0.011	-0.027***	0.007***	0.004	0.012**
	(0.011)	(0.010)	(0.003)	(0.003)	(0.005)
Observations	2,861	2,861	1,042	2,507	2,861
DD Matching - IPW					
Conflict	-0.017	-0.029***	0.007**	0.004	0.014***
	(0.013)	(0.011)	(0.003)	(0.004)	(0.005)
Observations	2,866	2,866	1,121	2,512	2,866

Notes: Numbers in parentheses denote standard errors clustered at the country-treatment level. All regression specifications include the full list of covariates that are lagged by five years, quadratic peace years, country fixed effects, year fixed effects, and quadratic country peace years. Asterisks denote statistical significance as follows.
*** $p<0.01$, ** $p<0.05$, and * $p< 0.10$

Table 11. Results from Falsification (Placebo) Test

	$ln(\bar{y}_{ct})$	gpi_{ct}	g_{ct}	gg_{ct}^{ethnic}	gg_{ct}^{wealth}
False Incidence:					
Placebo	0.029	0.027	0.009	-0.006	-0.010
	(0.044)	(0.027)	(0.007)	(0.023)	(0.012)
Economic Activity:					
ln(Real GDP per capita)	-0.001	-0.007	-0.011	-0.056**	0.022
	(0.080)	(0.038)	(0.017)	(0.023)	(0.020)
ln(Oil production per capita)	-0.001	-0.003	-0.001	-0.006	-0.004
	(0.011)	(0.009)	(0.003)	(0.006)	(0.003)
Demographics:					
ln(Total population)	0.366*	-0.034	-0.111*	-0.130***	-0.073
	(0.193)	(0.103)	(0.058)	(0.032)	(0.056)
Percent 15-24 years	-3.957**	-0.475	-0.082	-0.537	1.04***
	(1.572)	(0.730)	(0.456)	(0.524)	(0.354)
Political Structure:					
Democracy	0.069	-0.039	-0.02***	0.002	-0.003
	(0.043)	(0.033)	(0.004)	(0.008)	(0.016)
Anocracy	0.040	-0.048**	-0.013**	0.013*	0.004
	(0.033)	(0.022)	(0.005)	(0.007)	(0.010)
Quadratic Peace Years:					
Peace years	-0.04***	-0.013	0.014*	0.012**	0.006
	(0.008)	(0.014)	(0.007)	(0.005)	(0.005)
Peace years squared	0.000	-0.000	-0.000**	-0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.201	0.782	1.452***	1.630***	0.522
	(1.472)	(0.993)	(0.514)	(0.338)	(0.454)
Observations	976	976	340	861	976

Notes: Numbers in parentheses denote standard errors clustered at the country-treatment level. All regression specifications include the full list of covariates that are lagged by five years, quadratic peace years, country fixed effects, year fixed effects, and quadratic country peace years. Asterisks denote statistical significance as follows.
*** p<0.01, ** p<0.05, and * p< 0.10

Table 12. Average Effect of Conflict, under Alternate Measures of Inequality

	gap_{ct}	t_{ct}	gt_{ct}^{ethnic}	gt_{ct}^{wealth}	cov_{ct}	$gcov_{ct}^{ethnic}$	$gcov_{ct}^{wealth}$
DD - No Matching							
Conflict	0.136	0.037**	0.001	-0.002	0.051**	0.006	0.003
	(0.135)	(0.018)	(0.003)	(0.007)	(0.025)	(0.009)	(0.014)
Observations	2,866	1,371	2,517	2,866	1,371	2,517	2,866
DD Matching - Kernel							
Conflict	0.300**	0.025***	0.001	0.000	0.027**	0.011	0.013
	(0.127)	(0.009)	(0.002)	(0.005)	(0.010)	(0.008)	(0.012)
Observations	2,861	1,042	2,507	2,861	1,042	2,507	2,861
DD Matching - IPW							
Conflict	0.292**	0.039***	0.001	0.003	0.046***	0.012	0.017
	(0.128)	(0.014)	(0.002)	(0.005)	(0.016)	(0.009)	(0.012)
Observations	2,861	1,042	2,507	2,861	1,042	2,507	2,861

Notes: Column headings refer to the gender gap in years of schooling (gap_{ct}), Theil index (t_{ct}), group Theil index (gt_{ct}), coefficient of variation (cov_{ct}), and group coefficient of variation ($gcov_{ct}$). Numbers in parentheses denote standard errors clustered at the country-treatment level. All regression specifications include the full list of covariates that are lagged by five years, quadratic peace years, country fixed effects, and year fixed effects. Asterisks denote statistical significance as follows.
*** p<0.01, ** p<0.05, and * p< 0.10