EdWorkingPaper No. 23-733

The Impact of Armed Conflict on College Students

Hernando Grueso
George Washington University

Given the spike of homicides in conflict zones of Colombia after the 2016 peace agreement, I study the causal effect of violence on college test scores. Using a difference-in-difference design with heterogeneous effects, I show how this increase in violence had a negative effect on college learning, and how this negative effect is mediated by factors such as poverty, college major, degree type, and study mode. A 10% increase in the homicide rate per 100,000 people in conflict zones of Colombia, had a negative impact on college test scores equivalent to 0.07 standard deviations in the English section of the test. This negative effect is larger in the case of poor and female students who saw a negative effect of approximately 0.16 standard deviations, equivalent to 3.4 percentage points out of the final score. Online and short-cycle students suffer a larger negative effect of 0.14 and 0.19 standard deviations respectively. This study provides among the first evidence of the negative effect of armed conflict on college learning and offers policy recommendations based on the heterogeneous effects of violence.

VERSION: February 2023

Suggested citation: Grueso, Hernando. (2023). The Impact of Armed Conflict on College Students. (EdWorkingPaper: 23-733). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/a0dv-7761

The Impact of Armed Conflict on College Students*

Hernando Grueso†
George Washington University

February 2023

Abstract

Given the spike of homicides in conflict zones of Colombia after the 2016 peace agreement, I study the causal effect of violence on college test scores. Using a difference-in-difference design with heterogeneous effects, I show how this increase in violence had a negative effect on college learning, and how this negative effect is mediated by factors such as poverty, college major, degree type, and study mode. A 10% increase in the homicide rate per 100,000 people in conflict zones of Colombia, had a negative impact on college test scores equivalent to 0.07 standard deviations in the English section of the test. This negative effect is larger in the case of poor and female students who saw a negative effect of approximately 0.16 standard deviations, equivalent to 3.4 percentage points out of the final score. Online and short-cycle students suffer a larger negative effect of 0.14 and 0.19 standard deviations respectively. This study provides among the first evidence of the negative effect of armed conflict on college learning and offers policy recommendations based on the heterogeneous effects of violence.

* I would like to thank Stephanie Cellini, Leah Brooks, James Foster, Burt Barnow, and Maria Marta Ferreyra for their valuable feedback. I also would like to thank the Trachtenberg School at the George Washington University for the generous fellowship they provided me while I was conducting this research. All mistakes are mine.
† The George Washington University, Trachtenberg School of Public Policy & Administration. Email: hgrueso@gwu.edu

1. Introduction

Studies about the impact of armed conflict on education have focused on children and teenagers but little is known about its effects on higher education. Evidence worldwide shows the negative effects of violence on educational achievement[1] and attainment[2], but this evidence corresponds to students attending elementary, middle, and high school. College students are different in nature because they tend to be more independent from their parents and more able to change locations. Furthermore, college students tend to be more heterogeneous based on their pursued degree programs, major, and study mode (in-person or online). The above attributes are also affected by individual characteristics such as gender and poverty status. All these differences create a unique context mediating the effects of violence on college achievement.

Despite the lack of research about the effects of violence on higher education, there is research about its effects on some cognitive mechanisms that affect college performance. Evidence from psychology shows that exposure to armed conflict among college students causes anxiety and depression, and this evidence is available for contexts such as Kashmir (Dar and Deb, 2020) and Colombia (Tamayo-Agudelo and Bell, 2019). Depression is known to undermine school performance among college students (e.g., Al Qaisy, 2011; Ruz et al., 2018), and these findings have been identified as key mechanisms explaining the negative

[1] Evidence about the negative effect of armed conflict on educational achievement comes from Palestine (Brück, Di Maio, & Miaari, 2019), Israel (Shany, 2018), Mexico (Michaelsen & Salardi, 2020; Orraca-Romano, 2018), Costa Rica (Gimenez & Barrado, 2020), Brazil (Deole, 2018), and the US (Aizer, 2008; Gershenson & Tekin, 2018; Sharkey, 2018; Sharkey, Schwartz, Ellen, & Lacoe, 2014; Sharkey, Tirado-Strayer, Papachristos, & Raver, 2012; Sharkey, 2010; Beland & Kim, 2016; Lacoe, 2016; Miller et al., 2019; Laurito et al., 2019).

[2] Evidence about this negative effect on educational attainment comes from countries such as Côte d'Ivoire (Dabalen and Paul, 2014), Timor-Leste (Justino, Leone, and Salardi, 2014), Nepal (Silwal, 2016), Rwanda (Akresh & de Walque, 2008; Guariso & Verpoorten, 2018), Iraq (Dywakar, 2015), Perú (León, 2012), Guatemala (Chamarbagwala & Morán, 2011) and in Europe (Ichino & Winter-Ebmer, 2004; Omoeva et al., 2018).

effect of armed conflict on middle and high school achievement (e.g., Ang, 2021; Deole, 2018; Chang and Padilla-Romero, 2019; Laurito et al., 2019).

The existing literature on high school test scores reports an average negative effect of violence of approximately 0.1 standard deviations (e.g., Michaelsen & Salardi; 2020, Orraca-Romano, 2018; Shany, 2018). The present study provides new insights showing how this negative effect on college test scores varies depending on the student characteristics and their specific degree program. The main policy implication of this analysis comes from identifying which type of college students are more vulnerable to the negative effects of violence in the Colombian case.

In this paper, I study the impact of armed conflict on educational achievement among college students. I use college exit test scores as a measurement of educational achievement, and I study the heterogeneous effects of violence among poor and non-poor college students. The main hypothesis is that violence has a greater negative effect on poor college students. Furthermore, I explore differences across majors, degree types, and study mode.

I use data from Colombia to study the effect of armed conflict on college learning. This country represents a unique opportunity for this study because of an exit test that is a graduation requirement for all college students. Furthermore, this case is unique because of an external shock that shifted violence trends after the 2016 peace agreement with the Revolutionary Armed Forces of Colombia—FARC. Homicide rates constantly declined between 2012 and 2016 (during the peace talks) and spiked right after in former FARC territories.

I use a difference-in-difference (DD) design to test the causal effect of the increase in violence after 2016 on college student test scores. I also explore the heterogeneous effects of this external shock on poor and non-poor students. Using administrative records on college students, I calculate a multidimensional poverty index (MPI)—using the Alkire-Foster (AF) methodology (Alkire and Foster, 2011)—to differentiate poor from noon-poor college students. The outcome variable in the DD design corresponds to individual test scores in four subject areas from the national exams Saber Pro and Saber TyT: math, English, reading, and writing. The treatment variable is a dummy indicating which students lived in a municipality with FARC presence at the moment of the peace agreement (2016).

The DD results show that on average, the spike of violence after the Colombian peace process reduced college test scores by around 0.05 standard deviations in the English section of the test. This impact is larger in the case of poor students who saw an average negative effect of 0.16 standard deviations in the same section. This reduction is equivalent to approximately 3.4 percentage points in the final score. The DD coefficients in the rest of the subject areas are not distinguishable from zero at conventional levels.

I explore the heterogeneous effects of violence by sex and type of degree program. Female students suffer a slightly greater negative effect on their English section equivalent to 0.07 standard deviations (1.5 percentage points). However, in the case of poor female students the negative effect is the same compared to men, equivalent to 0.16 standard deviations. Online students suffer a negative effect equivalent to 0.14 standard deviation in the English section and it does not seem to be a difference between poor and non-poor students. Finally, students enrolled in short-cycle degree programs (e.g., associate's or vocational) face a negative effect of 0.19 standard deviations (4.2 percentage points) in their English section without a difference between poor and non-poor. Like in the general DD results, the coefficients of the other subject areas here are not statistically significant.

I also explore heterogeneous effects by major. Students enrolled in business majors seem to suffer a negative effect of violence equivalent to 0.06 standard deviations in their English test. In the case of poor students, this negative effect is equivalent to 0.12. Engineering students seem to face a negative effect equivalent to 0.16 standard deviations in the English test and only affecting poor students. I did not find any statistically significant coefficients when looking at other majors such as teaching and pedagogy, accounting, and law. The above results are robust using multiple poverty measurement criteria.

Based on the results presented here, policymakers might find it interesting to learn that not all college students are affected in the same way by the Colombian armed conflict. Online and short-cycle students seem to be most of the most vulnerable groups. In light of the increased emphasis on online education following the COVID-19 pandemic, policymakers should take note of this and specifically focus on the well-being of online students living in conflict zones. Female and multidimensionally poor students are also among the most vulnerable groups. Policies aimed at increasing access to higher education should take into account the specific challenges faced by women living in conflict zones of the country. For example, using different cutoffs for admissions or scholarship benefits can help mitigate the greater negative impact faced by these vulnerable groups.

Even though English seems to be the main subject area affected by conflict in this study, it is important noticing that English as a foreign language is a rare skill in Colombia. The country ranks low in the EF English Proficiency Index, having the position 17 out of 20 countries in Latin America (EF, 2021). A possible explanation for the sensitivity of this test score to variations in violence levels, is that being English a rare skill it is not easy to replace English teachers if they leave conflict zones during periods of increased violence. I explore this and alternative hypotheses in the discussion section of the paper.

This paper is divided into five sections after this introduction. The next section provides background information on the higher education sector in Colombia. The third section presents the data sources and sample. The fourth section introduces the empirical design. The fifth section discusses the results, and the last section concludes and offers policy recommendations.

2. Background

To understand the different ways in which violence affects higher education in Colombia, it is important to understand the different types of higher education institutions in the country. There are four types of higher education institutions: universities, university institutions, technological institutions, and professional technical institutions. *Universities* corresponds to research centers, allowed to offer bachelor's and postgraduate degree programs. *University institutions* are non-research centers, allowed to offer bachelor's and "specialization" degrees. Specializations are short postgraduate programs underneath the master's level. *Technological institutions* offer short-cycle degree programs known as "tecnológico" which are equivalent to an associate degree in the US with and with an average total length of three years. *Professional technical institutions* are those offering a "técnico profesional" degree, equivalent to a vocational training in the US with a total length of around two years (OECD et al. 2012, 32). Approximately, 30% of all students attending higher education in Colombia are enrolled in some sort of partial or fully online education (Ministry of Education website 2019).

There is a correlation between income and the type of higher education institution attended by students in Colombia. Wealthier students tend to attend universities and to be enrolled in bachelor's degree programs, while lower-income students tend to attend professional technical institutions offering short-cycle programs (Ferreyra et al., 2021). It is difficult to disentangle to what extent the negative effect of violence on college achievement is driven by the student's socioeconomic status or by the type of degree program. In the empirical strategy, I try to account for these different effects by conducting separate analyses by major and degree type. I separately look at the effect of armed conflict on students attending similar types of degree programs, and then looking at outcome differences between poor and non-poor students within those specific programs. I also include degree fixed effects in the main empirical strategy to try to disentangle these different impacts.

The existing literature on the negative effect of violence on education in Colombia has focused on middle and high school education. Some of these studies estimate the effect of violence by using panel data (e.g., Duque, 2019), instrumental variables (e.g., Munevar Meneses et al., 2019; Gómez Soler, 2016), and difference-in-difference designs (Prem et al., 2021). However, there are not studies looking at the effect of violence on higher education and exploring its heterogeneous effects by different types of degree programs. This paper contributes by filling up this gap in the literature. Furthermore, I go a step further comparing outcome differences based on individual characteristics such as poverty and gender. I also explore differences based on majors and study mode (online or in-person).

Selection is an issue mainly affecting college education, and young males are more vulnerable to it in the event of armed conflict (e.g., Blattman and Annan, 2010; Brown and Velásquez, 2017). When high school graduates decide whether to pursue higher education, armed conflict has the potential to dissuade them from pursuing it. Some of them get recruited by regular and irregular armies, others become heads of household, and others get even killed. Therefore, a change in test scores after a violence increase, could be driven by changes in the characteristics of student cohorts (e.g., less males take the exam after 2016). I conduct separate analysis only looking at female and male samples, and include gender controls in the empirical strategy to account for this possible issue.

Another possible source of selection is that lower-income students in Colombia tend to have higher dropout rates (Melguizo et al. 2016). Considering that the poor are more vulnerable to the negative effects of armed conflict in the country (e.g., Ibáñez & Moya, 2006; Loaiza-Quintero et al., 2018a; Loaiza Quintero et al., 2018b), an increase of violence could result in higher dropout rates among them. Based on the demographic trends before and after the peace agreement that I check in the following section, I do not have a reason to believe that higher dropout rates among the poor after 2016 could be driving my results. Even though there is a decrease in poverty levels after the peace agreement, it occurs at a same rate in FARC and non-FARC municipalities which represent the treatment and comparison groups in this study.

Finally, detailed background on the Colombian armed conflict and how violence increased in conflict zones after 2016 is documented by Grueso (2022). According to the author, due to a power vacuum in former FARC territories after the peace agreement, the homicide rate per 100,000 people increased by approximately 10% between 2016 and

2019. Most of the victims are ex-guerrilla members and civilians who advocate for human rights and environmental conservation. These civilians are also known as "social leaders". The main hypothesis explaining the homicide increase in former FARC territories after 2016, is the war between remaining criminal groups trying to control black markets such as drug trafficking and illegal mining. Social leaders are an obstacle for these criminal groups in their attempt to control former FARC territories.

3. Data

This paper is based on data from the Colombian Institute for the Evaluation of Education (ICFES). ICFES conducts twice per year the college exit tests Saber Pro and Saber TyT. Saber Pro focuses on students attending bachelor's degree programs and Saber TyT on students attending short-cycle degree programs. Both tests are mandatory graduation requirements and have a similar structure focused on four general subject areas: math, reading, writing, and English. The main difference between both test is in their specialized subject areas that are not taken into consideration in this analysis. I also use the high school test Saber 11 to control for the individual performance of each student during high school in the English, reading, and math subject areas.

The data include observations of all the students who were in their last year of college between 2014 and 2019 in Colombia. The total sample size is 1,127,614 observations at the individual level, which excludes missing values and students who took the test more than once, and keeping only observations that allowed the match between college (Saber Pro and Saber TyT) and high school (Saber 11) test scores. I also include demographic information at the student level collected along with the college exit tests.

Additional data on homicides at the municipality level are taken from the Colombian National Administrative Department of Statistics (DANE). I calculate homicide rates per 100,000 people using population records from the most recent national census (DANE, 2018). Finally, I classify which municipalities used to have FARC presence at the moment of the peace agreement based on the research conducted by the Mission for Electoral Observation (MOE, 2016), and the Foundation for Peace and Reconciliation (PARES, 2015).

Table 1 compares descriptive statistics between FARC and non-FARC municipalities and showing trend differences before and after the peace agreement. Approximately 7% of the students live in FARC municipalities which tend to be more violent. The homicide rate per 100,000 people in FARC municipalities increased from 38 to 40 after 2016. The opposite trend occurred in non-FARC municipalities where the same rate dropped from 26 to 23. This difference in violence trends between FARC and non-FARC municipalities corresponds to the treatment effect in this study.

College test scores are the outcomes of interest and according to Table 1, students living in FARC municipalities have on average a lower performance in terms of the math and reading scores compared to non-FARC students. However, these differences are consistent before and after the peace agreement suggesting that selection effects are not a problem driving this paper's results.

A complementary way to check for outcome differences between FARC and non-FARC municipalities is by looking at their pre-trends. Figure 1 shows that outcome pre-trends are similar in the case of poor students, and Figure 2 shows that this is even consistent when using a different poverty line. I formally test for pre-trend differences in section 5 below, using an event study approach over the model specifications that are introduced in section 4.

Poverty is a key variable of interest explaining the heterogeneous effects of violence in this study. A proxy for poverty levels among college students is the social stratification scale (SES) ranging from 1 (poorest neighborhoods) to 6 (richest neighborhoods). According to Table 1, the average SES in FARC municipalities is lower than in non-FARC municipalities, and this average scale does not have a significant change after 2016. This could suggest that the socioeconomic status of the neighborhood where the student lives might not be a precise proxy to capture short-term income changes. For example, a person who becomes wealthier in a short period of time might still be living in a poorer neighborhood.

Another proxy for socioeconomic status is the multidimensional poverty index (MPI) that I explain in the following section. Table 1 shows that the MPI is higher in FARC regions suggesting that these municipalities are poorer compared to non-FARC. However, poverty levels decrease symmetrically by approximately 4 percentage points in both municipalities suggesting that attrition is not a problem affecting the treatment group.

Finally, Table 1 shows a good balance between FARC and non-FARC municipalities in terms of individual characteristics; however, some of them changed after 2016. Before 2016, the average age is 22 years and 57% of the students in both samples are female. After 2016, the average age increases to 23 in both samples and the share of female students increases to 60% and 58% in FARC and non-FARC municipalities respectively. This change could be explained by a higher recruitment rate among males during armed conflict who drop out of college to join regular and irregular armies. I include gender controls in the empirical strategy to account for the possible changes in the female-male distribution affecting my results. I also checked differences by degree type and study mode shares after 2016 and did not find any significant shifts in trends that could explain my results.

4. Empirical Design

The guiding research questions in this essay are: *what is the impact of the Colombian armed conflict on college test scores? And, to what extent is this impact different in the case of poor college students?* The hypothesis to be tested based on the literature review is that *armed conflict intensity has a negative effect on college test scores and that this effect is greater in the case of poor students who are more vulnerable to the effects of violence*.

The empirical strategy is based on the following difference-in-difference design:

$$College\ Test\ Scores_{it} = \beta_0 + \beta_1 FARC_m + \beta_2 D_{t>2016} + \beta_3 \cdot (D_{t>2016} \times FARC_m) + \gamma X'_{it} + \mu_t + \theta_m + \varepsilon_{itm}\,, \quad (1)$$

The outcome variable corresponds to college standardized test scores[3] in four subject areas—math, reading, writing, and English—at the student level (i) and by semester-year (t). The first independent variable is an indicator for whether the student lives in a municipality (m) that used to have FARC presence before the peace agreement ($FARC_m$), and the second independent variable is a dummy indicating the time periods after the peace agreement signing in 2016 ($D_{t>2016}$). The treatment effect is defined by the interaction term $D_{t>2016} \times FARC_m$ which indicates the municipalities of the country that saw an increase in violence after the peace agreement beginning in the second semester of

[3] Test scores were standardized using z-scores by semester-year (subtracting the mean and dividing by the standard deviation).

2016. I use $FARC_m$ instead of the homicide rate to account for the problem of endogeneity between homicides and test scores[4].

The regression also includes a vector with individual controls (X'_{it}), semester fixed effects (μ_t), municipality fixed effects (θ_m), and the error term (ε_{itm}). The individual controls include *age* (in years), *female* (female=1, male=0), father's and mother's employment status (unemployed=0, informal worker=1, blue-collar worker=2, skilled worker=3, executive or high-level worker=4), SES (1-6), whether the individual is an online student (1,0), the MPI score (0-1), and the high school standardized test scores (Saber 11) in the reading, math, and English subject areas. All the results are calculated using clustered standard errors at the municipality level. In some specifications, I take out the municipality fixed effects to look at differences not only within but also across FARC and non-FARC areas.

To assess the heterogeneous effect of violence on the test scores of poor students, I interact the key elements of the DD design in equation 1 with an MPI indicator (poor=1, non-poor=0), as follows[5]:

$$\begin{aligned} College\ Test\ Scores_{it} = {} & \beta_0 + \beta_1 FARC_m + \beta_2 D_{t>2016} + \beta_3 \cdot (D_{t>2016} \times FARC_m) \\ & + \beta_4 \cdot (FARC_m \times MPI_{it}) \\ & + \beta_5 \cdot (D_{t>2016} \times MPI_{it}) \\ & + \beta_6 \cdot (D_{t>2016} \times FARC_m \times MPI_{it}) + \beta_7 MPI_{it} \\ & + \gamma X'_{it} + \mu_t + \theta_m + \varepsilon_{itm}, \end{aligned} \quad (2)$$

The treatment effect on the poor is therefore given by adding the coefficients $\beta_3 + \beta_6$. Following the same logic in equation 1, I also estimate equation 2 with and without

[4] More violent areas might also have higher levels of poverty and lack of public services, which is correlated with lower school performance.
[5] As a robustness check, I conduct the same analysis in equation 1 but using two different subsamples for poor and non-poor students. The results are the same as in equation 2.

municipality and semester fixed effects and dropping $D_{t>2016}$ and $FARC_m$ after the inclusion of both effects.

The multidimensional poverty index (MPI) is calculated according to the AF methodology (Alkire and Foster, 2011). Table 2 Proposes an MPI definition that is like the official Colombian definition but adjusted to the available demographic variables that are recorded along with the Saber Pro and Saber TyT tests. This definition is based on three dimensions: *education*, *work*, and *living standards*. Six poverty indicators are used within these three dimensions: schooling, child labor, formal employment, unemployment, and assets. These indicators follow similar cutoff lines (z) of the Colombian and the Global MPI definitions. Dummy variables are created based on these cutoffs to indicate if a student should be considered deprived in each of these poverty indicators (deprived=1, not deprived=0).

Within the education dimension, a student is deprived of *schooling* if she is older than 24 during the last year of college (indicating delayed or disrupted schooling); and deprived in terms of *child labor*, if she is younger than 18 and works more than 20 hours per week. Within the work dimension, a student is deprived of *formal employment*, if either of her parents is an informal worker (e.g., self-employed as a farmer, blue-collar worker, or maid); and deprived in terms of *unemployment*, if any of her parents does not have a job while actively looking for one. Within the living standards dimension, a student is deprived of *assets* if the household in which the student lives does not have a car and less than two of the following assets: computer, washing machine, oven, and microwave.

Equal weights are given to each dimension following according to the Colombian official MPI definitions. This means that each of the three dimensions receives a ⅓ weight, and this weight is equally divided between the total number of indicators in each dimension. The MPI score is calculated for each student i according to the following equation:

$$\begin{aligned} MPI\ Score_i = {} & 0.16 * Schooling\ +\ 0.16 * Child\ Labor \\ & + 0.16 * Informality\ +\ 0.16 * Unemployment \\ & + 0.33 * Assets \end{aligned} \tag{3}$$

A student is classified as multidimensionally poor if her MPI score is higher than ⅓. This threshold is known as the cross-dimensional cut-off line (k) and is the same one used by the Global and Colombian MPI definitions. I create an indicator MPI variable to classify the students that are considered multidimensionally poor (1) and the ones that are not (0). As a robustness check, the same regression analysis is conducted using a more restrictive cut-off line of k=½ and different weighting structure of the MPI: (1) a higher weight given to the education dimension (Edu=2/3, Work=1/6, LS=1/6), (2) a higher weight given to the work dimension (Edu=1/6, Work=2/3, LS=1/6), and (3) a higher weight given to the living standards dimension (Edu=1/6, Work=1/6, LS=2/3).

Appendix Table 13 provides a comparison of different MPI definitions and their trends from 2014 until 2018. According to the official definition calculated by the National Administrative Department of Statistics (DANE), the Colombian MPI decreased from 21.9% in 2014 to 19.6% in 2018. The Global MPI for Colombia is only available for 2015 but it shows a similar estimate of 20.2%. The estimates based on college data, used in this paper, show that the national MPI went from 15% in 2014 to 15.1% in 2018. This mismatch in estimates occurs because the population of college students in the country is not representative of the national average. However, the estimates are not that different, and the trends seem to be similar.

5. Results

The first step to interpret the results in this study is to test the identifying assumptions of the DD approach. A key identifying assumption is that the treated and comparison groups would have evolved similarly in the absence of an intervention. Following the same specifications of the DD design in equation 1, I test for the existence of pre-trends between FARC and non-FARC municipalities in Table 3 using and event study approach and the homicide rate per 100,000 people at the municipality level as the main outcome. If my identifying assumption is accurate, the interaction term $D_t \times \ FARC_m$ should only have positive statistically significant coefficients for t>2016. In fact, the results in Table 3 show that only coefficients after 2016 are positive and statistically significant.

Another important assumption is that there were no other major events explaining the shift in test scores after 2016. One of the components of the peace agreement was the government investment in social development programs to improve the livelihoods of people living in conflict zones. In consequence, the Colombian government started the implementation of these programs after the peace agreement. However, if there was any significant impact on education out of these programs it should have been positive. This means that I could potentially be underestimating the negative effect of violence on test scores. Another important change after the peace agreement is the arrival of a new government in 2018. This new government openly opposed the peace agreement, which could have contributed to the return to the war of some former guerrilla members. Indeed, Table 3 shows that the difference in homicide rates between FARC and non-FARC municipalities is only statistically significant since 2018 which would attenuate my results. My estimates will reflect the reduced form effect of these combined changes since 2016.

Figure 1 shows the results of an event study approach to test outcome differences in math and English standardized test scores between FARC and non-FARC municipalities before the peace agreement. The results are calculated using the same specifications in equation 1 and they show similar pre-trends in both sections of the test for the case of multidimensionally poor students. Figure 2 shows that this assumption still holds when using a more restrictive MPI with a cross-dimensional cutoff line of $k=½$.

The above identification tests suggest that the spike in homicide rates after the Colombian peace agreement mainly occurred in FARC municipalities, and mainly affecting the learning outcomes of poor college students. These assumptions hold for the math and English sections of the Saber Pro and Saber TyT tests.

Table 4 shows the results of the DD analysis on the math section of the test. Once controlling for individual characteristics, semester, degree, and municipality fixed effects, the increase of violence after the peace process does not seem to have a statistically significant effect on test scores. Table 5 shows the same results but in the case of the reading, English, and writing sections of the test. Columns 3 shows that, once controlling for individual characteristics, semester, degree, and municipality fixed effects, the increase of violence after the peace process has a negative impact of 0.08 standard deviation on English test scores. According to column 4, this negative impact is greater in the case of poor students who see a decrease in their English tests equivalent to 0.05+0.10=0.15 standard deviations. All these coefficients are statistically significant at the 0.01 level. The coefficients for the reading and writing sections of the test are not statistically significant. Appendix Table 1 corroborates the above findings but conducting a separate analysis in the subset of poor and non-poor students.

Table 6 shows the same results, but in the case of female college students. Column 5 shows that once controlling for semester, degree, and municipality fixed effects, the increase of violence after the peace process has a negative impact of almost 0.1 standard deviations in the English test of female students. This negative effect is a bit larger than the general one reported in Table 5. Column 6 also shows a slightly larger negative impact of 0.065+0.094=0.16 standard deviations in the case of poor female students. I did not find statistically significant coefficients in the case of the math, reading, and writing sections of the test.

Table 7 shows the same information but in the case of online college students. Columns 5 and 6 indicate that once controlling for semester, degree, and municipality fixed effects, the increase of violence after the peace process has an average negative of 0.15 standard deviations in the English test of online students. The DD coefficients interacted with MPI are not statistically significant suggesting that there is no difference between poor and non-poor students in the case of online learning. Like in the above results, the coefficients for math, reading, and writing are not statistically significant.

Table 8 replicates the above findings but only looking at college students enrolled in short-cycle degree programs. Columns 5 and 6 show that once controlling for semester, degree, and municipality fixed effects, the increase of violence after the peace process has an average negative effect of 0.2 standard deviations in the English test of short-cycle college students. Column 4 shows that including the regular controls, the increase of violence has a negative effect of 0.03 standard deviation on the reading test score among short-cycle students. Again, the results suggest that there are no visible differences between poor and non-poor students. The DD coefficients are not statistically significant in the case of math.[6]

I test differences by college major in Appendix Tables 2 to 6. Columns 5 and 6 in those tables show that considering the regular controls, the increase of violence after the peace agreement has a negative effect of 0.11, 0.08, and 0.05 standard deviations in the English test taken by students enrolled in pedagogy, business, and engineering respectively. In the case of business and engineering majors, poor students saw a greater decrease in their English test scores equivalent to 0.05+0.07=0.12 and 0.16 standard deviations respectively. In the case of law, students saw negative effect equivalent to 0.12 standard deviations and only affecting poor students. I did not find any statistically significant coefficients in the case of accounting majors.

Finally, I conduct robustness checks using different poverty measurement criteria to replicate the main DD findings. Appendix Tables 7 to 9, calculate equation 2 but using alternative MPI weighting structures. Table 7 puts a higher weight on the education dimension of poverty, Table 8 puts a higher weight on the work dimension, and Table 9 on the living standards dimension. Table 10 uses a symmetrical weighting structure (w=1/3) but with a higher cross-dimensional cut-off line (k=1/2). Table 11 uses a censored MPI score (only considering poor students) instead of the MPI dummy, as a proxy to the effect of poverty severity. And Table 12 uses an approximation to an income poverty measurement based on the social stratification scale (SES=1). All the above robustness checks are consistent with the main DD findings.

[6] Even though results in writing show small statistically significant positive effects, I do not analyze them because of the lack of similar pre-trends.

6. Conclusions and Policy Recommendations

This paper evaluates the impact of armed conflict on college achievement. Using data from Colombia, I provide new evidence on how violence affects college learning. Given the spike in homicides in conflict zones of Colombia after the 2016 peace agreement, I show how this increase in violence has a negative impact on college test scores. The existing literature focuses on the negative effects of violence on middle and high school learning. My results show that in the case of higher education, violence has heterogeneous effects depending on factors such as the degree type, major, and the study mode (online vs. in-person). This negative effect is also mediated by demographic variables such as sex and socio-economic status. In general terms, my results show that the negative effects of violence are larger for the case of female and poor college students.

The policy implications of my paper help to identify which groups of college students are the most vulnerable to the negative effects of violence. Online and short-cycle (e.g., associate's and vocational) students are the most vulnerable to the negative effects of violence. Given the general push for online education after the COVID-19 pandemic, policymakers should pay special attention to the situation of online students living in conflict zones of Colombia. Online learning brings new possibilities to expand access to higher education, but it is still susceptible to the regional negative effects of violence.

Another policy implication is that being female and being poor exacerbates the negative effects of violence on college learning. Policy makers should also pay special attention to those groups living in conflict zones who face greater vulnerabilities. The design of adequate policies to expand the access to higher education should take into consideration which groups of students are the most vulnerable given the dynamics of violence in Colombia. This is especially important considering that the access to higher education is one of the key mechanisms that contributes to poverty alleviation and intergenerational mobility. Violence, therefore, can be seen as a poverty trap that undermines the chances of vulnerable students to break the cycle of poverty.

One of the interesting and recurrent findings in this paper is that the spike of violence after 2016 in Colombia seems to mainly have affected the English section of the college test. A possible explanation is a correlation between income and English skills, considering that students who attended bilingual schools tend to come from higher-income backgrounds. If this is the case, lower-income students who are more vulnerable to the negative effects of violence could be driving the shift in trends considering that they are doing worse, especially in that subject area. However, the average social stratification scale (SES) in Table 1 increased after 2016 suggesting the opposite trend. An alternative explanation is that English teachers are more likely to leave conflict zones in the event of violence. Considering that English is a rare skill in Colombia, it is more difficult to replace English teachers, and this might explain the drop in English test scores. Additionally, if math teachers leave, school might relocate teachers from English to math since it is a more important subject. There is no information about this phenomenon in the literature and therefore, further research is needed to help understand why the increase of violence after 2016 mainly affected English test scores among college students in Colombia.

Given the lack of research on violence and higher education, there is still a gap in the literature on what are the mechanisms explaining this negative effect. A possible hypothesis based on previous high school research, is that this negative effect on test scores is mediated by the anxiety and depression caused by the exposure to violence.

Further research is also needed to understand what are the mechanisms explaining the negative effect of violence on college learning.

References

Akresh, R., & De Walque, D. (2008). Armed conflict and schooling: Evidence from the 1994 Rwandan genocide. *Policy Research Working Paper 4606*, The World Bank.

Aizer, A. (2008). *Neighborhood violence and urban youth* (No. w13773). National Bureau of Economic Research.

Al-Qaisy, L. M. (2011). The relation of depression and anxiety in academic achievement among group of university students. *International Journal of Psychology and Counselling*, 3(5), 96-100.

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

Blattman, C., & Annan, J. (2010). The consequences of child soldiering. *The Review of Economics and Statistics*, 92(4), 882-898.

Beland, L. P., & Kim, D. (2016). The effect of high school shootings on schools and student performance. *Educational Evaluation and Policy Analysis*, 38(1), 113-126.

Brown, R., & Velásquez, A. (2017). The effect of violent crime on the human capital accumulation of young adults. *Journal of Development Economics*, 127, 1-12.

Brück, T., Di Maio, M., & Miaari, S. H. (2019). Learning the hard way: The effect of violent conflict on student academic achievement. *Journal of the European Economic Association*, 17(5), 1502-1537.

Chang, E., & Padilla-Romo, M. (2019). The effects of local violent crime on high-stakes tests. *Haslam College of Business*, Working Paper No. 2019-03.

Dabalen, A. L., & Paul, S. (2014). Estimating the effects of conflict on education in Côte d'Ivoire. *The Journal of Development Studies*, 50(12), 1631-1646.

Dar, A. A., & Deb, S. (2020). Psychological distress among young adults exposed to armed conflict in Kashmir. *Children and Youth Services Review*, 118, 105460.

Deole, S. S. (2018). Human capital consequences of violence in schools: Estimating the impact of violence in schools on education outcomes in Brazil. *Review of Development Economics*, 22(1), 287-310.

Duque, V. (2019). Violence and children's education: Evidence from administrative data. *Economics Working Paper 2019-16,* The University of Sydney.

Education First —EF (2021). EF English Proficiency Index: A Ranking of 112 Countries and Regions by English Skills. Retrieved from https://www.ef.com/assetscdn/WIBIwq6RdJvcD9bc8RMd/cefcom-epi-site/reports/2021/ef-epi-2021-english.pdf

Ferreyra, M. M., Díaz, L. D., Urzúa, S., & Bassi, M. (2021). *The fast track to new skills: short-cycle higher education programs in Latin America and the Caribbean.* World Bank Publications.

Gershenson, S., & Tekin, E. (2018). The effect of community traumatic events on student achievement: Evidence from the beltway sniper attacks. *Education Finance and Policy*, 13(4), 513-544.

Gimenez, G., & Barrado, B. (2020). Exposure to crime and academic achievement: A case study for Costa Rica using PISA data. Studies in Educational Evaluation, 65, 100867.

Gómez Soler, S. C. (2016). Educational achievement at schools: Assessing the effect of the civil conflict using a pseudo-panel of schools. *International Journal of Educational Development*, 49, 91-106.

Guariso, A., & Verpoorten, M. (2018). Armed conflict and schooling in Rwanda: Digging deeper. Peace Economics, Peace Science and Public Policy, 25(1).

Grueso, H. (2022). Heterogeneous Effects of Violence on Student Achievement: Evidence from Colombia. (EdWorkingPaper: 22-624). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/j2cn-nw69

Ibáñez, A. M., & Moya, A. (2006). The impact of intra-state conflict on economic welfare and consumption smoothing: Empirical evidence for the displaced population in Colombia. *Available at SSRN 1392415*.

Ichino, A., & Winter-Ebmer, R. (2004). The long-run educational cost of World War II. *Journal of Labor Economics*, 22(1), 57-87.

Justino, P., Leone, M., & Salardi, P. (2014). Short-and long-term impact of violence on education: The case of Timor Leste. *The World Bank Economic Review*, 28(2), 320-353.

Kim, H. (2019). Beyond monetary poverty analysis: the dynamics of multidimensional child poverty in developing countries. *Social Indicators Research*, 141(3), 1107-1136.

Lacoe, J. (2016). Too scared to learn? The academic consequences of feeling unsafe in the classroom. *Urban Education*, 1-34.

Laurito, A., Lacoe, J., Schwartz, A. E., Sharkey, P., & Ellen, I. G. (2019). School climate and the impact of neighborhood crime on test scores. *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 5(2), 141-166.

León, G. (2012). Civil conflict and human capital accumulation the long-term effects of political violence in Perú. *Journal of Human Resources*, 47(4), 991-1022.

Loaiza Quintero, O. L., Muñetón Santa, G., & Vanegas López, J. G. (2018a). An exploratory assessment of the relationship between multidimensional poverty and armed conflict: The case of Antioquia, Colombia. *Revista Desarrollo y Sociedad*, (80), 11-51.

Loaiza Quintero, O. L., Muñetón Santa, G., & Vanegas, J. G. (2018b). Forced displacement and Multidimensional Poverty in Antioquia, Colombia: an assessment by means of a Seemingly Unrelated Regression. *Journal of Regional Research*, 41(1), 167-190.

Melguizo, T., Sanchez, F., & Velasco, T. (2016). Credit for low-income students and access to and academic performance in higher education in Colombia: A regression discontinuity approach. *World Development*, 80, 61-77.

Michaelsen, M. M., & Salardi, P. (2020). Violence, psychological stress and educational performance during the "war on drugs" in Mexico. *Journal of Development Economics*, 143, 102387.

Miller, P., Votruba-Drzal, E., & Coley, R. L. (2019). Poverty and academic achievement across the urban to rural landscape: Associations with community resources and stressors. *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 5(2), 106-122.

Misión de Observación Electoral, MOE. (2016). Mapas de riesgo electoral. Plebiscito para la refrendación del acuerdo de paz Gobierno-FARC. Retrieve from https://www.academia.edu/27730893/Mapas_de_Riesgo_Electoral._Plebiscito_para_la_refrendaci%C3%B3n_del_acuerdo_de_paz

Munevar-Meneses, S. M., Silva-Arias, A. C., & Sarmiento-Espinel, J. A. (2019). Exposure to armed conflict and academic achievement in Colombia. *Desarrollo y Sociedad*, (83), 13-53.

OECD/International Bank for Reconstruction and Development/The World Bank (2012), Reviews of National Policies for Education: Tertiary Education in Colombia 2012, OECD Publishing. http://dx.doi.org/ 10.1787/9789264180697-en

Omoeva, C., Hatch, R., & Moussa, W. (2016). The effects of armed conflict on educational attainment and inequality. *Education Policy and Data Center Working Paper No. 18-03*.

Orraca-Romano, P. P. (2018). Crime Exposure and Educational Outcomes in Mexico. *Ensayos-Revista de Economía*, 37(2).

Foundation Peace and Reconciliation—PARES (2015). Los Mapas del Conflicto Armado. Retrieved from https://pares.com.co/wp-content/uploads/2015/04/mapas-del-conflicto.png

Prem, M., Vargas, J. F., & Namen, O. (2021). The human capital peace dividend. *Journal of Human Resources*, 0320-10805R2.

Ruz, M. E. A., Al-Akash, H. Y., & Jarrah, S. (2018). Persistent (anxiety and depression) affected academic achievement and absenteeism in nursing students. *The Open Nursing Journal*, 12, 171.

Shany, A. (2018). Too Scared for School? The Effects of Terrorism on Student Achievement. *Working Paper*, retrieved from https://ieca.org.il/wp-content/uploads/2019/07/Too-Scared-for-School.pdf

Sharkey, P. (2010). The acute effect of local homicides on children's cognitive performance. *Proceedings of the National Academy of Sciences*, 107(26), 11733-11738.

Sharkey, P. T., Tirado-Strayer, N., Papachristos, A. V., & Raver, C. C. (2012). The effect of local violence on children’s attention and impulse control. *American Journal of Public Health*, 102(12), 2287-2293.

Sharkey, P., Schwartz, A. E., Ellen, I. G., & Lacoe, J. (2014). High stakes in the classroom, high stakes on the street: The effects of community violence on student's standardized test performance. *Sociological Science*, 1, 199.

Sharkey, P. (2018). *Uneasy peace: The great crime decline, the renewal of city life, and the next war on violence*. WW Norton & Company.

Schwartz, D., & Gorman, A. H. (2003). Community violence exposure and children's academic functioning. Journal of educational psychology, 95(1), 163.

Silwal, S. (2016). Resilience amidst conflict? The effect of civil war exposure on secondary education. *International Journal of Development and Conflict*, 6(2), 97-120.

Tamayo-Agudelo, W., & Bell, V. (2019). Armed conflict and mental health in Colombia. *BJPsych international*, 16(2), 40-42.

Figure 1. Estimates of the effect of violence after the Colombian peace process on college test scores of poor students using leads and lags in an event study model (MPI=1, K=1/3)

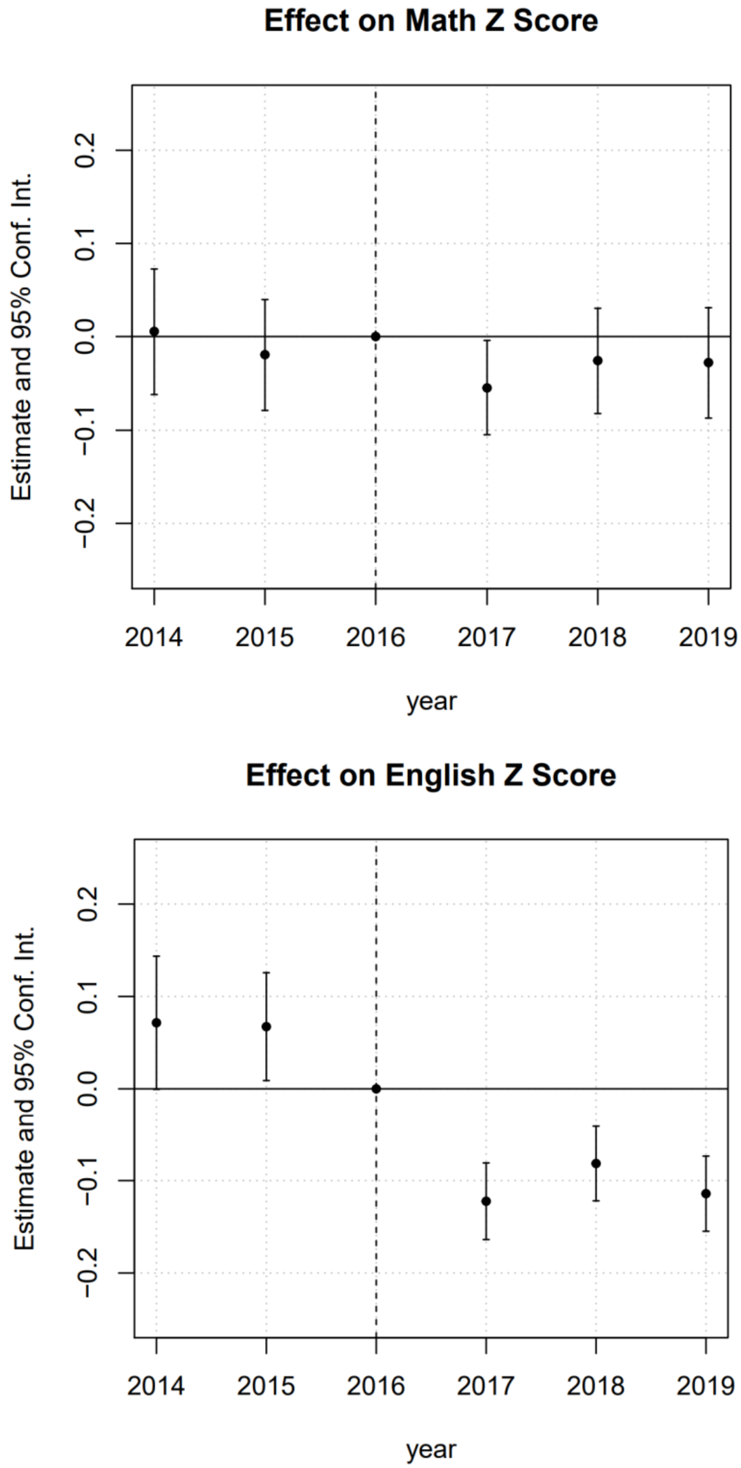

Figure 2. Estimates of the effect of violence after the Colombian peace process on college test scores of poor students using leads and lags in an event study model (MPI=1, K=1/2)

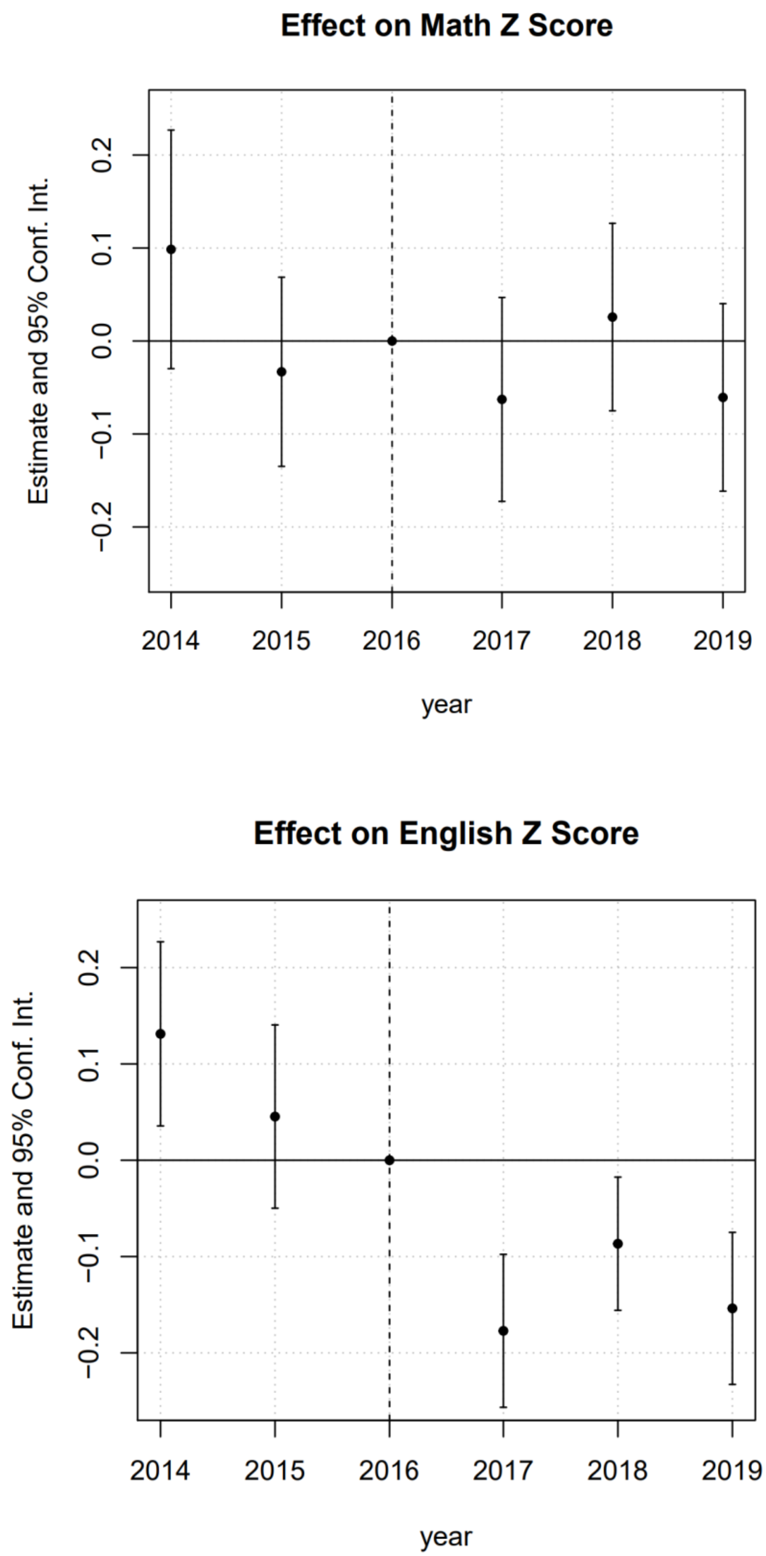

Table 1—Descriptive Statistics, Selected Variables for the 2014-II - 2019-II Periods

	FARC			Non-FARC		
	Obs.	Mean	St. Dev.	Obs.	Mean	St. Dev.
Panel A. Pre- 2016						
Math Z Score	21,516	-0.21	0.94	357,575	0.14	1.03
Reading Z Score	21,516	-0.26	0.94	357,575	0.14	1.01
Homicide Rate	21,516	38.02	22.88	357,575	24.55	15.72
MPI	21,516	0.33	0.47	357,575	0.16	0.36
SES	21,516	1.78	0.84	357,575	2.61	1.13
Age	21,516	22.53	3.01	357,575	22.21	2.52
Female	21,516	0.57	0.50	357,575	0.57	0.50
Panel B. Post-2016						
Math Z Score	53,251	-0.21	0.95	768,564	0.17	1.01
Reading Z Score	53,251	-0.26	0.95	768,564	0.16	1.00
Homicide Rate	53,251	39.93	27.46	768,564	22.65	15.06
MPI	53,251	0.27	0.44	768,564	0.12	0.33
SES	53,251	1.84	0.90	768,564	2.63	1.14
Age	53,251	23.45	3.18	768,564	23.02	2.83
Female	53,251	0.60	0.49	768,564	0.58	0.49
No. Municipalities		187			909	

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES), National Administrative Department of Statistics (DANE), and the Mision for Electoral Observation (MOE). Panel A corresponds to municipalities in 2016 (before the peace agreement) and Panel B to municipalities after 2016.

Table 2—MPI Definition Based on SaberPro Data

Dimensions	Indicators	W	Z
Education	Schooling	0.16	The student is older than 24 at the last year of college.
	Child Labor	0.16	The student is less than 18 years old and works more than 20 hours per week.
Work	Formal Employment	0.16	Any of the parents is an informal worker
	Unemployment	0.16	Any of the parents is unemployed
Living Standard	Assets	0.33	The student's household does not own a *car* and less than two of the following: - Computer - Washing machine - Oven - Microwave

Table 3—Test of Treatment Effect Identification: Event Study on Homicide Rate per 100,000 People

	Homicide Rate per 100,000 People	
	(1)	(2)
*FARC * D(t=2014)*	3.082	1.090
	(2.972)	(3.113)
*FARC * D(t=2015)*	-0.518	-1.424
	(2.739)	(2.807)
*FARC * D(t=2017)*	1.698	1.664
	(2.321)	(2.469)
*FARC * D(t=2018)*	6.643**	7.998***
	(2.97)	(3.08)
*FARC * D(t=2019)*	6.680**	7.990**
	(3.05)	(3.21)
Municipality FE	X	X
Year FE		X
Observations	1,009,828	1,009,828
R2	0.79	0.80

Note: Data are taken from the National Administrative Department of Statistics (DANE). The outcome corresponds homicide rate per 100,000 people at the municipality level (calculated based on population records from 2018). All the coefficients were calculated with OLS regressions and using clustered standard errors at the municipality level. Time periods are from 2014 to 2019. *p<0.1; **p<0.05; ***p<0.01

Table 4—Impact of Violence on Math Test Scores

	Math Z Score			
	(1)	(2)	(3)	(4)
*FARC * D(t>2016)*	0.022	0.009	0.021	0.008
	(0.02)	(0.01)	(0.03)	(0.02)
FARC	-0.131***		-0.130**	
	(0.05)		(0.05)	
*FARC * D(t>2016)*MPI*			-0.026	-0.027
			(0.02)	(0.02)
*FARC*MPI*			0.02	0.02
			(0.02)	(0.01)
*D(t>2016)*MPI*			0.051***	0.057***
			(0.01)	(0.01)
MPI			-0.094***	-0.066***
			(0.02)	(0.01)
Semester FE	X	X	X	X
Degree FE	X	X	X	X
Municipality FE		X		X
Observations	1,127,614	1,127,614	1,127,614	1,127,614
R2	0.36	0.37	0.36	0.37

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions (education, work, and living standards), and a student is considered as poor if her MPI score is greater than 1/3. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Table 5—Impact of Violence on Other Test Scores

	Reading Z Score		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)
*FARC * D(t>2016)*	0.031	0.026	-0.080***	-0.050***	0.063*	0.063*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
*FARC * D(t>2016)*MPI*		-0.022		-0.103***		-0.013
		(0.02)		(0.03)		(0.02)
*FARC*MPI*		0.028		0.118***		0.017
		(0.02)		(0.03)		(0.02)
*D(t>2016)*MPI*		0.078***		0.02		0.029**
		(0.01)		(0.02)		(0.01)
MPI		-0.060***		0.01		-0.017**
		(0.01)		(0.02)		(0.01)
Semester FE	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X
Observations	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614
R2	0.32	0.32	0.47	0.47	0.08	0.08

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions (education, work, and living standards), and a student is considered as poor if her MPI score is greater than 1/3. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Table 6—Impact of Violence on the Test Scores of Female Students

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	0.004	0.003	0.033	0.026	-0.093***	-0.065***	0.085**	0.083**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
*FARC * D(t>2016)*MPI*		-0.023		-0.019		-0.094***		-0.012
		(0.02)		(0.03)		(0.03)		(0.02)
*FARC*MPI*		0.021		0.021		0.112***		0.019
		(0.02)		(0.02)		(0.03)		(0.02)
*D(t>2016)*MPI*		0.043***		0.076***		0.02		0.035**
		(0.01)		(0.01)		(0.02)		(0.01)
MPI		-0.056***		-0.061***		0.029**		-0.034***
		(0.01)		(0.01)		(0.01)		(0.01)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	643,796	643,796	643,796	643,796	643,796	643,796	643,796	643,796
R2	0.33	0.33	0.33	0.33	0.47	0.47	0.08	0.08

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions (education, work, and living standards), and a student is considered as poor if her MPI score is greater than 1/3. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Table 7—Impact of Violence on the Test Scores of Online Students

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.029*	-0.032*	-0.001	-0.001	-0.156***	-0.144***	0.01	0.008
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
*FARC * D(t>2016)*MPI*		0.001		-0.008		-0.001		0.000
		(0.02)		(0.03)		(0.03)		(0.03)
*FARC*MPI*		-0.008		0.011		0.024		-0.001
		(0.02)		(0.02)		(0.02)		(0.03)
*D(t>2016)*MPI*		0.020**		0.025**		-0.077***		0.02
		(0.01)		(0.01)		(0.02)		(0.01)
MPI		-0.090***		-0.082***		0.043***		-0.076***
		(0.02)		(0.01)		(0.01)		(0.02)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	176,564	176,564	176,564	176,564	176,564	176,564	176,564	176,564
R2	0.30	0.30	0.26	0.26	0.27	0.27	0.07	0.07

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions (education, work, and living standards), and a student is considered as poor if her MPI score is greater than 1/3. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Table 8—Impact of Violence on the Test Scores of Short Cycle Degree Programs

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.026	-0.032	-0.021	-0.033*	-0.205***	-0.194***	0.050**	0.056**
	(0.02)	(0.02)	(0.01)	(0.02)	(0.04)	(0.04)	(0.02)	(0.03)
*FARC * D(t>2016)*MPI*		0.014		0.035		0.038		-0.023
		(0.02)		(0.03)		(0.03)		(0.03)
*FARC*MPI*		-0.004		0.004		0.026		-0.001
		(0.02)		(0.02)		(0.02)		(0.02)
*D(t>2016)*MPI*		0.00		(0.01)		-0.155***		0.01
		(0.01)		(0.01)		(0.01)		(0.01)
MPI		-0.078***		-0.049**		0.093***		-0.064***
		(0.02)		(0.02)		(0.01)		(0.01)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	357,182	357,182	357,182	357,182	357,182	357,182	357,182	357,182
R2	0.33	0.33	0.30	0.30	0.35	0.35	0.07	0.07

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions (education, work, and living standards), and a student is considered as poor if her MPI score is greater than 1/3. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Appendix Table 1—The Effect of Violence on Education Using Subsamples for Poor and Non-Poor Students

	Poor				Non-Poor			
	Math Z Score		*English Z Score*		*Math Z Score*		*English Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.01	-0.03	-0.141***	-0.148***	0.02	0.01	-0.045**	-0.050***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
FARC	-0.088**		-0.007		-0.134**		-0.108***	
	(0.033)		(0.011)		(0.054)		(0.029)	
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE		X		X		X		X
Observations	171,824	171,824	171,824	171,824	955,790	955,790	955,790	955,790
R2	0.30	0.33	0.24	0.26	0.35	0.37	0.46	0.47

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions (education, work, and living standards), and a student is considered as poor if her MPI score is greater than 1/3. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Appendix Table 2—Impact of Violence on the Test Scores by Major: Pedagogy and Teaching

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	0.028	0.051	0.069	0.065	-0.104***	-0.108***	0.152**	0.138*
	(0.03)	(0.04)	(0.05)	(0.05)	(0.02)	(0.03)	(0.06)	(0.07)
*FARC * D(t>2016)*MPI*		-0.084**		-0.020		0.023		0.010
		(0.04)		(0.05)		(0.05)		(0.05)
*FARC*MPI*		0.025		0.000		0.002		0.005
		(0.02)		(0.04)		(0.04)		(0.03)
*D(t>2016)*MPI*		0.057***		0.061***		-0.030		0.057**
		(0.02)		(0.02)		(0.03)		(0.03)
MPI		-0.013		-0.021		-0.005		-0.001
		(0.02)		(0.02)		(0.03)		(0.02)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	64,343	64,343	64,343	64,343	64,343	64,343	64,343	64,343
R2	0.32	0.32	0.37	0.37	0.38	0.38	0.14	0.14

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions (education, work, and living standards), and a student is considered as poor if her MPI score is greater than 1/3. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Appendix Table 3—Impact of Violence on the Test Scores by Major: Business

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.01	-0.016	0.028	0.016	-0.081***	-0.055**	0.008	0.013
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
*FARC * D(t>2016)*MPI*		0.001		0.013		-0.069*		-0.023
		(0.05)		(0.05)		(0.04)		(0.05)
*FARC*MPI*		0.012		0.041*		0.101***		0.027
		(0.02)		(0.02)		(0.03)		(0.04)
*D(t>2016)*MPI*		0.053***		0.092***		0.016		0.02
		(0.02)		(0.02)		(0.02)		(0.02)
MPI		-0.022*		-0.029***		0.108***		-0.015
		(0.01)		(0.01)		(0.01)		(0.01)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	169,846	169,846	169,846	169,846	169,846	169,846	169,846	169,846
R2	0.31	0.31	0.26	0.26	0.45	0.45	0.08	0.08

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions (education, work, and living standards), and a student is considered as poor if her MPI score is greater than 1/3. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Appendix Table 4—Impact of Violence on the Test Scores by Major: Accounting

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.036	-0.042	-0.002	-0.028	-0.045	-0.043	-0.078*	-0.064
	(0.03)	(0.03)	(0.05)	(0.05)	(0.03)	(0.04)	(0.05)	(0.05)
*FARC * D(t>2016)*MPI*		0.033		0.094		0.037		-0.059
		(0.06)		(0.06)		(0.05)		(0.12)
*FARC*MPI*		0.049		-0.025		0.056		0.048
		(0.05)		(0.05)		(0.04)		(0.05)
*D(t>2016)*MPI*		0.01		0.03		-0.058***		0.02
		(0.02)		(0.03)		(0.02)		(0.03)
MPI		-0.023		0.013		0.059**		-0.029
		(0.02)		(0.02)		(0.02)		(0.03)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	39,511	39,511	39,511	39,511	39,511	39,511	39,511	39,511
R2	0.31	0.31	0.26	0.26	0.31	0.31	0.09	0.09

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions (education, work, and living standards), and a student is considered as poor if her MPI score is greater than 1/3. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Appendix Table 5—Impact of Violence on the Test Scores by Major: Law

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.004	-0.007	0.043	0.035	-0.024	-0.006	0.082	0.075
	(0.03)	(0.03)	(0.05)	(0.05)	(0.03)	(0.04)	(0.08)	(0.09)
*FARC * D(t>2016)*MPI*		0.058		0.060		-0.116**		0.057
		(0.11)		(0.09)		(0.06)		(0.09)
*FARC*MPI*		0.057		0.020		0.121***		0.031
		(0.07)		(0.07)		(0.04)		(0.08)
*D(t>2016)*MPI*		-0.055**		(0.01)		0.04		(0.02)
		(0.03)		(0.04)		(0.04)		(0.04)
MPI		0.030		0.065*		0.038		0.058**
		(0.02)		(0.04)		(0.03)		(0.03)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	50,486	50,486	50,486	50,486	50,486	50,486	50,486	50,486
R2	0.32	0.32	0.34	0.34	0.49	0.49	0.12	0.12

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions (education, work, and living standards), and a student is considered as poor if her MPI score is greater than 1/3. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Appendix Table 6—Impact of Violence on the Test Scores by Major: Engineering

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	0.054**	0.059***	0.045*	0.045*	-0.048***	-0.015	0.019	0.026
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
*FARC * D(t>2016)*MPI*		-0.072*		-0.064		-0.159***		-0.025
		(0.04)		(0.04)		(0.04)		(0.07)
*FARC*MPI*		0.042		0.041		0.124***		0.050
		(0.03)		(0.04)		(0.03)		(0.03)
*D(t>2016)*MPI*		0.107***		0.132***		0.068***		0.01
		(0.02)		(0.02)		(0.02)		(0.02)
MPI		-0.025*		-0.049***		0.036***		0.017
		(0.02)		(0.01)		(0.01)		(0.01)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	178,620	178,620	178,620	178,620	178,620	178,620	178,620	178,620
R2	0.40	0.40	0.31	0.31	0.49	0.49	0.10	0.10

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions (education, work, and living standards), and a student is considered as poor if her MPI score is greater than 1/3. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Appendix Table 7—Robustness Check of the Effect of Violence on Test Scores using Alternate MPI Weights: Higher Weight on Education

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	0.002	0.015	0.005	0.01	-0.106***	-0.082***	0.095***	0.095***
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
*FARC * D(t>2016)*MPI*		-0.052**		-0.019		-0.131***		0.002
		(0.03)		(0.02)		(0.04)		(0.03)
*FARC*MPI*		-0.009		-0.009		0.112***		-0.02
		(0.02)		(0.02)		(0.03)		(0.03)
*D(t>2016)*MPI*		0.093***		0.048***		0.02		0.058***
		(0.01)		(0.02)		(0.03)		(0.01)
MPI		-0.055***		-0.033***		(0.04)		-0.040***
		(0.01)		(0.01)		(0.03)		(0.01)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614
R2	0.37	0.37	0.32	0.32	0.47	0.47	0.08	0.08

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions and giving a greater importance to the education dimension of poverty (MPI Weights: Edu=2/3, Work=1/6, LS=1/6). A student is considered as poor if her MPI score is greater than 1/3. The following alternative MPI weights give a higher Time periods are from 2014-2 to 2019-2.
*p<0.1; **p<0.05; ***p<0.01

Appendix Table 8—Robustness Check of the Effect of Violence on Test Scores using Alternate MPI Weights: Higher Weight on Work

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	0.002	0.01	0.005	0.012	-0.106***	-0.004	0.095***	0.111**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)
*FARC * D(t>2016)*MPI*		-0.019		-0.015		-0.130***		-0.019
		(0.02)		(0.02)		(0.03)		(0.02)
*FARC*MPI*		0.004		0.014		0.166***		0.033
		(0.02)		(0.02)		(0.04)		(0.02)
*D(t>2016)*MPI*		0.067***		0.063***		0.116***		0.027***
		(0.01)		(0.01)		(0.02)		(0.01)
MPI		-0.035***		-0.039***		-0.067***		-0.019***
		(0.01)		(0.00)		(0.01)		(0.01)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614
R2	0.37	0.37	0.32	0.32	0.47	0.47	0.08	0.08

Note:Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions and giving a greater importance to the work dimension of poverty (MPI Weights: Edu=1/6, Work=2/3, LS=1/6). A student is considered as poor if her MPI score is greater than 1/3. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Appendix Table 9—Robustness Check of the Effect of Violence on Test Scores using Alternate MPI Weights: Higher Weight on Living Standards

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	0.002	-0.002	0.005	-0.002	-0.106***	-0.079***	0.095***	0.101***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
*FARC * D(t>2016)*MPI*		-0.013		-0.013		-0.076**		-0.03
		(0.02)		(0.02)		(0.03)		(0.02)
*FARC*MPI*		0.015		0.027		0.107***		0.041**
		(0.02)		(0.02)		(0.03)		(0.02)
*D(t>2016)*MPI*		0.047***		0.072***		0.01		0.028***
		(0.01)		(0.02)		(0.02)		(0.01)
MPI		-0.065***		-0.062***		(0.02)		-0.026***
		(0.02)		(0.01)		(0.02)		(0.01)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614
R2	0.37	0.37	0.32	0.32	0.47	0.47	0.08	0.08

Note:Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions and giving a greater importance to the living standards dimension of poverty (MPI Weights: Edu=1/6, Work=1/6, LS=2/3). A student is considered as poor if her MPI score is greater than 1/3. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Appendix Table 10—Robustness Check of the Effect of Violence on Test Scores Using an Alternate MPI Cut-off Line

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	0.002	0.003	0.005	0.003	-0.106***	-0.098***	0.095***	0.092***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
*FARC * D(t>2016)*MPI*		-0.050*		0.022		-0.105***		0.018
		(0.03)		(0.04)		(0.03)		(0.04)
*FARC*MPI*		0.012		-0.013		0.125***		-0.036
		(0.02)		(0.03)		(0.04)		(0.03)
*D(t>2016)*MPI*		0.071***		0.03		-0.045**		0.060***
		(0.01)		(0.02)		(0.02)		(0.02)
MPI		-0.075***		-0.027		0.074***		-0.021
		(0.01)		(0.02)		(0.02)		(0.02)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614
R2	0.37	0.37	0.32	0.32	0.47	0.47	0.08	0.08

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) is based on three dimensions (education, work, and living standards), and a student is considered as poor if her MPI score is greater than 1/2. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Appendix Table 11—Effect of Violence on Test Scores According to MPI Severity

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	0.002	-0.002	0.005	-0.003	-0.106***	-0.078***	0.095***	0.100***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
*FARC * D(t>2016)*MPI Score*		-0.027		-0.009		-0.155***		-0.06
		(0.04)		(0.04)		(0.05)		(0.04)
*FARC*MPI Score*		0.013		0.031		0.212***		0.058*
		(0.03)		(0.04)		(0.06)		(0.03)
*D(t>2016)*MPI Score*		0.088***		0.125***		0.01		0.065***
		(0.02)		(0.03)		(0.04)		(0.02)
MPI Score		-0.130***		-0.116***		0.05		-0.037**
		(0.03)		(0.03)		(0.04)		(0.02)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614
R2	0.37	0.37	0.32	0.32	0.47	0.47	0.08	0.08

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, SES, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. The multidimensional poverty index (MPI) score is based on three dimensions (education, work, and living standards). Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Appendix Table 12—Effect of Violence on Test Scores According to SES=1

	Math Z Score		*Reading Z Score*		*English Z Score*		*Writing Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	0.002	-0.007	0.005	-0.012	-0.106***	-0.069***	0.095***	0.078***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
*FARC * D(t>2016)*SES*		-0.016		-0.022		-0.064***		-0.011
		(0.02)		(0.02)		(0.02)		(0.05)
*FARC*SES*		0.017		0.022		0.087***		0.015
		(0.02)		(0.02)		(0.02)		(0.04)
*D(t>2016)*SES*		0.059***		0.100***		-0.035**		0.080***
		(0.01)		(0.01)		(0.01)		(0.01)
SES		-0.079***		-0.119***		0.152***		-0.048**
		(0.01)		(0.01)		(0.03)		(0.02)
Semester FE	X	X	X	X	X	X	X	X
Degree FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614	1,127,614
R2	0.37	0.37	0.32	0.32	0.47	0.47	0.08	0.08

Note: Data are taken from the Colombian Institute for the Evaluation of Education (ICFES) and the Mision for Electoral Observation (MOE). All the coefficients were calculated with OLS regressions, with clustered standard errors at the municipality level, and including a vector for individual characteristics (sex, age, father's and mother's employment status, father's and mother's education, online instruction, MPI score, and standardized high school test score in reading, math, and English subject areas). The outcome variable corresponds to college standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. Poor students are those with a social stratification scale (SES) level equal to 1. Time periods are from 2014-2 to 2019-2. *p<0.1; **p<0.05; ***p<0.01

Appendix Table 13: MPI Comparison According to Multiple Definitions

	Colombian MPI				
	2014	2015	2016	2017	2018
UNDP & OPHI Global	.	19.5%	.	.	.
DANE	21.9%	20.2%	17.8%	.	19.6%
ICFES	15.0%	17.4%	11.8%	12.5%	15.1%

Note: the data were calculated using official records from the United Nations Development Programme (UNDP), the Colombian National Department of Statistics (DANE), and the Colombian Institute for the Evaluation of Education (ICFES). The ICFES calculation corresponds to an alternative definition introduced in this paper that considers three dimensions: education, work, and living standards.