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Heterogeneous Effects of Violence on Student Achievement

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Heterogeneous Effects of Violence on Student Achievement[*]

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Abstract

In this paper, I study the causal relationship between violence and human capital accumulation. Due to a power vacuum left in conflict zones of Colombia after the 2016 peace agreement, large spikes in violence were reported in the municipalities of the country dominated by the rebel group FARC. I compare student test scores in municipalities that experienced the increase in violence to the ones that did not, before and after the national peace agreement. I find that a 10 percent increase in the homicide rate reduces average high school test scores by approximately 0.03 standard deviations. However, this impact is greater in the case of poor students who suffered a reduction of about 0.1 standard deviations per subject area, equivalent to 3.3 percentage points out of the final score. I also consider heterogeneity by gender finding a slightly larger negative impact on female students. This disparate effect on women and on the poorest students adds new evidence to the literature on the effects of armed conflict on learning outcomes.

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1. Introduction

The negative effect of violence on education is well documented in the literature, however, we know little about which factors can exacerbate or cushion this impact. Poverty is one potential factor that may exacerbate the effect of violence, but it remains underexplored in the literature. Existing evidence worldwide shows how violence undermines educational achievement[1] and attainment[2] but it does not show the extent to which poverty mediates this negative effect. Not only are poor families more likely to live in neighborhoods with high rates of violence (e.g., Giménez-Santana, Caplan & Drawve, 2018) but they may be disproportionately affected by violent incidents (Alloush and Bloem, 2022).

Researchers document many possible mechanisms explaining the negative effects of violence on education. Some of them are physical, such as the recruitment of children during civil wars (Blattman & Annan 2010); destruction of infrastructure; and human displacement (Justino, 2011). Others are psychological, such as depression (Schwartz & Gorman, 2003), lower ability to concentrate (Sharkey et al. 2012; Liew et al. 2008), lack of sleep (Heissel et al., 2017; Heissel et al., 2018; El-Sheikh et al., 2019; El-Sheikh et al., 2011), and the distress caused by the exposure to homicides and violent assaults (Miller et al., 2019; Ang, 2021; Laurito et al., 2019; Deole, 2018; World Bank, 2011; Chang and Padilla-

[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).

Romero, 2019). All these mechanisms may be more problematic for poor households, as they are less likely to have the resources and support needed to mitigate and recover from these effects.

In this paper, I study how exposure to violence affects high-school students' achievement, measured in standardized test scores, and to what extent this effect differs by socioeconomic status and gender. The main hypothesis is that violence disproportionately undermines educational achievement among poor high-school students. The relevance of this research question comes from understanding the extent to which violence exacerbates the gap in access to higher education and I add to the literature by studying the distributional effects of violence.

I use data from Colombia to study how violence affects high-school students' test scores. The Colombian case represents a unique opportunity for this study because recent historical events shifted violence trends. In 2016, the Colombian government signed a peace agreement with the largest guerrilla group in Latin America—FARC. Violence steadily declined during the peace talks (2012-2016), but it spiked in former FARC municipalities right after the peace agreement signing. The war between remaining criminal organizations in an attempt to control former FARC territories seems to be the main reason why violence increased after 2016 (HRW, 2021).

I employ a difference-in-difference (DD) design, to compare educational achievement in municipalities that see a spike in violence after the Colombian peace agreement with those that do not, before and after the agreement. I explore heterogeneous effects in the DD design, by looking at outcome difference for poor and non-poor students. I further explore the literature by using a multidimensional poverty index (MPI) following the Alkire-Foster (AF) methodology (Alkire and Foster, 2011) to classify the students as poor and non-poor. This methodology provides a comprehensive measure of poverty that goes beyond one-dimensional approaches (e.g., income) and takes into consideration a wider set of indicators to measure poverty (e.g., living conditions, access to education, employment). The outcome variable in the DD design corresponds to individual test scores in four subject areas from the national exam Saber 11: math, reading, social science, and natural science. The treatment variable is an indicator for whether a student lives in a municipality that had a 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 11th grade test scores by around 0.03 standard deviations. However, this impact is larger for poor students who experience a reduction of approximately 0.1 standard deviations in each subject of the test. This reduction is equivalent to 3.2 percentage points in the final score, taking into consideration its effect in each of the four test subject areas. One potential consequence of these disparate effects may be to widen gaps in access to higher education, considering that these test scores are used to determine college admission. This is especially worrisome, considering that poor students already have greater difficulties in accessing higher education.[3]

Similar results are found in the literature on exposure to violence, which generally finds a negative effect of around 0.1 standard deviations on test scores, mainly affecting the math section of the test (e.g., Michelsen & Salardi, 2020; Orraca-Romano, 2018; Shany, 2018). In the Colombian case, I find that this negative effect is primarily driven by learning

[3] In Latin America, the enrollment rate in higher education is 10% among the poor while it is 77% among higher income individuals (UNESCO, 2020).

losses of poor students, and it is evenly distributed across the math, reading, and natural science test subject areas.

I also contribute to the literature by exploring heterogeneity by sex. I find a slightly larger negative effect of violence on women. This negative effect is approximately 0.02 standard deviations larger than the general results. While the difference is small, it could be that women are more likely to experience sexual violence during armed conflict (Comisión de la Verdad, November 26, 2018). All my results are statistically significant and robust to different poverty measurement criteria.

The findings in this paper suggest that greater efforts to reduce homicides in the municipalities that used to have FARC presence might have positive effects on the education outcomes among the poor. These positive effects on education might also help to reduce chronic poverty in the country, as education is essential for escaping poverty (Santos, 2011) and improving intergenerational mobility (Becker et al. 2018).

This paper is divided into five sections after this introduction. The next section provides background information about the Colombian context. 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

In 2016, the Colombian government ended a 50-year-old war with the Revolutionary Armed Forces of Colombia (FARC)—the largest guerrilla group in Latin America at the time. This peace process was celebrated internationally, including the Nobel Peace Prize awarded in 2016 to the former president Juan Manuel Santos. However, despite the multiple social, political, and economic benefits of this event, an increase in homicides has been recorded in the territories that used to have a FARC presence.

Homicides decreased substantially in Colombia during the time of the peace talks (2012-2016), but they spiked right after the signature of the peace agreement. Figure 1 shows that the national homicide rate per 100,000 people increased by around 10% between 2016 and 2019. Violence against social leaders and ex-guerrilla members seems to be the driver behind the increase in violence (UN, 2020). The term "social leaders" is used to designate a diverse group of environmental and human rights activists, living in remote areas of the country, and who have advocated against problems such as human rights, land grabbing, deforestation, and illegal mining. It is estimated that more than a thousand social leaders have been killed in Colombia since the peace agreement was signed, and a third of this total corresponds to indigenous peoples and afro-descendants (Ethnic Commission for Peace and the Defense of Territorial Rights, November 2020).

Different actors are behind the killing of social leaders in Colombia. A war between remaining criminal organizations started after 2016 in an attempt to control former FARC territories. These organizations include smaller guerrilla movements, paramilitary groups associated with international cartels, and FARC factions that did not adhere to the peace process (Castro et al., 2020). The control of illicit economies such as illegal mining and drug trafficking is the main driver of this war, and social leaders who opposed these interests have been systematically killed (HRW, 2021). Death threats associated with the advocacy work of social leaders characterize the systematicity of these killings (Revista Semana, June 2020).

Figure 2 shows the map of FARC presence in 2015, right before FARC demobilization. The yellow municipalities indicating FARC presence correspond to remote areas of the country and outside the main city centers. Figure 3 compares the homicide rate in FARC and non-FARC municipalities, before and after the 2016 peace agreement. This figure shows how homicides in FARC areas spiked right after the agreement while they were going down in the rest of the country.

To understand the resurgence of violence in Colombia it is important to acknowledge the political context after the peace process. In 2018, a conservative government that openly opposed the peace agreement was elected and tried to renegotiate its terms including the pardon granted to former guerrilla leaders (Casey, May 2019). One year later, two of the original FARC peace negotiators abandoned the agreement and returned to their underground activities (Daniels, August 2019). One of them was killed two years later in Venezuela by another FARC dissident organization (Revista Semana, July 2021). Fortunately, most ex-guerrilla members remained loyal to the peace despite its current challenges. In February 2021, Mr. Rodrigo Londoño—who signed the agreement on FARC's behalf, wrote an open letter to Ex-President Santos asking him to mediate with the current government to protect the peace given the systematic killing of social leaders and ex-guerrilla members. In his response, Ex-President Santos recognized that those systematic killings are the main concern obstructing the peace agreement implementation[4].

The negative effect of the Colombian armed conflict on education attainment is documented in the literature (e.g., Wharton and Uwaifo Oyelere, 2011; Rodriguez and

[4] A copy of these open letters can be found in the following link: https://www.resumenlatinoamericano.org/2021/02/14/colombia-carta-de-juan-manuel-santos-a-rodrigo-londono/

Sanchez, 2012; Fergusson, Ibáñez, and Riaño, 2019); however, evidence about its negative effect on educational achievement is still inconclusive. Some studies have documented the negative effect of the conflict on test scores using instrumental variables (Munevar Meneses et al., 2019; Gomez Soler, 2016), while others have documented average test score improvements in the most violent areas of the country using the same methodology (Gamboa, García & Vargas, 2014). Attrition caused by human displacement seems to be the main reason why average test scores can improve in violent areas.

The attrition hypothesis suggests that poor students are more exposed to violence and therefore, they are more likely to be killed or to leave municipalities located in conflict zones. The main assumption in this hypothesis is that violence is concentrated in the poorest neighborhoods within each municipality. This assumption is supported by existing evidence about the geographical correlation between violence and wealth in municipalities of Colombia (e.g., Giménez-Santana, Caplan & Drawve, 2018). If this hypothesis is true, the displacement of poor students would cause an increase in average test scores at the municipality level, considering that the most advantaged students living in the safest neighborhoods are less likely to emigrate. The correlation between income and educational attainment in Colombia is also documented in the literature (e.g., Melguizo, Sanchez & Velazco, 2016).

Recent studies have provided new evidence about the negative effect of violence on test scores in Colombia by trying to control for the problem of attrition. Some of these attempts have used instrumental variables with non-parametric adjustments (Reyes Cita, 2019) and the comparison of school outcomes based on early childhood exposure to violence (Duque, 2019). This study adds to this literature by assessing educational achievement with different causal methods and using more years of data. According to Table 1, demographic characteristics did not change between FARC and non-FARC areas, before and after the peace agreement. This suggests that attrition might not be a problem affecting my data. Only poverty levels decreased after the peace agreement, but they did at the same rate within FARC and non-FARC municipalities. I control for demographic characteristics and poverty levels in the DD analysis conducted in this paper.

Prem et al. (2021) conduct a similar study in Colombia but looking at the effect of the FARC's ceasefire declared in 2014. Using a DD design between 2009 and 2018, the authors find that the decrease of violence during the negotiation of the peace process had a positive effect on elementary and middle school test scores. The key mechanism explored by the authors is a reduction of dropout rates, given the significant reduction of human displacement and children's recruitment in FARC zones. My paper complements these findings but showing what happened when violence increased after the peace agreement and looking at its heterogeneous effects by gender and socioeconomic status. Furthermore, my data focuses on high school graduates who use their test scores to apply for college.

Existing studies have also explored possible mechanisms explaining the negative effect of violence on education in Colombia. Some of these mechanisms are the reduction of public expenditure on education—to compensate for higher policing expenses—violent acts as a direct obstacle for school attendance, and the death of family members that forces children to abandon school at an early age (Ferguson, Ibáñez, and Riaño, 2019). Other mechanisms are associated with poverty traps such as the loss of assets (Ibáñez & Moya 2010), loss of productive lands, human displacement, and human capital depreciation in the transition from rural to urban areas (Ibáñez 2008).

A complex dynamic characterizes the relationship between poverty and conflict in Colombia. On the one hand, conflict zones tend to have higher levels of poverty than the rest of the country (Loaiza Quintero et al., 2018a). This evidence is consistent with international studies suggesting that armed conflict increases poverty via food insecurity (Gates et al., 2012; Messer and Cohen, 2004; Guha-Sapir and Gomez, 2006; Brück, 2006). On the other hand, spikes of poverty in urban areas are also associated with the arrival of human displacement coming from conflict zones (Ibáñez & Moya, 2006; Loaiza-Quintero, Muñetón-Santa and Vanegas, 2018; Loaiza Quintero et al., 2018b). Including poverty indicators in the empirical strategy helps me to acknowledge this complex dynamic between poverty and violence in conflict zones of Colombia.

Previous international studies have tried to measure for the heterogeneous effect of violence on poor students but without controlling for the endogenous relationship between violence and poverty. Evidence from Mexico (Orraca-Romano, 2015; Jarillo et al., 2016) and Costa Rica (Gimenez & Barrado, 2020) suggest that violence has a larger negative effect on the test scores of lower-income students. Nevertheless, as the authors recognize (Gimenez & Barrado, 2020), the relationship between exposure to homicides and test scores is endogenous, because it is not possible to disentangle homicides from other socio-economic factors that also affect school performance. My empirical strategy provides a more reliable source of evidence, because I use as treatment variable a dummy indicating which municipalities used to have FARC presence during the peace process instead of using homicide rates. Taking into consideration that only FARC municipalities saw an increase in violence after the peace agreement, I look at significant differences in test scores before and after the peace agreement signing in 2016.

3. Data

The main data source for this analysis comes from the Colombian Institute for the Evaluation of Education (ICFES), a government institution that conducts the standardized high school test, Saber 11, twice per year. This test is a requirement for college application, and it is intended to assess the skills and knowledge of students about to graduate from high school. The test is available in all the municipalities, and it is taken synchronously nationwide during two available dates during the year. Students have the option to study for the test by attending extracurricular preparation institutions or by getting access to old exams. Some high schools directly prepare their seniors by offering review classes and mock tests.

Test scores are available in four main subject areas: math, reading, social science, and natural science. The test also includes information on individual characteristics such as age, sex, geographical location, and socio-economic background. Additional data about crime at the municipality level is taken from the Colombian National Administrative Department of Statistics (DANE, according to its acronym in Spanish). I calculate homicide rates per 100,000 people using population data at the municipality level from the 2018 national census.

This study uses a pooled cross-sectional dataset including 10 semesters from 2014 to 2019. Earlier and later years are excluded due to methodological changes in Saber 11. The subject areas were simplified into fewer categories starting in the second semester of 2014. Furthermore, due to the COVID-19 pandemic, the Colombian Ministry of Education decided to conduct the 2020 test online and to make it optional for college applications.

These methodological changes affect the comparability of observations before 2014 and after 2019.

The total sample size is around 2.4 million observations—including all the 1,103 municipalities in the country. This sample excludes observations with missing values and only keeps students over 12 years old. The data on FARC municipalities before the peace agreement is taken from the Mission for Electoral Observation (MOE, 2016), and the Foundation for Peace and Reconciliation (PARES, 2015). Both are NGOs devoted to studying the consequences of the armed conflict in Colombia. FARC municipalities are identified based on public records of violent attacks, interviews, and news articles. Figure 2 describes the treatment group that corresponds to municipalities with FARC presence at the moment of the peace agreement.

Table 1 provides descriptive statistics of selected variables making comparisons between FARC and non-FARC municipalities, and before and after the peace agreement. On average, students in former FARC municipalities tend to have lower standardized test scores in math and reading comprehension compared to students in non-FARC municipalities. However, these outcome variables have similar pre-trends before the peace agreement.

Figure 4 shows that pre-trends are similar for FARC and non-FARC municipalities in the reading section of the exam. Pre-trends are different for the math section. In light of this difference, I consider a smaller sample of students under 19 years of age. This group corresponds to traditional students who still live with their parents, and it represents 83% of the total sample. Figure 5 shows similar pre-trends in the reading and math section of the exam once considering the smaller sample of students under 19. I show in the results section that the findings are similar when using this restricted sample size.

Table 1 also shows that homicide rates are higher in FARC municipalities. While the average homicide rate in non-FARC municipalities went from 23 to 22 per 100,000 people after the peace process, it increased from 41 to 44 in FARC municipalities during the same period. This exclusive increase of homicide rates in FARC municipalities is expected because it represents the treatment effect after 2016.

FARC areas also tend to have a higher incidence of multidimensional poverty. The poverty incidence among high school students in FARC municipalities before the peace agreement was 21% and it was 13% in non-FARC municipalities. Both numbers decreased by approximately 30% after the peace process, suggesting that differential attrition caused by the displacement of poor people away from violent areas might not be a problem affecting the treatment group (FARC). An alternative approach to individual wellbeing can be derived from the socio-economic stratification scale (SES). This scale is used by the Colombian government to calculate utility bills based on different income levels across geographical areas. It goes from one—indicating the lowest income geographical areas, to six—indicating the highest income ones. On average, individual students living in FARC and non-FARC municipalities of the sample belong to levels one and two of that scale.

Finally, there is a good balance of individual characteristics between FARC and non-FARC municipalities and before and after the peace process. The average age is 18 years, about half of the students in the sample are female, and approximately a fifth of them live in rural areas. This balance is important because it indicates that observations in the treatment and the control groups are comparable.

Two additional possible sources of attrition are the test costs and the case of high school graduates not interested in applying for college. The total test cost is around 18 US dollars (72,000 Colombian pesos) which can be a barrier for lower-income families. In the empirical strategy, I include individual controls for income and poverty levels to address this possible data bias. Another possible attrition source is the case of students not interested in attending college. From the total of 666,000 students who graduated from high school in 2020 (Ministry of Education, 2020a & 2020b), 654,000 of them took the Saber 11 test (ICFES, 2021). This means that approximately 98% of high school graduates took the test indicating low levels of attrition.

4. Empirical Design

To assess the impact of local violence on the test scores of high school students, I use the following difference-in-difference (DD) regression, comparing former FARC zones of Colombia before and after the peace process.

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

The outcome variable corresponds to high school standardized test scores[5] in four subject areas—math, reading, social science, and natural science—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

[5] Test scores were standardized using z-scores by semester-year (subtracting the mean and dividing by the standard deviation). To provide an adequate interpretation of results, it is important to acknowledge the limitations of test scores as an objective measurement of student learning. At best, standardized test scores should be interpreted as ordinal and not cardinal variables considering that they are sensitive to the types of questions that are asked in an exam (Jacob and Rothstein, 2016). For example, cumulative questions can result in big score differences if a student gets one of them wrong.

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 2016.

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), *rural* (rural=1, urban=0), SES (1-6), 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) and indicators for household assets such as a washing machine, internet connection, computer, television, and an oven or microwave. All the results are calculated using clustered standard errors at the municipality level. In some specifications, I leave off the municipality fixed effects to look at variations not only within but also across FARC and non-FARC municipalities.

Goodman-Bacon (2020) discusses a possible bias in DD designs including time and unit fixed effects, also known as two-way fixed-effect models. This bias occurs in the case of time-varying treatment effects where units receive the treatment in different periods. In such case, previously treated groups can be included in the control group creating a bias in the results. This source of bias is not a concern affecting my results because I am using a pooled cross-sectional dataset where the treated units are not included in previous periods. The DD design in this study only compares average differences in test scores between municipalities with different violence trends before and after 2016. Following the specification of two-way fixed-effect models, I drop the main effects, $D_{t>2016}$ and $FARC_m$

because both variables are already subsumed in the semester and municipality fixed effects.

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[6]:

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

The key hypothesis to understand the relevance of the MPI interactions is that poor high school students are more exposed to violence and therefore, more vulnerable to its negative effects than non-poor students. Taking into consideration that the treatment in this analysis ($FARC_m$) varies at the municipality level, it makes intuitive sense to contrast the results between poor and non-poor students because poor individuals tend to live in the most violent areas within each municipality (e.g., Giménez-Santana, Caplan & Drawve, 2018). The treatment effect on the poor is therefore given by adding the coefficients $\beta_3 + \beta_6$. Following the same logic discussed for equation 1, I also estimate equation 2 with and without 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). This approach provides a more comprehensive

[6] 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.

approximation of poverty that goes beyond single poverty indicators such as income. While income describes the suspected means that are assumed to achieve development, multidimensional poverty describes actual development goals such as education, health, and living standards.[7] In fact, there is empirical evidence about the mismatch between income-based and multidimensional poverty measures suggesting that people living above the poverty line (e.g., more than $1.90 per day around the world) might not have access to adequate living standards, health, and education. The empirical evidence of this mismatch is available for countries such as Ethiopia, India, Peru, Vietnam (Kim, 2019; Roelen, 2017), Rwanda (Salecker, Ahmadov & Karimli, 2020), Germany (Suppa, 2016), and China (Alkire & Shen, 2017).

Table 2 provides a comparison between the official MPI definition used by the Colombian government and the Global MPI definition used by the United Nations Development Programme (UNDP). Both definitions have a common ground in terms of the *education* and *health* dimensions. The Global MPI includes a third dimension of *living standards* with indicators for access to drinking water, sanitation, cooking fuel, electricity, housing, and assets. Alternatively, the Colombian MPI includes three additional dimensions that are *housing*, *work*, and *childhood and youth*. Some of the indicators in these additional dimensions resemble the ones included in the Global MPI *living standards* dimension such as access to drinking water and sanitation. However, the Colombian definition goes beyond a basic living standard approach and includes indicators for employment, childcare, and

[7] The multidimensional approach is inspired in Sen's definition of poverty, according to which it should be understood as a deprivation of *capabilities* that are related to "[...] our ability to achieve various combinations of functionings that we can compare and judge against each other in terms of what we have reason to value" (Sen 2009, p. 233).

household quality. These indicators reflect policy priorities defined by the Colombian government.

It is not possible to exactly replicate the Global or the Colombian MPI definitions using information from the Saber 11 data; however, it is possible to construct an approximation by taking elements from both criteria. Table 3 proposes an alternative definition based on three dimensions: *education*, *work*, and *living standards*. Six poverty indicators are used within these three dimensions: schooling, child labor, formal employment, unemployment, overcrowding, 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 as deprived in each of the poverty indicators (deprived=1, not deprived=0).

Within the education dimension, a student is deprived of *schooling* if she is older than 18 during the last high school year (indicating delayed or disrupted schooling); and deprived in terms of *child labor*, if she is younger than 16 and works more than 20 hours per week. Within the work dimension, a student is deprived of *formal employment*, if any 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 in terms of *overcrowding* if the number of people per bedroom in her household is greater than two, and 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 assigned to each dimension following the same strategy of the Colombian and the Global 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. Following the Alkire-Foster (AF) methodology, an MPI score is calculated for each student *i* according to the following equation:

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

Finally, 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). It is important to mention that a limitation of this alternative MPI definition introduced here, is that it does not include indicators for the health dimension that are common in the two official definitions mentioned above. Nevertheless, this alternative definition still provides a more comprehensive approach to poverty measurement compared to simpler income-based approaches. 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 7 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 ICFES data, used in this paper, show that the national MPI went from 14.6% in 2014 to 9.4% in 2018. This mismatch in estimates occurs because the population of graduate high school 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.

Before moving forward with the results section, it is important to discuss the identifying assumptions of the DD approach. A key identifying assumption of this method is that the treated and control groups would have evolved similarly in the absence of a policy intervention. I cannot observe this, but I can observe whether the outcomes in both groups evolved similarly before the peace agreement. I test for the existence of violence pre-trends in Figure 3. This figure shows that the average homicide rate trend was similar between FARC and non-FARC municipalities before the peace agreement. Homicides in FARC areas dramatically increased after 2016 and the same did not happen in non-FARC municipalities.

I further test the above identifying assumptions in Table 4. My analysis follows an event study approach similar to the DD design in equation 1, but it is conducted at the municipality level and having the homicide rate per 100,000 people as the outcome variable. If my identifying assumption holds, the interaction $D_t \times FARC_m$ should only have positive statistically significant coefficients for $D_{t>2016}$ and not for earlier years. As expected, only after 2016 the interaction term has statistically significant coefficients.

To have a correct interpretation of results, another important assumption is that the increase of violence after 2016 is the only significant event with an impact on test scores. Along with the 2016 peace agreement, the Colombian government started to implement socioeconomic development programs intended to improve the livelihood of people living in conflict zones. If anything, those programs should have had a positive impact on high school learning which would suggest that I am underestimating the negative effects of violence here. Another important change is the arrival of a new government in 2018 that openly opposed the peace agreement. This new political scenario could have contributed to the increase of violence after 2016, and in fact, Table 4 shows that the difference in homicide rates between FARC and non-FARC municipalities is precisely statistically significant since 2018 which would attenuate my results. My estimates will reflect the reduced form effect of these combined changes since 2016.

Finally, Figure 4 shows the results of an event study approach to test outcome differences in learning outcomes 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 the reading section of the test. Even though pre-trends were different for the math section, Figure 5 shows that this difference goes away once considering a smaller sample of students under 19 years of age who represent 83% of the total sample size. All the results in this study are similar when only looking at this subset of students under 19 but I prefer to keep the larger sample size while controlling for age differences in the DD design.

5. Results

The identification tests above suggest that the spike of violence after the peace process mainly occurred in FARC municipalities. The results of my main specification assessing the impact of the peace agreement on standardized test scores indicate that this spike of violence mainly affected the learning outcomes of poor students living in FARC municipalities. Table 5 shows the DD analysis on the math section of the test. According to columns 1 and 2, once controlling for individual characteristics, semester, and municipality fixed effects, the increase of violence after the peace process has a negative impact of approximately 0.04 standard deviations on math test scores. However, columns 3 and 4 show that once including the interaction terms with the multidimensional poverty indicator (MPI), poor students experienced a larger negative impact of approximately 0.029+0.041=0.07 standard deviations in the math test score (equivalent to 0.34 percentage points). Appendix Table 1 corroborates these findings but conducting a separate analysis in the subset of poor and non-poor students. All the coefficients are statistically significant at the 0.05 level.

Table 6 shows the same results for the reading, social science, and natural science sections of the test. Columns 1, 3 and 5 show that once controlling for individual characteristics, semester and municipality fixed effects, the increase of violence after the peace process had a negative effect of approximately 0.03, 0.06, and 0.04 standard deviations on the reading, social science, and natural science subject areas of the test, respectively. Columns 2 and 6 show that once including the MPI interaction terms, this negative effect on poor students was approximately 0.06+0.03=0.09 standard deviations on the reading and natural science subject areas (equivalent to 0.9 percentage points).

Column 4 shows that the coefficient of the triple interaction term is not statistically significant, suggesting that there is no difference between poor and non-poor in the case of the social science subject area.

Table 7 shows the same results but in the subset of female students. According to columns 1, 3, 5 and 7, once controlling for individual characteristics, semester and municipality fixed effects, the increase of violence after the peace process had a negative effect of 0.05, 0.03, 0.07, and 0.05 standard deviations on the math, reading, social science, and natural science subject areas respectively. These negative effects are larger for the case of female students suggesting that this segment of the population is more vulnerable to violence. Column 4 shows that this impact is higher in the case of poor female students who saw an average negative effect of 0.03+0.04=0.07 in reading. The coefficients of the triple interaction term in columns 2, 6 and 8 are not statistically significant suggesting that there are no differences between poor and non-poor female students in the math, social science, and natural science subject areas.

Table 8 replicates the DD results but with the subset of students under 19 years of age. Columns 1 and 5 show that once controlling for individual characteristics, semester and municipality fixed effects, the increase of violence after the peace process had a negative effect of 0.02 and 0.06 standard deviations in the math and social science subject areas respectively. The same results were not statistically significant for the reading and natural science sections. Columns 2, 4, and 6, show that these impacts were higher on poor students who saw a decrease of 0.03, 0.07, and 0.04 standard deviations on the math, reading, and natural science sections of the test. Column 6 shows that the coefficient of the triple interaction term is not statistically significant, suggesting that there is no difference between poor and non-poor in the case of the social science subject area.

Appendix Tables 2, 3, and 4 replicate the above results but using different weighting structures in the calculation of the MPI score. In these tables, I test whether the calculation of the MPI affects my results. Appendix Table 2 gives a higher weight to education dimension (Edu=2/3, Work=1/6, LS=1/6), Appendix Table 3 gives a higher weight to the work dimension (Edu=1/6, Work=2/3, LS=1/6), and Appendix Table 4 gives a higher weight to the living standards dimension (Edu=1/6, Work=1/6, LS=2/3). Only in Appendix Table 2, where the education dimension receives a higher weight, the coefficient of the triple interaction effect $D_{t>2016} \times FARC_m \times MPI_{it}$ is not statistically significant. These results suggest that the lack of living standards and formal employment in the household, might be the main poverty mechanisms explaining the greater negative effect of violence on learning outcomes among the poor. The results also suggest that the way I calculate the MPI is unlikely to explain by itself the findings in this paper.

Appendix Table 5 provides another robustness check but using a more restrictive cross-dimensional cut-off line of k=1/2. Column 4 shows that once controlling for individual characteristics, semester and municipality fixed effects, the increase of violence after the Colombia peace process had a negative effect of approximately 0.1 standard deviations on the standardized reading test scores of poor high school students. This coefficient is statistically significant at the 0.01 level, and shows a larger effect compared to the results obtained with the less restrictive cross-dimensional cut-off poverty line (k=1/3). A larger negative impact on poorer students, suggests that the poorer students are, the more vulnerable they are to the negative effects of violence. The coefficients of the triple interaction effect were not statistically significant in the rest of subject areas.

To approximate the gradual effect of violence on test scores, Appendix Table 6 replicates the same DD analysis but using the MPI score grouped by quintiles (instead of the MPI indicator—0,1) in the triple interaction effect. Columns 2, 4, and 8 show that once controlling for individual characteristics, semester and municipality fixed effects, an increase of 20% in the severity of poverty given the increase of violence after the peace agreement, has a negative impact of approximately 0.2 standard deviations in the math, reading, and natural science subject areas. This corroborates that the poorer the students are, the more vulnerable they seem to be to the negative effects of violence. The same results are not statistically significant in the social science subject area which is consistent with the above main results.

6. Conclusions and Policy Recommendations

This paper evaluates the effects of exposure to violence on high school students' achievement. To do so, I look at the Colombian case. My analysis provides new evidence on the negative effects of violence on standardized test scores in the aftermath of the Colombian peace process. It shows that the spike in homicides in former FARC municipalities of the country negatively impacted learning outcomes. The results also show that the effect of violence was much stronger for the case of poor students compared to others, specifically in the math, reading, and natural science subject areas of the test. They also show that female students are more vulnerable to the negative effects of violence in Colombia.

The policy implications of this paper's findings go beyond documenting the negative effect of violence on education. One key implication of this research is that violence can exacerbate poverty by limiting human capital formation among already poor people. Education has the potential to promote intergenerational mobility and in the context of Colombia, violence has the power to truncate this potential, perpetuating intergenerational poverty. This is especially true, considering that Saber 11 scores are used in Colombia to apply for college. Therefore, a reduction of 0.1 standard deviations in the average test scores among the poor, could result in reductions of college-going or lower college quality for students who do attend. This result also suggests that poor students exposed to violence may have not learned as much during high school.

A back-of-the-envelope calculation suggests that an average 10% increase in the homicide rate after the peace process in Colombia—equivalent to a change from the mean of 25 homicides per 100,000 people in 2016 to 27.5 homicides per 100,000 people in 2019, could have resulted in a drop of approximately 4% in the average Saber 11 test scores among poor students living in former FARC municipalities. This calculation takes into consideration impacts across multiple subject areas where the poor saw an approximate average decrease of 1 percentage points in math, reading, social science, and the natural science sections of the test (the same effects are not recorded in the case of non-poor students).

Some of the mechanisms reported in the literature to explain the negative effect of violence on education in Colombia are physically obstacles for school attendance due to violent attacks, the death of family members forcing students to drop out from school (Ferguson, Ibáñez, and Riaño, 2019), loss of assets (Ibáñez & Moya 2010), loss of productive lands, and human displacement (Ibáñez 2008). All these mechanisms can be exacerbated by poverty. My findings suggest that MPI indicators such as unemployment, lack of formal employment, and lack of adequate living standards are associated with the negative effects of violence on the learning outcomes among poor high school students. The findings also indicate that the poorer students are, the more vulnerable they seem to be to the negative effects of violence.

An additional finding that is currently underexplored in the literature is that female students face a larger negative effect of armed conflict on their learning outcomes. This larger negative effect can be explained due to additional challenges faced by women in conflict zones of Colombia. Some of them are the target of sexual violence and tend to become heads of households when male household members are killed (Comisión de la Verdad, November 26, 2018). Further research is needed to better understand the mechanism explaining the negative effect of violence on learning outcomes in Colombia.

Finally, it is worth noting that previous literature findings identify math test scores as the subject area with the largest negative effects of violence (e.g., Orraca-Romano, 2018; Michaelsen & Salardi, 2018; Brück, Di Maio, & Miaari, 2019). My findings here show that in the case of poor students, this negative effect is evenly distributed across subject areas, being slightly higher in the reading and natural science sections. This could indicate that poor students suffer a general disruption of their learning process during times of conflict. The isolated effect on math reported in the literature, could suggest lower concentration abilities experienced by non-poor students at the moment of the exam. Further research is needed to understand these causal mechanisms and, in that way, the heterogeneous effects of violence across subject areas.

Understanding the long-lasting effects of violence on educational achievement among the poor could motivate the Colombian government to increase expenditure on programs to increase access to higher education for students living in conflict zones. My findings also suggests that there might be positive spillover effects from security improvements in former FARC territories. Strengthening security and reducing violent crime in these territories can enhance the human capital of the most vulnerable social groups. Future research should consider looking at the longer-term impacts of violence on human capital investments and its impacts on intergenerational mobility and the well-being of the next generation.

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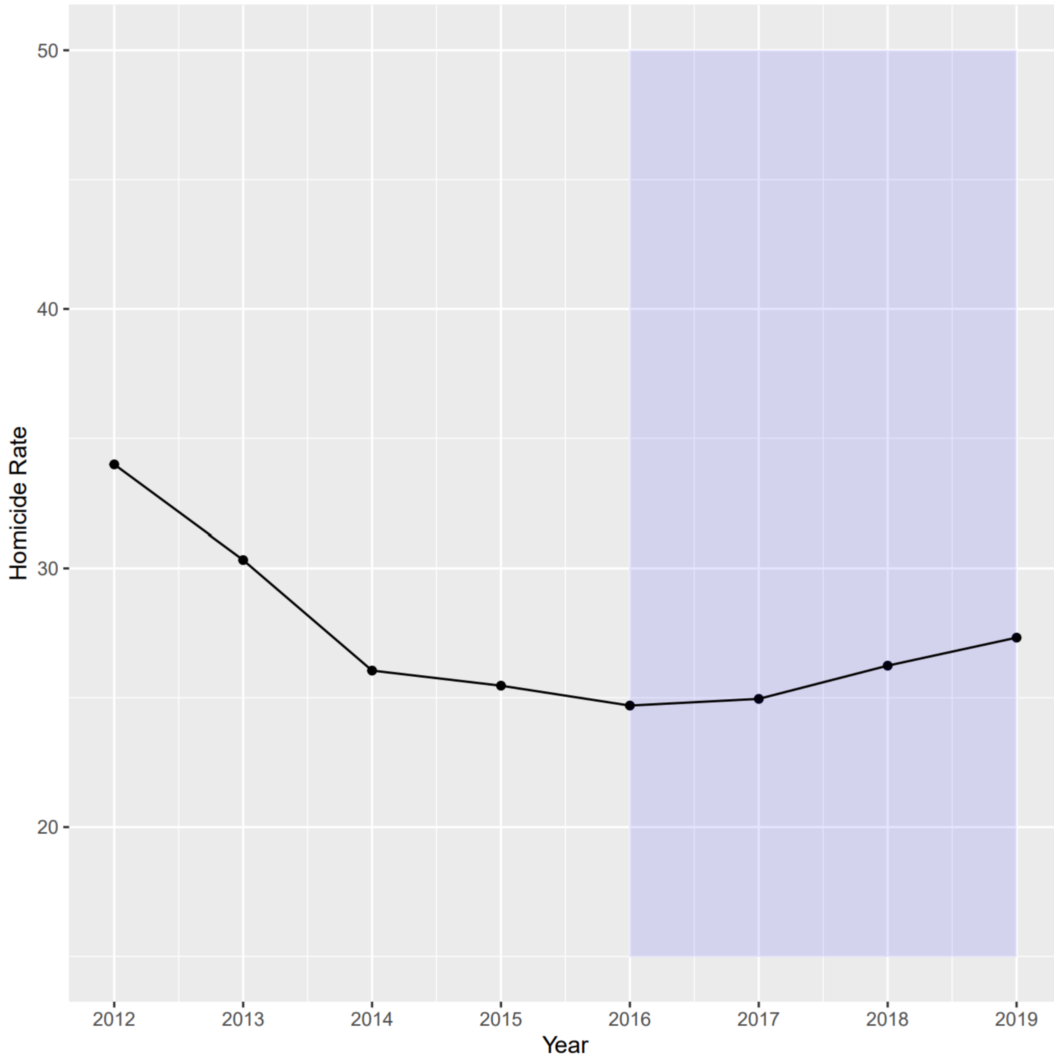
Figure 1. Homicide rate per 100,000 people in Colombia

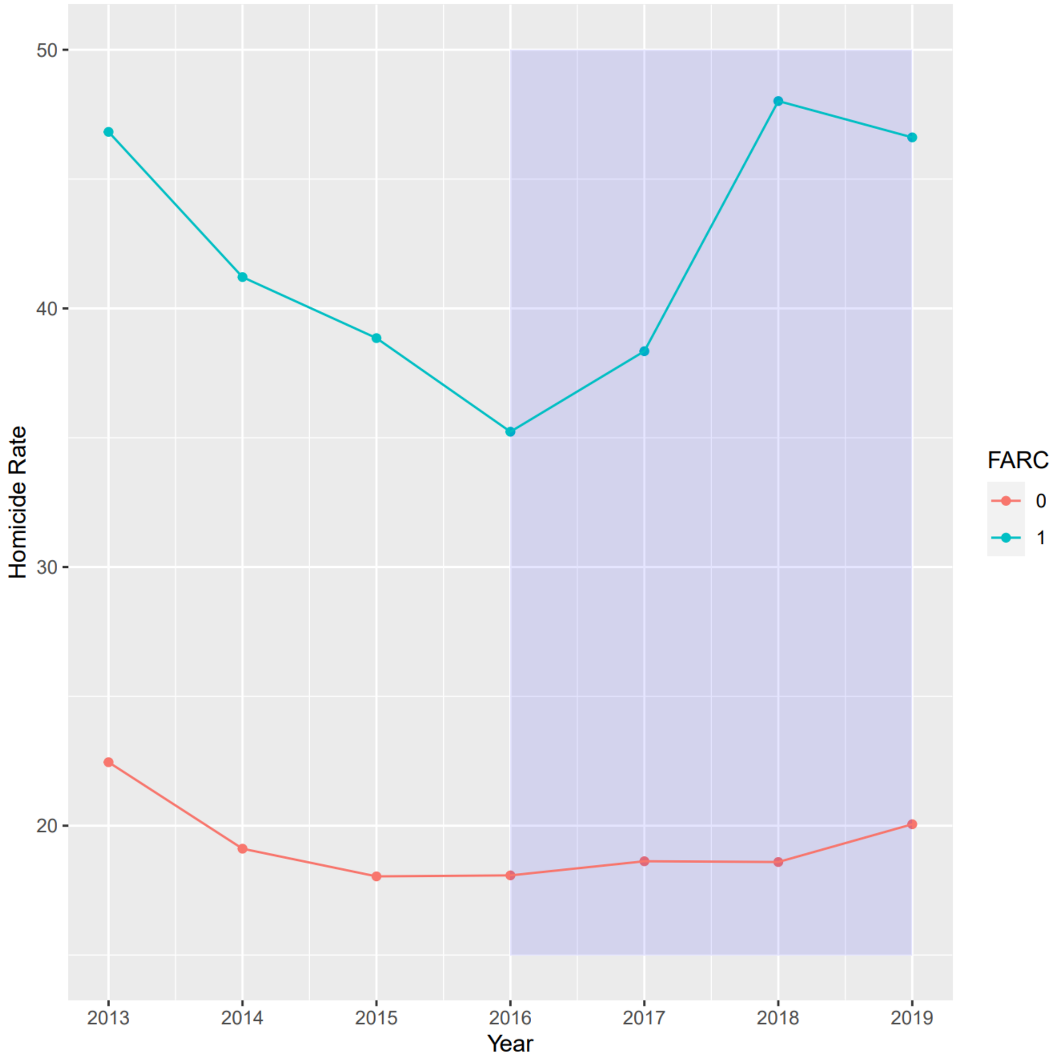


Note: The shaded area corresponds to the time periods after the peace treaty. The homicide rate was calculated using data from the Colombian National Administrative Department of Statistics (DANE).

Figure 2. Map of FARC Municipalities before the Peace Agreement

Note: Map taken from Foundation Peace and Reconciliation (PARES, 2015).

Figure 3. Pre- and post-trends of outcome variables in FARC and non-FARC municipalities: Homicide rates per 100,000 people



Note: The shaded area corresponds to the time periods after the peace treaty. The homicide rate was calculated using data from the Colombian the National Administrative Department of Statistics (DANE). The data about municipalities with FARC presence was taken from Misión de Observación Electoral (MOE, 2016).

Figure 4. *Estimates of the effect of violence after the Colombian peace process on high school test scores using leads and lags in an event study model*

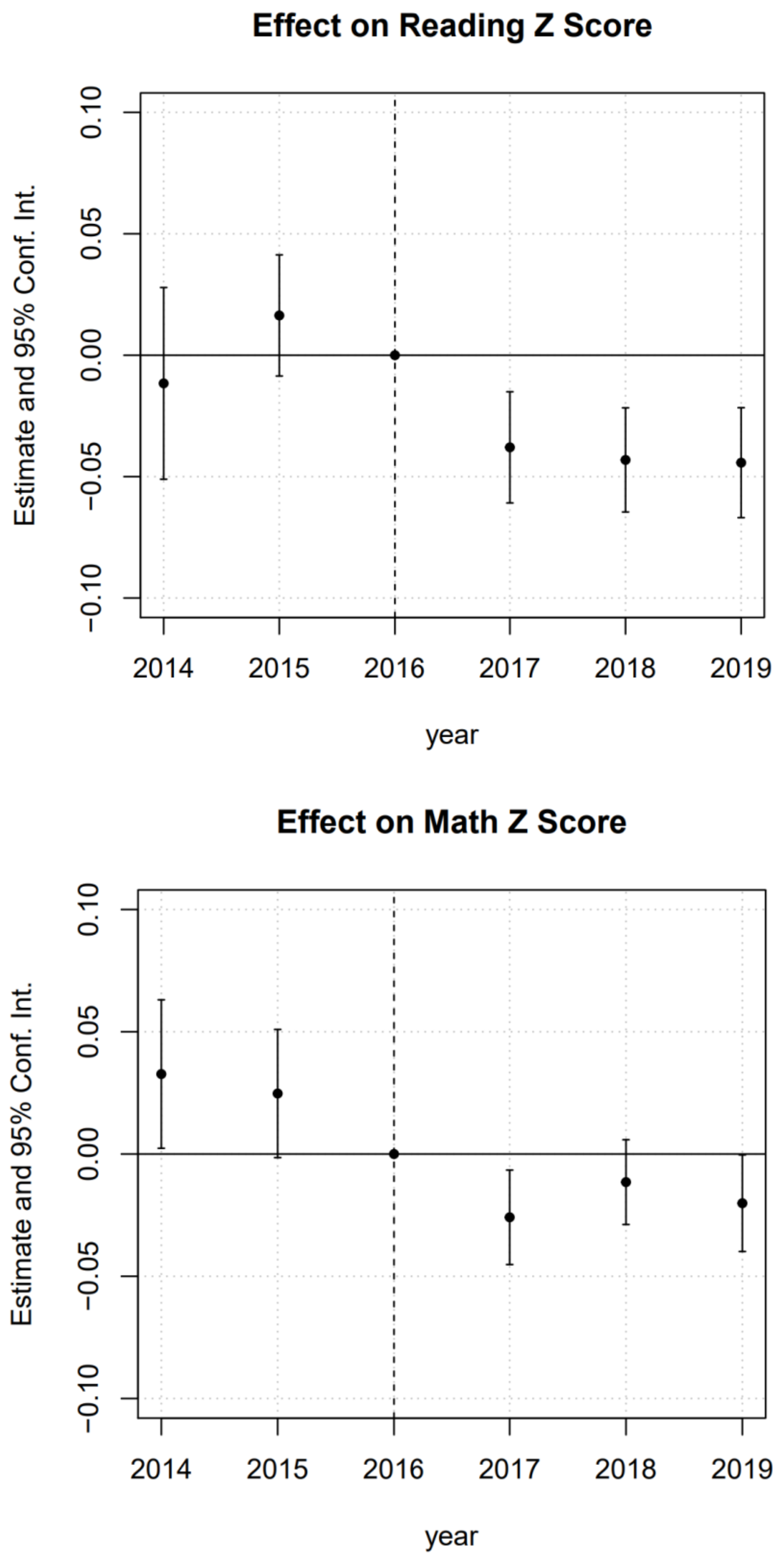


Figure 5. Estimates of the effect of violence after the Colombian peace process on high school test scores using leads and lags in an event study model (Age<19)

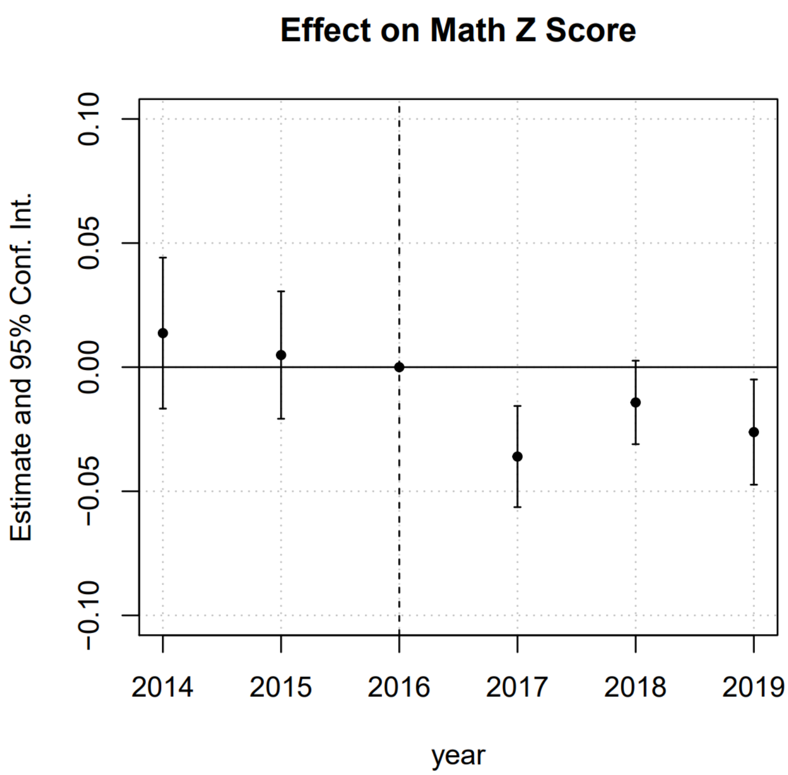


Table 1—Descriptive Statistics, Selected Variables for the 2014-II - 2019-II Periods

	FARC			Non-FARC		
	Obs.	Mean	St. Dev.	Obs.	Mean	St. Dev.
Panel A. Pre- 2016						
Math Z Score	108,192	-0.21	0.94	759,332	0.07	1.02
Reading Z Score	108,192	-0.23	0.95	759,332	0.07	1.01
Homicide Rate	108,192	40.82	31.70	759,332	23.22	19.63
MPI	108,192	0.21	0.41	759,332	0.13	0.34
SES	108,192	1.41	0.68	759,332	1.99	1.02
Age	108,192	18.36	4.03	759,332	17.93	3.77
Female	108,192	0.56	0.50	759,332	0.54	0.50
Rural	108,192	0.24	0.43	759,332	0.13	0.33
Panel B. Post-2016						
Math Z Score	201,789	-0.17	0.98	1,384,469	0.11	0.99
Reading Z Score	201,789	-0.19	0.98	1,384,469	0.10	0.99
Homicide Rate	201,789	43.81	39.09	1,384,469	22.04	19.10
MPI	201,789	0.16	0.37	1,384,469	0.10	0.30
SES	201,789	1.63	0.90	1,384,469	2.13	1.08
Age	201,789	17.98	3.23	1,384,469	17.66	2.97
Female	201,789	0.56	0.50	1,384,469	0.54	0.50
Rural	201,789	0.24	0.43	1,384,469	0.13	0.34
No. Municipalities		188			925	

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—Official Colombian and UNDP MPI Definitions

Official Definition, Colombia

Dimensions	W	Z	Indicators
Education	0.1	Average years of schooling of people over 15 years old within the household is less than 9.	Schooling
	0.1	At least one person over 15 years old within the household does not know how to read and write.	Literacy
Health	0.1	At least one household member does not have health insurance.	Health Insurance
	0.1	At least one household member could not access health services if needed during the last 30 days.	Health Access
Housing	0.04	The household does not have direct access to drinking water	Access to clean water
	0.04	The household does not have direct access to an improved sanitation	Sanitation
	0.04	Dirt is the main material of the floors	Quality of Floors
	0.04	The main material of the walls is raw wood, zinc, cardboard, or fabric	Quality of Walls
	0.04	The number of people per bedroom in the household is greater than 2.	Overcrowding
Work	0.1	At least one household member works without contributing to a retirement fund.	Formal Employment
	0.1	At least one household member in working age has been unemployed for 12 months or more	Long-term Unemployment
Childhood & Youth	0.05	At least one household member is above the normal age range at her school class (i.e., 11th grade = 17 years old)	Schooling Lag
	0.05	At least one household member between 6 and 16 years old is not attending school	School Absenteeism
	0.05	At least one household member below 5 years old does not have access to childcare	Childcare Services
	0.05	At least a household member below 17 years old spends most of her time working	Child Labor

Global MPI, UNDP

Dimensions	W	Z	Indicators
Education	0.16	No household member aged 10 years or older has completed six years of schooling.	Years of Schooling
	0.16	Any school-aged child is not attending school up to the age at which he/she would complete class 8.	School Attendance
Health	0.16	An adult under 70 years of age or a child is undernourished.	Nutrition
	0.16	Any child under the age of 18 years has died in the five years preceding the survey.	Child Mortality
Standard of Living	0.05	The household does not have access to improved drinking water (according to SDG guidelines) or safe drinking water is at least a 30-minute walk from home, round trip.	Drinking water
	0.05	The household's sanitation facility is not improved (according to SDG guidelines) or it is improved but shared with other households.	Santation
	0.05	The household cooks with dung, wood, charcoal or coal.	Cooking fuel
	0.05	The household has no electricity.	Electricity
	0.05	Housing materials for at least one of roof, walls and floor are inadequate: the floor is of natural materials and/or the roof and/or walls are of natural or rudimentary materials.	Housing
	0.05	The household does not own more than one of these assets: radio, TV, telephone, computer, animal cart, bicycle, motorbike or refrigerator, and does not own a car or truck.	Assets

Source: Oxford Poverty and Human Development Initiative (OPHI, 2019) & Colombian National Administrative Department of Statistics (DANE, 2017)

Table 3—MPI Definition Based on ICFES Data

Dimensions	Indicators	W	Z
Education	Schooling	0.16	The student is older than 18 at the last year of high school.
	Child Labor	0.16	The student is less than 16 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	Overcrowding	0.16	The number of people per bedroom in the household is greater than two
	Assets	0.16	The student's household does not own a *car* and less than two of the following: - Computer - Washing machine - Oven - Microwave

Table 4—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)*	4.848	4.348
	(3.203)	(3.305)
*FARC * D(t=2015)*	0.112	-0.754
	(2.348)	(2.426)
*FARC * D(t=2017)*	1.899	2.396
	(1.816)	(1.911)
*FARC * D(t=2018)*	10.997***	12.305***
	(3.04)	(3.11)
*FARC * D(t=2019)*	10.588***	11.695***
	(3.17)	(3.27)
Municipality FE	X	X
Year FE		X
Observations	2,453,782	2,453,782
R2	0.08	0.68

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 5—Impact of Violence on Math Test Scores

	Math Z Score			
	(1)	(2)	(3)	(4)
*FARC * D(t>2016)*	-0.039***	-0.038***	-0.033**	-0.029**
	(0.01)	(0.01)	(0.01)	(0.01)
FARC	-0.047		-0.052	
	(0.03)		(0.04)	
*FARC * D(t>2016)*MPI*			-0.027*	-0.041**
			(0.02)	(0.02)
*FARC*MPI*			0.018	0.031**
			(0.02)	(0.02)
*D(t>2016)*MPI*			-0.01	-0.014**
			(0.01)	(0.01)
MPI			-0.056***	-0.010
			(0.01)	(0.01)
Semester FE	X	X	X	X
Municipality FE		X		X
Observations	2,453,782	2,453,782	2,453,782	2,453,782
R2	0.19	0.24	0.19	0.24

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 (rural area, sex, age, father's employment status, mother's employment status, SES, and assets such as washing machine, oven or microwave, internet, computer, and TV). The outcome variable corresponds to Saber 11 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 Other Test Scores

	Reading Z Score		*Social Science Z Score*		*Natural Science Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)
*FARC * D(t>2016)*	-0.029**	-0.022	-0.063***	-0.066***	-0.042***	-0.032*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
*FARC * D(t>2016)*MPI*		-0.060***		0.004		-0.055***
		(0.02)		(0.02)		(0.02)
*FARC*MPI*		0.048***		0.012		0.049***
		(0.01)		(0.02)		(0.02)
*D(t>2016)*MPI*		0.064***		0.030***		0.024***
		(0.01)		(0.01)		(0.01)
MPI		-0.069***		-0.040***		-0.030***
		(0.01)		(0.01)		(0.01)
Semester FE	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X
Observations	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782
R2	0.21	0.21	0.19	0.19	0.22	0.22

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 (rural area, sex, age, father's employment status, mother's employment status, SES, and assets such as washing machine, oven or microwave, internet, computer, and TV). The outcome variable corresponds to Saber 11 standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. FARC is omitted from the regressions because of the inclusion of municipality fixed effects. 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 Female Students

	Math Z Score		*Reading Z Score*		*Social Science Z Score*		*Natural Science Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.053***	-0.045**	-0.032**	-0.027*	-0.072***	-0.078***	-0.051***	-0.043**
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
*FARC * D(t>2016)*MPI*		-0.024		-0.042***		0.029		-0.04
		(0.02)		(0.02)		(0.02)		(0.02)
*FARC*MPI*		0.021		0.039***		-0.005		0.038**
		(0.02)		(0.01)		(0.02)		(0.02)
*D(t>2016)*MPI*		-0.041***		0.056***		0.013		0.002
		(0.01)		(0.01)		(0.01)		(0.01)
MPI		0.01		-0.071***		-0.032***		-0.017**
		(0.01)		(0.01)		(0.01)		(0.01)
Semester FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	1,325,585	1,325,585	1,325,585	1,325,585	1,325,585	1,325,585	1,325,585	1,325,585
R2	0.23	0.23	0.22	0.22	0.19	0.19	0.23	0.23

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 (rural area, sex, age, father's employment status, mother's employment status, SES, and assets such as washing machine, oven or microwave, internet, computer, and TV). The outcome variable corresponds to Saber 11 standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. FARC is omitted from the regressions because of the inclusion of municipality fixed effects. 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 Students Under 19 Years of Age

	Math Z Score		*Reading Z Score*		*Social Science Z Score*		*Natural Science Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.023*	-0.021	-0.018	-0.014	-0.064***	-0.064***	-0.026	-0.024
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
*FARC * D(t>2016)*MPI*		-0.031*		-0.066***		-0.012		-0.039**
		(0.02)		(0.02)		(0.02)		(0.02)
*FARC*MPI*		0.036***		0.061***		0.037**		0.051***
		(0.01)		(0.02)		(0.02)		(0.02)
*D(t>2016)*MPI*		0.048***		0.108***		0.042***		0.079***
		(0.01)		(0.01)		(0.01)		(0.01)
MPI		-0.009		-0.073***		-0.025**		-0.033***
		(0.01)		(0.01)		(0.01)		(0.01)
Semester FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	2,048,904	2,048,904	2,048,904	2,048,904	2,048,904	2,048,904	2,048,904	2,048,904
R2	0.22	0.22	0.19	0.19	0.18	0.18	0.21	0.21

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 (rural area, sex, age, father's employment status, mother's employment status, SES, and assets such as washing machine, oven or microwave, internet, computer, and TV). The outcome variable corresponds to Saber 11 standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. FARC is omitted from the regressions because of the inclusion of municipality fixed effects. 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		*Reading Z Score*		*Math Z Score*		*Reading Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.050***	-0.065***	-0.062***	-0.076***	-0.033**	-0.029**	-0.028**	-0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
FARC	-0.073**		-0.068**		-0.047		-0.067**	
	(0.030)		(0.034)		(0.04)		(0.03)	
D(t>2016)								
Semester FE	X	X	X	X	X	X	X	X
Municipality FE		X		X		X		X
Observations	290,015	290,015	290,015	290,015	2,163,767	2,163,767	2,163,767	2,163,767
R2	0.11	0.18	0.07	0.13	0.16	0.21	0.15	0.18

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 (rural area, sex, age, father's employment status, mother's employment status, SES, and assets such as washing machine, oven or microwave, internet, computer, and TV). The outcome variable corresponds to Saber 11 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—Robustness Check of the Effect of Violence on Test Scores using Alternate MPI Weights: Higher Weight on Education

	Math Z Score		*Reading Z Score*		*Social Science Z Score*		*Natural Science Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.038***	-0.023	-0.029**	-0.022	-0.063***	-0.067***	-0.042***	-0.026
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
*FARC * D(t>2016)*MPI*		-0.027		-0.030*		0.01		-0.033
		(0.02)		(0.02)		(0.02)		(0.02)
*FARC*MPI*		0.071***		0.072***		0.050***		0.088***
		(0.02)		(0.02)		(0.02)		(0.02)
*D(t>2016)*MPI*		0.031***		0.082***		0.029***		0.055***
		(0.01)		(0.01)		(0.01)		(0.01)
MPI		-0.055***		-0.095***		-0.058***		-0.077***
		(0.01)		(0.01)		(0.01)		(0.01)
Semester FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782
R2	0.24	0.24	0.21	0.21	0.19	0.19	0.22	0.23

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 (rural area, sex, age, father's employment status, mother's employment status, SES, and assets such as washing machine, oven or microwave, internet, computer, and TV). The outcome variable corresponds to Saber 11 standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. FARC is omitted from the regressions because of the inclusion of municipality fixed effects. 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 3—Robustness Check of the Effect of Violence on Test Scores using Alternate MPI Weights: Higher Weight on Work

	Math Z Score		*Reading Z Score*		*Social Science Z Score*		*Natural Science Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.038***	-0.02	-0.029**	-0.018	-0.063***	-0.065***	-0.042***	-0.025
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
*FARC * D(t>2016)*MPI*		-0.033**		-0.036**		0.005		-0.037*
		(0.02)		(0.02)		(0.02)		(0.02)
*FARC*MPI*		0.072***		0.073***		0.052***		0.089***
		(0.02)		(0.02)		(0.02)		(0.02)
*D(t>2016)*MPI*		0.024***		0.074***		0.025***		0.050***
		(0.01)		(0.01)		(0.01)		(0.01)
MPI		-0.057***		-0.099***		-0.060***		-0.076***
		(0.01)		(0.01)		(0.01)		(0.01)
Semester FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782
R2	0.24	0.24	0.21	0.21	0.19	0.19	0.22	0.23

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 (rural area, sex, age, father's employment status, mother's employment status, SES, and assets such as washing machine, oven or microwave, internet, computer, and TV). The outcome variable corresponds to Saber 11 standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. FARC is omitted from the regressions because of the inclusion of municipality fixed effects. 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 4—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*		*Social Science Z Score*		*Natural Science Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.038***	-0.02	-0.029**	-0.016	-0.063***	-0.060**	-0.042***	-0.024
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
*FARC * D(t>2016)*MPI*		-0.036**		-0.041***		-0.004		-0.041**
		(0.02)		(0.02)		(0.02)		(0.02)
*FARC*MPI*		0.076***		0.078***		0.061***		0.092***
		(0.02)		(0.02)		(0.02)		(0.02)
*D(t>2016)*MPI*		0.029***		0.073***		0.020**		0.051***
		(0.01)		(0.01)		(0.01)		(0.01)
MPI		-0.029***		-0.070***		-0.030***		-0.043***
		(0.01)		(0.01)		(0.01)		(0.01)
Semester FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782
R2	0.24	0.24	0.21	0.21	0.19	0.19	0.22	0.23

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 (rural area, sex, age, father's employment status, mother's employment status, SES, and assets such as washing machine, oven or microwave, internet, computer, and TV). The outcome variable corresponds to Saber 11 standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. FARC is omitted from the regressions because of the inclusion of municipality fixed effects. 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 5—Robustness Check of the Effect of Violence on Test Scores Using an Alternate MPI Cut-off Line

	Math Z Score		*Reading Z Score*		*Social Science Z Score*		*Natural Science Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.038***	-0.036***	-0.029**	-0.028**	-0.063***	-0.064***	-0.042***	-0.040**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
*FARC * D(t>2016)*MPI*		-0.036		-0.060**		0.027		-0.026
		(0.03)		(0.03)		(0.03)		(0.03)
*FARC*MPI*		0.029		0.034		-0.02		0.03
		(0.03)		(0.02)		(0.03)		(0.03)
*D(t>2016)*MPI*		-0.105***		0.00		0.010		-0.071***
		(0.01)		(0.02)		(0.01)		(0.02)
MPI		-0.006		-0.067***		-0.072***		(0.02)
		(0.01)		(0.01)		(0.01)		(0.01)
Semester FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782
R2	0.24	0.24	0.21	0.21	0.19	0.19	0.22	0.22

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 (rural area, sex, age, father's employment status, mother's employment status, SES, and assets such as washing machine, oven or microwave, internet, computer, and TV). The outcome variable corresponds to Saber 11 standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. FARC is omitted from the regressions because of the inclusion of municipality fixed effects. 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 6—Effect of Violence on Test Scores According to MPI Severity

	Math Z Score		*Reading Z Score*		*Social Science Z Score*		*Natural Science Z Score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FARC * D(t>2016)*	-0.038***	0.018	-0.029**	0.009	-0.063***	-0.060**	-0.042***	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
*FARC * D(t>2016)*MPI Score*		-0.213***		-0.177***		-0.003		-0.208***
		(0.05)		(0.05)		(0.07)		(0.06)
*FARC*MPI Score*		0.343***		0.301***		0.219***		0.388***
		(0.07)		(0.06)		(0.06)		(0.08)
*D(t>2016)*MPI Score*		0.116***		0.254***		0.094***		0.193***
		(0.02)		(0.02)		(0.03)		(0.02)
MPI Score		-0.527***		-0.646***		-0.532***		-0.596***
		(0.03)		(0.03)		(0.02)		(0.04)
Semester FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782	2,453,782
R2	0.24	0.24	0.21	0.21	0.19	0.19	0.22	0.23

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 (rural area, sex, age, father's employment status, mother's employment status, SES, and assets such as washing machine, oven or microwave, internet, computer, and TV). The outcome variable corresponds to Saber 11 standardized test scores, and FARC is an indicator of the municipalities in the country with FARC presence in 2015. FARC is omitted from the regressions because of the inclusion of municipality fixed effects. 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 7: 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	14.7%	13.6%	13.4%	9.9%	9.4%

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.