H i C N Households in Conflict Network

The Human Capital Peace Dividend

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Abstract: While the literature has documented negative effects of conflict on educational outcomes, there is surprisingly very little evidence on the effect of conflict termination on human capital. We fill this gap by showing how the permanent ceasefire declared by FARC's insurgency during peace negotiations with the Colombian government caused a large differential reduction on school dropout rates in the areas affected by FARC violence prior to the ceasefire, relative to other areas. Importantly, this is not driven by child soldiering. Rather, our evidence suggests that the dropout reduction responds to the falling victimization rates in areas that experienced FARC violence.

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1. INTRODUCTION

Civil war is an enormous obstacle to development as it entails large economic and social costs (see for example, Goldin and Lewis, 1975; Collier, 1999; Abadie and Gardeazabal, 2003). Of these, perhaps the most important is the loss in human capital because of its effect on long term labor market and health outcomes (Mincer, 1974, Almond et al., 2018; Barker, 1998; Cunha and Heckman, 2007). A lower productivity, in addition, lowers the opportunity cost for individuals to engage in illegal activities (Becker, 1968), thus triggering a long-run vicious cycle of violence and lack of opportunities, even after conflict has ended (Justino et al., 2014; Unesco, 2011; Leon, 2012, Duque, 2017).[1]

But, can the end of a conflict counteract at least partially the human capital loss generated by violence? The best of our knowledge the empirical evidence on this is extremely scarce. We study the effect of the recent efforts to end the five-decade-long conflict in Colombia on school dropout and conclude that this is indeed the case (at least in our context). Specifically, using a *difference-in-differences* empirical strategy, we find the permanent ceasefire declared by the *Revolutionary Armed Forces of Colombia* (FARC from the Spanish acronym) in the context of a peace process with the Colombian government was followed by a large short-term reduction in dropout rates in municipalities formerly affected by FARC violence, relative to other areas.[2]

This finding is far from obvious conceptually, as there are arguments for and against this possibility. On the one hand, when violence stops, the conditions for children to return to school may be more favorable, including the enrollment of former child

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[1]Additional long-term consequences of the effect of conflict on human capital include the delayed transition from agriculture to manufacturing, due to the shrinkage of sectors that specialize in human-capital intensive labor (Fergusson et al., 2019).

[2]The ceasefire was declared on December 20 of 2014 and constituted one of the main milestones of the four-year long peace process that started in October 2012. Because it was largely met, it signaled a credible commitment by FARC to lay down their weapons. On August 29 of 2016 FARC and the government reached a definitive bilateral ceasefire and later that year the final peace agreement was signed by both parties, putting an end to a five-decade long conflict.

soldiers and the perception of safety in general. On the other hand, war is destructive and targeted infrastructure may include school facilities and the roads necessary for children to attend schools. Also, the returns from schooling may be low after conflict especially if violence disrupts markets and exchange. Finally, winning parties may restrict access to education to the defeated side by creating racial, ethnic or religious requirements for enrollment (see Bush and Saltarelli, 2000; and Shemyakina, 2011). Surprisingly, however, how the end of conflict affects educational outcomes in the short run has been seldom studied.

This contrasts sharply with the large literature that provides abundant and compelling evidence on the effect of conflict on human capital. Through the occurrence of killings, injuries, displacement, trauma and disease, civil war causes large reductions in both the stock of human capital and its growth rate. In a recent review of the mounting sub-national evidence, Justino (2016) separates the mechanisms of the effect of conflict on human capital into supply and demand channels. Supply channels include the destruction of infrastructure, social capital and markets, the depletion of financial resources, and teacher victimization and absenteeism.[3] Demand channels include child labor – used to cope with war-driven impoverishment or to replace household labor due to death, injury or recruitment–, poor health conditions resulting from conflict exposure –including malnourishment, stress during pregnancy and psychological trauma– and child soldiering.[4] In addition to the effect that stems from the incidence of civil wars, other violent contexts are also detrimental to human capital. For instance, Monteiro and Rocha (2017) show that drug wars in Rio de Janeiro's *favelas* reduce student's test scores.

[3]See for instance, see Akbulut-Yuksel (2014), Akresh and de Walque (2011), Chamarbagwala and Morán (2011), Leon (2012), Shemyakina (2011) and Justino (2012).

[4]For evidence of the effect of conflict on child labor see Akresh and de Walque (2011), and Rodríguez and Sánchez (2012). The effect of conflict on health outcomes is studied by Ichino and Winter-Ebmer (2004), Shemyakina (2011), Bundervoet et al. (2009), Agüero and Deolalikar (2012), Parlow (2012), Camacho (2008), and Valente (2014) among others. Child soldiering has received less attention in the literature probably due to lack of reliable data. One exception is Blattman and Annan (2010).

Our estimates of the effect of the end of the conflict with FARC are large and robust. Specifically, we find that municipalities exposed to FARC violence prior to the ceasefire experience a 19% reduction in dropout rates after the ceasefire compared to other areas. Importantly, moreover, the dropout reduction is larger in places that experienced more intense violence. To the extent that this reduction in school dropout translates to higher primary and secondary school graduation for these children, this would imply differential wage returns of, respectively, 11% and 23% in rural areas, and of 46% and 26% in urban areas (Vargas, 2013). This implies that the productivity gain of the end of the conflict with FARC is potentially extremely large.

These results are robust to using different measures of exposure to FARC violence, to using as control areas only municipalities affected by violence perpetrated by other armed groups or municipalities matched in terms of several pre-ceasefire characteristics, to the inclusion of department-year fixed-effects, as well as to controlling for differential changes in dropout after the ceasefire, parametrized by various pre-ceasefire municipality characteristics.[5] Our results are also robust to conducting the analysis at the school level, thus including school fixed effects. We find that schools located in areas affected by FARC violence experience an 18% reduction in dropout rates after the ceasefire, a figure remarkably similar to that estimated using municipal-level variation.

We also explore the potential mechanisms that relate the end of violence with a reduction in dropout rates. While we find that the recruitment of children decreased in formerly FARC-affected areas, a back of the envelope calculation suggests that child recruitment can only explain a small fraction of the estimated reduction in dropout rates (up to 9%). Moreover, we find no heterogeneous effects by gender, age or the urban vs. rural location of schools. Rather, our evidence is consistent with the main

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[5]We also show that our results are not driven by any specific department or treated municipality, and conduct a permutation tests by randomly assigning the FARC violence treatment many times, thereby ruling out that our results arise by chance.

mechanism being the large post-ceasefire reduction in victimization.[6] Indeed, the reduction in dropout rates are larger in places that had more land mines prior to the ceasefire and where there was more violent territorial contestation. This evidence is consistent with the overall victimization mechanism, and suggest that the end of the conflict with FARC allowed families to take their kids back to school.

Importantly, our estimates are attenuated in areas with higher suitability for growing coca bushes (used to produce cocaine) and that experienced higher coca eradication in the years prior to the start of the ceasefire. This is important as it suggests that highly profitable (often illegal) economic activities reduce the human capital peace dividend given by the reduction in dropout rates, as they increase the opportunity cost of attending school.

This paper contributes to several strands of the literature. First, as mentioned above, educational outcomes should not necessarily respond symmetrically to conflict and to the lack of it. The empirical literature has focused on the effect of violence on such outcomes, especially on the long-term impacts. But the evidence on how conflict termination affects school attainment, school completion, dropout rates and in general human capital accumulation (in either the short or the long run) is scarce. As violence-affected countries move forward in the process of transitioning to peace, it is important to understand how individuals in affected areas respond to the absence of violence. Second, while previous studies have focused on the post-conflict welfare of either ex-combatants (Blattman and Annan, 2010) or veterans (Angrist, 1989), there is little evidence on the welfare of civilians, which is the focus of this paper. Third, we contribute to recent efforts to study the consequences of the end of the Colombian conflict. These papers highlight important unintended negative consequences in terms of the security of local leaders (Prem et al., 2019a) and deforestation (Prem et al.,

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[6]FARC's offensive activity dropped by 98% after the ceasefire (CERAC, 2016).

2019b). That school dropout is largely reduced following the ceasefire provides a silver lining in the light of this evidence.

The rest of the paper is organized as follows. Section 2 provides some background on the Colombian case. Section 3 summarizes the data sources. Section 4 describes the identification strategy to estimate the effect of the ceasefire on school dropout. Section 5 reports the main findings and robustness, section 6 investigates the potential mechanisms behind our main results, and section 7 concludes.

2. CONTEXT

2.1. **Colombia's education system and school dropout.** The education system in Colombia comprises one year of preschool, five years of primary education, four years of lower secondary education and two years of upper secondary education. In 2014, 87% of the schools in Colombia were public and out of those, 78% were located in rural areas (OECD, 2016). All children between five and fifteen years old are legally required to attend preschool plus nine years of compulsory basic schooling. However, it is estimated that 20% of the students do not continue studying beyond primary school (OECD, 2016), and only 65% of boys and 77% of girls complete lower secondary education (Radinger et al., 2018).

One of the main factors associated with early school dropout is violence exposure (García et al., 2010). Unilateral attacks as well as bilateral clashes between armed groups threaten families and communities and, according to OECD (2016), school-age children are more likely than other age groups to be affected by violent death, recruitment and displacement. Indeed, Rodríguez and Sánchez (2010, 2012) show that armed conflict reduces educational attainment and decreases the academic achievement of students that attend schools in conflict-affected areas in Colombia. In addition, Fergusson et al. (2019) find that individuals exposed to intense violence during the 'La

Violencia' civil war that took place in the 1940s and 1950s achieved up to 0.3 less years of education and were more likely to work in less productive sectors as adults.

2.2. **Colombia's civil war and the peace process.** Colombia's civil conflict started with the foundation of left-wing guerrillas FARC and the *National Liberation Army* (ELN from the Spanish acronym) in the mid 1960s. Guerrillas claim to represent the rural poor and have fought for over 50 years with the stated aim of overthrowing the government. In order to finance the protracted war, both groups have been profiting from several forms of illegal activities localized within the Colombian territory (Richani, 1997). This implies that sub-national territorial dominance is an important intermediate objective of the armed groups, and the infliction of violence on both military and civilian targets is a mean of achieving it.

The conflict was a Cold War proxy until the end of the 1980s, but escalated during the 1990s fueled by the involvement of the guerrillas in illegal drug trafficking and the consolidation of anti-guerrilla right wing paramilitary groups. In the mid 1990s, the paramilitaries effectively became a third force in the conflict, when splintered paramilitary armies colluded under the umbrella organization of the *United Self-Defense Groups of Colombia* (AUC by its Spanish acronym). The 5-decade long, three-sided Colombian conflict resulted in over 8.5 million people formally registered with the state as victims of the conflict.[7]

On October 2012 the Colombian government and FARC started peace negotiations in Cuba. While the four-year long process was characterized by constant ebb and flow, one of the most significant milestones was the establishment of a permanent ceasefire by FARC on December 20, 2014. In fact, as a result of the ceasefire, FARC withdrew their troops to more remote areas where military contact with government security forces and other armed groups was unlikely to take place. This explains why FARC's

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[7]Source: Victims' Registry, from the Unit for the Victims Assistance and Reparation, March 2018 figure (https://www.unidadvictimas.gov.co/en).

offensive activities drop by 98% during this period (CERAC, 2016).

To further understand the recent dynamics of the conflict, in Figure 1 we present the evolution of violence related to conflict in municipalities exposed and non-exposed to FARC violence. Panel A shows the time-series of violent cases (i.e. selective murders, attacks on populations, terrorists attacks, among others), while panel B presents the victims from anti-personnel mines, one of the main strategies of victimization during conflict. In both cases it can be seen that there is a sizable reduction starting in 2014, and by 2016 the gap between the two types of municipalities is fully closed. In addition, Table A.1 in the Appendix reports the change in the average number of violent events in the same groups of municipalities before and after the ceasefire. The table shows that there is a systematic reduction in violence in all categories in municipalities formerly exposed to FARC after the ceasefire. For example the number of war-related actions dropped by 71% and the victims from anti-personnel mines plummeted by 64% after the start ceasefire in municipalities exposed to FARC violence in the years leading to it.

In this paper, we show that FARC's inability to exert violence by their own initiative, or to respond violently to actions perpetrated either by the military or other armed groups during the ceasefire (which was largely met until replaced by the bilateral definitive ceasefire and the subsequent disarmament of FARC in 2016) generated a sizable reduction in the incidence of violence in municipalities previously affected by FARC. In turn, this increased the incentive of children to attend school and remain in it.

3. Data

We build a municipality-year level panel to study the effect of the permanent ceasefire on school dropout. We focus on the period from 2011 to 2016, which includes the start of the presidential term of Juan Manuel Santos, who initiated peace negotiations with

FARC in 2012.[8] Our sample consists of 1,092 municipalities with a population of less than 200,000. We drop from our sample large cities and capitals of the department which are less affected by conflict and largely urbanized.[9] We now describe the main variables and the data sources.

3.1. **Education data.** To construct the main dependent variable of our analysis we rely on the Colombian school census (officially called "Form C-600"), which is collected yearly by the Department of Statistics and the Ministry of Education. Specifically, we compute a municipality-level weighted average of the school-specific dropout rates using as weights the share of the school-level enrollment over the entire school population of the municipality. In turn, dropout rates at the school level are computed at the share of students that leave a school during the academic year relative to the initial enrollment.[10]

Table 1 reports descriptive statistics of the municipal dropout rate during the part of the sample period that preceded the ceasefire (2011-2014). During that period, 4.7% of the students left their school during the academic year. The dropout rate was higher in schools located in rural areas (5.1% vs. 4.4% in urban schools) and in public schools (4.8% vs. 3% in private schools). Moreover students left their school more often during secondary education (5.6% vs. 3.7% for primary education) and boys were more likely to dropout (5.4% vs 4% for girls).

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[8]Santos was ultimately awarded the Nobel Peace Prize in 2016 "for his resolute efforts to bring the country's more than 50-year-long civil war to an end."

[9]Our results are robust to using all the country's municipalities.

[10]Note that, because we do not have individual-level data for students with identifiers, our measure does not differentiate the students who leave a school in the middle of the academic year to move to a different school from those who dropout altogether. In addition, it does not include any student who leaves a school before enrolling to the next grade. The potential bias coming from missing these two types of students goes in opposite directions and so its sign is a priori unknown. However, because most of the school switching takes place prior to the start of a new academic year, we believe the scope for any such bias –which in any case is likely classical– is limited.

3.2. **Conflict data.** To construct a measure of exposure to FARC violence prior to the start of the ceasefire, we use the conflict dataset originally compiled by Restrepo et al. (2004), and updated through 2014 by Universidad del Rosario. This dataset codes violent events recorded in the *Noche y Niebla* reports from the NGO *Centro de Investigación y Educación Popular* (CINEP) of the Company of Jesus in Colombia, which provides a detailed description of the violent event, its date of ocurrence, the municipality in which it took place, the identity of the perpetrator, and the count of the victims involved in the incident.[11]

We first created a continuous measure based on the total number of FARC attacks over 10,000 inhabitants that took place from 2011 to 2014 in a municipality. This is the period elapsed after president Juan Manuel Santos took office and before the beginning of the permanent ceasefire. Second, we created a discrete measure that identifies municipalities 'highly exposed to FARC violence'. We did so by dropping the bottom quartile of the continuous measure. Third, we also computed a measure of the extensive margin of violence exposure, as well as an indicator of high exposure based on the median of the empirical distribution of our continuous violence measure.

3.3. **Descriptive statistics.** Table 1 reports descriptive statistics of our violence exposure measures during the period 2011-2014. Further, Table 2 shows that, consistent with the findings of Rodríguez and Sánchez (2010, 2012), there were level differences in school dropout between municipalities exposed and non-exposed to FARC conflict prior to the start of the ceasefire. Municipalities exposed to FARC violence had higher dropout rates. This pattern is robust across different types of schools and students. Table 2 also suggests that municipalities that experienced FARC-violence prior to the

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[11]*Noche y Niebla* sources include "1. Press articles from more than 20 daily newspapers of both national and regional coverage. 2. Reports gathered directly by members of human rights NGOs and other organizations on the ground such as local public ombudsmen and, particularly, the clergy." (Restrepo et al. 2004, p. 404). Notably, since the Catholic Church is present in even the most remote areas of Colombia, we have extensive coverage of violent events across the entire country.

ceasefire were, on average, different to non-exposed municipalities in several other characteristics. These include the share of rural population, the distance to the department's capital and the poverty index.[12]

In the Panel A of Figure 2 we report the evolution of dropout rates for municipalities exposed and not exposed to FARC violence. First, the figure points to a secular decrease in dropout rates in the whole country during our entire sample period. This is likely a result of the implementation of public policies that aimed at expanding the coverage of education, as well as of direct interventions that were designed to increase instruction time and reach out-of-school students (OECD, 2016). Another important pattern that emerges by examining Panel A of Figure 2 is that municipalities highly exposed to FARC violence prior to the ceasefire had higher dropout rates. Moreover, this gap seems constant over the entire pre-ceasefire period. However after the ceasefire the gap between both types of municipalities started closing.

An alternative way to explore this reduction in the dropout wedge of municipalities that were exposed to FARC violence and those which were not, is to look at the spatial distribution of the change in school dropout and overlay it with exposure to FARC violence. In Figure 3 we present (in blue) the difference in average dropout rates between 2016 and 2015 minus the average dropout rates between 2014 and 2011. A darker blue signifies a larger reduction. Further we include red dots to highlight the municipalities highly exposed to FARC violence prior to the ceasefire, where darker red shows more exposure. Because municipalities filled with darker blue tend to have darker red dots, this graphical analysis suggests that the reduction in school dropouts was larger in municipalities most affected by violence perpetrated by FARC over the period 2011-2014. In the rest of the paper we study these suggestive patterns with more rigour and detail.

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[12]The information on municipal characteristics comes from an annual panel of Colombian municipalities, constructed by the *Center of studies on Economic Development* (CEDE by the Spanish acronym), a think-tank at Universidad de los Andes.

4. Empirical Strategy

4.1. **Main specification.** Our identification strategy exploits the timing of the permanent ceasefire announced by FARC on December 20, 2014, as well as the spatial distribution of the exposure to FARC violence across municipalities prior to the ceasefire. More formally, using the subindex m to denote municipalities, d to denote departments, and t to denote time, we estimate the following *difference-in-differences* model:

$$(4.1) \qquad y_{mdt} = \alpha_m + \lambda_{dt} + \beta(Cease_t \times FARC_m) + \sum_{c \in \mathbf{X_m}} \gamma'(c \times Cease_t) + \varepsilon_{mdt}$$

where y_{mdt} is our measure of school dropout, $FARC_m$ measures pre-ceasefire exposure to FARC violence in municipality m, and $Cease_t$ is a dummy that takes the value one after the start of the permanent ceasefire. α_m are municipality fixed effects and λ_{dt} are department-year fixed effects. These control respectively for any observed or unobserved municipal-level time invariant heterogeneity and for any time shocks that affects simultaneously all the municipalities of the same department. X_m are municipality characteristics measured before the ceasefire that we interact with the time indicator that identifies the ceasefire period to flexibly control for differential changes pre- and post-ceasefire parametrized by each one of the municipal attributes. Finally, ε_{mdt} is the error term, which we cluster at the municipality level.[13]

All regressions are weighted by the number of students enrolled in 2014 in each municipality. In this way we give the same weight to every student and thus our coefficient of interest, β, captures the differential change before and after the ceasefire in school dropout in municipalities exposed to FARC violence versus those that were not exposed to FARC violence.

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[13]As a robustness we estimate our model using a variance-covariance matrix that takes into account cross-sectional dependence in the error term following Conley (1999) and Conley (2016).

4.2. **Identifying assumption.** The main assumption behind our *difference-in-differences* model is that in the absence of the ceasefire, dropout rates in municipalities exposed to FARC violence would have evolved similarly to dropout rates in municipalities non-exposed to FARC violence. The validity of this "parallel trends" assumption can be partially assessed by estimating the following equation:

$$(4.2) \qquad y_{mdt} = \alpha_m + \lambda_{dt} + \sum_{j \in T} \beta_j (FARC_m \times \delta_j) + \sum_{c \in \mathbf{X_m}} \gamma'(c \times Cease_t) + \epsilon_{mdt}$$

where T includes all years in our sample except from 2014, which is the year before the ceasefire. Therefore the parameters β_j can be interpreted as the difference in dropout in municipalities exposed to FARC violence and municipalities non-exposed, in year j relative to the year at the end of which the ceasefire started.

4.3. **Potential mechanisms.** We can use the variation across student, school or municipal-level characteristics to estimate heterogenous effects that can shed some light regarding the underlying mechanisms of the main effect of interest. In particular, the change in dropout rates after the ceasefire may be explained by either pre-ceasefire child recruitment into FARC or by the generalized victimization of civilians in places affected by FARC violence. We thus divide a set of potential mechanisms into these two categories and test whether the estimated average effects entail some variation across these key dimensions.

To test for heterogeneous effects across student, school, or municipal-level characteristics, we augment the main specification in equation (4.1) by adding a third interaction term. Specifically, let the student/school/municipal characteristic Z (measured before the ceasefire) be a potential mechanism of interest. We estimate:

$$(4.3) \qquad y_{mdt} = \alpha_m + \delta_{dt} + \beta_1(Cease_t \times FARC_m \times Z) + \beta_2(Cease_t \times Z) + \beta_3(FARC_m \times Z)$$
$$+ \beta_4(FARC_m \times Cease_t) + \sum_{c \in \mathbf{X_m}} \gamma'(c \times Cease_t) + \mu_{mdt}$$

Our coefficient of interest, β_1, captures the differential change in dropout rates in places exposed to FARC violence for students/schools/municipalities with characteristic Z. Note that the results coming from this test are suggestive about potential mechanisms, but not necessarily causal. They have to be interpreted with caution.

Using the above specifications we estimate the impact of the December 2014 permanent ceasefire on school dropout rates in areas previously exposed to FARC violence (equation 4.1), the dynamic persistence of this effect (equation 4.2), and heterogeneous effects (equation 4.3). The next section reports the estimated results.

5. Results

5.1. **Main findings.** In Table 3 we report the coefficients resulting from estimating equation 4.1 for two different versions of exposure to FARC violence prior to the ceasefire. In Columns 1 to 3 we use a standardized measure of the number of FARC attacks over the municipal population. Alternatively, in Columns 4 to 6 we use an indicator that identifies the municipalities in the top three quartiles of exposure to FARC attacks. Municipality fixed effects are included in all specifications. Columns 1 and 4 include year fixed effects and no controls, Columns 2 and 5 include department×year fixed effects and no controls and Columns 3 and 6 include the latter but also control for differential changes in dropout rates after the ceasefire due to several pre-ceasefire municipality characteristics.[14] The standard errors in parentheses are clustered at the municipality level. For robustness, in square brackets we report `p-values` that take into account the potential cross-sectional dependence in the error term (Conley, 1999, 2016).[15]

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[14]These include the logarithm of population, the share of rural population, a poverty index, and the distance to the department capital.

[15]As an additional exercise to assess the robustness of our standard errors, we follow Bertrand et al. (2004) and collapse our data before and after the ceasefire to deal with potential serial correlation. Table A.3 of the Appendix reports these results, which reassure the validity of the baseline estimates of Table 3.

Using the continuous measure of exposure and the specification with year fixed effects and no controls (Column 1) our results suggest that a one-standard-deviation increase in the number of FARC attacks per 10.000 inhabitants over the period 2011-2014 causes a statistically significant decrease in dropout rates of 0.19 percentage points after the ceasefire relative to the rest of municipalities. The equivalent model using the indicator of high exposure to FARC attacks over the same period (Column 4), suggests that municipalities highly exposed to FARC violence experienced a significant reduction in dropout rates of 0.84 percentage points. This effect corresponds to a 19% decrease in the baseline dropout rate. Both the magnitude and the statistical significance of these results are robust to estimating the more demanding models, which include department×year fixed-effects (Columns 2 and 5), and differential changes parametrized by pre-ceasefire controls (Columns 3 and 6).

5.2. **Identifying assumption.** In this subsection we asses the validity of our empirical strategy.

5.2.1. *Dynamic difference-in-differences.* We first report the coefficients coming from estimating equation 4.2 in Panels B and C of Figure 2. Panel B (C) presents the estimates that result from using our continuous (dichotomous) measure of exposure to violence. In both cases, it can be seen that before the ceasefire the coefficients are not statistically significant and are close to zero. This points to the absence of differential trends in dropout rates before the ceasefire between municipalities that were exposed to FARC violence and places that were not. Thus, this provides support for the use of a *difference-in-differences* empirical strategy to estimate the effect of the ceasefire on dropout rates in Colombia.

Panels B and C of Figure 2 also show that, after the start of the ceasefire, the coefficients become negative and statistically significant.

5.2.2. *Differential pre-trend?* We also conduct a more parametric test for the existence of differential trends during the pre-ceasefire period in the spirit of Muralidharan and Prakash (2017). In this test we interact a linear trend with our measure of exposure to FARC violence and test for the significance of this coefficient prior to the ceasefire. We find no evidence for differential trends before the ceasefire (see Table A.2 of the Appendix).

5.2.3. *Placebo treatment period.* Further, we also perform a placebo exercise using the date in which the government and FARC achieved the first important milestone of the peace process. On May 26, 2013 the parties reached an agreement on the first point of the peace process agenda, namely to carry out a comprehensive rural reform including regulating land use and access, discouraging unproductive land, improving land property titles, investing in rural infrastructure, and providing technical assistance and subsidies to improve agricultural production.[16] This was the first out of six partial agreements reached prior to signing the final peace accord on September 2016.

The regressions for this exercise follow the structure of equation (4.1) but instead of a *Cease* time indicator we include a *Placebo Cease* one, which takes the value one for the years 2013 and 2014. For this analysis we focus on the sample period between 2011 and 2014, so as to capture pre-ceasefire effects. We find that there is no differential change in dropout rates in areas exposed to FARC violence relative to FARC-free areas after this agreement was reached (see Table A.6 in the Appendix). These results are consistent with the absence of differential pre-trends before the ceasefire and support our main result, namely that the differential evolution of dropout rates between these two types of municipalities is driven by the ceasefire.

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[16]See *Colombia's Agreement to End Conflict and Build Peace*, available from http://www.altocomisionadoparalapaz.gov.co/herramientas/Documents/summary-of-colombias-peace-agreement.pdf (last accessed July 21, 2019).

5.3. **Further robustness.** We now assess the robustness of our main findings to a series of empirical exercises that we present in this subsection.

5.3.1. *Dropout or enrollment?* First, we would like to corroborate that our main finding, namely that dropout rates decreased differentially after the start of the ceasefire in municipalities previously exposed to FARC violence, comes from a reduction in the numerator of our dropout rate measure (i.e. a reduction in the [log of] total dropout in the municipality) and not from an increase in the denominator (i.e. an increase in the [log of] total enrollment). Columns 1 and 2 of Table 4 show this is indeed the case: the decrease in dropout rates is coming from 19% more children leaving the school during the academic year in the municipalities previously affected by FARC, and not by any differential surge in school enrollment in these municipalities.

5.3.2. *School fixed effects.* Second, we conduct the same analysis at the school level, which allows us to add school-level fixed effects. We present these results on Columns 3 and 4 of Table 4 and find results that are remarkably similar to those estimated at the municipality level. Based on the most demanding specification (Column 4), schools located in municipalities previously affected by FARC violence had a differential decrease of 1.04 percentage points in school dropout rates after the start of the ceasefire. Also in line with the municipal level estimates, this effect comes from an 18% decrease in the number of students dropping out from school (Column 6), and not from a differential change in school-level enrollment following the ceasefire (Column 5).

5.3.3. *Measurement of exposure to FARC violence.* Third, Columns 1 to 3 of Table 5 report the robustness of our baseline results to using three alternative measures of exposure to FARC violence. The first one (Column 1) is based on the the extensive margin of exposure, and it is equal to one if the municipality experienced at least one FARC attack over the period 2011-2014. This measure has the advantage of being less prone to measurement error in identifying municipalities exposed to FARC violence.

The second (Column 2) is a more stringent measure of "high exposition" to FARC violence, as it is an indicator that takes value one for municipalities above the median of the empirical distribution of per capita FARC attacks conditional on experiencing at least one attack.

The comparison of the estimated results reported in these two columns is important, as it implies that the post-ceasefire gains in schooling (driven by the reduction in dropout rates) are larger in places that experienced more violence. On the one hand, municipalities that witnessed at least one attack by FARC prior to the ceasefire experienced a 0.56 percentage points reduction in dropout rates (Column 1). This is equivalent to 12% of the average dropout rate in control municipalities. On the other, places that suffered FARC violence above the median (conditional on experiencing at least one attack) experienced a 0.95 percentage points reduction in dropout rates (Column 2). This is equivalent to 21% of the average.[17]

The third column of Table 5 is a measure taken from an alternative source, namely the *Centro Nacional de Memoria Histórica* which records all the selective killings perpetuated by FARC.[18] Specifically, we code a dummy variable that takes the value of one in municipalities with at least one episode of selective killings over the period 2011-2014. Our results are robust to using any of these three alternative dependent variables, both in terms of magnitude and significance.

5.3.4. *Municipality characteristics.* Recall that our preferred specification (Columns 3 and 6 of Table 3) includes municipality characteristics before the ceasefire interacted with the ceasefire dummy. Column 4 of Table 5 reports a version of this regression in

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[17]Monteiro and Rocha (2017) find a similar pattern for the case of the effect of violence between drug gangs on educational outcomes in Rio de Janeiro. Specifically, student test scores are inversely proportional to the intensity of the drug violence that takes place in Rio's *favelas*.

[18]Selective killings are defined as an intentional homicide of up to three individuals in state of defenselessness by an illegal armed group in one single event. If four or more people are killed the event is called a "massacre".

which, following Belloni et al. (2014), the controls are selected using machine learning. In this way we are agnostic about which municipality characteristics are more related to dropout rates and exposure to FARC violence.[19] Our results show to be robust to this exercise.

Alternatively, we can estimate a propensity score for the indicator of being highly exposed to FARC violence and add it in the main specification as the only one municipal characteristics, interacted with the ceasefire period indicator.[20] This control captures differential changes in dropout rates given by many observable characteristics pre-ceasefire that are related to the exposure to FARC violence. Column 5 of Table 5 shows that our results are robust to this specification.

5.3.5. *Comparison municipalities.* One threat to our identification is that municipalities exposed to FARC violence are different to areas not exposed, and that in 2014 there was some "shock" (other than the ceasefire) that differentially affected these municipalities because of such characteristics but not because of the prior exposure to FARC violence. To alleviate this concern we estimate our main model using different control municipalities, which we select using different matching procedures. First, we keep in our sample only municipalities that have been exposed to violence from FARC *or other armed groups* between 2011 and 2014.[21] In this way we are keeping constant the exposure to conflict related violence. The main assumption behind this strategy is that in absence of the ceasefire, the trend in dropout rates in municipalities previously affected by FARC violence would have been the same than in municipalities affected

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[19] The set of potential controls includes the logarithm of population, the size of the municipality, the distance to department capital, the share of rural population, a poverty index, the municipal tax revenue per capita, the municipal fiscal deficit, a coca suitability measure estimated by Mejía and Restrepo (2015), the average elevation of the municipality and the illiteracy rate. The model selects as relevant controls the poverty index, the fiscal deficit, the average elevation, and the illiteracy rate.

[20] We use the following pre-ceasefire characteristics to construct the propensity score the same set of controls mentioned on footnote refallcont.

[21] Exposure here is defined in the extensive margin, so these are municipalities that suffered at least one attack by *any* illegal armed group over the period 2011-2014.

by violence from violence perpetrated by other armed groups. Column 6 of Table 5 shows that our estimates are robust to using these municipalities as the controls.

Alternatively, following Crump et al. (2009), based on the estimated propensity score described in the previous paragraph we truncate the sample in order to increase the overlap of treated and control municipalities in terms of various municipality characteristics. We perform this truncation in two different ways: following a rule-of-thumb cut-off of 10% and using the optimal cut-off suggested by Crump et al. (2009), which in our case is 3.8%. Columns 7 and 8 of Table 5 show that our results are also robust to this sample truncation strategy.

5.3.6. *Placebo simulation.* We also conduct a permutation test by randomly assigning an indicator of *FARC-violence-pre-ceasefire exposure* to all municipalities. This test provides us with a distribution-free estimate of the probability that our coefficient of interest arises by chance. We perform two different versions of this test. First, we randomize the assignment at the country level. Second, we do so at the department level. In both cases the random assignment is consistent with the observed distribution of municipalities exposed to FARC violence. Reassuringly, our estimated coefficient (red vertical line) is above the 99th percentile of the resulting distributions (see Panel A and B of Figure A.1 in the Appendix).

5.3.7. *Floor effects?* Recall from Panel A of Figure 2 that the level of the dropout rates is higher in municipalities exposed to FARC violence than in other areas. One concern about this level difference is that our findings could be the results from a "floor effect". That is, it is harder to reduce dropout rates in non-violence affected municipalities, which have lower rates to begin with. To deal with this potential threat, in Table A.5 of the Appendix we re-estimate our main specification after re-scaling the dependent variable by pre-ceasefire dropout levels. In this way, the estimated effects can be

interpreted as being relative to the pre-ceasefire dropout level of each municipality. Our results are robust to this alternative specification.

5.3.8. *Outliers?* A final concern is that our results may be driven by large outliers in dropout rates for specific municipalities. In Table A.4 of the Appendix we show that our results are robust to using three different *winsorization* cut-offs, thus alleviating this potential concern.

Alternatively, we also check whether our main results are driven by a particular treated municipality or by one specific department.[22] In Figure 4 we present the robustness to both of these tests. In general all coefficients remain stable and statistically significant.

6. MECHANISMS

In this section we explore the empirical relevance of several potential mechanisms through which the absence of violent conflict reduces dropout rates in municipalities previously affected by FARC violence. We explore the role of the recruitment of child soldiers, the overall victimization of civilians in areas affected by FARC violence, the destruction of school infrastructure, and the potentially mitigating effect of profitable economic opportunities.

6.1. **Recruitment of child soldiers.** According to official records, FARC is responsible for 54% of the 16.879 identified cases of illegal child recruitment into armed groups in Colombia between 1960 and 2016. Most of these children were boys (68%), and were recruited when they were between 12-16 years old (CNMH, 2017).[23] Clearly, to the extent that the recruitment of children stops after the *de jure* or *de facto* end of a conflict, and especially so if the formerly recruited children go back to school after their group demobilizes, child recruitment during conflict is an obvious candidate for

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[22]Colombia has 32 departments, equivalent to US states.
[23]These patterns are consistent those found for the case of Uganda's Lord's Resistance Army (Blattman and Annan, 2010; Beber and Blattman, 2013).

explaining our findings.

Our test of whether this is the case is twofold. First, we estimate our main empirical specification (equation (4.1)) using as dependent variable the number of children recruited by any armed group as well as the number of cases of recruitment.[24] The results are reported on Table 6. We find a significant reduction in recruitment equivalent to 1.3 children (and 1.2 cases) after the ceasefire in municipalities affected by FARC violence. This reduction represents 6% of the average and 0.24 of the standard deviation of all the recruitment that took place during our pre-ceasefire sample period.

Does this finding support the validity recruitment as the main mechanism? Hardly. To show why, we perform a bounding exercise to understand whether the magnitude of the effect found for dropout rates can be driven by the estimated change in child recruitment. Specifically, we take the year of the highest recruitment prior to the ceasefire and divide it by the number of municipalities exposed to FARC violence, obtaining three recruited children per affected municipality on average. Now, assuming that all of these stayed at the school after the start of the ceasefire, then this can only explain 8.5% of the average estimated reduction in the school dropout rate.[25]

As a second test of the empirical relevance of the child recruitment mechanism to explain our results, we estimate equation 4.3 to explore potential heterogeneous effects across key student or school characteristics that are likely correlated with the recruitment of child soldiers. In particular, we are interested in learning whether the reduction of school dropout is higher for boys, for kids in the age window that is associated with the highest incidence of abduction of children, or for for rural or public schools, which

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[24]Unfortunately, there is no longitudinal data on child recruitment that distinguishes the group responsible for the abduction.

[25]To see why recall that the estimated average dropout reduction is 19% (see Column 2 of Table 4). Also, the average enrollment in municipalities affected by FARC violence is 186.8. Now, $\frac{3}{0.19*186.8} \approx 0.085$.

are more likely to be located in areas where the abduction of children takes place, relative to schools located in urban areas or to private schools. The results are reported on Columns 1 to 4 of Table 7. We find no statistically significant differential effects for kids in primary school age (age 6 to 11, Column 1) or for girls (Column 2).[26] We also do not find any differential effect for rural (Column 3) or public schools (Column 4).

Taken together, these results suggest that even if child soldiering is a phenomenon of foremost importance in the Colombian conflict, for the case of the reduction in dropout following the start of the ceasefire other mechanisms are likely more relevant empirically.

6.2. **Victimization.** Households affected by violence are likely to remove their kids from school because of uncertainty and perceptions of fear (Justino, 2016). This is potentially quite relevant in our context, as the Colombian conflict resulted in around 8.6 million officially recognized victims. This amount to over 17% of the country's population. Victimization events include forced displacement, killings, and kidnappings.[27] School's infrastructure and resources were not exempt from violence (CNMH, 2017). School facilities were used at different stages of the conflict as supply centers and camping areas by both illegal armed groups and state security forces. Moreover, both students and teachers faced threats and indoctrination attempts and were exposed to various forms of attacks, being often caught in crossfire. Records from Colombia's teachers' unions (Fecode, by its Spanish acronym) show that during the period 2009-2014, there were on average 22 homicides of teachers per year. Instead, after the start of the ceasefire (during 2015-2016), when FARC's bellicose activity dropped by 98%, there were 8 homicides per year on average (Fecode, 2016).

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[26]For the case of the age of recruitment, in Figure 5 we also present the point estimates by grade level, it can be seen that the effect is similar across all school grades.

[27]See the Victims' Registry of the Colombian Unit for the Attention and Reparation of Victims, available at https://www.unidadvictimas.gov.co (last accessed on July 22, 2019).

Overall, students and teachers attending and working schools located in conflict affected areas faced a non-negligible risk of victimization. We assess whether our main results are driven by the large reduction of victimization following the ceasefire. To that end, we estimate equation 4.3 to explore if there are any heterogeneous effects in municipalities that, prior to the ceasefire suffered particularly high levels of violence. We do so by looking at violence perpetrated by other armed groups (in addition to FARC) -hence identifying areas that were more contested and which therefore experienced more violence-, as well as at episodes of explosion of land mines, which represents one of the main strategies of inflicting fear to the civilian population during the conflict.

The results from these tests are reported in Columns 5 and 6 of Table 7. They suggest that, indeed, the reduction in school dropout rates following the start of the ceasefire are larger in municipalities that faced more violence during the period 2011-2014.

We further investigate the victimization mechanism by studying if there are any spillovers on dropout rates in municipalities surrounding municipalities that were exposed to FARC violence. We do so by estimating our main specification (equation 4.1) but adding an additional interaction term between a dummy that takes the value of one for municipalities that share a border with a municipality exposed to FARC violence before the start of the ceasefire and the ceasefire period indicator. Table A.7 of the Appendix reports these results. We find a marginally significant reduction in dropout rates in neighboring municipalities (with `p-values` equal to 10.5% in Column 1 and 8% in Column 2). The effect is also smaller in magnitude for neighbors compared to the average effect on an exposed municipality. Specifically, the dropout reduction in neighboring municipalities ranges between 28% and 56% of the main effect. In Column 2 we can reject that the estimated effect is statistically the same in both types of municipalities.

Overall, and in contrast to the case of child soldiering, we do find strong evidence consistent with the hypothesis that our estimated effects related to the reduction of dropout after the start of the ceasefire are at least partially driven by the decrease in victimization rates.

6.3. **School conditions.** In Table 8 we rule out that the reduction in dropout rates is explained by a differential change in school conditions or the supply of schooling in municipalities affected by FARC violence. Specifically, we do not find any significant differential increase in the student-teacher ratio (Column 1) or the number of teachers (Column 2). We also do not find any differential change in the opening of new schools (Columns 3 and 4).[28] This is not surprising given the short-term span of the analysis.

6.4. **Economic opportunities.** We end our analysis by showing suggestive evidence that our estimated effects of the impact of the ceasefire on school dropout is likely a lower bound of the true causal effect. This is the case if the *de facto* end of the conflict with FARC induced a differential surge in (legal or illegal) profitable economic activities in municipalities previously affected by violence perpetrated by this armed group. Prem et al. (2019b), find that deforestation rates increased substantially after the ceasefire in places with FARC presence, and that this is explained by large extractive economic activities rather than by low scale subsistence agriculture. To the extent that economic opportunities increase the opportunity cost of attending school, this points to a force that would drive school dropout in the opposite direction relative to our findings.

To test this conjecture somewhat more formally, we estimate equation model 4.3 to look at the differential change in school dropout after the ceasefire in municipalities

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[28]We define school opening as the number of schools that show up in a municipality during a particular year and that were not in the database the year before. The information on the school identifiers is taken from the yearly school census (Form C-600) collected by the Department of Statistics and the Ministry of Education.

with higher coca suitability (as computed by Mejía and Restrepo, 2015) or that experienced higher levels of coca eradication prior to the ceasefire (in addition of having been exposed to FRAC violence). Indeed, because of its unusually large profitability, coca production is likely to attract child labor. This is actually one of the most important results of Angrist and Kugler (2008). Moreover, recent reports show that coca cultivation has been increasing since 2013 with peak records in 2016 and 2017.[29]

Columns 7 to 10 of Table 7 report the estimated results. Consistent with the conjecture that the opportunity cost of attending school increases in places with more coca cultivation, we find that the decrease in dropout rates is attenuated in municipalities with more exposure to coca production.

7. Conclusion

In this paper we study the effect on school dropout rates of Colombia's recent efforts to bring the conflict with the FARC insurgency to an end. Our findings show that the permanent ceasefire declared by FARC during peace negotiations with the government triggered a large differential reduction on school dropout rates in the areas most affected by FARC violence prior to the ceasefire, relative to other areas. Specifically, we find that municipalities exposed to FARC violence prior to the ceasefire experience a 19% reduction in dropout rates after the ceasefire compared to other areas. We rule out that this effect is entirely driven by recruitment and posit that the main mechanism has to do with plummeting victimization rates following the ceasefire.

A decrease in school dropout following the end of conflict is a necessary condition to counteract the long-term human capital costs of civil war, which has been estimated for a variety of countries and contexts. The importance of it cannot be emphasized enough.

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[29]See https://www.insightcrime.org/news/analysis/colombia-cocaine-production-breaks-new-record-levels-unodc-report/ (last accessed on July 3rd, 2019).

According to Unesco (2011), while 65% of primary-school-age children attend school in conflict-affected countries, the same figure for comparable low-income countries is 86%.

In the specific case of Colombia, our findings highlight the importance of the process of peace consolidation in the country. The peace agreement was signed in September of 2016 but got rejected by a 0.5% vote margin in a referendum that took place on October that year. In 2018, the party that promoted the "No" vote raised to power and the implementation of the agreement (which was endorsed by Congress on December 2016 after the negotiating team made some adjustments following the electoral defeat in the referendum) has slowed down significantly since then. The human capital peace dividend highlighted in this paper points to the importance of reverting this trend. We encourage the government and other stakeholders in Colombia to do so.

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FIGURE 1. **Evolution of Conflict**
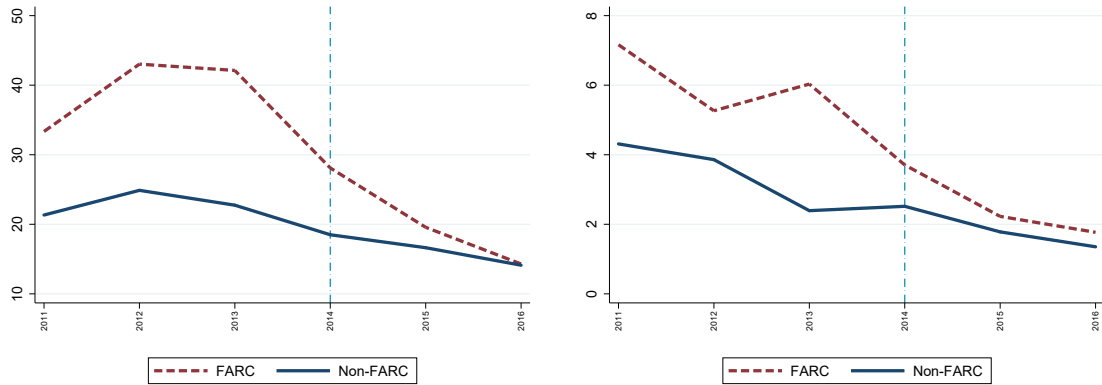
A. Violent Cases   **B.** Mines Victims

Notes: This figure presents the evolution of conflict for exposed and non-exposed municipalities to FARC violence as recorded by the *Centro Nacional de Memoria Histórica.* Panel A presents the average number of violent cases in a municipality (including selective murders, attacks on populations, terrorists attacks, damage to propery and civilians, forced disappearance, anti-personnel mines, massacres, kidnappings, sexual violence and recruitment) and Panel B presents the average number of victims of anti-personnel mines and unexploded ammunitions in a municipality.

FIGURE 2. **Raw data dynamics and point estimates**
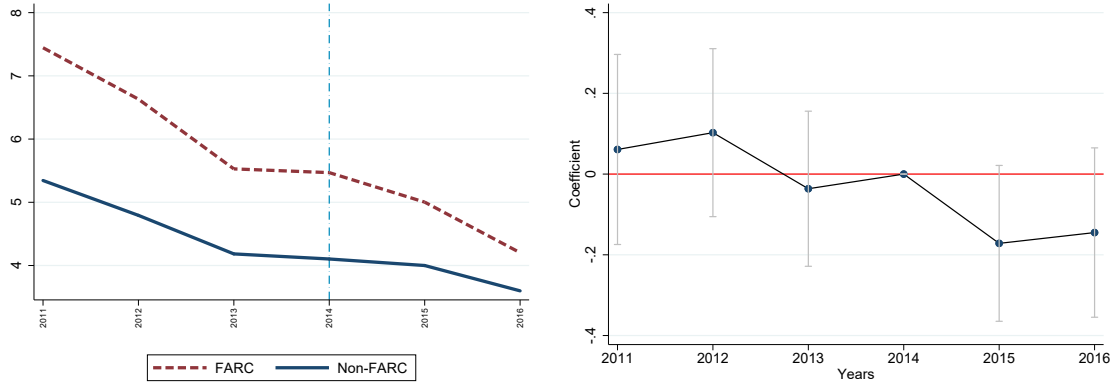
A. Raw data

B. Point estimates: continuous
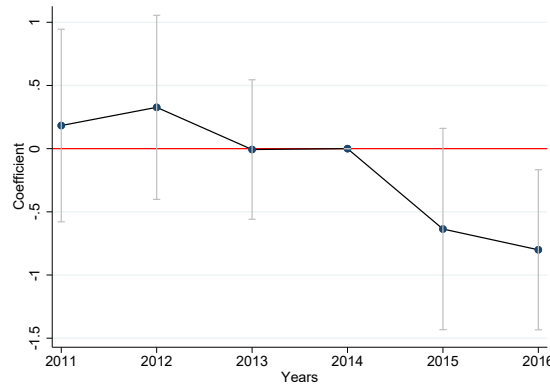
C. Point estimates: discrete

Notes: This figure presents the evolution of dropouts for exposed and non-exposed municipalities to FARC violence. Panel A presents the raw data. Panel B and C presents the coefficients from our dynamic specification presented in equation (4.2). Panel B uses our continuous treatment, while Panel C uses the discrete version. We present the point estimates of the regression and the confidence of interval at the 95%.

FIGURE 3. **Change in school droputs and exposure to FARC violence**
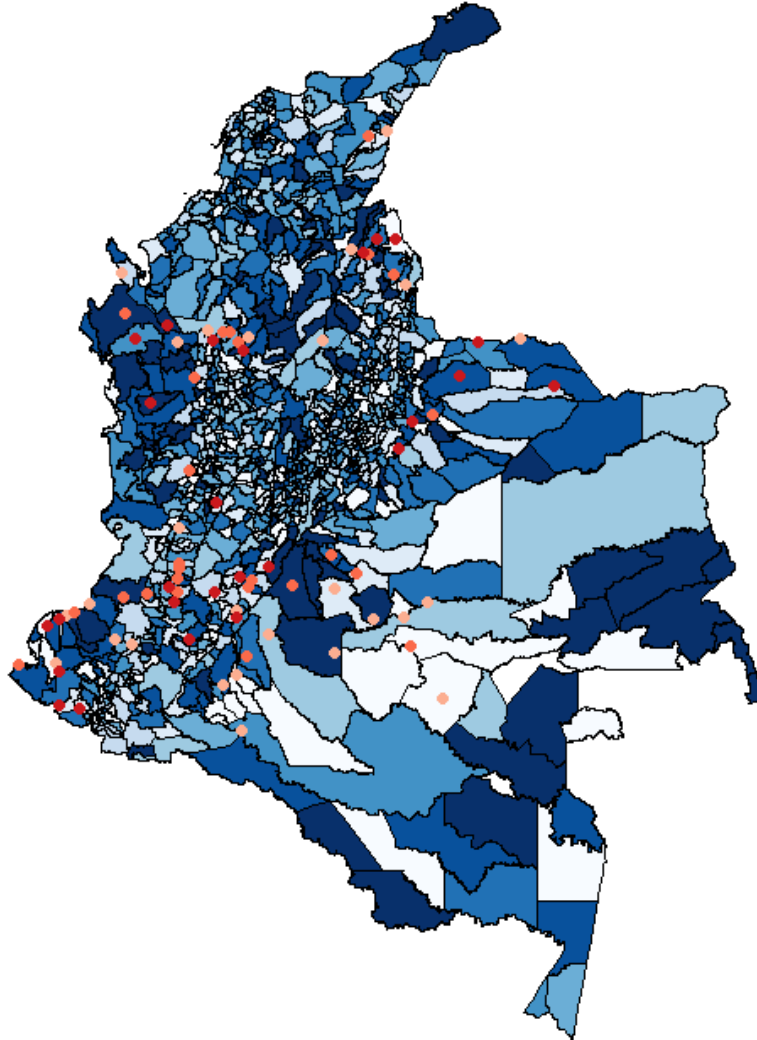
Notes: This figure map presents the spatial distribution of the change in school dropout between 2016-2015 and 2014-2011, and the spatial distribution of attacks per capita by FARC previous to the ceasefire. Darker blue means a larger reduction in school dropout after the ceasefire, while darker red means higher number of attacks per capita.

FIGURE 4. **Robustness to exclude one municipality with FARC presence at the time**
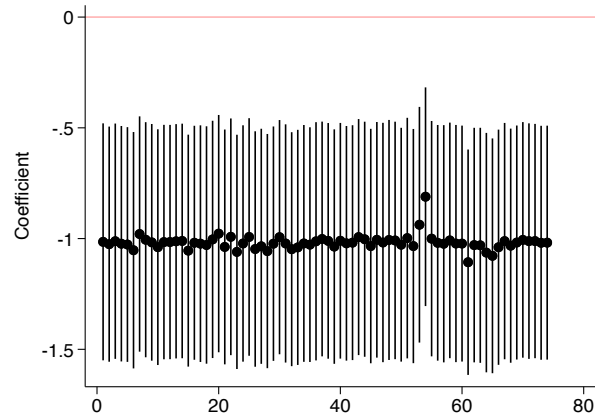
A. Exclude Exposed Municipalities
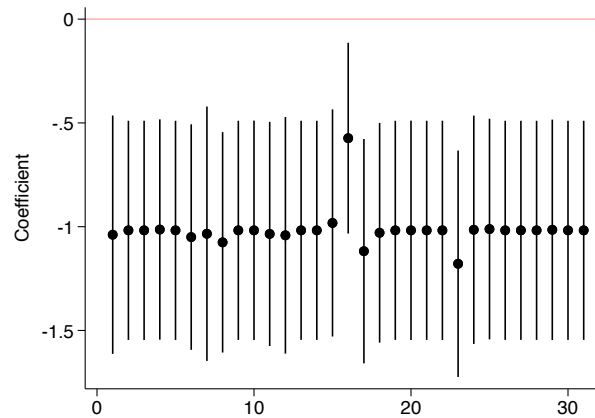
B. Exclude Department

Notes: This figure presents the results our main specification. In Panel A we drop one of the FARC affected municipalities at the time, while Panel B removes one department at the time.

FIGURE 5. **Effects by grade level**
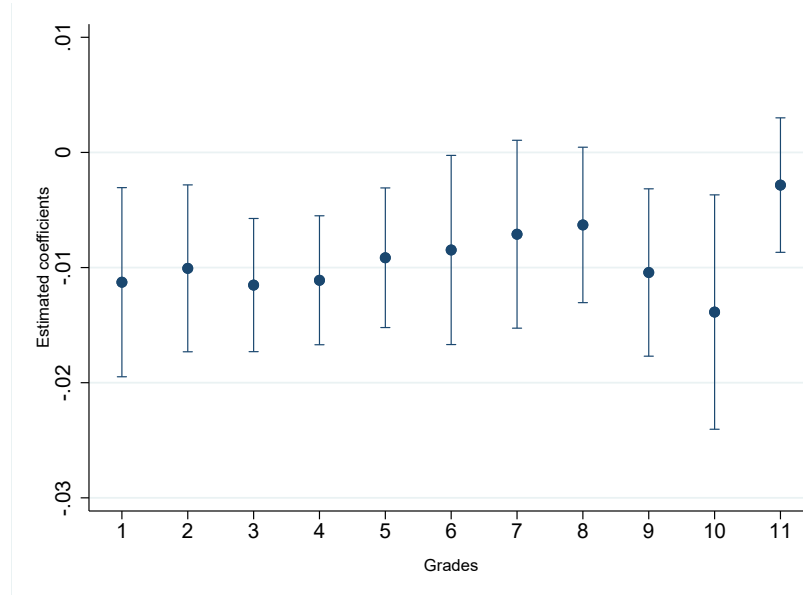
Notes: This figure presents the estimated coefficients from eleven separate regressions using the dropout rate at the grade level as the dependent variable.

TABLE 1. Summary Statistics

	(1) Mean	(2) Mean (unweighted)	(3) Standard deviation	(4) Median	(5) Min	(6) Max
Dropout rate	4.72	4.72	2.47	4.48	0.00	38.67
Dropout rate (Rural)	5.19	5.10	3.46	4.72	0.00	66.67
Dropout rate (Urban)	4.47	4.35	2.72	4.20	0.00	25.57
Dropout rate (Public)	4.92	4.77	2.48	4.69	0.00	38.67
Dropout rate (Private)	2.06	2.95	4.45	1.04	0.00	73.91
Dropout rate (Primary)	3.92	3.74	2.55	3.57	0.00	38.67
Dropout rate (Secondary)	5.56	5.63	3.03	5.22	0.00	48.15
Dropout rate (Girls)	4.06	4.02	2.26	3.84	0.00	42.31
Dropout rate (Boys)	5.36	5.39	2.77	5.09	0.00	36.73
FARC attacks per 10,000 inhab	0.11	0.12	0.46	0.00	0.00	9.80
Exposed to FARC	0.13	0.09	0.34	0.00	0.00	1.00
Highly exposed to FARC	0.07	0.07	0.12	0.26	0.00	1.00
Rural population	0.45	0.59	0.26	0.45	0.02	1.00
Poverty index	65.24	70.30	19.75	68.77	14.27	100.00
Distance to capital	80.40	82.87	61.11	64.57	0.00	493.08
Population	20,929.17	20,929.17	48,648.88	33,214.00	284.00	199,264.00
Municipalities			1092			

Notes: This table presents summary statistics for the main variables of interest. All the columns present weighted versions of the summary statistic, except for Column 2.

TABLE 2. Dropout by exposure to FARC violence before the ceasefire

| | (1) | (2) | (3) |
| | | Exposure to FARC violence | |
	Avg without FARC	Continuous	Discrete
Dropout rate	4.57	0.34***	1.65***
	(2.45)	(0.06)	(0.18)
Dropout rate (Rural)	4.94	0.58***	2.36***
	(3.38)	(0.10)	(0.28)
Dropout rate (Urban)	4.36	0.21***	1.30***
	(2.70)	(0.07)	(0.22)
Dropout rate (Public)	4.78	0.30***	1.52***
	(2.47)	(0.06)	(0.18)
Dropout rate (Private)	2.03	0.17	0.28
	(4.51)	(0.11)	(0.34)
Dropout rate (Primary)	3.76	0.33***	1.78***
	(2.47)	(0.07)	(0.21)
Dropout rate (Secondary)	5.40	0.35***	1.47***
	(3.02)	(0.07)	(0.21)
Dropout rate (Boys)	3.92	0.31***	1.50***
	(2.23)	(0.06)	(0.17)
Dropout rate (Girls)	5.20	0.37***	1.80***
	(2.75)	(0.07)	(0.20)
Share of rural pop	0.43	0.04***	0.12***
	(0.26)	(0.00)	(0.02)
Distance to capital	77.70	5.58***	23.43***
	(60.16)	(1.63)	(7.50)
Poverty index	63.87	3.64***	12.81***
	(20.12)	(0.46)	(1.31)
Ln population	10.41	-0.04	-0.02
	(0.99)	(0.02)	(0.11)
Municipalities	1092		

Notes: This table presents univariate regressions based on municipality characteristics before the ceasefire. Column 1 presents the average of each variable before the ceasefire for municipalities non-exposed to FARC violence. Columns 2 and 3 present estimated coefficient and standard errors from univariate regressions for the continuous and discrete treatment.

TABLE 3. Dropout, exposure to FARC violence, and ceasefire

Dependent variable: School dropout rate

	(1)	(2)	(3)	(4)	(5)	(6)
	Exposure to FARC attacks			Highly exposed		
Cease × FARC	-0.19***	-0.18**	-0.13**	-0.84***	-1.02***	-0.80***
	(0.07)	(0.07)	(0.06)	(0.24)	(0.27)	(0.23)
	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]
Observations	6,523	6,523	6,523	6,523	6,523	6,523
Municipalities	1092	1092	1092	1092	1092	1092
R-squared	0.704	0.735	0.740	0.705	0.737	0.741
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Dept-Year FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Mean DV	4.425	4.425	4.425	4.425	4.425	4.425
SD DV	3.003	3.003	3.003	3.003	3.003	3.003

Notes: This table presents the results from the main specification in equation (4.1). *Exposure to FARC attacks* is defined as FARC attacks over population, and is standardize by the mean and standard deviation to ease interpretation. *Highly exposed* is a discrete measure that takes the value one for municipalities with attacks over population in the top-3 quartiles. *Cease* is a dummy that takes the value one for the period after 2014. Columns 3 and 6 add predetermined municipal controls interacted with the ceasefire dummy. This controls include logarithm of the population in 2010, share of rural population, poverty index, and distance to the department capital. Robust standard errors are clustered at the municipality level and presented in parenthesis. In square brackets we present the p-values for standard errors control for spatial and first-order time correlation (see Conley, 1999, Conley, 2016). We allow spatial correlation to extend to up to 279 km from each municipality's centroid to ensure that each municipality has at least one neighbor. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE 4. Enrollment, dropouts, and school level analysis

| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Municipality level regressions | | School level regressions | | | |
	Enrollment	Dropouts	Dropout rate		Enrollment	Dropouts
Cease × FARC	-0.04	-0.19***	-1.24***	-1.04**	0.00	-0.18**
	(0.03)	(0.07)	(0.43)	(0.49)	(0.03)	(0.09)
Observations	6,523	6,523	140,933	140,933	140,933	140,933
R-squared	0.981	0.903	0.119	0.539	0.971	0.739
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
Dept-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No
Municipalities	1092	1092	1092	1092	1092	1092
Mean DV	7.589	4.293	4.619	4.619	4.619	4.619
SD DV	1.151	1.420	7.515	7.515	7.515	7.515
School FE			No	Yes	Yes	Yes
Schools			39178	39178	39178	39178

Notes: This table presents results for enrollment, dropout, and school level analysis. Columns 1 and 2 show results from our baseline specification in equation (4.1), but uses as a dependent variable the logarithm of enrollment (Column 1) and logarithm of total dropout (Column 2) at the municipality level. In Columns 3 and 4 we present a version of equation (4.1), but at the school level. In Columns 5 and 6 we present school level analysis for the logarithm of enrollment and logarithm of total dropout. *FARC* is a discrete measure that takes the value one for municipalities with attacks over population in the top-3 quartiles. *Cease* is a dummy that takes the value one for the period after 2014. Robust standard errors are clustered at the municipality level and presented in parenthesis. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE 5. Robustness exercises

Dependent variable: School dropout

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FARC measures			Machine learning controls	Pscore × Cease	Municipalities with conflict	Truncate sample based on pscore	
	Extensive margin	Attacks above median	FARC measured by selective killings				10%	3.8%
Cease × FARC	-0.56***	-0.95***	-0.55***	-0.71***	-0.74***	-0.98***	-1.23***	-0.81***
	(0.21)	(0.33)	(0.17)	(0.27)	(0.24)	(0.27)	(0.40)	(0.28)
Observations	6,523	6,523	6,523	6,523	6,523	3,302	1,802	4,366
R-squared	0.736	0.736	0.736	0.739	0.739	0.739	0.749	0.741
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dept-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipalities	1092	1092	1092	1092	552	1092	301	730
Mean DV	4.43	4.43	4.43	4.43	4.43	4.73	5.48	4.81
SD DV	3.00	3.00	3.00	3.00	3.00	2.84	3.10	2.98

Notes: This table presents the results for a series of robustness exercises. See section 5.3 for details about each exercise. *Cease* is a dummy that takes the value one for the period after 2014. Robust standard errors are clustered at the municipality level and presented in parenthesis.. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE 6. Effects on Recruitment

	Victims of recruitment	Recruitment cases
Cease × FARC	-1.27**	-1.17**
	(0.50)	(0.50)
Observations	6,523	6,523
R-squared	0.552	0.608
Municipality FE	Yes	Yes
Year FE	No	No
Dept-Year FE	Yes	Yes
Municipalities	1092	1092
Mean DV	20.29	20.29
SD DV	5.256	5.256

Notes: This table presents results from our baseline specification in equation (4.1), but uses as a dependent variable the number of victims of recruitment (Column 1) and the number of recruitment cases (Column 2) at the municipality level as recorded by the *Centro de Memoria Histórica*. *FARC* is a discrete measure that takes the value one for municipalities with attacks over population in the top-3 quartiles. *Cease* is a dummy that takes the value one for the period after 2014. Robust standard errors are clustered at the municipality level and presented in parenthesis. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE 7. Heterogeneous effects by exposure to violence and coca production

Dependent variable: School dropout

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Student characteristics		School characteristics				Municipality characteristics			
							Coca suitability		Coca eradication	
	Primary	Girls	Rural	Public	OAG	Mines victims	Continuous	Discrete	Continuous	Discrete
Cease × FARC × Z	-0.25	0.10	-0.71	-0.52	-0.30*	-0.10*	0.65***	1.69***	-0.38***	-2.35***
	(0.25)	(0.12)	(0.68)	(0.61)	(0.17)	(0.06)	(0.24)	(0.40)	(0.09)	(0.47)
Cease × FARC	-0.84***	-1.06***	-0.54*	-0.38	-0.66***	-0.77***	-1.25***	-2.16***	-0.67***	-0.33
	(0.28)	(0.30)	(0.31)	(0.46)	(0.24)	(0.28)	(0.30)	(0.35)	(0.25)	(0.23)
Cease × Z	-0.10	0.28***	-0.28**	-0.31***	-0.13***	0.03	-0.16**	-0.15**	0.12***	0.07
	(0.07)	(0.03)	(0.11)	(0.10)	(0.05)	(0.05)	(0.06)	(0.06)	(0.04)	(0.05)
Observations	12,937	13,046	12,138	8,804	6,523	6,523	6,523	6,523	6,523	6,523
R-squared	0.716	0.736	0.646	0.758	0.738	0.737	0.738	0.739	0.738	0.739
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dept-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipalities	1092	1092	1092	1092	1092	1092	1092	1092	1092	109
Mean DV	4.354	4.419	4.453	3.934	4.428	4.428	4.428	4.428	4.428	4.428
SD DV	3.530	3.190	3.579	4.027	3.003	3.003	3.003	3.003	3.003	3.003

Notes: This table presents heterogeneous effects based on student, school, and municipality characteristics. *Cease* is a dummy that takes the value one for the period after 2014. *FARC* is a discrete measure that takes the value one for municipalities with attacks over population in the top-3 quartiles. *OAG* is a measure of exposure to other armed groups as in Prem et al. (2019a). *Mines victims* is a standardize measure of the number of victims related to mines. *Coca suitability* includes the standardize index for coca suitability from Mejía and Restrepo (2015) (*Continuous*) and a dummy for municipalities above the median of the empirical distribution (*Discrete*). *Coca eradication* is the total area air spayed during 2011-2014 over the the municipality area. The continuous measure is an standardized by the average and standard deviation, while the discrete is a dummy for municipalities above the median of the empirical distribution among the ones that experienced air spraying. Robust standard errors are clustered at the municipality level and presented in parenthesis. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE 8. Effects on school conditions

	(1) School resources		(3) School openings	(4)
	Student-teacher ratio	Teachers	Intensive margin	Extensive margin
Cease × FARC	-0.05	-4.74	0.42	-0.03
	(0.48)	(33.31)	(0.59)	(0.05)
Observations	6,519	6,523	6,523	6,523
R-squared	0.656	0.981	0.368	0.500
Municipality FE	Yes	Yes	Yes	Yes
Dept-Year FE	Yes	Yes	Yes	Yes
Municipalities	1092	1092	1092	1092
Mean DV	20.29	180	0.26	0.12
SD DV	5.26	246.2	2.75	0.32

Notes: This table presents results from our baseline specification in equation (4.1), but uses as a dependent variable the student-teacher ratio (Column 1), the number of teachers (Column 2) at the municipality level, the number of schools that open (Column 3), and a dummy for the opening of at least one school (Column 4). *FARC* is a discrete measure that takes the value one for municipalities with attacks over population in the top-3 quartiles. *Cease* is a dummy that takes the value one for the period after 2014. Robust standard errors are clustered at the municipality level and presented in parenthesis. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.
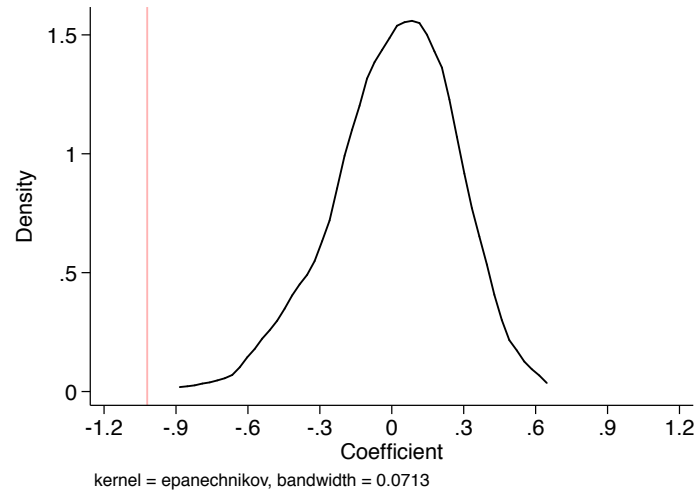
FIGURE A.1. **Distribution of placebo treatments**

A. At country level
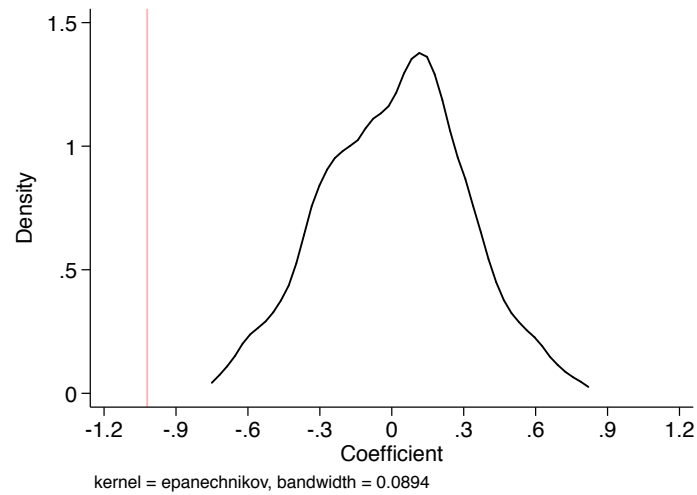
B. At department level

Notes: This figure presents the distribution of placebo treatments. Panel A randomize the assignment of a municipality to have FARC presence before the ceasefire using based on the number of municipalities highly exposed (74). Panel B does the same exercise but the assignment is based on the number of municipalities highly exposed within the department. We run the regressions using the specification from Column 5 in Table 3. The red line presents the coefficient of Column 5 of Table 3. In both cases the pvalue, i.e. the number of cases where the placebo effect shows a larger decrease in dropout after the ceasefire, is 0.

TABLE A.1. Changes in conflict

	No FARC			FARC		
	Pre	Post	Change	Pre	Post	Change
War actions (cases)	3.71	1.76	-53%	10.33	3.01	-71%
Selective Murders (cases)	2.26	1.79	-21%	4.09	2.52	-38%
Terrorists attacks (cases)	1.08	1	-7%	1.06	1	-6%
Damage to property (cases)	3.14	1.77	-44%	4.8	1.99	-59%
Forced disappearance (cases)	1.9	2.96	56%	2.11	1.08	-49%
Anti-personnel Mines (cases)	3.04	1.51	-50%	5.12	1.7	-67%
Recruitment (cases)	1.54	1.51	-2%	2.24	1.33	-41%
Kidnappings (cases)	1.63	1.28	-21%	2.67	2.21	-17%
Sexual Violence (cases)	1.77	1.29	-27%	2.41	1.59	-34%
War actions (victims)	2.17	1.37	-37%	4.84	2.42	-50%
Selective Murders (victims)	2.64	2.03	-23%	4.79	2.9	-39%
Forced disappearance (victims)	2.1	3.38	61%	2.37	1.08	-54%
Anti-personnel Mines (victims)	3.27	1.57	-52%	5.54	2	-64%
Massacres (victims)	5.49	5.5	0%	5.94	4.5	-24%
Recruitment (victims)	1.65	2.05	24%	2.41	1.44	-40%
Kidnappings (victims)	2.05	4.25	107%	4.01	3.92	-2%
Sexual Violence (victims)	1.79	1.29	-28%	2.48	1.59	-36%

Notes: This table presents the average number of cases and victims by type of attack for exposed and non-exposed municipalities to FARC violence as recorded by the *Centro Nacional de Memoria Histórica.* The *Pre* column presents the average between 2011 and 2014, while the *Post* column presents the average between 2015 and 2017. The column change presents the percentage change between the *Pre* and *Post*.

TABLE A.2. Dropout, FARC presence, and pre-ceasefire differential trends

Dependent variable: School dropout relative to pre-ceasefire level

	(1) Exposure to FARC attacks	(2) Highly exposed
Linear trend × FARC	-0.03	-0.09
	(0.04)	(0.13)
Observations	4,354	4,354
R-squared	0.755	0.755
Municipality FE	Yes	Yes
Dept-Year FE	Yes	Yes
Municipalities	1091	1091
Mean DV	4.719	4.719
SD DV	3.058	3.058

Notes: This table presents test for differential trends in the pre-ceasefire period. *Exposure to FARC attacks* is defined as FARC attacks over population, and is standardize by the mean and standard deviation to ease interpretation. *Highly exposed* is a discrete measure that takes the value one for municipalities with attacks over population in the top-3 quartiles. Robust standard errors are clustered at the municipality level and presented in parenthesis. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE A.3. Dropout, exposure to FARC violence, and ceasefire: Collapse before and after the ceasefire

	(1)	(2)	(3)	(4)	(5)	(6)
	Exposure to FARC attacks			Highly exposed		
Cease × FARC	-0.19***	-0.18**	-0.13**	-0.85***	-1.02***	-0.80***
	(0.07)	(0.07)	(0.06)	(0.24)	(0.27)	(0.23)
Observations	2,182	2,182	2,182	2,182	2,182	2,182
Municipalities	1091	1091	1091	1091	1091	1091
R-squared	0.881	0.889	0.895	0.882	0.891	0.897
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Dept-Year FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Mean DV	4.286	4.286	4.286	4.286	4.286	4.286
SD DV	2.566	2.566	2.566	2.566	2.566	2.566

Dependent variable: School dropout rate

Notes: This table presents the results from the main specification in equation (4.1), but we collapse the data before and after the ceasefire taking the average of the dependent variable. *Exposure to FARC attacks* is defined as FARC attacks over population, and is standardize by the mean and standard deviation to ease interpretation. *Highly exposed* is a discrete measure that takes the value one for municipalities with attacks over population in the top-3 quartiles. *Cease* is a dummy that takes the value one for the period after 2014. Columns 3 and 6 add predetermined municipal controls interacted with the ceasefire dummy. This controls include logarithm of the population in 2010, share of rural population, poverty index, and distance to the department capital. Robust standard errors are clustered at the municipality level and presented in parenthesis. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE A.4. Dropout, FARC presence, and ceasefire: Robustness to winsorization

	Dependent variable: School dropout					
	(1)	(2)	(3)	(4)	(5)	(6)
	Exposure to FARC attacks			Highly exposed		
Winsorization level:	1%	2.5%	5%	1%	2.5%	5%
Cease × FARC	-0.17**	-0.15**	-0.13**	-0.96***	-0.86***	-0.75***
	(0.07)	(0.07)	(0.07)	(0.26)	(0.26)	(0.25)
Observations	6,523	6,523	6,523	6,523	6,523	6,523
R-squared	0.740	0.745	0.749	0.742	0.746	0.750
Municipalities	1092	1092	1092	1092	1092	1092
Municipiality FE	Yes	Yes	Yes	Yes	Yes	Yes
Dept-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	4.425	4.425	4.425	4.425	4.425	4.425
SD DV	3.003	3.003	3.003	3.003	3.003	3.003

Notes: This table presents the results from the main specification in equation (4.1). The dependent variable is winsorized at 1%, 2,5%, and 5% to deal with potential outliers. *Exposure to FARC attacks* is defined as FARC attacks over population, and is standardize by the mean and standard deviation to ease interpretation. *Highly exposed* is a discrete measure that takes the value one for municipalities with attacks over population in the top-3 quartiles. *Cease* is a dummy that takes the value one for the period after 2014. Robust standard errors are clustered at the municipality level and presented in parenthesis. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE A.5. Relative dropout, FARC presence, and ceasefire

Dependent variable: School dropout relative to pre-ceasefire level

	(1)	(2)	(3)
		Relative to:	
	2011	2014	Avg 2011-14
Cease × FARC	-0.12**	-0.18*	-0.12**
	(0.05)	(0.10)	(0.05)
Observations	6,475	6,342	6,523
R-squared	0.565	0.601	0.289
Municipality FE	Yes	Yes	Yes
Year FE	No	No	No
Dept-Year FE	Yes	Yes	Yes
Municipalities	1084	1059	1092
Mean DV	0.915	1.473	0.970
SD DV	0.753	3.120	0.798

Notes: This table presents the results from the main specification in equation (4.1). The dependent variable is school dropout relative to pre-ceasefire dropout in the same municipality. We use as a denominator the dropout in 2011, 2014, and the average between 2011 and 2014. *Exposure to FARC attacks* is defined as FARC attacks over population, and is standardize by the mean and standard deviation to ease interpretation. *Highly exposed* is a discrete measure that takes the value one for municipalities with attacks over population in the top-3 quartiles. *Cease* is a dummy that takes the value one for the period after 2014. Robust standard errors are clustered at the municipality level and presented in parenthesis. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE A.6. Dropout and exposure to FARC violence before the ceasefire

Dependent variable: School dropout

	(1)	(2)	(3)	(4)	(5)	(6)
	Exposure to FARC attacks			Highly exposed		
Placebo Cease × FARC	-0.10	-0.09	-0.09	-0.26	-0.27	-0.27
	(0.08)	(0.07)	(0.07)	(0.31)	(0.26)	(0.26)
Observations	4,354	4,354	4,354	4,354	4,354	4,354
R-squared	0.756	0.786	0.786	0.755	0.786	0.786
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Dept-Year FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Municipalities	1091	1091	1091	1091	1091	1091
Mean DV	4.719	4.719	4.719	4.719	4.719	4.719
SD DV	3.058	3.058	3.058	3.058	3.058	3.058

Notes: This table presents the results from the main specification in equation (4.1) but for the pre-ceasefire period and uses as post period the sign of the first agreement between FARC and the government during the peace negotiation in Havana. *Exposure to FARC attacks* is defined as FARC attacks over population, and is standardize by the mean and standard deviation to ease interpretation. *Highly exposed* is a discrete measure that takes the value one for municipalities with attacks over population in the top-3 quartiles. *Placebo Cease* is a dummy that takes the value one for the period 2013 and 2014. Columns 3 and 6 add predetermined municipal controls interacted with the ceasefire dummy. This controls include logarithm of the population in 2010, share of rural population, poverty index, and distance to the department capital. Robust standard errors are clustered at the municipality level and presented in parenthesis. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE A.7. Dropout, exposure to FARC violence, and placebo ceasefire

	Dependent variable: School dropout	
	(1) Extensive margin	(2) Highly exposed
Cease $\times$ FARC	-0.44*	-0.93***
	(0.23)	(0.27)
Cease $\times$ FARC Neighbor	-0.25	-0.26*
	(0.16)	(0.15)
Observations	6,523	6,523
R-squared	0.736	0.737
Municipality FE	Yes	Yes
Dept-Year FE	Yes	Yes
Municipalities	1092	1092
Mean DV	4.428	4.428
SD DV	3.003	3.003
p-value H0: $\beta_1 = \beta_2$	0.57	0.04

Notes: This table presents the results from the main specification in equation (4.1) and adds an interaction term between municipalities neighboring municipalities affected by FARC and the ceasefire dummy. *FARC Neighbor* is a dummy that takes the value one if at least one neighbor of the municipality was affected by FARC violence pre-ceasefire. *Extensive margin* is a discrete measure that takes the value one for municipalities with at least one attack. *Highly exposed* is a discrete measure that takes the value one for municipalities with attacks over population in the top-3 quartiles. *Cease* is a dummy that takes the value one for the period after 2014. Robust standard errors are clustered at the municipality level and presented in parenthesis. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.