Violence and Children's Education: Long-Term Effects and Heterogeneity*

Valentina Duque
University of Michigan

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Abstract. This paper exploits the sharp escalation of violence in Colombia in the 1980s to investigate the long-run effects of violence on education, comparing siblings within the universe of students in the public school system. Results show that a higher homicide rate in the first years of life is associated with higher school dropout, lower educational attainment, and lower achievement test scores 20 years later. I also find evidence of heterogeneous impacts across outcomes and household SES. I discuss the findings through a model of human capital accumulation with violence and heterogeneous agents.

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1. Introduction

Academic success plays a central role on earnings and economic well-being (Card, 1999). There is clear evidence that individual, home, and school characteristics can each have causal impacts on educational outcomes (Black, Devereux, and Salvanes, 2007; Royer, 2009; Chetty et al., 2011; Deming et al., 2014). In this paper, I investigate one potentially important determinant of differences in academic outcomes: being born and growing up in a violent region. With recent onsets of violence across the world[1], a key task for researchers and policy makers alike is to analyze the effects of these shocks to better design policies that help mitigate the adverse effects on children's human capital.

While there is a growing evidence pointing to the contemporaneous effects of violence on individual's education, there is little research on the long-run cumulative impacts of early-life exposures to violence. This gap in the literature is particularly important because research has shown a strong relationship between early-life environments and future outcomes (Barker, 1998; Cunha and Heckman, 2007; Almond and Currie, 2011; Almond, Currie, and Duque, 2017).[2]

This paper is the first to link early-life violence and long-term educational outcomes using multiple sources of administrative data to study how violence exposure over the life-course, from in-utero to adolescence, is related to educational attainment and achievement at ages 17-24. I exploit a large and unprecedented rise in homicide rates in Colombia during the 1980s that was associated with the surge in drug trafficking (see Figure 1).Over the course of one decade, the homicide rate went from 0.3 homicides per 1,000 inhabitants to more than 0.8.[3] The escalation of crime was accompanied by a sharp spatial concentration of violence, with the wealthiest and more economically developed regions experiencing a dramatic ten-fold increase in homicide rates and with little change in violence in other places (see Appendix Figures 1 and 2).

To estimate the effects of violence on individual long-term outcomes, this paper exploits the temporal and geographic variation in homicides rates across municipalities-months-years and compares siblings within the same family who were exposed to varying levels of violence in their lives. The combination of a difference-in-difference strategy with a mother fixed-effect

[1]One out of nine children across the world are born and raised in countries affected by repeated cycles of criminal violence (UNICEF, 2016).

[2]Studies exploring how particular adverse in-utero and early childhood shocks such as famines and malnutrition, weather shocks, disease and pandemics, radiation fallout, and pollution affect human capital, have found significant declines on adult's health, educational attainment, and wages (Aguilar and Vicarelli, 2012; Almond, 2006; Almond, Edlund, and Palme, 2009; Bleakley 2007, 2010; Maccini and Yang, 2009; Almond and Mazumder, 2011; Van den Berg, Lindeboom, and Portrait, 2006).

[3]By the end of the 1990s, the homicide rate in the country was three times that of other particularly violent countries in the region such as Brazil or Mexico.

approach helps disentangle the effect of violence from other types of socioeconomic disadvantage that correlate with educational outcomes. I measure violence using the monthly-year and municipality homicide rate. Homicide rates are the primary threat to civilians, are highly correlated with the occurrence of other violent actions such as robberies, attacks, and explosions (Sanchez and Nunez, 2007), and are more reliable than other measures of crime, which are not always reported by the police (Levitt and Rubio, 2000).

Using Census data and two sources of school administrative records –the universe of students in public schools and the universe of the end-of-high school exam takers – merged to the universe of poor households in Colombia, allows me to observe long-term outcomes linked to location and exact date of birth for almost 300,000 individuals born in the 1980s in Colombia. The richness of the micro- and violence data enables me to measure violence exposures during key human capital developmental stages such as the 9-month in-utero period, the early and late childhood, and the primary-school and adolescence years. I focus on educational outcomes such as school dropout, years of schooling, and end-of-high school national standardized test scores that broadly capture persistent health, cognitive, and non-cognitive impacts caused by early-life exposure to violence, as well as any potential compensatory and reinforcing parental or school investments.

Results suggest that, an increase of a standard deviation in homicide rates in an individual's early-childhood (ages 0-3) is associated with a 6.3% increase in the probability of dropping out from high school, a 0.2 decline in years of schooling (a 1.9% decline with respect to the mean), a 0.17 decline in years of schooling post-high school graduation (a 1.4% decline with respect to the mean), and a 0.09 standard deviation decline in high school achievement test scores (a 0.9% decline with respect to the mean). These findings are robust to an extensive set of falsification tests and analyses of potential sources of selection bias.

I then examine the potential heterogeneity in the effects of violence shocks by mother's education (a Proxy for household socioeconomic status [SES]). Results indicate that violence reinforces students' outcomes relative to their expected outcome. For instance, while more disadvantaged students (the group most likely to drop out from school) experience a decline in the probability of completing primary (5^{th} grade) as violence increases, children born to mothers in the middle of the education distribution (the group that generally completes high-school) face a decline in high school completion, and high socioeconomic students (who are on average more likely to enter college) are less likely to accumulate more college years.

To help rationalize the empirical findings of the paper, I construct a simple theoretical model to study the effects violence shocks on educational choices across heterogeneous agents. In the model, violence affects the ability of individuals to accumulate human capital at school, and therefore decreases the returns to schooling relative to working in the labor market. As a consequence, the model predicts that, when comparing different groups of individuals who are exposed to different levels of violence, those that experience more violence would optimally accumulate less schooling, which is consistent with the empirical results. Moreover, the empirical findings provide evidence on the theoretical model's mechanism: Individuals who study and who are exposed to violence tend to have lower test scores, which suggest they accumulate less human capital. Finally the model also helps rationalize the results on heterogeneity across household socioeconomic status. In particular, the model predicts that if one focuses on a particular educational outcome (e.g., high school completion), only individuals around a certain socioeconomic level are affected by violence (i.e., and not very poor individuals who would always tend to drop out from school or very rich individuals who would always study).

This paper contributes to the related literature along several dimensions. First, to my knowledge, this is the first study to show the long-term effects of violence exposure over the life course on productivity at school as measured by test scores.[4] As discussed in the theoretical model, productivity at school can be a relevant mechanism driving the effects of violence on school attendance. I am able to estimate these effects due to the unique quality of the data that allows linking school records with census data and with information on the place and date of birth for the universe of low income households in Colombia.

Second, this is the first paper to document that different groups of children (measured by a mother's education) are affected by early-life shocks along different measures of school attainment (i.e., dropout, high school completion, college entrance). I show that these heterogeneous effects are consistent with a novel theoretical framework of human capital formation with violence shocks across heterogeneous agents. In addition to help rationalize the implications on educational outcomes across groups, the framework offers different pathways through which a child could be impacted by the shock. For instance, the fact that certain subgroups – i.e., children of low educated mothers who are exposed to violence shocks in early-life–, receive fewer

[4]This study complements recent evidence on the short-term impact of terrorist attacks on test scores (Bruck, Di Maio, and Miaari, 2014; Monteiro and Rocha, 2016; Rodriguez and Sanchez, 2012).

compensating later life investments could suggest that household budget constraints may likely be a mechanism.[5]

Third, this paper provides new evidence on the effects of violence on long-term educational outcomes exploiting variation within siblings exposed to different intensities of violence from in-utero up to age 15. Most of previous research has focused on more contemporaneous effects of violence (i.e., measuring the effects within the same year or within just a couple of years after the shock) and little is known about the persistent impacts of earlier exposures.[6] In addition, most of past studies do not account for mother fixed-effects, hence these studies are not able to control for household time-invariant characteristics that might be correlated with both the probability of residing in an area with high violence and with investing few resources on a child's human capital. I show here that not accounting for a mother fixed-effect can lead to potential biases in the estimates of violence.

This paper also relates to the literature that has explored the impacts of civil wars or internal conflicts on education, through its effects on (destruction of) infrastructure, economic losses, and teacher absence (Akbulut-Yuksel, 2014; Akresh and De Walque, 2011; Chamarbagwala and Moran, 2011; Leon, 2012; Shemyakina, 2011). Two additional differences between these studies and the present paper are that i) this research focuses on more disruptive forms of violence, which are often associated with economic and political turmoil and ii), these studies provide little evidence regarding the potential impacts of shocks on student achievement.

The study highlights the idea that environmental factors such as violence exposure, even if experienced indirectly and in low doses, can exacerbate existing inequalities, particularly education gaps. This paper also suggests the moderating role of family investments. While those who were exposed to more violence in their early life tend to have worse educational outcomes, family resources seems to moderate these effects.

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework. Section 3 briefly describes the historical elements associated with the rise in violence in Colombia in the 1980s. Sections 4 and 5 present the different sources of microdata and the empirical strategy, and Section 6 shows the findings of the effects of violence on education. Lastly, Section 7 performs some robustness tests to show that the results can be interpreted

[5]While previous research has documented changes in household resources as a possible pathway through which violence reduces human capital (Minoiu and Shemyakina, 2014), to my knowledge, this is the first paper to actually formalize this idea.

[6]Leon (2012) is an exception, that offered evidence on the effect of violence in the prenatal, early-childhood, primary school, and adolescence on years of education using data from Peru's civil conflict.

as lower-bound estimates of the impact of violence on education and section 8 provides a brief conclusion.

2. Theoretical Framework

In this section, I construct a theoretical framework to analyze the effects of violence shocks on educational outcomes. The model builds on several earlier contributions in related literatures including the work by Becker (1964), Card (1999, 2001), Cunha and Heckman (2007), and Almond, Currie, and Duque (2017).

I consider a simple environment in which individuals' human capital is determined by their choice of school attendance, their initial individual abilities, and their parental background and investments. The choice of school attendance can be related to the empirical results analyzed in the subsequent sections of the paper.

The model has three periods, $t = 0, 1, 2$. Period 0 is aimed at capturing an initial stage (e.g., in-utero and childhood) in which individuals are exposed to different levels of violence, denoted v_0; period 1 is a stage in which individuals accumulate human capital or work in the labor market (e.g., from age 15 to 24); and period 2 a later stage in which they all work (e.g., after age 24). To formalize this, it is assumed that individuals are endowed with a unit of time in periods 1 and 2. In period 1, the unit of time can be dedicated to accumulate education or to work in the labor market and earn a wage. In period 2, the individual can only dedicate her time endowment to labor market activities. In period 1 individuals are also endowed with an income transfer, which could represent an income transfer from the parents to the child. This transfer introduces the variation across individuals in terms of their socioeconomic status (i.e., high SES families transfer higher income to their children than low SES families). In both periods individuals consume.

In period 1 the individual has access to the following technology to accumulate education (similar to Cunha and Heckman, 2007):

$$h_{i,2} = g(s_{i,1}, \theta_{i,1}, X_i, I_{i,1}), \tag{1}$$

where $h_{i,2}$ denotes the level of education of individual i at the beginning of period 2, $s_{i,1}$ denotes the choice of school attendance in period 1, which takes the value of 1 if the individual attends school and 0 otherwise; $\theta_{i,1}$ is a variable representing the individual's skills or abilities in period 1 (higher values of $\theta_{i,1}$ stand for higher levels of skills), X_i is a variable summarizing parental characteristics (e.g., mother's SES; higher values of X_i stand for higher SES), and

$I_{i,1}$ are parental investments in a child's human capital in period 1 (e.g., parenting). I assume that all individuals who do not attend school have an education level $\underline{h}$, i.e., $g(0,\theta,X,I) = \underline{h}$ $\forall\{\theta,X,I\}$ and $h_{i,1} = \underline{h}$ $\forall\{\theta,X,I\}$; and that individuals who attain school achieve a higher level of education than those who do not attain school $g(1,.) > g(0,.)$ $\forall\{\theta,X,I\}$. Finally, as standard, I assume that $\frac{\partial g(1,\theta,X,I)}{\partial \theta} > 0$ ("self-productivity" as in Heckman [2007]), $\frac{\partial g(1,\theta,X,I)}{\partial X} > 0$, and $\frac{\partial g(1,\theta,X,I)}{\partial I} > 0$.

It is assumed that an individual's period 1 abilities, $\theta_{i,1}$, and parental investments, $I_{i,1}$, depend on violence experienced in period 0, v_0:

$$\theta_{i,1} = \Theta(\theta_{i,0}, X_i, I_{i,0}, v_{i,0}), \qquad I_{i,1} = \mathcal{I}(\theta_{i,0}, X_i, I_{i,0}, v_{i,0}). \tag{2}$$

As standard, I assume that period 1 abilities and parental investments monotonically increase with socioeconomic status: $\frac{\partial \Theta(.)}{\partial X_i} > 0$ and $\frac{\partial \mathcal{I}(.)}{\partial X_i} > 0$.[7] I further assume that the individual's abilities are negatively affected by violence ($\frac{\partial \Theta(.)}{\partial v_0} < 0$), capturing the empirical findings documenting that early-life exposure to violence can affect child's health, cognitive, and non-cognitive outcomes (Duque, 2017).[8] Regarding parental investments, it can be the case that parents could respond by compensating ($\frac{\partial \mathcal{I}(.)}{\partial v_0} > 0$) or reinforcing the initial violence shock ($\frac{\partial \mathcal{I}(.)}{\partial v_0} < 0$) (see Almond and Mazumder, 2013, and references therein). However, I assume that even if parents try to compensate the negative effects of violence on their child's human capital, they are not able to fully compensate these effects, i.e., $\frac{\partial g(1,\theta,X,I)}{\partial v_{i,0}} < 0$ $\forall\{\theta,X,I\}$ (which is consistent with the empirical evidence found in subsequent sections).[9]

It is assumed that the wage that an individual obtains from working in the labor market is related to her human capital:

$$w_{i,t} = f(h_{i,t}), \tag{3}$$

where $w_{i,t}$ is the individual i's wage in period t measured in terms of consumption goods, and $f(.)$ is a differentiable and increasing function, with $f(\underline{h}) = \underline{w} > 0$. Equation (3) can be thought as a production function or a function relating an individual's wage to her human capital acquired in period 1 (Becker, 1964; Card, 2001). These assumptions imply that, if the

[7] Previous empirical studies have documented these relationships (see, for instance, Carneiro, Meghir, and Parey (2012) and Currie and Moretti (2003)).

[8] In Section 6, I discuss in detail the potential mechanisms through which violence can reduce individual human capital. In particular, I refer to stress, nutrition, household resources, and supply-side mechanisms (e.g., school-infrastructure).

[9] Note that this assumption imposes an upper bound on parental compensatory responses:

$$g_4\left(1,\theta_{i,1},X_i,I_{i,1}\right)\mathcal{I}_4(\theta_{i,0},X_i,I_{i,0},v_{i,0}) < g_2\left(1,\theta_{i,1},X_i,I_{i,1}\right)\Theta_4(\theta_{i,0},X_i,I_{i,0},v_{i,0})$$

.

individual drops out from school (i.e., $s_{i,1} = 0$), she will perceive a lower wage than if she attends school. Let $\mathcal{W}(\theta_{i,1}, X_i, I_{i,1}) = f(g(1, \theta_{i,1}, X_i, I_{i,1}))$ denote the wage in period 2 if the individual attends school.

The individual has preferences defined over consumption in periods 1 and 2 of the following form:

$$U = \log(c_{i,1}) + \beta \log(c_{i,2}) \tag{4}$$

where $\beta \in (0, 1)$ is the subjective discount factor and $c_{i,t}$ denotes consumption of individual i in period t.

The budget constraint of the individual in period 1 is given by:

$$c_{i,1} = y_{i,1} + \underline{w}\mathbb{I}_{\{s_{i,1}=0\}}, \tag{5}$$

where $y_{i,1}$ is the income transfer to individual i in period 1 that is assumed to be increasing in X_i, and $\mathbb{I}$ is the indicator function. For simplicity I have assumed that the individual does not have access to borrowing between period 1 and 2 (this assumption can be particular relevant for low income families in a developing country such as Colombia). In period 2 her budget constraint is given by:

$$c_{i,2} = \underline{w}\mathbb{I}_{\{s=0\}} + \mathcal{W}(\theta_{i,1}, X_i, I_{i,1})\,\mathbb{I}_{\{s=1\}}. \tag{6}$$

The individual i's problem is to choose $s_{i,1}$ to maximize (4) subject to (1), (2), (3), (5), and (6), taking as given $\{v_{i,0}, \theta_{i,0}, X_i, y_{i,1}\}$.

To determine the individual's optimal school-attendance decision, note that the value of attending school is given by:

$$V^s(y_{i,1}, \theta_{i,1}, X_i, I_{i,1}) = \log(y_{i,1}) + \beta \log(\mathcal{W}(\theta_{i,1}, X_i, I_{i,1})). \tag{7}$$

And the value of dropping out from school is, in turn, given by:

$$V^d(y_{i,1}) = \log(y_{i,1} + \underline{w}) + \beta \log(\underline{w}). \tag{8}$$

The individual will find optimal to drop out from school if $V^d(y_{i,1}) \geq V^s(y_{i,1}, \theta_{i,1}, X_i, I_{i,1})$. Operating in (7) and (8) one can show that this implies that the individual will drop out from school if

$$y_{i,1} \leq y_i^* \equiv \frac{\underline{w}}{e^{\beta}\left(\frac{\mathcal{W}(\theta_{i,1}, X_i, I_{i,1})}{\underline{w}}\right) - 1}. \tag{9}$$

Therefore, the optimal decision takes a threshold form, in which if the individual's income is below y_i^* she will drop out from school.

A simple implication of this model is that the higher the X_i, the more incentives an individual has to accumulate more education. This implication is consistent with empirical evidence that shows that individuals with more socioeconomic status (e.g., mother's education) study more (Section 6 shows these results).

We can now characterize the effect of violence on education:

PROPOSITION **1.** *Let $G(\theta_{i,0}, X_i, I_{i,0}, v_{i,0})$ denote the c.d.f. of initial conditions across individuals, and $\mathbb{E}(s_i|v)$ the mean level of education across individuals conditional on a level of violence $v_0 = v$. As violence increases, the proportion of individuals accumulating education declines: $\frac{\partial \mathbb{E}(s_i|v)}{\partial v} < 0$.*

Proof. See Appendix B. □

The intuition behind this proposition is that violence affects the productivity of an individual at school: the higher the level of violence, the lower the level of education that an individual accumulates at school, and therefore the lower the wage she would earn if she studies. Hence, a higher share of individuals will drop out from school when exposed to initial violence. Consistent with this result, Section 6 provide evidence that as violence increases, the average years of schooling declines.[10] Moreover, the empirical results provide evidence of one potential mechanism: As violence increases, test scores decline, suggesting that individuals who study and who are exposed to violence accumulate less human capital.

With the model we can also study heterogeneity in the effects of violence on education across individuals. Figure 2 shows the distribution of years of schooling by mothers' education, which illustrates that children in high SES families accumulate more education than children in low SES households. In relation to this fact, the model would predict the following:

PROPOSITION **2.** *There exists an X^H for which if $X_i \geq X^H$, $s_{i,1} = 1\ \forall v_0$, and an X^L for which if $X_{i,1} \leq X^L$, $s_{i,1} = 0\ \forall v_0$. Hence v_0 will affect $s_{i,1}$ only for $X_i \in [X^L, X^H]$.*

Proof. See Appendix B. □

The result derived above implies that, violence only seems to affect the decisions on 'how much education to accumulate' for a particular group for which these decisions are binding

[10]Previous studies on the effects of violence on educational attainment have documented a decline in years of schooling (Akbulut-Yuksel, 2014; Akresh and De Walque, 2011; Leon, 2012; Shemyakina, 2011).

(i.e., for those around a certain income threshold). This is because, independently of the level of violence (assumed to be bounded $v_0 \in [\underline{v}, \overline{v}]$), if income is very high, individuals will always study, and if income is sufficiently low, individuals will never study.

Results presented in the empirical section show the following patterns as violence increases: i) low SES children are more likely to drop out from primary school (5^{th} grade); ii) high SES students are more likely to accumulate fewer years of college; and iii), middle SES students are less likely to complete high school (11^{th} grade) (and among those who complete high school, students are less likely to obtain a better grade in the end-of-high-school exam).

3. Background

In this section, I briefly describe the historical elements associated with the rise in violence in Colombia in the 1980s, which was closely related to the rise in drug trafficking from Colombia to the U.S. (Castillo, 1987). Following previous studies, police reports, and newspaper articles, I highlight three key factors that contributed to this rise.[11]

First, there was a dramatic increase in the international demand for cocaine in the early-1980s (United Nations Office on Drug and Crime, 2012). This increase coincided with the introduction of crack cocaine in the U.S. markets – a cheap, addictive, and potent form of cocaine–, which represented an important technological change that lowered the price of illicit substances (i.e., cocaine) and expanded the market to a wider range of consumers (Fryer et al., 2013).[12]

Second, following the shift in the demand for cocaine (mainly from the U.S.), there was a rapid response in the supply of cocaine. Colombian traffickers of cannabis who by the late 1970s and early 1980s were smuggling small quantities of marijuana to the U.S., found enormous economic incentives in the "cocaine boom" of the mid 1980s (UNODC, World Drug Report, 2012; Castillo, 1987; Thoumi, 2002). Three factors were crucial to understand the smooth transition of Colombian marijuana traffickers to the cocaine industry: i) they already knew potential transportation routes to move drugs from South America to the U.S.; ii) they already had access to important distribution networks in some of the largest U.S. cities (e.g., Miami,

[11] I should note that this paper focuses on the spike in homicide rates in the 1980s and hence excludes from the analysis the intensification of Colombia's armed conflict, which took place more than a decade after the period of interest considered here. A number of studies have examined the impacts of the armed conflict in the late 1990s and early 2000s on human capital outcomes (e.g., Camacho, 2011; Duque, 2017; Rodriguez and Sanchez, 2012).

[12] Los Angeles Times (September 20, 1987) "Rising 'Crack' Epidemic: Colombia Now Stung by Curse of Cocaine": http://articles.latimes.com/1987-09-20/news/mn-8919_1_epidemic-proportions.

New York, and Los Angeles); and iii) they were strategically close to coca-leaf producing markets such as Bolivia and Peru.

Colombia only became a major coca leaf producer by the end of the 1980s (Sanchez, 2007), so in the early 1980s, these trafficking organizations outsourced the coca paste from neighboring Andean countries that had historically produced it by its indigenous groups. The paste was later processed into pure cocaine in local laboratories and then transported to the U.S. (the main destination) and Europe (Castillo, 1987; Thoumi, 2002). The business grew so fast that by 1991, more than 80 percent of the cocaine that reached the United States had been produced in Colombia (Borrell, 1988; Gaviria, 2000; The Economist, December 24, 1994; El Espectador, November 26, 1986). Both the enormous profits derived from the drug industry and the attempts made by drug organizations to enforce their 'property rights', converted these small traffickers into powerful and violent drug cartels. One example was the famous Medellin cartel, led by the drug lord Pablo Escobar.

A third factor associated with the rise in violence in the 1980s was the rapid transfer of criminal knowledge and criminal technology from drug traffickers to local criminals (Gaviria, 2000).[13] In sum, the combination of these factors with an increasing tension between drug cartels and the Colombian authorities[14], resulted in the massive rise in homicide rates observed in the 1980s (see Figure 1).

One noteworthy characteristic of the rise in violence during this period was that not all regions in the country experienced the same intensity in violence (see Appendix Figure 2). For instance, while Medellin and Cali, the country's second and third most important cities, faced an increase in homicide rates of 700% (going from 0.5 to 4 homicides per 1,000 inhabitants in 1980-91) and 300% (going from 0.3 to 1.2 homicides per 1,000 inhabitants in 1980-91), respectively, other important cities such as Tunja or Neiva experienced little or no change in violence. The concentration of homicide rates in large and wealthy areas was explained, for the most part, by the fact that the cocaine industry was headquartered in these areas (Gaviria, 2000) (see Appendix Figure 2).

In this paper, I exploit the monthly-year-municipality level variation in homicide rates associated with the drug boom of the 1980s and the variation in violence exposure across siblings,

[13]Gaviria argued that, "local criminals benefited from the cocaine cartels expertise in international crime operations. For instance, they learned from the cartels operations how to buy arms in international black markets, launder illegal money, make explosives, etc." (p. 16).

[14]That included a bloody campaign of bombings and the killing of some of Colombia's leading figures (Gaviria, 2000).

which allows me to identify with greater precision the effects of violence on education, net of other potential confounders and omitted variables.

4. Data

4.1. *Microdata*

The richness of the data is one of the major strengths of this study. I use several sources of large-scale micro data for the analysis: the 2005 population Census, the universe of students in Colombia's public school system, the universe of Icfes exam takers, and the 2005 "universe of the poor". I describe each of these datasets below.

4.1.1. *The 2005 Population Census*

The Census was obtained from IPUMS - International (Minnesota Population Center, 2011)[15]; it includes basic demographic and socioeconomic characteristics for a 10% representative sample of the total population (the sample is 4 million individuals in total), as well as several indicators of educational attainment (i.e., school grade, years of schooling, etc.). In addition to providing a large sample of individuals and being nationally representative, the Census has the virtue of reporting the exact date and municipality of birth for each individual, as well as the municipality where an individual's mother lived while she was pregnant, which enables me to identify the level of violence to which a person was exposed during his/her early life.[16]

In addition to using the Census, I employ the following three sources of administrative data:

4.1.2. *The Universe of Students in Colombia's Public Schools: the R-166*

The first source of administrative data is the core database of the Ministry of Education that reports school progression records at the individual-year levels. This dataset began with the 'Resolution 166' of 2004 that mandated the Ministry to collect and report detailed information on the school progression of all students enrolled in the public school system in Colombia, starting in the first year a child entered the school system (e.g., first grade) up to high school graduation (or dropout).[17] [18] In this paper, I use the universe of students in R-166 from 2005

[15]The Census can be accessed here: https://international.ipums.org/international/.
[16]A potential limitation of the Census is that, it does not contain individual identifiers that could allow linking individuals across other datasets.
[17]More information on this resolution is found here: http://www.mineducacion.gov.co/1759/w3-article-163147.html.
[18]The school cycle is divided into three categories: basic primary (grades one through five), basic secondary (grades six through nine), and middle secondary (grades ten and eleven). After finishing 11^{th}th grade, students can enroll in college. Students usually start school at ages 5 to 7, and the minimum mandatory school level for students is 9^{th} grade, a period referred to as basic education.

to 2012 (approximately 82 million student-year observations). A unique advantage of using the R-166, is that these are the only administrative data that include information on the exact municipality of birth for each student.

4.1.3. *The End-of-High School Exam: the Icfes*

The second source of administrative data is the Icfes national high school exit exam provided by the *Institute for the Promotion of Higher Education*, the former acronym for the agency that administers the exam.[19] The Icfes is similar to the SAT in the U.S. It is taken by high school seniors regardless of whether they intend to apply to college and it includes separate tests on math, Spanish, social studies, sciences, and an elective subject. I use information on all students who took this exam from 2000 to 2009 (approximately one million observations).

4.1.4. *The "Universe of the Poor": the Sisben*

Lastly, I use the core data of Sisben 2005 which provides information on a student's household characteristics. The Sisben is a proxy means test index used as a targeting mechanism for social programs in Colombia. It serves as an indicator of households economic well-being and is based on a cross-section sample of Colombian low-income households. The Sisben is usually referred to as the "census of the poor" or the "universe of the poor". This dataset include demographic and socioeconomic information on 33 million people (60% of the total population).[20]

I use students' and their parents' full names (first and middle names and fathers' and mothers' maiden names), birth dates (day, month, year), and national identifications (type of ID document and number) to link individuals (and their families) across R-166, Icfes, and Sisben datasets. Since the Census data do not provide individual-level identifiers that could allow matching it with the administrative data, I conduct separate analysis on the Census and on the Administrative sample.

4.2. *Sample of Interest*

I focus on individuals between 17 and 24 years of age (i.e., those who were born in the 1980s in Colombia). I restrict the sample to these ages because these are the oldest cohorts in my sample, considering that the data on violence starts in 1979. I also restrict the sample to individuals with exact date and municipality of birth. The sample of interest in this paper includes 142,000 individuals in the Census and 241,000 in the administrative data.

[19]More than 90% of high school graduates take the Icfes exam.
[20]Colombia's population is around 45 million.

4.2.1. *Outcome Variables*

The following list describes the outcomes of interest:

(1) Primary completion, a dummy variable, takes the value of one when an individual has finished 5^{th} grade and zero otherwise.
(2) High school graduation, a dummy variable, takes the value of one when an individual has finished 11^{th} grade and zero otherwise.
(3) Years of schooling, a discrete variable, indicates the total number of completed years of education that an individual has attained.
(4) Years of schooling conditional on high school graduation, a discrete variable that indicates the total number of completed years of education after an individual has attained high school (serves as a Proxy for college entrance).
(5) End of high school test score (Icfes score), a continues variable that ranges from 0 to 100 indicating the Icfes test score.

Appendix Table 1 shows summary statistics on the sample of 17-24 year olds and their families, in both the Census and Administrative data. These statistics show that that mothers in the Census tend to be older, have more education, are more likely to be married, to live in urban areas, and to own their home. These differences are explained by the fact that the administrative data (i.e., Sisben) is representative of the low-income population of Colombia. The bottom of Appendix Table 1 shows outcome means. Eighty-eight percent of the sample completes 5^{th} grade, while only 50% graduates from high school. On average, students accumulate 9.1 years of schooling (3 more years than their mothers), and among those who finish HS, the average years of schooling is 11.9. In terms of educational achievement, the average Icfes score is 43.0 (with standard deviation 4.1).

4.3. *Data on Violence: Homicide Rates*

Data on violence come from two sources. First, the National Police Department that provide annual homicides that occurred in each of the 1,100 municipalities in Colombia since 1979.[21] Second, I use data from Vital Statistics Death Records which includes the number of violent deaths (homicides) that occurred in each municipality at the monthly level. Based on these two sources (annual level and monthly level) and information on municipality-year population statistics, I construct measures of homicide rate that are defined as total number homicides

[21]Information on homicide rate prior to 1979 is not available at the municipality-year level.

per thousand inhabitants in a given municipality in a given year or in a given trimester (of pregnancy).[22]

4.3.1. *Exposure to Violence During Critical Stages of Human Capital Formation*

Following previous research in developmental psychology, epidemiology, and more recently in economics, focused on sensitive periods for skill formation (Gluckman and Hanson, 2005; Heckman, 2008; Knudsen et al., 2006; Thompson and Nelson, 2001), I construct seven measures of violence exposure over the life-course: three measures for the prenatal period (one for each trimester using the trimester homicide rates), and four measures for the postnatal period: one for early childhood (ages 0-3), one for late childhood (ages 4-6), one for the primary school years (ages 7-11), and one for early adolescence years (ages 12-15).[23]

Appendix Table 2 shows descriptive information on these violence measures. On average, the sample of ages 17-24 was exposed to 0.4 homicides per 1,000 inhabitants in each of the three trimesters of pregnancy, to 0.5 homicides per 1,000 inhabitants in early childhood (ages 0 to 3), to 0.66 homicides per 1,000 inhabitants in late childhood (ages 4 to 6), to 0.66 homicides per 1,000 inhabitants in the preschool years (ages 7 to 11), and to 0.65 homicides per 1,000 inhabitants in early adolescence (ages 12 to 15).

5. Methods

I estimate the effects of violence over the life-course on educational outcomes at ages 17–24 using two models, one that controls for a rich set of covariates, and one that accounts for time-invariant mother characteristics. Equation 10 describes the first model:

$$Y_{ijdmt} = \beta_0 + \sum_{q=1}^{3} \beta_q^u Violence_{jmt}^{trim_q} + \sum_{r=1}^{4} \beta_r^c Violence_{jmt}^{childhood_r} + \gamma \mathbf{X_i} + \alpha_\mathbf{j} + \alpha_\mathbf{m} + \alpha_\mathbf{t} + \theta_\mathbf{d}(\mathbf{t}) + \epsilon_\mathbf{ijdmt}, \tag{10}$$

[22] I need the second source of information on homicides in order to construct measures of violence exposure at the trimester (i.e., of pregnancy) level.

[23] To identify each trimester of pregnancy I count backwards nine months from the date of birth of the child. Since I do not have information on the duration of pregnancy (i.e., gestation weeks), I also test my results assuming that the child was born prior to completing his/her nine months of pregnancy (i.e., 8 months) (results are substantially similar to assuming a nine-month gestational period). Similarly, I construct measures for early and late childhood, and for the primary school years, by taking an average of the municipality-year homicide rate during a child's 1st, 2nd, and 3rd years of life (early childhood), during a child's 4th, 5th, and 6th years of life (late childhood), during a child's 7th up to 11th years of life (primary school years), and during a child's 12th up to 15th years of life (adolescence years).

where the subscript i refers to an individual, j municipality of birth, d department of birth, and m and t to the month and year of birth. The variable $\boldsymbol{Y}$ denotes the educational outcome. $Violence^{trim_1}$, $Violence^{trim_2}$, and $Violence^{trim_3}$ represent the level of violence (homicide rate) to which a child was exposed to during the first, second, and third trimesters of pregnancy, and $Violence^{childhood_1}$, $Violence^{childhood_2}$, $Violence^{childhood_3}$, and $Violence^{childhood_4}$ represent the level of violence during early (ages 0-3) and late (ages 4-6) childhood, and during primary school (ages 7-11) and early adolescence (ages 12-15). X includes a set of child characteristics such as gender, race, and age dummies (17, 18–19, 20–22, 23+), as well as dummies for mother's age in years (less than 35, 36–45, 44–55, 55+), education (no education, completed primary or less, HS or less, more than HS), marital status (married, cohabiting, single, other), whether the household is a homeowner, and whether it lives in the urban sector. In addition to these controls, models that use the administrative data also control for whether the household has access to piped water and sewage, household size, and dummies for the age and the calendar year at which a student took the Icfes exam, and for school schedule (full time, morning, evening, night, or weekend). The terms α_j, α_t, and α_m are fixed effects at the municipality, year, and month of a child's birth. The geographic fixed effects help absorb time-invariant differences at the municipality level while the time fixed effects absorb factors that vary over time but are invariant to the municipalities. For example, α_j helps account for constant differences in poverty level across municipalities. The term $\theta_d(t)$ represents department-specific linear and quadratic time trends that control for differences in economic development across regions that change over time (e.g., investments in health services) and that could potentially affect human capital investments. These trends also allow me to account for differential trends in education across departments over the time period of analysis. ε is the random error term. Errors are clustered at the municipality level to account for within-municipality serial correlation in the observations. The key coefficients of interest are $\beta_1^u - \beta_3^u$ and $\beta_1^u - \beta_4^c$, as they describe the impacts of violence in each trimester of pregnancy and from birth up to age 15.

The second model controls for mother fixed-effects and is estimated using equation 11. The only covariates included in this model are child's gender and age in month dummies (in matrix $\tilde{X}$), municipality, year, and month of a child's birth dummies, and municipality time trends. The term μ_f indexes families.

$$Y_{ijdmt} = \sum_{q=1}^{3} \beta_q^u Violence_{jmt}^{trim_q} + \sum_{r=1}^{4} \beta_r^c Violence_{jmt}^{childhood_r} + \gamma \tilde{\mathbf{X}}_\mathbf{i} + \alpha_\mathbf{j} + \alpha_\mathbf{m} + \alpha_\mathbf{t} + \theta_\mathbf{d}(\mathbf{t}) + \mu_(\mathbf{f}) + \epsilon_\mathbf{ijdmt}, \tag{11}$$

This model exploits the sample of siblings in both Census and Sisben data to control for observed and unobserved time-invariant characteristics of the mother (and family), which may be correlated with both the probability of residing in a municipality with high violence and with experiencing "worse" educational outcomes. For instance, if a family belongs to a demographic group that is likely to be particularly impacted by violence, the family may also be less likely to invest in their child's health and education. Hence, the identification in this framework, would come from differences in violence exposure between siblings from the prenatal period up to age 15.

Finally, to examine heterogeneous impacts by mother's education, I stratify the sample by children in households where the mother has no education, primary or less, high school or less, or more than high school. I focus on these four groups because these are the relevant margins for maternal education to affect child investments in developing countries.[24]

6. Results

6.1. *Mother Characteristics and Violence Exposure*

Before estimating the long-run effects of violence on education, I examine the associations between mothers' characteristics and violence exposure over a child's life that provide information on potential sorting across families. Table 1 shows that there are some observable differences between mothers who are exposed to different levels of violence in their child's life. For example, column 1 suggests that mothers in my sample who are aged 35 or below, were more likely to be exposed to a high homicide rate in the year before conception. Also, as violence increases during a child's late childhood (ages 4-6), the proportion of young mothers (i.e., age 35 or less) decreases. Column 4 indicates that violence in the third trimester and at ages 4-6 is associated with a higher proportion of uneducated mothers (i.e., with primary education or less) and in column 6, that the proportion of highly educated mothers falls as violence increases when the child is between 7 and 11 years old. In sum, these results show that in the cross-section, violence is associated with mothers' age, education, and with being single. These differences highlight

[24]Also, the Sisben data only report mothers' education in these four categories.

the need to include maternal fixed effects to limit comparisons to differences across siblings to the same mother.

6.2. *School Dropout and Educational Attainment*

Table 2 shows the effects of violence on the probability of completing primary education (5^{th} grade) and high-school (11^{th} grade), and on years of schooling and years of schooling conditional on high school completion (a Proxy for college years of education), using OLS and mother fixed-effects models in the Census. I only report the coefficients of interest, however, all models include the covariates described in equations 10 and 11.

Overall, results show that violence exposure increases dropout rates and reduces educational attainment and that the effects are particularly concentrated during childhood, from birth up to age 6. For instance, results on HS completion in column 3 indicate that if violence increases by a standard deviation (SD) at ages 0 to 3, the probability that a 20 year old graduates from HS falls by 6.3%[25] whereas if the increase in violence occurs at ages 4-6, the effect would be 5.4%. To facilitate the interpretation of the effects, the bottom of Table 2 reports what would be the percent decline for each outcome given a one SD increase in homicide rate at ages 0 to 3.

Comparing the OLS and mother FE estimates shows that, while on average the two sets of results are similar in magnitude and qualitatively tell the same story, there are some marked differences for some of the outcomes. For instance, the mother fixed-effects results on primary completion shown in column 2 suggest that, changes in violence occurring during the first trimester of pregnancy as well as during ages 4-6 significantly reduce primary completion, which contrasts with the OLS result in column 1 in which violence in the third trimester as well as in the period from birth up to age 11, adversely impact the outcome. Moreover, the magnitude of the effect of violence at ages 4-6 has almost doubled with respect to the OLS estimate. The mother fixed-effect result implies that children who were exposed to a SD increase in violence at ages 4-6 experience a 1.8% decline in primary, while in the OLS model this effect is 1.0%.

Hence, this finding reinforces the idea that in order to appropriately identify the effect of violence on children, it is important to control for maternal fixed-effects that eliminates the time-invariant component of the unobserved heterogeneity that exists between mothers that are facing differing levels of violence during pregnancy.

[25]To calculate this effect, I multiply a one standard deviation increase in violence at ages 0-3 (that according to Appendix Table 2 is 0.55 homicides per 1,000 inhabitants), times the coefficient (-0.057), and divide this number by the outcome mean (0.50), which is also shown in Table 2.

Using the mother fixed-effects specification, I find that as violence increases by a SD in early childhood (ages 0-3), HS completion, years of schooling, and years of schooling conditional on high school completion fall by 6.3%, 2% (equivalent to 0.2 years decline), and 1.4% (equivalent to 0.2 years decline) (respectively), with respect to the mean.

In terms of the theoretical framework developed in Section 3, this finding provides empirical support for Proposition 1, that: $\frac{\partial \mathbb{E}(s_i|v)}{\partial v} < 0$.

Of note is the null effect of homicide rates two and three years prior to birth, which provides support for the identification strategy.

How do these estimates compare to those in the literature? In terms of the magnitude of the effects, I find that my estimates are in the range of those found in the literature although smaller. For instance, among those studies examining effects of school-age exposure to war, Akresh and de Walque (2011) found that children exposed to Rwanda's 1994 genocide achieved 0.5 fewer years of schooling as adults; Shemyakina (2011) found effects of 0.6 years for the case of Tajikistan's civil conflict; Rodriguez and Sanchez (2012) focusing on Colombia's armed conflict during the 1990s, found effects of 0.2 years; and Chamarbagwala and Moran (2011) using data on Guatemala's conflict, found a decline between 0.12 and 1.09 years. Fewer studies have focused on prenatal or early childhood exposures. To my knowledge, Leon (2012) for the case of Peru's civil conflict, provided the first evidence on long-term impacts of violence on education, which indicated that, individuals who were exposed since prior to birth, experienced a significant decline in years of education of at least 0.3.

6.3. *Educational Achievement*

Table 3 shows OLS and mother fixed-effects estimates of violence on school achievement using administrative data. Results show that violence exposure at ages 0-3 reduces the Icfes test score and that controlling for a mother's time invariant characteristics, leads to a larger decline in the outcome. In particular, column 1 shows that as the homicide rate increases by a standard deviation at ages 0-3, the Icfes falls by 0.02 standard deviations (OLS specification) while column 2 suggests a 0.09 SD decline after accounting for a mother's FE.

Comparing the effects of violence on educational achievement (Icfes score) with those found on educational attainment (HS completion, years of schooling, etc.), I find that despite using two different datasets (i.e., Census vs. administrative records) and focusing on two different sets of outcomes and perhaps different segments of the population (i.e., the Sisben only focuses on the low-income households), the timing in which these exposures tend to affect the outcome

is strongly consistent (i.e., the largest impacts are found in childhood), suggesting the presence of critical stages of human capital formation.

In light of the theoretical framework, this empirical findings could be interpreted as one potential mechanism driving the effects of violence on school dropout and lower educational attainment, which is lower student productivity at school.

To my knowledge, this is the first paper to actually show that violence experienced in early-life can have persistent impacts on individual's productivity as measured by achievement test scores. While previous research has shown short-term impacts, it was unclear whether these effects could last over time. For instance, Rodriguez and Sanchez (2012), for the case of Colombia, found that high school exposure to (a 1 SD increase in) violent attacks perpetrated by armed groups in the late 90s and early 2000s, reduced Icfes test scores by three quarters of a SD. Bruck, Di Maio, and Miaari (2014) exploiting the temporal and geographic variations in the intensity of the Palestine-Israel's conflict from 2000 to 2006, found that within a year exposure to a 1 SD increase in the number of fatalities experienced during high school reduced the probability of passing the end of high-school exam in that same year by 1%. Lastly, Monteiro and Rocha (2016) for Brazil, found that exposure to gang violence at the favela level, reduced students (5^{th} graders) math test scores by 0.054 SD in the same academic year.

6.4. *Potential Mechanisms*

Previous research has shown that violence can affect child development through a number of mechanisms that could help explain the timing of the effects shown in Tables 2 and 3. First, violence is a major source of stress that could affect mothers and children's health and health behaviors through stress, anxiety, or changes in nutrition. Declines in nutrition and chronic stress in the first years of a child's life can be particular detrimental for fetal and newborn health and cognitive outcomes through changes in the immune and behavioral systems that may lead to permanent alterations in the body's systems (Denckel-Schetter, 2011; Gluckman and Hanson, 2005) or through impaired development of the brain, thereby diminishing the mental skills of infants (Huizink et al., 2003). Some studies have associated stress in early life with lower schooling attainment and verbal IQ scores, and with higher incidence of chronic health conditions at age 7 (Aizer, Stroud, and Buka, 2012) and later in life (Thompson, 2014). Researchers have also identified that child's height (a key measure of child development in developing countries) can be particularly sensitive to shocks occurring during the first 1000 days of life (Stein and Lumey, 2000; Kramer, 1987; Victora et al., 2010), of which violence is a

particularly harmful one (Grantham-McGregor et al., 2007). Recent research has shown that violence is associated with declines in child's height (Akresh et al., 2012; Duque 2017).

Second, stress (due to violence) may compromise the family environment by affecting parental mental health and family relationships, weakening parenting quality that in turn may hinder human capital development (Campbell, 1991; Repetti et al., 2002). Sharkey et al. (2012), for example, found that local violence is positively associated with higher parental distress, suggesting that parental responses may be a likely pathway by which local violence affects young children. Lastly, violence could also limit the amount and quality of resources in the local community (supply-side mechanisms). For instance, it can disrupt the economy (i.e., reduce household economic resources), destroy infrastructure (e.g., hospitals, schools), reduce the quality of public services (exodus of skilled medical doctors, teachers), and limit investments (e.g., resources may be crowded away from education and healthcare to military spending during wars), all of which affect human capital.[26]

6.5. *Heterogeneous Results by Household's Socioeconomic Status*

A recurring empirical finding in the literature is that low socio-economic (SES) families are less able to protect themselves against shocks. I examine differences in impacts by SES, by focusing on heterogeneous effects by maternal education. In particular, I focus on households where the mother has: i) no education, ii) primary or less (i.e., 1 to 5 years of schooling), iii) HS or less (6 to 11 years of schooling), or iv), more than HS.[27] In what follows, I only present estimates from mother fixed-effects models since these provide the more reliable estimates of violence on education.

6.5.1. *School Dropout and Educational Attainment by Mothers' Education*

Table 4 shows the effects of violence on primary and HS completion by mother's education using Census data. Overall, these findings suggest that the risk of primary and HS dropout is only concentrated among children of low educated mothers. For instance, children of mothers

[26]A number of studies have provided evidence on potential supply-side mechanisms. Leon (2012) showed that attacks against teachers in conflict-affected areas during Peru's political conflict decreased educational attainment; Rodriguez and Sanchez (2012) showed that negative economic shocks and lower school quality due to violence increased school dropout and child labor in Colombia; Akbulut-Yuksel (2014) also found that school-facility destruction and teacher absence in WWII Germany accounted for declines in education, and malnutrition and destruction of health services worsened the health outcomes of cohorts exposed to the war. Minoiu and Shemyakina (2012) found that household economic losses helped explain declines in children's height during Cote d'Ivoire's civil conflict. Moreover, in a related literature, Hernandez (2016) found that violence acted as a key mechanism limiting the positive spillovers of economic booms on educational attainment in Colombia.

[27]I focus on these four groups because these are the relevant margins of mother's education in developing countries and to be consistent with the education categories in the Sisben data.

with no education or with primary or less, are 9.2% and 2.5% (respectively) less likely to complete primary, while little impact is observed among students in more advantaged households. Similarly, the negative impacts of violence on HS graduation are only experienced by children of mothers with primary or less education (a decline of 4.6%).[28]

Table 5 shows results by mother's education on years of schooling and years of schooling post-HS graduation (college years). These results contrast with those in Table 4 in the sense that, the largest declines in the outcomes are not necessarily concentrated among the most disadvantaged kids. For instance, while a one SD increase in homicides in early life (i.e., at ages 4-6) is associated with a 2.2% reduction in years of schooling after HS completion among children of mothers with some college education (i.e., the most educated), there is no effect on children of mothers with primary or less nor among those of uneducated mothers. One possible explanation for this result is that, even in the absence of violence, less advantaged students are less likely to accumulate high levels of education, hence, violence is not as binding for them as it is for other better-off groups in this particular dimension.

Results in Tables 4 and 5 directly relate to both the descriptive evidence shown in Figure 2, which shows that children in high SES families accumulate more education than children in low SES households, and to Proposition 2 in the conceptual framework, which predicts that there exists an X (e.g., mother's education) below/above which violence does not affect children's educational outcomes.

6.5.2. *Educational Achievement by Mothers' Education*

The findings on Icfes by mother's education are presented in Table 6 and these show that violence exposure in early-life is associated with significant declines in test scores particularly among children of families in the middle of the education distribution. In particular, I find that a one SD increase in homicide rates at ages 0-3 reduces Icfes by 0.10 SD for those born to mothers with primary or less and by 0.18 SD for those of mothers with HS or less. In contrast, children of uneducated mothers or children of highly educated mothers do not seem to experience any change in their test score.[29] Again, the result on children of low SES mothers can be explained by the fact that even in the absence of violence, these individuals do not complete HS and are therefore less likely to take the Icfes exam (see Figure 3).

[28]Little impact is observed among students in households where the mother has no education, likely due to the fact that only 18% of these children actually attend HS.

[29]Of note, however, is the magnitude of the coefficient of violence exposure at ages 0-3 on children in high SES families (i.e., -1.09), which is relatively large, although not statistically significant.

In sum, results presented in Tables 4, 5, and 6 suggest the following patterns: i) low SES students exposed to violence are more likely to drop out from school very early (i.e., in 5^{th} grade); ii) high SES students attain fewer college years (years of schooling after HS graduation); and iii), children of mothers in the middle of the SES distribution are negatively affected in all dimensions: more likely to drop out from HS and to achieve lower test scores. In other words, violence seems to be (negatively) reinforcing the key educational margin of each group (i.e., low SES students are less likely to complete HS, so violence increases the probability of HS dropout for them).

7. Robustness Checks

In this section, I analyze potential sources of selection bias such as fertility, mobility, and survival.

Fertility. Violence could affect a woman's fertility decisions by either influencing her desired number of children or by delaying her decision to become pregnant. If violence affects some women more than others, this may result in a biased estimate of violence on education.

To test for the presence of selective fertility, I examine the association between violence and a mother's total fertility after a (focal) child (i.e., the number of children she has after her first child born in the 1980s) and the association between violence and the timing of fertility (i.e., the time between two subsequent births). Results shown in Appendix Table 3 suggest that there is some evidence on selective fertility: for instance, column 1 shows that uneducated mothers whose children are exposed to high violence at ages 4-6, are more likely to have a subsequent birth, and column 2 indicates that as violence increases, these same mothers with no education are also more likely to have that additional birth within a shorter inter-pregnancy interval. If this relationship is indicative and consistent with the type of selection that exists on unobserved characteristics (e.g., less educated mothers self-selecting in their child's early childhood to have more births as violence increases), a maternal fixed effect model would be helpful to eliminate this heterogeneity that could bias estimates of violence on education.

Mobility. Endogenous migration in response to (or in expectation of) high violence could also induce (an upward) bias in my estimates of violence on education, if households who migrate due to an increase in homicide rates are different to those that don't migrate, in dimensions that could affect a child's education (e.g., if families who migrate from high-violence places to low-violence ones are wealthier or more educated than those who stay).

To asses the importance of selective migration, I first examine the proportion of migrants in the data (i.e., those who were born in a different municipality to where they were interviewed). Appendix Table 4 shows that 75% of the sample reports having been born in the municipality where they were interviewed and that children born in less educated households tend to migrate less than children in other families.[30] Second, to empirically examine how endogenous migration affects my estimates on education, one possible way is to estimate whether the effects of violence in the full sample differ to those in the sample of non-movers. Appendix Table 5 shows mother fixed-effects estimates of violence on years of education for the full sample and for the sample of non-movers, and by mothers' education. Results indicate that the negative effects of violence are always larger in the sample of non-migrants than in the full sample (even by education groups). For instance, column 4 shows that exposure to a one standard deviation increase in homicide rates at ages 4-6 leads to a 9.6% decline in the number of years of education of non-migrant children born to mothers with no education versus a 5.6% decline in the full sample (movers and non-movers) of children of similarly uneducated mothers (column 3). The fact that the effects are larger among the non-migrants suggests that these families tend to be a less-positively selected sample that even in the absence of violence would invest little in their child's education. Thus, the fact that this paper includes both movers and non-movers to estimate the effects of violence on education suggests that the true impacts may actually be larger than those found here.

A third step in the analysis of endogenous migration focuses on the potential effects of the internal forced displacement (IFD) on my estimates. The IFD has been one of the most dramatic consequences of the recent armed conflict, where more than 3.5 million people have been forced to migrate since 1997 (around 8% of the total population) (United Nations, 2010).[31] Appendix Figure 3 shows the number of forced migrants since 1979 in Colombia. As the figure illustrates,

[30]Although the Census asks about reasons for migration (e.g., reasons such as: migrating for better economic opportunities, for education opportunities, for family reasons, for health-related reasons, etc.), this question is only asked to those who have (recently) migrated over the last 5 years (i.e., since year 2000). However, the fact that only 1% of the recent migrants reported "violence or insecurity" as their main reason for migrating, which was a time when violence was even higher to that in the 1980s, reveals that migration due to violence in the 1980s might not have been a prominent factor influencing household's migration. The Administrative data do not ask about reasons for migration.

[31]The IFD groups have very low socioeconomic indicators, including educational attainment and health status. Identifying internally displaced populations (IDP) in the Census 2005 is only possible for those who have recently been forced to move (in the last 5 years).

forced displacement is a relatively recent phenomenon in the country and as such, I assume that it did not affect the early lives of the cohorts who were born in the 1980s in the country.[32]

I conclude that there is little evidence that could suggest that endogenous migration due to violence could be driving the estimates of homicide rates on long-term educational outcomes.

Survival. Lastly, I analyze how violence affects the probability of survival. Selective survival can occur if, for instance, violence increases the probability of mortality disproportionately among the frailer fetuses or children, leading to healthier babies or children surviving. In this case, the effects of violence on education would result in a lower-bound estimate of the true impact.

One way to test for selective survival is to explore whether changes in violence are associated with changes in the sex ratio or in the cohort size. Several studies have shown that boys are biologically weaker and more susceptible to diseases and premature death than girls (Naeye et al, 1971; Waldron, 1985), and that they are more vulnerable to environmental factors in early-life (Pongou, 2013). Therefore, focusing on these two measures could be informative to understand potential demographic imbalances linked with violence.

I assess the importance of selective survival by regressing, at the municipality-month-year level, the sex ratio and cohort size of the cohorts of interest (i.e., individuals born in the 1980s), on the violence that occurred when these cohorts were in their early stages of life. Appendix Table 6 shows that a one standard deviation increase in violence in the second trimester of pregnancy leads to a 1% decline in the sex ratio and a standard deviation increase in violence at ages 4-6 is associated with an 11% increase in the cohort size.

Now, I examine the link between violence and child mortality at the household level using complementary data such as the Demography and Health Survey (DHS) that provide detailed demographic information on children below age 5.[33] Using the three earliest waves of the DHS that mostly coincide with the period of interest, (i.e., 1986, 1990, and 1995), I estimate the association between early-life violence exposure and the probability that a child dies before age 1 and before age 3.[34] Appendix Table 7 shows that there is evidence that suggests that children of low educated mothers exposed to violence in their second trimester are more likely to die at ages 1 or 3 (columns 2 and 3) compared to children in other families. The fact that the effects tend to be concentrated in the second trimester could be suggestive of maternal stress

[32]Furthermore, while I cannot identify IDPs prior to year 2000, the number of IDPs in the Census is small (they represent 5% of the recent migrants and are approximately 2% of the total sample), providing some additional evidence that internal migration in the sample is not particularly driven by violence.

[33]I use DHS data because the Census do not provide information on child mortality.

[34]Unfortunately, due to data limitations I am not able to examine child mortality at later ages.

as a potential mechanism in the in-utero period (Aizer et al., 2016). Since children of low SES mothers are more likely to attain less education even in the absence of violence, I conclude that this type of selection bias will likely result in estimates of violence that represent a lower bound if one way that violence affects human capital is through an increased probability of child mortality.[35]

8. Conclusions

This paper contributes to the literature on the effects of violence on human capital. To my knowledge, this is the first paper to show that early-life exposures have persistent effects on individuals' productivity, as measured by test scores at age 20, using a large and representative data set that link school records with census data and with information on the place and date of birth for the universe of low income households in Colombia. I also contribute to this research by exploiting a research design aimed at overcoming several threats to inference due to family disadvantage and the difficulties involved in measuring violence exposure in critical periods of human capital formation. In particular, this paper exploits the temporal and geographic variation in crime and violence associated with the proliferation of drug cartels in the 1980s, which was greatly influenced by the huge increase in the international demand for cocaine in the 1980s, and with a maternal fixed-effects strategy that is necessary to eliminate omitted variable bias. To help rationalize the findings, I construct a novel theoretical framework with violence shocks on educational choices across heterogeneous agents. From the model we learn about potential pathways and potential heterogeneity that can underlie a given empirical result observed in the data.

Results show that early-life exposure to homicide rate increases the probability of primary school and HS dropout, reduces end-of-HS exam scores, and decreases years of schooling in college. Also, there is considerable heterogeneity in the effects of violence by mother's education. While students born to low educated mothers are more likely to drop out from school at early stages in their school cycle, those born to more advantaged mothers tend to attain fewer years of schooling at high levels of education (college). Lastly, those born to mothers in the middle of the education distribution, experience declines at both the extensive and intensive margins.

The estimates of violence found in this paper can be viewed as lower bounds on the true value. First, by using a measure of violence that captures changes in homicide rates at the municipality level, I am unable to point out whether, within a particular municipality there is actual sorting

[35]Other studies have shown evidence on the effects of in-utero violence exposure on health at birth outcomes (Brown, 2016; Camacho, 2008; Mansour and Rees, 2012; Quintana-Domeque and Rodenas-Serrano, 2016).

into who is being more or less exposed to violence. So, if families adopt preventive measures that reduce their exposure to violence or if they make additional investments on their child who was exposed to violence at birth, it is likely that the effect of violence that I observe is lower than the true effect. Second, I measure early-life violence exposure based on a child's municipality of birth. Since migration is always a challenge, if a family moves to a different municipality right after their child's birth, I will not be able to identify his/her 'current' homicide-exposure in that new location. So, although using the baseline (place of birth) municipality is more exogenous than the current residence, it may introduce an additional attenuation bias in the estimates. Despite the multiple sources of measurement error that could bias my estimates towards zero, it is clear that the results presented in this paper are economically meaningful. For instance, the effects on test scores are within the range of the effects of many educational interventions (Hanushek, 2006).

I conclude that violence contributed to exacerbate the gaps in educational outcomes between high and low SES children in Colombia during the 1980s, a result that may have disturbing implications considering the millions of children across the world who are born and raised in countries affected by repeated cycles of violence (UNICEF, 2016; World Bank, 2013).

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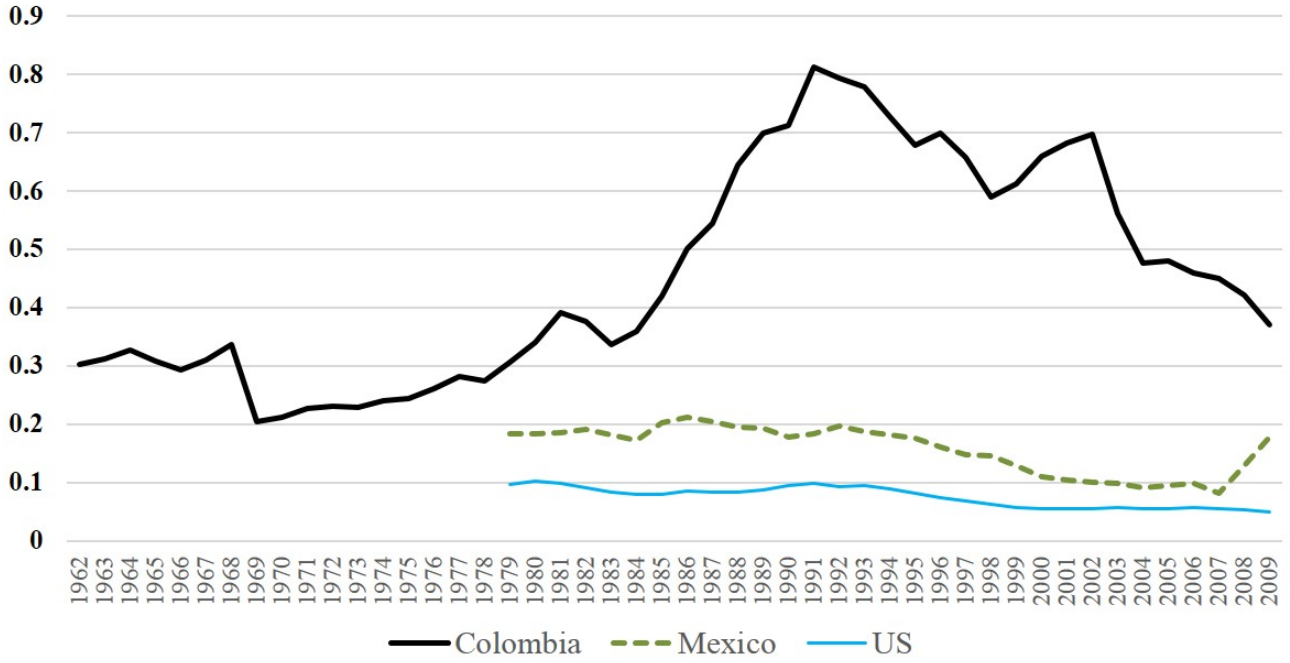
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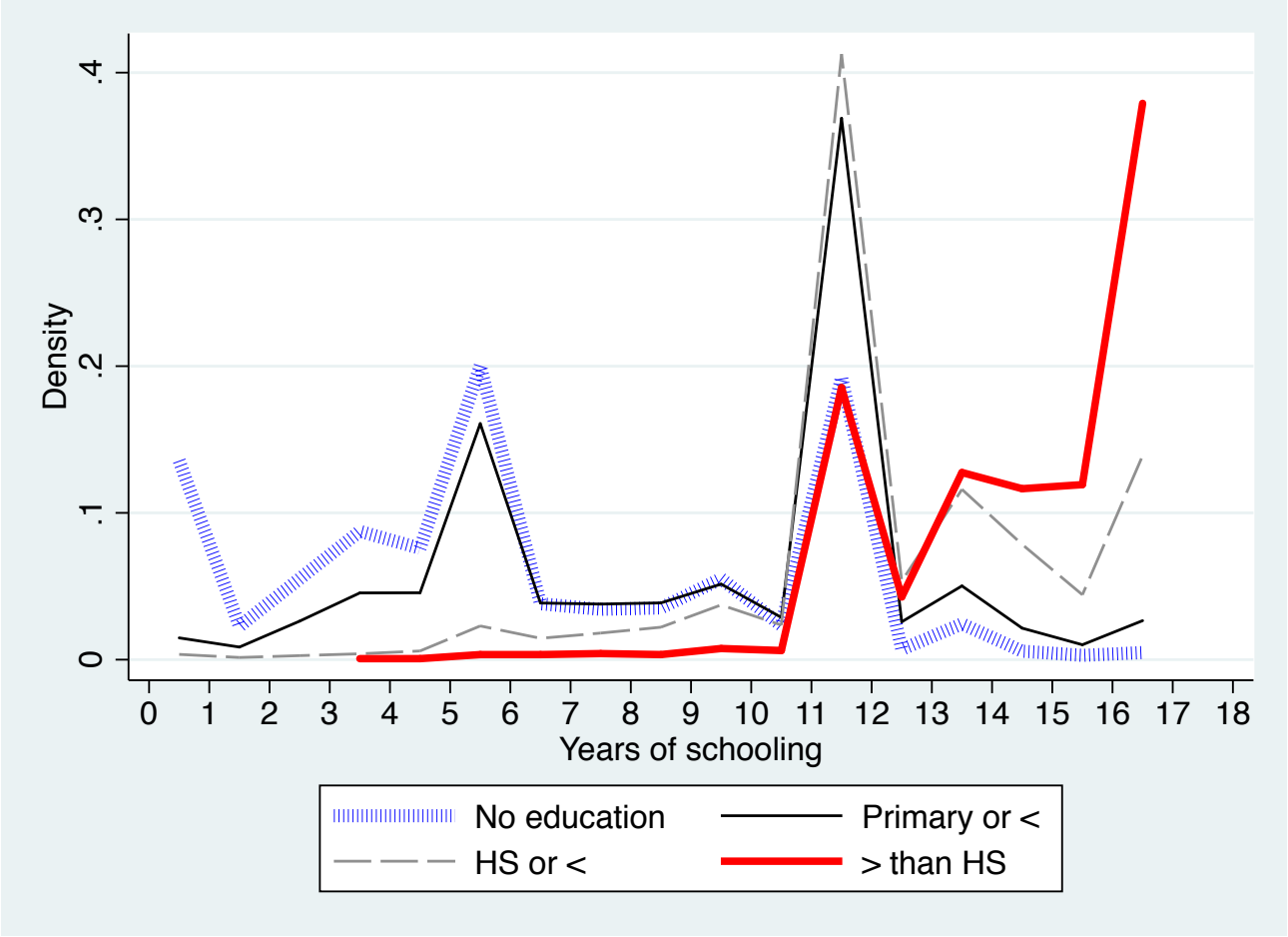
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FIGURE 1. Homicide Rate, 1962-2009
(homicides per 1,000 inhabitants)



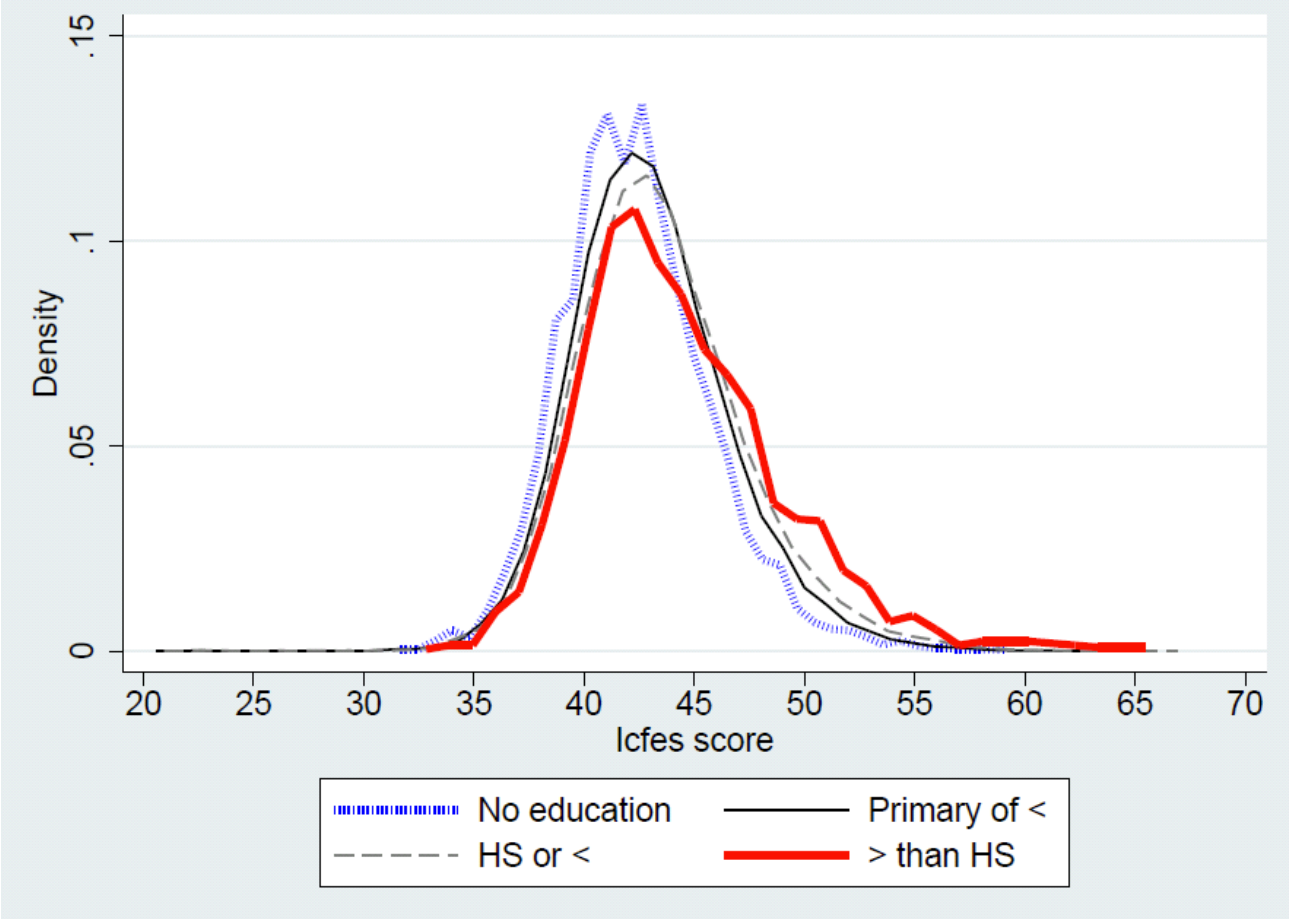
Sources: National Police Department (Colombia), National Institute of Statistics and Geography, INEGI (Mexico), Bureau of Justice Statistics (US)

FIGURE 2. Distribution of Years of Schooling at Ages 23-24 by Mothers' Education



Note: histogram of the years of education. The sample includes individuals aged 23 and 24 (oldest cohorts in the sample) in Census 2005.

FIGURE 3. Distribution of Icfes at Age 18 by Mothers' Education



Note: histogram of the Icfes score. The sample includes individuals aged 18 in the Administrative data.

TABLE 1. The Association Between Violence and Mothers' Characteristics Using Census Data

	Age <35	Age >55	No education	Primary or <	HS or <	> than HS	Married	Single
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Homicide rate 3 years before conception	-0.0030	-0.0028	0.0020	-0.0022	0.0021	0.0004	-0.0037	-0.0027
	[0.0049]	[0.0061]	[0.0078]	[0.0097]	[0.0089]	[0.0035]	[0.0099]	[0.0050]
Homicide rate 2 years before conception	0.0096*	-0.0062	-0.0061	0.0150	0.0022	-0.0061	0.0054	-0.0024
	[0.0055]	[0.0059]	[0.0071]	[0.0112]	[0.0076]	[0.0038]	[0.0089]	[0.0044]
Homicide rate Trimester 1	0.0040	0.0049	-0.0055	-0.0027	0.0048	0.0020	-0.0053	-0.0023
	[0.0032]	[0.0038]	[0.0039]	[0.0059]	[0.0050]	[0.0020]	[0.0055]	[0.0032]
Homicide rate Trimester 2	-0.0009	0.0019	0.0007	0.0028	-0.0025	0.0006	0.0051	0.0026
	[0.0024]	[0.0037]	[0.0043]	[0.0052]	[0.0051]	[0.0020]	[0.0053]	[0.0027]
Homicide rate Trimester 3	-0.0012	0.0041	-0.0007	0.0117*	-0.0112**	-0.0014	-0.0014	-0.0063*
	[0.0035]	[0.0046]	[0.0042]	[0.0068]	[0.0049]	[0.0023]	[0.0058]	[0.0033]
Homicide rate Ages 0-3	0.0078	-0.0032	0.0002	-0.0169	0.0206**	-0.0052	-0.0116	-0.0025
	[0.0079]	[0.0073]	[0.0078]	[0.0104]	[0.0097]	[0.0042]	[0.0105]	[0.0058]
Homicide rate Ages 4-6	-0.0121**	0.0155**	0.0016	0.0250**	-0.0246***	-0.0047	0.0123	-0.0009
	[0.0058]	[0.0062]	[0.0072]	[0.0108]	[0.0081]	[0.0038]	[0.0087]	[0.0042]
Homicide rate Ages 7-11	-0.0031	0.0146*	-0.0114	-0.0003	0.0172	-0.0077*	0.0053	-0.0063
	[0.0089]	[0.0087]	[0.0103]	[0.0129]	[0.0113]	[0.0045]	[0.0112]	[0.0064]
Homicide rate Ages 12-15	-0.0016	-0.0058	0.0031	0.0064	-0.0088	-0.0020	0.0031	-0.0024
	[0.0046]	[0.0055]	[0.0047]	[0.0075]	[0.0072]	[0.0023]	[0.0058]	[0.0028]
N	142,057	142,057	142,057	142,057	142,057	142,057	142,057	142,057

Note: sample includes mothers of individuals of ages 17-24 (born in the 1980s) in Census 2005. All models include controls fixed effects at the child's year, month, and municipality of birth, and department-specific time trends. Errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 2. OLS and Mother Fixed-Effects Estimates of Violence on School Dropout and Educational Attainment Using Census Data

	Primary completed (5th grade)		HS completed (11th grade)		Years of schooling		Years of schooling | HS completion	
	OLS (1)	Mother FE (2)	OLS (3)	Mother FE (4)	OLS (5)	Mother FE (6)	OLS (7)	Mother FE (8)
Homicide rate 3 yrs bef conception	0.0038	-0.0009	0.0074	0.0085	0.0418	-0.047	0.020	-0.0064
	[0.0078]	[0.0095]	[0.0116]	[0.0118]	[0.0585]	[0.0843]	[0.038]	[0.0918]
Homicide rate 2 yrs bef conception	-0.0102	0.0011	-0.0116	0.0092	-0.0741	0.0636	-0.025	0.0226
	[0.0070]	[0.0093]	[0.0093]	[0.0115]	[0.0488]	[0.0826]	[0.039]	[0.0873]
Homicide rate Trimester 1	0.0017	-0.0090*	-0.0056	-0.0049	0.0156	0.0017	0.014	0.1084**
	[0.0038]	[0.0055]	[0.0052]	[0.0065]	[0.0298]	[0.0387]	[0.019]	[0.0527]
Homicide rate Trimester 2	-0.0009	-0.0016	-0.0017	-0.0077	-0.0136	-0.017	0.012	0.0084
	[0.0039]	[0.0052]	[0.0050]	[0.0063]	[0.0325]	[0.0384]	[0.017]	[0.0494]
Homicide rate Trimester 3	-0.0070*	0.0012	-0.0062	0.0085	-0.0742*	0.0396	-0.003	0.0351
	[0.0036]	[0.0063]	[0.0056]	[0.0077]	[0.0412]	[0.0473]	[0.022]	[0.0624]
Homicide rate Ages 0-3	-0.0165*	-0.0098	-0.0571***	-0.0575***	-0.3853***	-0.3172***	-0.299***	-0.3034***
	[0.0087]	[0.0117]	[0.0172]	[0.0147]	[0.1048]	[0.0831]	[0.080]	[0.1138]
Homicide rate Ages 4-6	-0.0123**	-0.0218**	-0.0372***	-0.0313**	-0.4034***	-0.4913***	-0.219***	-0.2518***
	[0.0061]	[0.0099]	[0.0140]	[0.0119]	[0.0622]	[0.0616]	[0.048]	[0.0887]
Homicide rate Ages 7-11	-0.0175*	-0.0109	-0.0189	0.0157	-0.0866	-0.1750*	-0.065	-0.0435
	[0.0091]	[0.0137]	[0.0157]	[0.0168]	[0.0995]	[0.0901]	[0.114]	[0.1358]
Homicide rate Ages 12-15	-0.006	-0.0066	-0.0098	-0.0227**	0.0691	0.0612	0.091	0.0693
	[0.0046]	[0.0075]	[0.0098]	[0.0095]	[0.0568]	[0.0538]	[0.056]	[0.0767]
N	142,057	129,243	142,057	129,243	142,057	129,243	74,849	63,201
N of groups		97170		97170		97170		51669
Mean	0.88		0.50		9.1 (3.7)		11.9 (1.5)	
Effect in Ages 0-3 (% of mean)	-1.03%	-	-6.3%	-6.3%	-2.3%	-1.9%	-1.3%	-1.4%

Note: sample includes individuals of ages 17-24 (born in the 1980s) in Census 2005. Models include individual controls for gender, age, and race, mother's age, education, marital status, and whether the household is urban, fixed effects at the individual's year, month, and municipality of birth and department-specific linear and quadratic time trends. Errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 3. OLS and Mother Fixed-Effects Estimates of Violence on Educational Achievement Using Administrative Data

	Icfes score	
	OLS	Mother FE
Homicide rate 3 years before conception	0.0404	-0.0927
	[0.0489]	[0.1781]
Homicide rate 2 years before conception	-0.0340	-0.091
	[0.0472]	[0.1593]
Homicide rate Trimester 1	0.0104	-0.0161
	[0.0162]	[0.0748]
Homicide rate Trimester 2	0.0021	0.0698
	[0.0169]	[0.0680]
Homicide rate Trimester 3	-0.0269	0.1233
	[0.0223]	[0.1088]
Homicide rate Ages 0-3	-0.1419**	-0.6706***
	[0.0701]	[0.2518]
Homicide rate Ages 4-6	-0.0939	-0.2569
	[0.0937]	[0.2376]
Homicide rate Ages 7-11	-0.0819	-0.4071
	[0.103]	[0.3367]
Homicide rate Ages 12-15	0.0212	-0.2765
	[0.0653]	[0.1988]
N	241,104	81,029
N of groups		43,216
Mean (SD)	43.0 (4.1)	
Effect in Ages 0-3 (SD)	-0.02	-0.09

Note: sample includes individuals of ages 17-24 (born in the 1980s) in Sisben 2005, who took the Icfes exam in 2000-2009. All models include individual controls for gender, age, school schedule (full time, morning, evening, night, or weekend), head of household's gender, age, marital status, whether the household is urban, has access to piped water and sewage, household size, fixed effects at the individual's year, month, and municipality of birth, age and year when the student took the Icfes exam. Errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 4. Mother Fixed-Effects Estimates of Violence on School Dropout by Mothers' Education Using Census Data

	Primary completed (5th grade)				HS completed (11th grade)			
	No education (1)	Primary or less (2)	HS or less (3)	More than HS (4)	No education (5)	Primary or less (6)	HS or less (7)	More than HS (8)
Homicide rate Trimester 1	-0.0273**	-0.0131**	-0.0037	0.0119	-0.011	0.0013	-0.0234	0.0333
	[0.0138]	[0.0066]	[0.0060]	[0.0096]	[0.0119]	[0.0090]	[0.0202]	[0.0295]
Homicide rate Trimester 2	0.0123	0.0016	-0.0017	-0.0016	0.0106	-0.0017	-0.0037	-0.0075
	[0.0138]	[0.0067]	[0.0058]	[0.0096]	[0.0119]	[0.0091]	[0.0192]	[0.0296]
Homicide rate Trimester 3	-0.0002	0.0115	-0.0023	-0.0031	0.0102	-0.0096	-0.0235	0.0337
	[0.0178]	[0.0079]	[0.0072]	[0.0113]	[0.0155]	[0.0108]	[0.0247]	[0.0348]
Homicide rate Ages 0-3	0.0255	-0.0128	-0.0087	-0.0080	-0.0459	-0.0566***	0.0131	-0.0203
	[0.0347]	[0.0145]	[0.0121]	[0.0198]	[0.0298]	[0.0197]	[0.0418]	[0.0611]
Homicide rate Ages 4-6	-0.0776***	-0.0290***	0.0124	0.0021	0.0133	-0.0263*	-0.0476	-0.0448
	[0.0297]	[0.0105]	[0.0088]	[0.0146]	[0.0257]	[0.0144]	[0.0308]	[0.0450]
Homicide rate Ages 7-11	-0.0129	-0.0182	-0.0117	-0.0074	0.0456	-0.0084	-0.026	-0.1094
	[0.0374]	[0.0154]	[0.0143]	[0.0257]	[0.0326]	[0.0210]	[0.0484]	[0.0793]
Homicide rate Ages 12-15	-0.0225	0.0028	0.0053	0.0129	-0.0038	-0.0072	-0.0623*	0.0483
	[0.0203]	[0.0086]	[0.0090]	[0.0154]	[0.0180]	[0.0117]	[0.0313]	[0.0475]
N	21,343	79,503	43,846	12,329	21,343	79,503	43,846	12,329
N of groups	15,132	56,560	31,562	8,854	15,132	56,560	31,562	8,854
Mean	0.62	0.87	0.97	0.99	0.18	0.41	0.64	0.81
Effect in Ages 4-6 (% of mean)	-9.2%	-2.5%	-	-	-	-4.6%	-	-

Note: sample includes individuals of ages 17-24 (born in the 1980s) in Census 2005. All models include individual controls for gender, age, and race, mother's age, education, marital status, and whether the household is urban, fixed effects at the individual's year, month, and municipality of birth and department-specific linear and quadratic time trends. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 5. Mother Fixed-Effects Estimates of Violence on Educational Attainment by Mothers' Education Using Census Data

	Years of schooling				Years of schooling | HS completion			
	No education (1)	Primary or less (2)	HS or less (3)	More than HS (4)	No education (5)	Primary or less (6)	HS or less (7)	More than HS (8)
Homicide rate Trimester 1	-0.1174	-0.0144	-0.008	-0.0156	-0.0333	0.0700	0.0735	-0.0677
	[0.0986]	[0.0559]	[0.0520]	[0.1069]	[0.1616]	[0.0566]	[0.0844]	[0.1056]
Homicide rate Trimester 2	0.0644	-0.0219	-0.0303	0.0099	-0.0105	-0.0223	-0.0079	0.0393
	[0.0990]	[0.0565]	[0.0534]	[0.1074]	[0.1354]	[0.0558]	[0.0803]	[0.1019]
Homicide rate Trimester 3	0.0999	0.0332	0.0248	-0.0316	0.0378	-0.0110	0.0168	-0.0466
	[0.1284]	[0.0669]	[0.0645]	[0.1251]	[0.1498]	[0.0669]	[0.1055]	[0.1264]
Homicide rate Ages 0-3	-0.063	-0.1664	-0.1279	-0.5317**	-0.1163	0.0921	-0.2635	-0.5544**
	[0.2480]	[0.1221]	[0.1158]	[0.2143]	[0.3561]	[0.1206]	[0.1723]	[0.2164]
Homicide rate Ages 4-6	-0.4430**	-0.2449***	-0.2142**	-0.5341***	-0.0774	-0.0835	-0.3606***	-0.3657**
	[0.2139]	[0.0890]	[0.0855]	[0.1467]	[0.2595]	[0.0830]	[0.1128]	[0.1428]
Homicide rate Ages 7-11	0.1078	-0.0683	-0.0080	-0.5294**	0.1021	-0.0473	-0.3736*	-0.3468
	[0.2697]	[0.1302]	[0.1241]	[0.2485]	[0.3582]	[0.1306]	[0.1951]	[0.2500]
Homicide rate Ages 12-15	-0.2091	0.1066	0.1057	0.1277	-0.3253*	0.1049	0.0567	-0.0227
	[0.1461]	[0.0726]	[0.1329]	[0.1605]	[0.1966]	[0.0782]	[0.1282]	[0.1608]
N	21,343	79,503	43,846	12,329	3,848	33,459	31,122	10,712
N of groups	15,132	56,560	31,562	8,854	3,245	26,435	23,791	7,913
Mean (SD)	5.7 (3.88)	8.4 (3.40)	10.4 (2.63)	11.7 (2.44)	11.3 (0.91)	11.5 (1.2)	11.9 (1.43)	12.5 (1.77)
Effect in Ages 4-6 (% of mean)	-5.6%	-2.2%	-1.5%	-3.3%	-	-	-2.2%	-2.2%

Note: sample includes individuals of ages 17-24 (born in the 1980s) in Census 2005. All models include individual controls for gender, age, and race, mother's age, education, marital status, and whether the household is urban, fixed effects at the individual's year, month, and municipality of birth and department-specific linear and quadratic time trends. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 6. Mother Fixed-Effects Estimates of Violence on Educational Achievement by Mother's Education Using Admin Data

	No education	Primary or less	HS or less	More than HS
	(1)	(2)	(3)	(4)
Homicide rate Trimester 1	0.1548	-0.0773	-0.1918*	-0.2526
	[0.1823]	[0.0507]	[0.1126]	[0.2590]
Homicide rate Trimester 2	-0.0512	-0.0334	-0.1526	-0.1654
	[0.1975]	[0.0515]	[0.1198]	[0.5716]
Homicide rate Trimester 3	-0.1469	0.062	-0.0095	-0.3538
	[0.2242]	[0.0664]	[0.1468]	[0.6738]
Homicide rate Ages 0-3	-0.6647	-0.7819***	-1.5397***	-1.0989
	[0.4794]	[0.1447]	[0.2687]	[1.3130]
Homicide rate Ages 4-6	0.5459	0.1342	-0.6224**	-0.943
	[0.4144]	[0.1666]	[0.2487]	[1.1836]
Homicide rate Ages 7-11	-0.5334	-0.5591***	-0.7632**	0.3252
	[0.3374]	[0.1483]	[0.3136]	[1.3698]
Homicide rate Ages 12-15	-0.304	0.0555	-0.3121	0.6496
	[0.3430]	[0.1171]	[0.2580]	[1.1463]
N	5,278	50,539	23,054	2,158
Number of groups	3,075	26,520	12,223	1,398
Mean (SD)	42.0 (4.1)	42.5 (4.2)	43.4 (4.6)	44.8 (5.3)
Effect in Ages 0-3 (SD)	-	-0.10	-0.18	-

Note: sample includes individuals of ages 17-24 (born in the 1980s) in Sisben 2005, who took the Icfes exam from 2000 to 2009. All models include individual controls for gender, age, school schedule (full time, morning, evening, night, or weekend), head of household's gender, age, marital status, whether the household is urban, has access to piped water and sewage, household size, fixed effects at the individual's year, month, and municipality of birth, age and year when the student took the Icfes exam. Errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

********** *APPENDIX FOR ONLINE PUBLICATION* **********

A. Appendix: Figures and Tables

Appendix Table 1. Mother and Household Characteristics and Child Outcomes

	Census data	Admin data
Mother characteristics		
Age	46.72	45.11
	[6.79]	[11.12]
White	0.86	-
Black	0.10	-
Unknown/Other	0.04	-
No education	0.13	0.06
Primary or less	0.49	0.57
HS or less	0.29	0.34
More than HS	0.09	0.03
Married	0.51	0.38
Cohabiting	0.24	0.33
Single	0.07	0.09
Divorced /widow	0.18	0.20
Household size	3.57	5.68
	[1.19]	[2.40]
Urban household	0.83	0.75
Owns home	0.68	0.54
Access to water/sewage	-	0.73
Individual characteristics		
Age	20.12	18.52
	[1.97]	[1.78]
Female	0.52	0.51
White	0.86	-
Black	0.10	-
Unknown / Other	0.04	-
Outcomes		
5^{th} grade (Primary completion)	0.88	-
11^{th} grade (HS completion)	0.50	-
Years of schooling	9.10	-
	[3.68]	
Years of schooling | HS completion	11.91	-
	[1.50]	
Icfes (end of HS) test score	-	43.02
		[4.12]
N	142,057	240,168

Note: sample includes individuals of ages 17-24 (born in the 1980s) in Census 2005 and in the Administrative data (Sisben 2005, R-166, and Icfes).

Appendix Table 2. Homicide Rates
(homicides per 1,000 inhabitants)

	Mean	SD
Pregnancy: Trimester 1	0.38	0.47
Trimester 2	0.39	0.49
Trimester 3	0.37	0.47
Early childhood: Ages 0-3	0.49	0.55
Late childhood: Ages 4-6	0.66	0.73
Primary school years: Ages 7-11	0.66	0.66
Early adolescence: Ages 12-15	0.65	0.54

Note: means and standard deviations are calculated for the sample of interest (individuals born in Colombia in the 1980s).

Appendix Table 3. The Association Between Violence and Total Fertility and Timing of Fertility Using Census Data

	No educ			Primary or less			HS or less			More than HS		
	N of children (1)	Succeeding birth (months) (2)	Preceding birth (months) (3)	N of children (4)	Succeeding birth (months) (5)	Preceding birth (months) (6)	N of children (7)	Succeeding birth (months) (8)	Preceding birth (months) (9)	N of children (10)	Succeeding birth (months) (11)	Preceding birth (months) (12)
- 2 yrs	0.029	-0.446	1.094	-0.01	-0.889	-1.528	0.001	-0.09	1.70	0.005	-5.927*	-1.687
	[0.043]	[1.613]	[1.695]	[0.030]	[0.986]	[1.181]	[0.038]	[1.085]	[1.774]	[0.076]	[3.541]	[4.921]
Trim 1	-0.002	-1.398	0.353	-0.004	-0.428	-0.217	-0.032	0.328	-2.912***	0.002	0.49	-2.335
	[0.030]	[1.214]	[1.311]	[0.019]	[0.462]	[0.590]	[0.020]	[0.567]	[1.007]	[0.041]	[1.811]	[2.246]
Trim 2	0.028	0.302	0.138	-0.005	-0.369	1.154*	0.013	0.496	-0.33	-0.009	-0.114	-1.753
	[0.026]	[0.893]	[1.213]	[0.013]	[0.449]	[0.650]	[0.019]	[0.709]	[0.880]	[0.044]	[2.256]	[2.051]
Trim 3	0.034	-0.206	-1.694	0.055***	0.409	0.239	-0.035	0.265	-0.599	0.04	1.434	-2.84
	[0.034]	[1.194]	[1.3672]	[0.015]	[0.6281]	[0.772]	[0.022]	[0.735]	[1.054]	[0.050]	[2.524]	[2.691]
0-3	0.001	-1.477	-4.63	0.004	1.117	-0.254	0.01	-0.752	3.586*	0.049	-7.524	-1.784
	[0.066]	[1.969]	[3.391]	[0.032]	[1.039]	[1.510]	[0.038]	[1.513]	[1.864]	[0.085]	[4.625]	[5.520]
4-6	0.115**	-4.796**	0.265	0.027	-0.031	-0.489	0.041	-0.802	-0.919	-0.053	-3.704	3.26
	[0.053]	[2.025]	[2.525]	[0.031]	[1.133]	[1.195]	[0.030]	[1.211]	[1.763]	[0.081]	[4.309]	[4.766]
7-11	0.043	-1.227	-2.088	0.018	1.043	0.763	-0.004	0.148	-2.663	0.022	-6.809	-0.995
	[0.061]	[2.388]	[2.860]	[0.029]	[1.268]	[2.127]	[0.047]	[1.657]	[2.184]	[0.117]	[6.035]	[7.299]
12-15	-0.004	-0.114	1.682	0.005	-0.093	-0.037	-0.039	-0.949	2.503**	0.048	4.871	-7.491
	[0.040]	[0.949]	[2.132]	[0.024]	[0.507]	[1.018]	[0.024]	[0.834]	[1.267]	[0.068]	[3.935]	[6.055]
N	19,120	8,667	7,102	71,704	30,592	24,736	43,022	17,838	13,135	12,824	4,718	3,706

Note: sample includes all individuals of ages 17-24 (born in the 1980s) in Census 2005. The outcome is defined as the number of children born to a given mother; the succeeding birth interval (in months) after a given child is born, and the preceding birth interval (in months) before a given child is born. All models include individual and mother controls as well as month, year, and municipality of child's birth fixed effects. Errors are clustered at the municipality level. Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 4. Migration Using Census Data

% born in this municipality?	Full sample (1)	No education (2)	Primary or less (3)	HS or less (4)	More than HS (5)
Born in this municipality	75.15	85.19	75.69	71.13	72.50
Born in other municipality, same department	13.70	8.73	14.35	15.01	12.35
Born in other department	11.14	6.07	9.96	13.85	15.15
N	142,057	16,457	70,094	42,724	12,782

Note: sample includes all individuals of ages 17-24 (born in the 1980s) in Census 2005.

Appendix Table 5. Mother Fixed-Effects Estimates of Violence on Years of Education by Movers and Non-Movers and by Mother's Education

	Full sample		No education		Primary or less		HS or less		More than HS	
	Movers and Non-movers	Non-movers	Movers and Non-movers	Non-movers	Movers and Non-movers	Non-movers	Movers and Non-movers	Non-movers	Movers and Non-movers	Non-movers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Homicide rate Trimester 1	0.0017	0.0018	-0.1174	-0.1160	-0.0144	0.0095	-0.008	0.0644	-0.0156	-0.2045
	[0.0387]	[0.0475]	[0.0986]	[0.1067]	[0.0559]	[0.0652]	[0.0520]	[0.1048]	[0.1069]	[0.2464]
Homicide rate Trimester 2	-0.017	0.0295	0.0644	0.1060	-0.0219	-0.0009	-0.0303	-0.0147	0.0099	0.1567
	[0.0384]	[0.0477]	[0.0990]	[0.1067]	[0.0565]	[0.0658]	[0.0534]	[0.1060]	[0.1074]	[0.2485]
Homicide rate Trimester 3	0.0396	0.0678	0.0999	0.0137	0.0332	0.0626	0.0248	-0.0900	-0.0316	0.6556**
	[0.0473]	[0.0588]	[0.1284]	[0.1407]	[0.0669]	[0.0776]	[0.0645]	[0.1369]	[0.1251]	[0.2891]
Homicide rate Ages 0-3	-0.3172***	-0.3613***	-0.063	0.1281	-0.1664	-0.3187**	-0.1279	-0.1492	-0.5317**	-0.6436
	[0.0831]	[0.1069]	[0.2480]	[0.2855]	[0.1221]	[0.1484]	[0.1158]	[0.2190]	[0.2143]	[0.5200]
Homicide rate Ages 4-6	-0.4913***	-0.5298***	-0.4430**	-0.6708***	-0.2449***	-0.2945***	-0.2142**	-0.2056	-0.5341***	-0.8069*
	[0.0616]	[0.0800]	[0.2139]	[0.2432]	[0.0890]	[0.1083]	[0.0855]	[0.1649]	[0.1467]	[0.4181]
Homicide rate Ages 7-11	-0.1750*	-0.2204*	0.1078	0.2244	-0.0683	-0.1667	-0.0080	-0.4376*	-0.5294**	-0.7579
	[0.0901]	[0.1148]	[0.2697]	[0.3016]	[0.1302]	[0.1570]	[0.1241]	[0.2582]	[0.2485]	[0.6963]
Homicide rate Ages 12-15	0.0612	0.1440**	-0.2091	-0.0833	0.1066	0.1344	0.1057	0.2234	0.1277	0.2693
	[0.0538]	[0.0676]	[0.1461]	[0.1572]	[0.0726]	[0.0891]	[0.1329]	[0.1691]	[0.1605]	[0.3793]
N	129,243	115,970	21,343	17,969	79,503	58,372	43,846	29,928	12,329	8,668
N of groups	97,170	82,770	15,132	12,753	56,560	41,579	31,562	21,476	8,854	6,195
Mean (SD)	8.1 (4.1)	8.5 (4.1)	5.7 (3.9)	5.1 (4.0)	8.3 (3.6)	8.1 (3.6)	11.0 (2.8)	10.9 (2.8)	12.6 (2.7)	12.6 (2.6)
Effect in Ages 4-6 (% of mean)	-4.4%	-4.6%	-5.6%	-9.6%	-2.2%	-2.6%	-1.4%	-	-3.1%	-4.7%

Note: sample includes individuals of ages 17-24 (born in the 1980s) in Census 2005. A migrant family is defined as whether at least one sibling in the family was born in a different municipality where he/she was interviewed in 2005. All models include individual controls for gender, age, and race, fixed effects at the individual's year, month, and municipality of birth and department-specific linear and quadratic time trends. Models that focus on non-movers only do not include municipality of birth fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 6. The Association Between Violence and the Sex Ratio and Cohort Size Using Census Data

	Sex Ratio	Cohort Size
Homicide rate Trimester 1	-0.0131	15.52
	[0.0110]	[20.94]
Homicide rate Trimester 2	-0.0233**	-1.344
	[0.0106]	[17.30]
Homicide rate Trimester 3	-0.0046	-27.19
	[0.0111]	[17.47]
Homicide rate Ages 0-3	0.0155	7.21
	[0.0406]	[38.16]
Homicide rate Ages 4-6	-0.0137	96.41***
	[0.0223]	[35.23]
Homicide rate Ages 7-11	-0.0544	-2.86
	[0.0450]	[39.26]
Homicide rate Ages 12-15	-0.0091	13.63
	[0.0297]	[32.98]
N	142,057	142,057
Mean	1.004	626.84

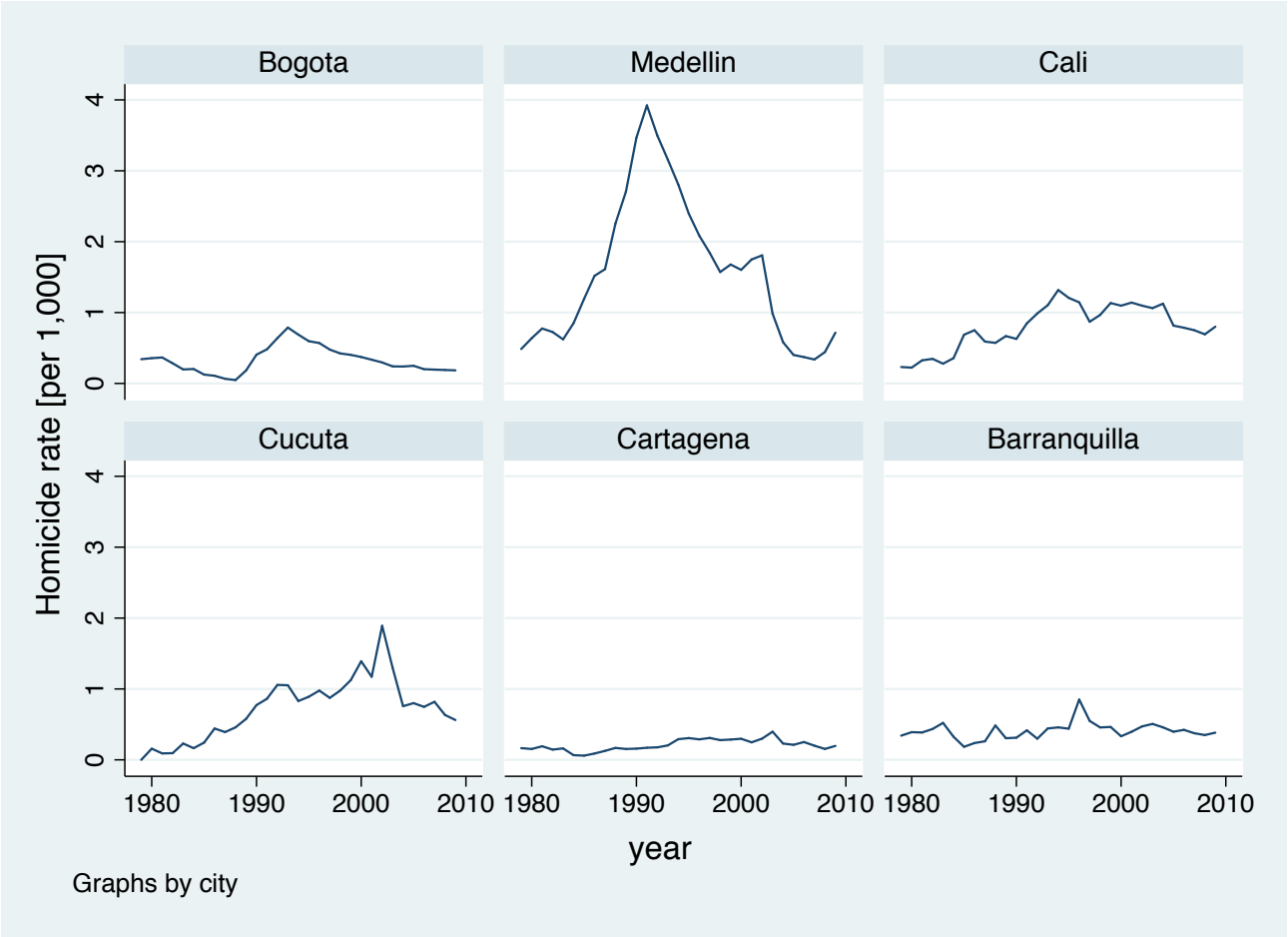
Note: the sample is a panel at the municipality-month-year levels. The sex ratio is defined as the number of boys per number of girls in a given year-municipality associated with the cohort of interest (those born in the 1980s). The cohort size is calculated as the number of individuals born in a given municipality-year associated during the 1980s. All models include fixed effects at the year, month, and municipality levels, department-specific time trends, and population weights. Errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 7. The Association between Violence and Child Mortality at Ages 1 and 3 by Mothers' Education Using the DHS

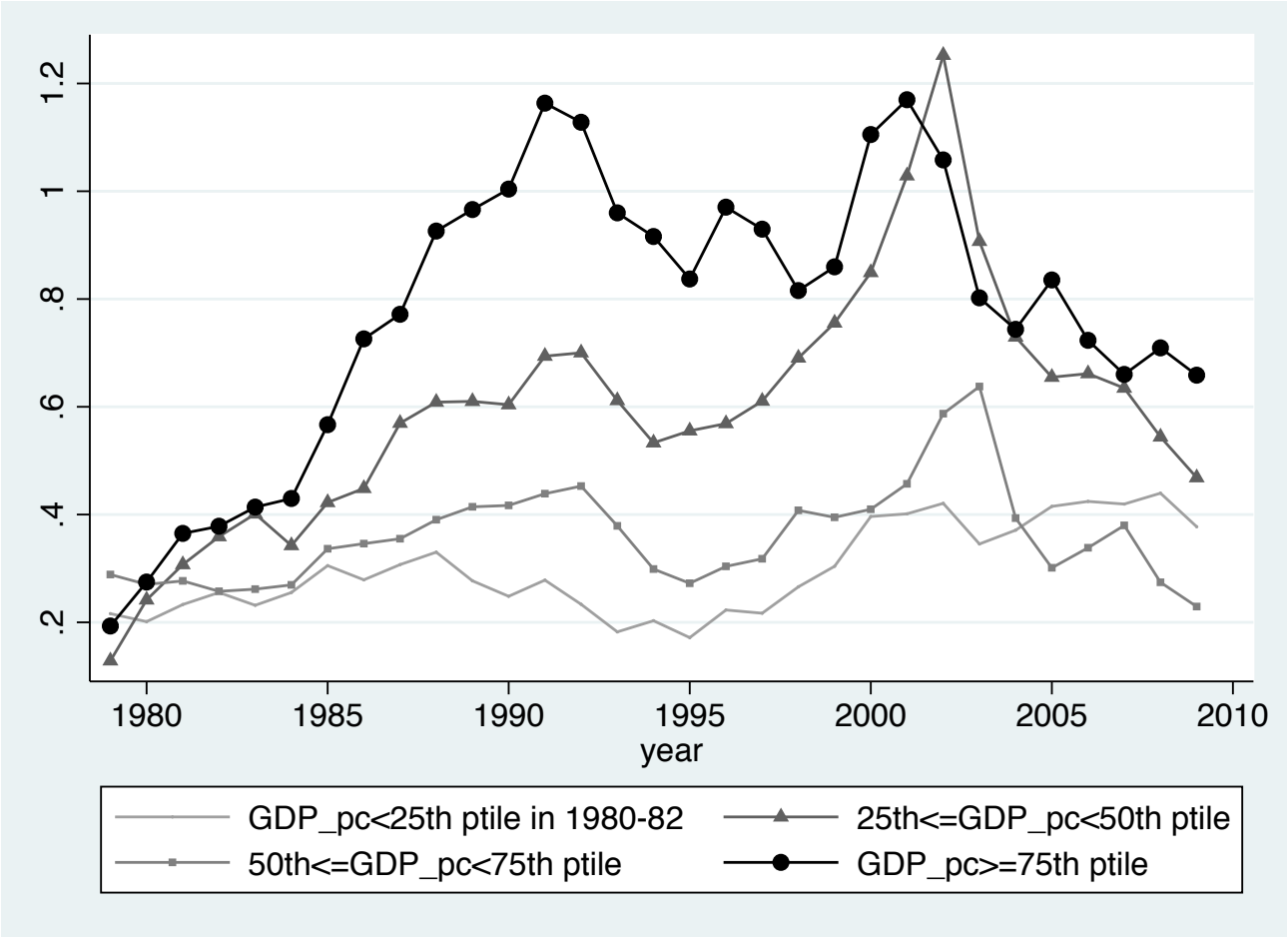
	Full sample	No education	Primary or less	HS or less	More than HS
	(1)	(2)	(3)	(4)	(5)
Outcome: Mortality in the 1st year of life					
Homicide rate Trimester 1	0.0009	0.0313	-0.0028	-0.0008	-0.0181
	[0.0050]	[0.0316]	[0.0085]	[0.0072]	[0.0133]
Homicide rate Trimester 2	0.0091	0.0416**	0.0149*	-0.0061	0.0001
	[0.0061]	[0.0199]	[0.0090]	[0.0069]	[0.0106]
Homicide rate Trimester 3	0.0014	0.0042	-0.0046	0.0043	0.0022
	[0.0043]	[0.0274]	[0.0078]	[0.0102]	[0.0079]
Homicide rate Age 0-1	-0.0000	0.0331	0.0033	0.0017	0.0202
	[0.0081]	[0.1166]	[0.0153]	[0.0138]	[0.0148]
N	10,807	607	5,139	4,429	632
Mean (%)	2.8	4.3	3.3	2.4	0.8
Outcome: Mortality in the 3rd year of life					
Homicide rate Trimester 1	0.0032	0.0523	-0.0041	0.0016	-0.0211
	[0.0054]	[0.0448]	[0.0084]	[0.0084]	[0.0154]
Homicide rate Trimester 2	0.0097	0.0527*	0.0160*	-0.0043	-0.0115
	[0.0063]	[0.0287]	[0.0094]	[0.0065]	[0.0170]
Homicide rate Trimester 3	0.0032	0.0207	-0.0021	0.0041	0.0239
	[0.0044]	[0.0278]	[0.0085]	[0.0089]	[0.0153]
Homicide rate Ages 0-3	-0.0104	-0.0739	0.0076	-0.0071	-0.0143
	[0.0112]	[0.1756]	[0.0145]	[0.0129]	[0.0207]
N	10,807	607	5,139	4,429	632
Mean (%)	3.0	4.8	3.5	2.5	1.1

Note: the sample includes families with a child below age 5 in the DHS data in waves 1986, 1990, and 1995. The outcomes of interest are dummies for whether a child died before age 1 or before age 3, and 0 otherwise. Models include individual and mother covariates as well as year, month, and municipality of birth fixed effects, wave fixed effects, and department-specific time trends. Errors are clustered at the municipality of birth. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Figure 1. Homicide Rate by City, 1980-2009 (homicides per 1,000 inhabitants)

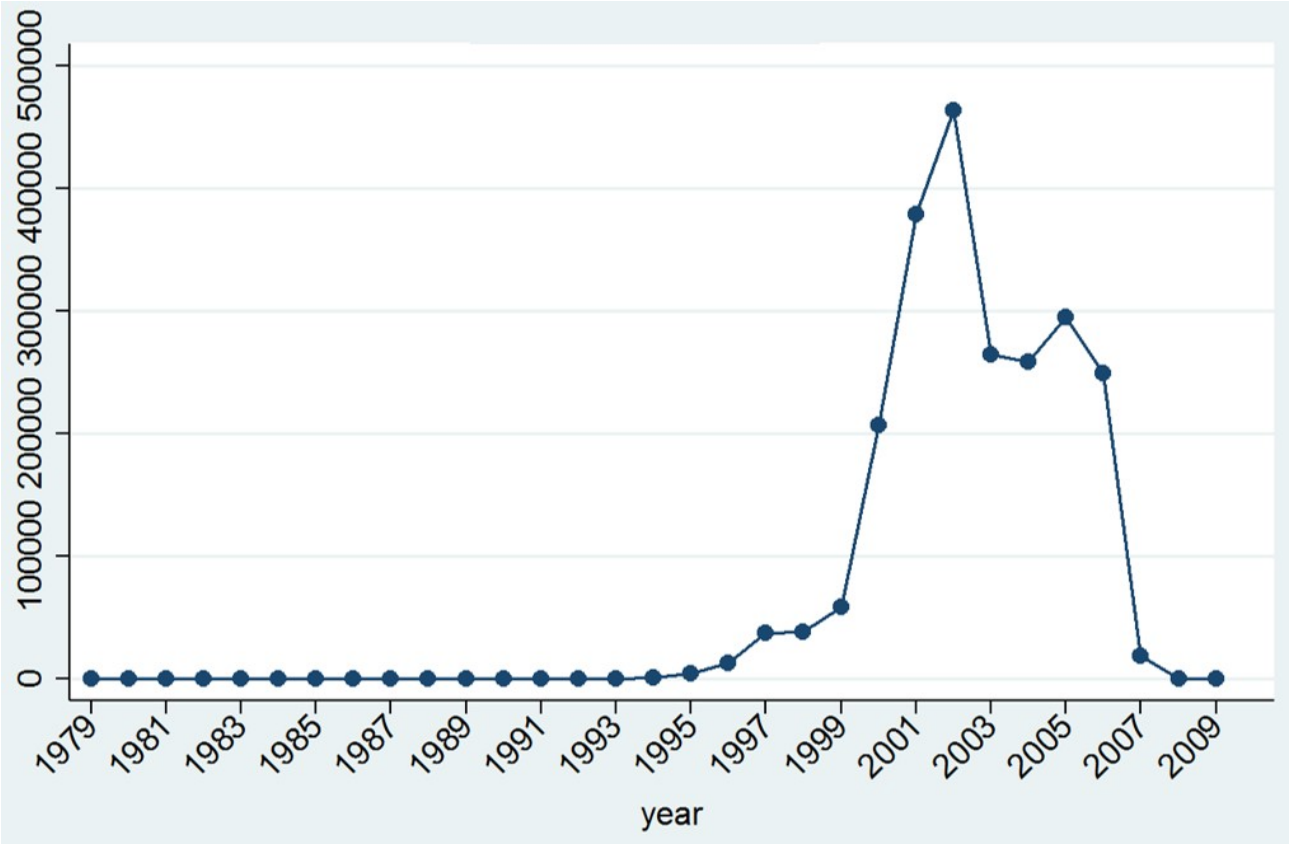


Appendix Figure 2. Homicide Rate in Colombia by GDP per capita in 1980-82 (homicides per 1,000 inhabitants)



Note: based on author's calculations.

Appendix Figure 3. Forced Displaced Population, 1979-2009
(total N)



Source: the National Agency *Acción Social* – Information System of the Displaced Population.

B. Appendix: Proofs

B.1. *Proposition 1*

Using an individual's decision rule of whether it is optimal to study (i.e., comparing (7) and (8)) and denoting by $G_y(y_i)$ the c.d.f. of transfers in the population of individuals, I can express the mean education level across individuals, conditional on a level of violence $v_0 = v$, as $E(s_i|v) = \int_{y_i^*}^{\infty} \mathrm{d}G_y(y_i)$. Note that $G_y(y_i)$ does not depend on v. Therefore, using Leibniz rule, $\frac{\partial E(s_i|v)}{\partial v} = -\frac{\partial y_i^*}{\partial v}\,\mathrm{d}G_y(y_i^*)$. The assumption that $\frac{\partial g(1,\theta_{i,1},X_i,I_{i,1})}{\partial v_{i,0}} < 0$ implies that $\frac{\partial \mathcal{W}(\theta_{i,1},X_i,I_{i,1})}{\partial v_{i,0}} < 0$ and $\frac{\partial y_i^*}{\partial v_{i,0}} > 0$. It follows that $\frac{\partial E(s_i|v)}{\partial v} < 0$.

B.2. *Proposition 2*

Let $\hat{\theta}_{i,1} \equiv \Theta(\theta_{i,0}, X_i, I_{i,0}, \overline{v})$ and $\hat{I}_{i,1} \equiv \mathcal{I}(\theta_{i,0}, X_i, I_{i,0}, \overline{v})$ denote, respectively, an individual's period 1 abilities and parental investment under the maximum level of violence, $\overline{v}$, given their initial abilities and parental characteristics $\{\theta_{i,0}, X_i, I_{i,0}\}$. Let $\hat{y}_i^* \equiv \frac{\underline{w}}{e^{\beta}\left(\frac{w\left(\hat{\theta}_{i,1},X_i,\hat{I}_{i,1}\right)}{\underline{w}}\right)^{-1}}$ denote the income threshold given $\{\hat{\theta}_{i,1}, X_i, \hat{I}_{i,1}\}$. Note that:

$$\frac{\partial \mathcal{W}\left(\hat{\theta}_{i,1}, X_i, \hat{I}_{i,1}\right)}{\partial X_i} = \mathcal{W}_1\left(\hat{\theta}_{i,1}, X_i, \hat{I}_{i,1}\right)\Theta_2(\theta_{i,0}, X_i, I_{i,0}, \overline{v}) + \mathcal{W}_2\left(\hat{\theta}_{i,1}, X_i, \hat{I}_{i,1}\right) + \\ + \mathcal{W}_3\left(\hat{\theta}_{i,1}, X_i, \hat{I}_{i,1}\right)\mathcal{I}_2(\theta_{i,0}, X_i, I_{i,0}, \overline{v}) > 0,$$

where the last inequality follows from the assumptions on functions $g(.)$, $\Theta(.)$, and $\mathcal{I}(.)$. Therefore, $\frac{\partial \hat{y}_i^*}{\partial X_i} < 0$. Given that $\frac{\partial y_i}{\partial X_i} > 0$, one can always find an X^H such that for any $X_i \geq X^H$ $y_i > \hat{y}_i^*$ and $s_{i,1} = 1$. The proof for the second part of the proposition is symmetrical.