UNIVERSITY OF COPENHAGEN

ESTIMATING THE EFFECT OF MEXICAN CARTEL-VIOLENCE ON HUMAN CAPITAL ACCUMULATION

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Abstract

Can drug-cartel conflicts affect human capital accumulation? This thesis explores the effect of cartel-violence on children's school grades and school attendance. Mexico's new wave of War on Drugs in 2007 started a period of turf wars against the government and between cartels fighting for the municipalities' control. The two main hypotheses are: i) Schools in municipalities that suffered drug-homicides and violence during the War on Drugs attained lower grades than schools in similar control municipalities; ii) The War on Drugs in Mexico decreased children' attendance to schools situated in drug-violent municipalities. The results suggest that going to school in a municipality with-drug-related homicides reduces the children's attendance by 0.3%.

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Section 1

Introduction

Intra-state violence and civil conflicts are not rare events in developing countries. According to the Uppsala Conflict Data Program (UCPD), more than 50% percent of the world's countries had suffered at least a year with 1000 or more casualties, which is considered a civil war. Mexico is one of the most prominent cases both in the number of deaths and in the persistency. Since the 1950s, Mexico has experienced different civil conflicts, but never enough to be a civil war until the Mexican Drug War escalation from 2007. The start of this period raised the amount of violence that has continuing effects nowadays. In 2019 alone, the number of deaths surpassed eleven times the requirement to be deemed a civil war. The current civil war in Mexico has a direct link with Drug Trafficking Organizations (DTOs) activities, commonly called drug-cartels. The hegemony of the political party PRI (Partido Revolucionario Industrial, by its acronym in Spanish) for seventy years and its ties to DTOs made that until 2000, cartels operated relatively quietly. With the political change, powerful DTOs such as the *Zetas* and the *Sinaloa Cartel* started to fight for the control of drug-trafficking routes to the United States. In the period of this study, from 2005 to 2010, the death toll is over 50.000 drug-related murders, rising an average of 80% per year since 2006 (SNSP, 2011).

Sadly, drug-related crimes have spillovers beyond the direct victims. The thesis focuses on one of the most vulnerable demographic groups to violence: children. It seeks to contribute to the existing literature studying the effect of drug-cartel violence on children's human capital accumulation. The selected proxies for human capital accumulation are national standardized school grades and school attendance. On the other hand, I have chosen drug-related homicides as a proxy for drug-cartel violence. While other proxies can be used for cartel-violence, drug-related homicides seem to be most straightforward. Also, homicides are less likely to be misreported or hidden by authorities.

There are multiple channels in which drug-violence can affect education, making any causal inference link empirically challenging. Mexican municipalities that suffer cartel-violence in the mid-2000s can also bear poverty, lack of strong institutions, or essential public services, that affect children's' educational attainments. I use Propensity Score Matching on selected municipalities to control for observable characteristics that influenced a municipality to be considered violent, combined with a Differences-in-Differences design to address the time-varying unobservables characteristics that affected municipalities over time. The empirical strategy's decision aims to provide a sample pool of municipalities with differences in drug-violence patters, but similar other characteristics.

The rest of the thesis is structured as follows. Section 2 presents Mexico's political background and its relation with the international cocaine Drug-market. Section 3 presents the literature on the topic, focusing on the latest research exploring the side effects and consequences of gang and drug-cartel violence. Section 4 shows the theoretical model that can explain the negative effect of institutional insecurity on human capital accumulation. Section 5 describes the source of all the variables used for the later empirical analysis, as well as the definition of treatment and controls. Section 6 presents the econometrical foundations of the paper and clarifying the different parametric decisions. Section 7 shows the results over math and language grades and school attendance. Section 8 presents robustness checks of the Difference-in-differences estimation model. Lastly, Section 9 concludes the thesis.

Section 2

The political roots of the 2007 Mexican War on Drugs

Drug-related homicides in Mexico are mostly targeted and willfully visual. They are messages to other cartels or groups threatening their position. Bodies showing signals of torture and bullet wounds are dumped into slums or hung by ropes in public places. Indirectly, Mexican towns and cities have become the battlefield for Drug Trafficking Organizations (DTOs) to retaliate between each other. Rios (2013b) refers to this situation as a *"self-reinforcing violent equilibrium"* that trap communities: confrontations between gangs incentivize the government to use military enforcement, and military operations trigger even more criminal confrontations. How did Mexico end up continually being in the top five countries with the most homicides per capita?

The conflict cannot be understood without mentioning the 72-year alliance between the *Institutional Revolutionary Party* (PRI) and the main Mexican drug-cartels, from 1928 until 2000 (Astorga and D. a. Shirk, 2010; D. Shirk and Wallman, 2015). On their side, the drug-cartels remained peaceful as long as the government did not interfere with their activities. DTOs acted as they were economic-cartels, cooperating in the oligopolistic drug industry and sharing the benefits. On the other side, the federal government allowed drug-trafficking, which did not involve violence or brutality, in exchange for large bribes. By 1970 Mexico was the most prominent intermediary of cocaine in the world, led by the *Guadalajara Cartel* and the *Cartel del Golfo*, the two biggest Mexican cartels at the time. Their job was to act as the logistics-partner of Colombian cartels, delivering their cocaine production to the U.S.

The close relationship between the Mexican state and DTOs continued during the 1980s. Scholars like Scott and Marshall (1998) refers to this political period as *"Cocaine Politics"*. Local police protected and facilitate cocaine cargos from cartels to the U.S., guiding the trucks and monitoring the American police radio surveillance. This relationship was particularly evident in some Mexican states. The brother-in-law of Antonio Toledo, the Guadalajara Cartel leader, ended up becoming the governor of Sinaloa in 1981 (Rios, 2013a). Drug-cartels maintained a close link with federal power, and the "peace treaty" continued until the change of political landscape. In 2000 a significant event shook the political arena. Vicente Fox, the leader of the political party *Partido Acción Nacional* (PAN) was elected as the new president of Mexico. With this change of government, the connection between cartels and political power was difficult to remain from 2000 on, as the Mexican cartels did not have the trust and political power anymore to ensure lack of law enforcement in their operations.

The end of the 72-years political term of PRI, followed by the dissolution of institutions under the umbrella of DTOs, like the *Procuradería General de la República* (Attorney General's Office), made the unique relations between Mexican drug-lords and government unworkable (Snyder and Duran-Martinez, 2009). The final break-down took place under the following PAN administration led by Felipe Calderón (2006–2012), in which fighting drug-cartels was the cornerstone of his policy views. In consequence, law enforcement took a new twist focusing on eradicating narcotics. As an illustrative example, just after ten days after the election of Calderón as President in December 2006, the military force started to raid and seizure drug-labs and drug processing hubs. During the Calderón period in the presidency, Mexico experienced one of the most violent periods of Latin America's recent history. It is impossible to know the counterfactual of Mexico without the political and military fight against drug-cartels. A very probable scenario is that law enforcement was inevitable regardless of the federal party in charge, as DTOs were taking control of entire communities and overpowering the police force at the time of the federal 2006 elections (Guerrero-Gutiérrez, 2011). These events mark the beginning of one of the most violent periods in Mexican modern history, a fight that does not seem to end (UNODC, 2019).

Section 3

Literature Review

Recent and extensive literature explores the different roots of violence in Mexico, including the effect of law enforcement, the change on commodity prices, the access to firearms, political party influence, or the capture of cartel kingpins, among others (O. Dube and Vargas, 2013; A. Dube, O. Dube, and García-Ponce, 2013; Calderón, 2015; Dell, 2015; O. Dube, García-Ponce, and Thom, 2016). What was the common denominator of all of these events that influenced the violence rates? Arguably, the main reason is that those shocks affected the dynamics and conflicts between drug organizations in illegal drug markets. In legal markets, firms resolve disputes by claiming property rights and making legally enforceable contracts. Drug-cartels do not have access to these tools because of their business' nature, and therefore have to exercise violence to solve disputes. The consequences of the use of violence go beyond a bigger homicides count. A second branch of the literature studies these consequences, trying to answer whether violence resulting from drug-related disputes and turf-wars has negative spillovers.

Robles, Calderón, and Magaloni (2013) argue that cartel-violence substantially affects the decisions of families, firms, and workers. Once the DTOs start fighting over the territories, agents internalize the cost of security and own-protection. This cost leads to an economic contraction of the entire municipality. They use two identification strategies. On one hand, they instrument the percentage of drugs seized in Colombia times the distance of the Mexican municipalities to U.S. They state that the interaction between these two phenomena creates an exogenous variable related to Mexican drug-activity but uncorrelated with economic activity. An augment of 10 homicides per 100.000 inhabitants is associated with 2% less working population, 0,5% less self-employed people, and a rise in 1.5% in unemployment. In the second empirical approach, they use synthetic controls to estimate the effect of drug-violence on economic activity. The logic behind synthetic controls is to create virtual Mexican municipalities that act as a counterfactual with similar characteristics for municipalities affected by drug-violence. The authors estimate that, without cartel-violence, the most affected municipalities would consume between 4.2% and 7.4% more electricity.

Some anecdotal evidence suggests that drug-cartels can provide economic support to communities by investing in infrastructure or creating jobs for low-income families. Can DTOs provide positive side-effects in the communities that they operate? Gutiérrez-Romero and Oviedo (2017) found opposite results in their study of the consequences of drug-violence and cartel-presence on local economies. The Mexican municipalities with at least one drug-related homicide from 2007 have a significant negative impact on their economies, including employment, manufacturing production, poverty, and inequality. The authors compare the municipalities' economic conditions that remained free of drug-related crime from 2000 to 2010, with very similar municipalities that started having this kind of crime in December 2006 and onwards. To measure the effect, they combined two econometric techniques: Difference-in-differences with Propensity score matching. The fundamental assumption is that control and treatment municipalities would have the same trends in their economies without the cartel violence element. This thesis followed Gutiérrez-Romero and Oviedo (2017) for the methodological strategy. Therefore, the specifics will be described more deeply later in Section 6.

The percentage of the population without enough income to buy a basic basket of food, pay for education, or health care raised in the order of 2.5% to 2.8% in the municipalities most affected by drug-related homicides against the peaceful ones. They also find very significant effects in migration patterns, with 0,3% more migrants from these municipalities to others with less violence. Unemployment was affected by 0.7% as well. Concerning the industry sector, in comparison with peaceful areas, around 25 fewer million dollars was produced in manufacturing, counting with 0,35% fewer workers. They do not find any positive effect in municipalities in which cartels are placed but no murders are registered. The findings suggest that DTOs did not provide any positive effects in their communities, not even when they worked without killing.

Focusing on human capital accumulation, one of the main inspirations for this paper comes from Jarillo et al. (2016). The paper investigates the effect of high-intensity violence events, such as turf and gang wars, on Mexican academic achievement. They use a panel of math test scores from the National Assessment of Academic Achievement (ENLACE) as the variable of interest. Turf wars in a particular month are defined if the number of firearms-related homicides surpasses a threshold of two standard deviations above its moving average of the previous four years. They argue that households respond differently to the usual crime than to spikes in violence. For example, high-intensity violent events might cause absenteeism in teachers and students, shorten the schooling time, the classes' duration, or even force schools to close for a while. Using a fix-effects model, they estimate a negative effect of 2.32 fewer points in the math scores if the school suffered a spike in violence that year and a cumulative negative effect of 1.32 fewer points for every month with violence spikes. One of the many curious results of the paper is that the effect is concentrated only in urban areas, being non-significant in rural areas. Furthermore, the exposure to turf wars in urban localities is correlated with children leaving school days early and absenteeism.

It is worth noticing that Jarillo et al. (2016) and this thesis shares a similar research question using similar data from the ENLACE program, but with some caveats and differences. First, it is not clear why the authors only use ENLACE math results and not Language as well, when both are available. It might be the case that math exams are better predictors of learning outcomes, but it is not discussed in the paper. In any case, it can be interesting to check if violence events have spillover effects on Language test scores, and hence I include them in the analysis. Second, fix-effects solve the endogeneity problem removing any constant characteristics across schools and years, both observed and unobserved, and capturing the changing effect on the dependent variable. However, if some schools are affected by time-varying confounders for the study period, the regression estimates are likely to be biased. For example, educational time-trends of the northern municipalities in Mexico could have been different than in southern municipalities. In this sense, using a different empirical strategy that addresses this problem can contribute to their results' robustness.

Lastly, the effect of cartel-violence on schools situated in municipalities that continuously suffer violence is not clear given the definition of *high-density violence* as two standard deviations above its moving mean. To illustrate this argument, Figure 3.1 shows two municipalities, both with seven high-density violence spikes according to the Jarillo et al. (2016) treatment definition. The main difference is that the municipality in Panel A, Juárez, suffers a large amount of violence regularly, and therefore the threshold of two standard deviations above the average is difficult to surpass. The municipality in Panel B, Ajalpan, has the same number of months with spikes in violence, but the threshold is roughly a hundred times lower than in Juárez.

Total number of high-density violence spikes in Juárez and Ajalpan, 2004 to 2012

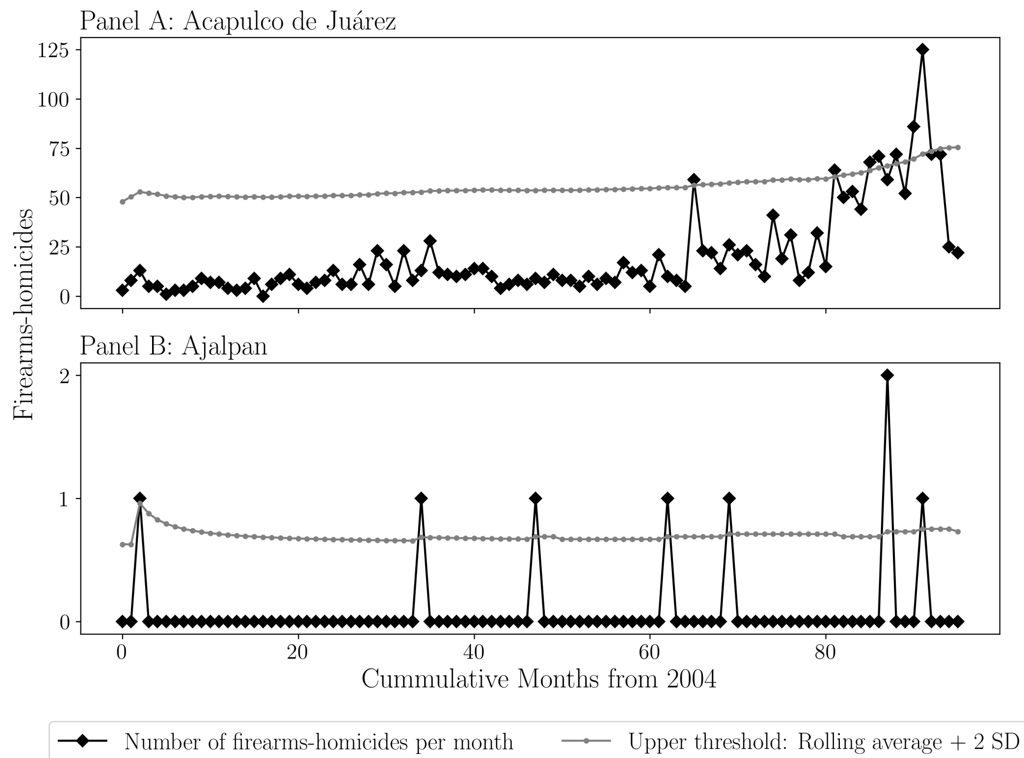

Figure 3.1: Source: Authors own calculation from SINAIS data. The number of firearms-homicides in Acapulco of Juárez (Panel A) and Ajalpan (Panel B) per month from 2004 (black line). The Upper threshold (grey line) is defined as the two standard deviations above its moving average from the last four years. Every month with firearms-homicides above the Upper-threshold is considered a month with high-density violence (Jarillo et al., 2016). Both Acapulco de Juárez and Ajalpan have seven months of high-density violence, regardless of marked differences in firearm-homicides between the two municipalities (vertical axis).

On average, the number of firearms-homicides is roughly 240 times higher in Juárez than in Ajalpan, but the high-intensity violence treatment indicator is the same by this metric.

Aside from the Jarillo et al. (2016) paper, Caudillo and Torche (2014) specifically investigate as well the relation of drug-violence with educational outcomes. They study the probability of failing elementary grades in school because of drug-related violence. The authors are able to track children's grades using panel data of primary schools from the school census. The paper's strength comes with the multiple empirical strategies that they use, including a fix-effects model, a first-differences model, and a GSIS model (*group-specific intercepts and slopes*) in which they group the schools depending on the federal state in which they are located to control for similar socioeconomic characteristics. Homicides rates have an adverse effect on failure percentage in the range of 0.004 to 0.02. While the magnitude seems small, it is meaningful comparing the effects of violence with the impact of large public programs. For example, one of the most famous conditional cash-transfer program called *Oportunidades* created a drop in failure rate in primary school of 0.006 %. Nevertheless, it has to be considered that the results of Caudillo and Torche (2014) rely on heterogeneous school grades. The grading practices can vary between types of schools, teachers, municipalities, and subjects, making the score comparison difficult. This is also the reason why homogeneous nationwide exams like ENLACE, mentioned before, were created to compare schools.

The last piece of evidence of turf war exposure influencing student achievement comes from Monteiro and Rocha (2017). In Rio de Janeiro, Brazil, the *favelas* face problems similar to the Mexican municipalities regarding gang conflicts: when different gangs try to gain control over the area, homicides rise. Using reports of the police hot-line, they can identify drug and gang conflicts located inside or on the favelas' border. Drug-conflicts events result in lower math test scores in 0.054 standard deviations. The effect is higher when the school is close to the event, and when the conflict happened right before the exam. The most singular piece of evidence from the paper comes from the long-impact of gang violence. They found that the effect of conflicts fades away in the long-run, and violence shocks have only a transitory impact in school grades.

Section 4

Theoretical Framework

The following section establishes the theoretical foundations of the thesis. I will develop a simplified version of the model proposed by Lopez Cruz (2016) to generate theoretical predictions of human capital accumulation in violent environments. It is simplified in the sense that it focuses on children's human capital equilibrium only, and it avoids mathematical proofs to keep a reasonable section length.

The model starts with a two-stage model of human capital H and street capital accumulation S. Street capital refers to *"the skills and knowledge useful for providing personal security in neighborhoods where it is not provided by state institutions"*. There is a trade-off between street capital and human capital accumulation. The time that children do not spend in school or other school related-tasks is used to get street skills that might be productive in the future. Also, street capital accumulation allows agents to use violence in the future.

In the first stage, the agent is a child, and the public safety or the quality of the schools is fixed and common-knowledge. These assumptions can be seen as the child's inability to migrate to better areas with safer quality schools, as she still does not produce any outcome to afford the migration. Children experience uncertainty about the precise returns of education in adulthood, because part of their future consumption can be taken away by the use of other agent's violence.

In the second stage, agents are adults and enjoy their consumption as a function of human capital and street capital. If those adults live in "violent areas" where public safety is not ensured, agents can use street capital earned during childhood to extract other agents' output. In the opposite case, with strong institutional public safety, agents cannot extract other agent's outcomes regardless of their street skills. For simplicity, the model considers two risk-neutral individuals $i = 1, 2$ - instead of a whole municipality or neighborhood of agents.

In the next sub-sections, I provide a more detailed description of the two agent phases, childhood and adulthood, and the hypotheses resulting from the model equilibria. The Figure in 4.1 summarizes the model.

4.1 Stage one: Childhood

In this sub-section, the model emphasizes the children's educational investment choices in a violent municipality.

During childhood, agents $i = 1, 2$ have a limited amount of time g to allocate to human capital H and street capital S. Children choose their time investments between human and street capital. Agents allocate a fraction g_i of time to street capital and the rest of the time $1 - g_i$ to human capital. Comparative advantages in education exist, and every agent has a high innate ability to learn B^h with a probability α and a low learning innate ability B^l with a probability $1-\alpha$. Children do not know their initial innate ability B, but they know that high innate ability is better for learning in school than low innate ability $B^h > B^l$.

The status of violent and non-violent municipalities are fix for the children, being p the probability of going to school in a violent municipality and $1-p$ otherwise. The accumulation of human capital H and street capital S are given by amount of time in childhood develop attending to school $1 - g_i$ or getting street skills g_i, respectively:

$$H_i = (1 - g_i)f(B_i) \quad and/or \quad S_i = g_i \tag{4.1}$$

Where $f(B_i)$ depicts the returns of education as an increasing function of the innate ability to learn B_i. The fraction of time that children invest in street capital do not depend on their innate ability.

4.2 Stage two: Adulthood

For this sub-section, I will explain how agents can use their different skills in the adult phase, given their first childhood stage decisions. Adults can produce in the formal sector of the economy depending on their accumulation of human capital, or to exercise violence in the informal sector using their accumulation of street capital:

$$Y_i = H_i(1 - z_i) \quad and/or \quad G_i = S_i z_i \tag{4.2}$$

Where Y_i is a product of her human capital acquired during childhood times the fraction of time z_i that she allocates to the production of goods. The violence parameter G_i is a product of her street capital times the fraction of time that she allocates to violent activities during adulthood.

To clarify, the original theoretical model by Lopez Cruz (2016) explores two maximization problems to explain two equilibrium results, one as children and one as an adult. As a child, agent i maximize her time g_i to maximize future consumption according to her abilities. As an adult, the agent maximizes her time z_i to maximize an optimal combination of Y_i and G_i. The following sub-sections only cover the children's equilibria, as the paper focuses on children's human capital accumulation. The equilibria of adult production is irrelevant for the latter hypotheses. For the aim of the thesis, it is only necessary to acknowledge that adults can use violence to produce an outcome, and this violence is an increasing function of their street capital invested as children ($G_i = S_i z_i$).

4.3 Childhood Capital Accumulation Equilibrium

During adulthood, each agent consumes goods according to their innate abilities and the composition of their school and streets skills. These outcomes and the incentives to acquire different skills depend on living in a peaceful municipality or a violent municipality. Assuming rationality, agents in their childhood make decisions to maximize the future consumption as adults. The expected consumption function is given by:

$$E(C_i) = p[(1-\alpha)C_i^P(B_i^l) + \alpha C_i^P(B_i^h)] + \tag{4.3a}$$
$$(1-p)[(1-\alpha)C_i^V(B_i^l|B_j^h) + \alpha C_i^V(B_i^h|B_j^l)] \tag{4.3b}$$

Equation part 4.3a refers to expected consumption in the case of living in a peaceful municipality ($p = 1$). Adult i consumption in this peaceful municipality (C_i^P) depends on the probability α of being born with high (B^h) or low innate school ability (B^l). Their consumption does not depend on other agent's abilities, as every agent only consumes their own payoff outcome. Therefore, their consumption is not conditional on other agent's innate abilities.

Equation part 4.3b refers to the case of living in a violent municipality ($p = 0$), in which agent i consumes C_i^V as adult. Again, agent i consumption depends on the probability (α) of being born with high or low innate school ability. It is worth noticing that the main difference in the two parts of the equation is the conditional ability operator. In the violent scenario, adult consumption depends on the innate ability of other agents j. For example, a child has incentives to acquire street capital to exercise violence over other agents in the future, knowing that she might have low innate school ability with some probability. In the previous sub-section, I described that she could produce output as an adult using the violent way. On the other hand, if it happens to be revealed later in life that the child is a high ability individual, she would prefer to product output using the human capital she developed as a child and not use violence. However, regardless of the ability type revealed in the second stage, they already acquired street capital as children in the first stage and made their investment decisions.

The children's street capital equilibrium decision is given by:

$$g_i^* = \text{ArgMax}\left\{E(C_i)\,(g_i, g_j)\right\}, \quad g_i \in [0,1] \tag{4.4}$$

Equilibrium values of street capital g_i maximizes children i consumption as adults given j's choice g_j, where $i \neq j$.

Figure 4.1 provides a graphical simplification of the model and describes the incentives scheme for children. In peaceful municipalities, the optimal level of children's street capital accumulation is zero ($S^* = 0$), given that every adult in the future enjoys their own consumption and total law enforcement avoids other agent's use of violence as a way to produce. Street

Incentive scheme of human and street capital accumulation in the childhood stage

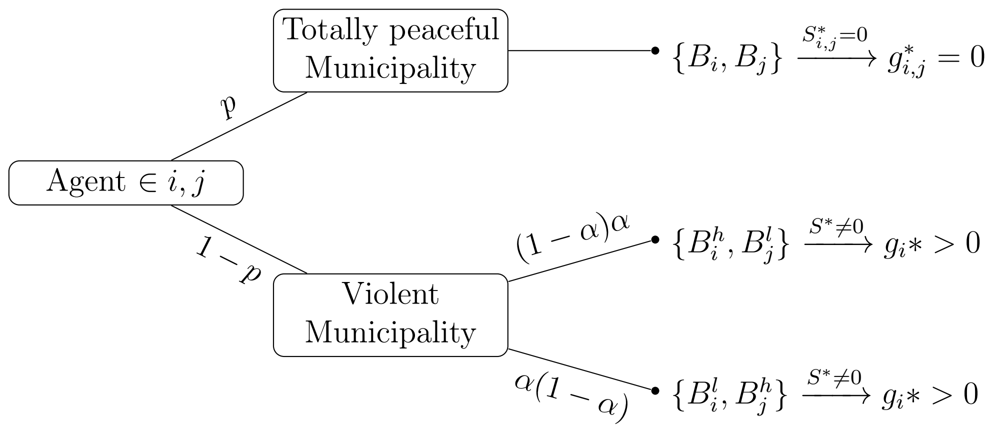

Figure 4.1: Author's own elaboration graphical simplification based on Lopez Cruz (2016)'s Section 3: "A model of street and human capital accumulation"

skills are not needed and institutional security is ensured ($g^* = 0$). In violent municipalities, children have incentives to acquire some positive street skills ($g^* > 0$) regardless of their comparative learning skills. With probability $(1-\alpha)\alpha$, the agent i has a positive learning comparative advantage over j: $B_i^l > B_j^h$, and therefore she is better-off accumulating human capital ($H^* > 0$), but also some street capital ($S^* > 0$) because she does not know her ability yet. With probability $\alpha(1-\alpha)$ the agent i has a negative learning comparative advantage over j, and therefore she is better-off street capital ($S^* > 0$), but for the similar reasons, also gets human capital ($H^* > 0$). Overall, in violent municipalities, children had incentives to get at least some street capital regardless of their ability.

Please note that the model probabilities also include that all the agents have high innate ability, and that all agents have low innate ability with probability $(1-\alpha)^2$ and α^2, respectively. These cases are not included in the graphic simplification because they are not relevant for the analysis. First of all, if we increase from two agents to multiple agents in a municipality, the likelihood of all the agents having the same school innate ability is close to 0. In the absence of institutional safety, they will always be people without opportunities to develop school skills incentivized to get street skills. Second and most important, it does not change the equilibria as children do not know α in the children phase of the model. The equilibrium is possible because their initial learning innate abilities are unknown in childhood, and they could exercise violence later in life to produce.

The theoretical equilibria provides the following prediction: in violent municipalities, less time is spent to accumulate human capital and more time to accumulate *'street capital'*.

$$\frac{\partial g^*}{\partial p} < 0 \tag{4.5}$$

Where g^* is the time that any young agent allocates to street capital accumulation and p is a dummy indicator for living in a peaceful municipality.

It might be hard to believe that children make educational choices on their own, or that they would choose to invest in street skills that allow to them to loot resources in the future. However, it exist plenty of evidence of drug-cartels recruiting children and giving them this kind of "education". Several fractions of the DTO *Los Zetas*, is known for actively recruiting kids to control the drug-routes (*Los Halcones*) and whistle when police come (*Los Ventana*). The most fierce teenagers (*Los Estacas*) receive military training from former police officers and military members in the cartel. These teens ranging from 10 to 16 years old are employed as foot soldiers for drug-transportation and fighting against other gangs.

Moltalvo (2012) estimates that at least 30.000 children joined drug-cartels in Mexico. In most cases, cartels employment is the only source of income for the children's family. They have to learn street skills out of necessity. Similar patterns of child recruitment are observed in other Mexican DTOs and drug-gangs in Brazil or Colombia (Garzón, 2008). Even local-governments in some Mexican municipalities have started giving children militar training and guns to protect themselves against drug-cartels (Meneghini, 2020). It is reasonable to think that time spent learning how to use guns (*street capital*) affected their time in school (*human capital*), and that skills learned during childhood hold different payoffs in adulthood depending on how violent is the municipality.

4.4 Hypotheses

Conflicts and wars not only affect human capital accumulation rational decisions, but also influence the well functioning of institutions, slow down economic activity, and damage social cohesion. Therefore, it is challenging to establish the mechanism of how the causal relation takes place. Justino (2012) provides a qualitative framework to analyze the mechanism between cartel-violence and educational outcomes. There are at least six possible factors to link drug-cartel violence with human capital investments in Mexico:

1. Lack of safety affects the decision of children and children's families on educational investment.

2. Violence diminishes the returns of education.

3. Cartels recruitment of children for criminal activity.

4. Children can fear Cartel's aggression, triggering households to attempt to protect them by keeping them at home.

5. Cartels target schools, disrupting the learning.

6. Drug-related homicides can force teachers, children, and families to migrate to more secure locations.

This thesis focuses on testing the predictions given by the theoretical model. Nonetheless, I acknowledge that there are multiple channels in which violence can affect human capital accumulation. Based on the theoretical predictions and qualitative framework, the paper test the following hypothesis:

H1: The escalation of violence in Mexico led to schools situated in drug-violent municipalities to attain lower (ENLACE) school grades.

H2: The War on Drugs in Mexico decreased the school attendance in schools situated in drug-violent municipalities.

If children living in violent municipalities spend less time schooling and the more time accumulating 'street capital', as the theoretical model predicts, we should expect less attendance and lower grades in violence-affected municipalities.

Section 5

Data

To test the hypotheses, first it has to be determined what it can be considered a violent municipality, and logical proxies for human capital accumulation. I collected data from several official sources, from municipal census data to nationwide exams. The following sub-sections explain the different variables taken as inputs for the empirical analysis and the descriptive statistics. Mexico is divided into 32 federal regions (*"Entidades federativas"*), which contain a total of 2457 municipalities (*"Municipalidades"*). All the data is collected at the municipality-level.

5.1 ENLACE Exam Grades

The National Assessment of Academic Achievement in Schools test (ENLACE, in Spanish) was a homogeneous exam to be carried out every year by the Secretary of Public Education (SEP) to all public and private basic level schools, including primary and secondary education. The main goal was to evaluate the performance level of children objectively from 6 to 15 years old. The exam was made according to PISA standards. The main subjects were Language (Spanish) and Mathematics. After the initial implementation, the government developed exams for more subjects, but only grades from the Language and Mathematics are available before and after the violence escalation of 2007. The data was collected from the National Institute for the Evaluation of Education (INEE, by its acronym in Spanish) for the years 2006,2007,2009 and 2010. Open-data for 2008 is missing. Sadly, I could not access the missing year since INEE is dissolved. With the

Mexican constitutional reform on May 15th of 2019, Mexico derogated the article that ensured the State's role to *"generate and disseminate information that contributes to the continuous improvement of the National Educational System."* (Derogado, 2019). I collected all the primary and secondary school grades available from close to 100.000 schools to test Hypothesis 1.

5.2 Economic conditions and school attendance

To be able to assess the school attendance before and after the treatment (Hypothesis 2), and several poverty measures, I collect census data from 2005 and 2010 from The General Secretary of the National Population Council (CONAPO, by its Spanish acronym). CONAPO is the official body in charge of estimating the global impact of the lack of essential services, such as access to electricity, water, education, or a bare income floor. Unfortunately, there is no official entity that provides GDP at the municipal level. However, patrimonial poverty and inequality trends are controlled using census data of 2000.

5.3 Cartel Presence

Cartel's previous presence to the start of the war in December 2006 was measured using Coscia and Rios (2012) open-data on criminal organizations. In her paper, she tracks systematically where the different gangs and cartels operate by collecting appearances of cartel information in Google News.

5.4 Drug-related homicides

The division between violent and non-violent municipalities is possible using data from the Empirical Studies Of Conflict (ESOC). ESOC collected all the homicides presumably related to rivalries between Drug Trafficking Organizations from December 2006 to September 2011. The project is a collaboration of intelligence agencies from the United States Government with the Mexican Ministry of National Defense and the Office of the Mexican Attorney-General. The paper uses drug-related homicides and cartel presence to determine the treatment status.

5.4.1 Treatment Group: violent municipalities

The treatment group is defined as the municipalities that have never had cartel presence before 2007, but experienced at least one drug-related homicide between December 2006 and December 2010. Hence, the schools and children living in those municipalities are considered affected by cartel-violence. These municipalities are proxied as *violent municipalities.* Cartel activity is expected to provide incentives to invest in street capital in detriment of human capital in this areas.

5.4.2 Control Group: non-violent municipalities

The control group is defined as the municipalities that had never had cartel presence before 2007 and did not experience any drug-related homicide afterward. These municipalities were relatively peaceful before and during the War on Drugs, and children on them in principle they would have no incentives (or have the opportunity) to invest in the street capital described in Section 4. These municipalities are proxied as *non-violent municipalities* or *peaceful municipalities.*

The main reason to combine data sets of cartel presence before the start of the War of Drugs and drug-related homicides after is because of data limitations. Before December 2006, there are no official drug-related homicides because they were not counting them (Rios, 2013b). Other papers follow a similar combination of measurement indicators to distinguish municipalities affected by drug-cartels (Robles, Calderón, and Magaloni, 2013; Gutiérrez-Romero and Oviedo, 2017). In total, 1326 municipalities fill the conditions of control or treatment status and ENLACE data is available. Those selected municipalities hold more than 100.000 schools that did the ENLACE exam for Mathematics and Language to any of their cohorts in primary and secondary schools (6 to 14 years old children).

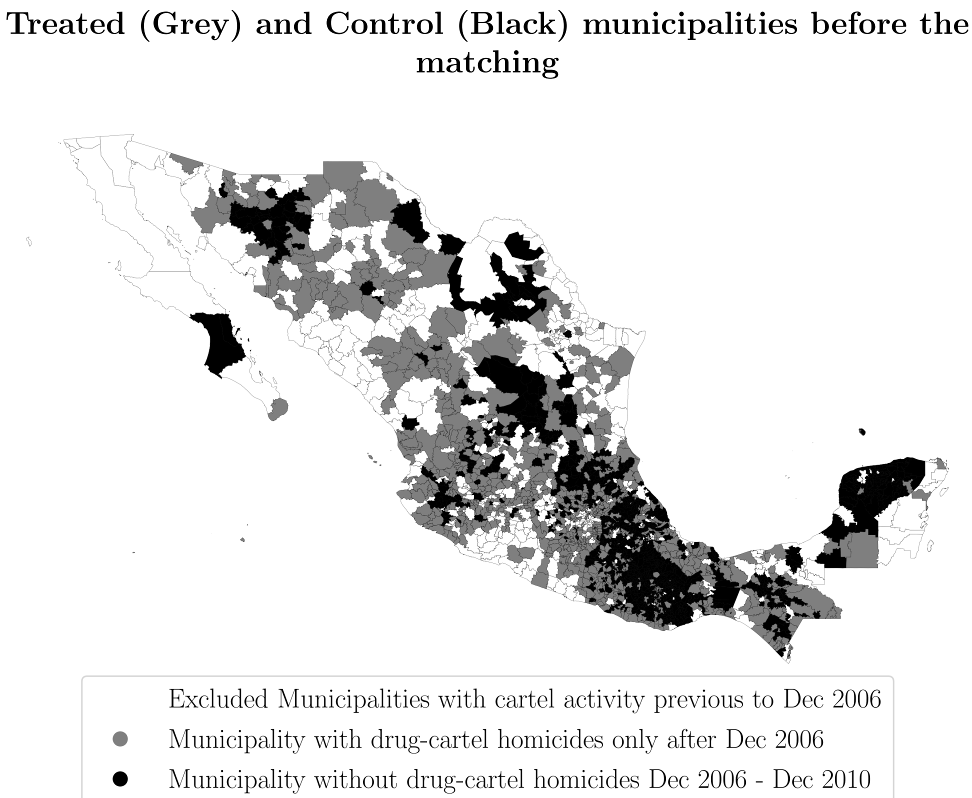

Figure 5.1: Municipalities with non cartel-presence before, but drug-homicides from December 2006 on versus free-cartel and drug-homicides municipalities

5.5 Firearms-homicides

According to the model, it would be expected that higher intensity of violence leads to lower investments in human capital. I use yearly firearms-homicides per 100.000 people to measure violence intensity in the municipality. Data on firearm-homicides was extracted from individual-level death certificates from the National Health Information System (SINAIS, by its Spanish acronym). The panel data is constructed by grouping all the yearly firearm-homicides in a municipality, from January 2004 to December 2011. Gathering the data was possible since SINAIS provides a unique code for the different causes of death. The following figure describes the total number of homicides by firearms from January 2004 to December 2011. By 2010, firearm-homicides aroused more than 3.5 times the level of 2006.

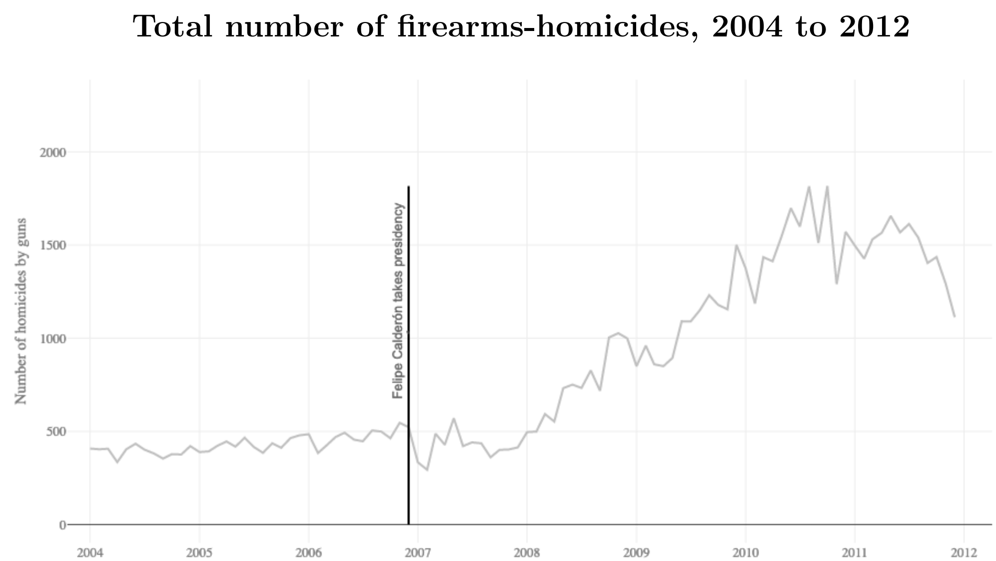

Figure 5.2: Total number of firearms-homicides in Mexico, 2004 to 2012. The data was extracted from SINAIS. Specifically, only deaths with the cause of death within the codes X930 to X959 were computed.

5.6 Distance to the U.S.

The distance to the United States is often cited as a source of inter-cartel violence. Municipalities closer to the border have fewer transportation costs associated, being a source of turf wars as they are precious for DTOs. To control for this factor, I controlled for the distance from each municipality to the destination market. First, I selected the 30 principal cities of entry to the United States from Mexico from official data (COLEF, 2002). Second, I gathered the latitude and longitude of those U.S. cities from Geodata (https://opencagedata.com/), and the latitude and longitude of every Mexican municipality (INEGI, 2010). Third, I have used the *haversine formula* (Robusto, 1957) to calculate the distance from every municipality to every U.S city, that takes into account the convexity of the Earth. Finally, I kept only the shortest distance for every municipality to the closest U.S. city.

5.7 Descriptive statistics

The following table shows the descriptive statistics of different socioeconomic variables of the municipalities in the control and treatment group. Besides the main data collected from the above sources, the municipal party in charge in 2006 is indicated by a *PRI* or *PAN* indicator using official electoral results.

Table 5.1: Descriptive statistics of the variables used for the analysis. Control and Treatment

Variable	$E(X_{non-violent})$	$\sigma_{non-violent}$	$E(X_{violent})$	$\sigma_{violent}$
Average years of schooling of the population 15 years and over in 2005	5.79	1.33	6.46	1.31
Percentage of households without electricity in 2005	5.28	6.12	5.31	8.97
Percentage of households without water system	16.12	18.64	17.52	18.90
Percentage of inhabitants under patrimonial poverty in 2000	72.35	19.60	61.14	19.58
Absolute Marginalization Index in 2005	0.16	0.86	-0.29	0.94
Rural municipality ($<$ than 5000 pop.)	0.26	0.44	0.09	0.29
Distance to the closest entry to U.S.	752.43	242.35	699.17	260.20
Homicide rate per 100.000 inhabitants in 2005	2.49	7.62	7.82	19.58
Log of total population in 2005	9.14	0.93	10.01	1.11
Percentage of workers that earn at much 2 times the minimum salary in 2005	71.69	13.75	58.16	14.96
Log of federal remittances in 2005	16.74	0.74	17.59	0.90
Gini Index in 2000	0.44	0.07	0.48	0.06
Municipality ruled by PAN only	0.24	0.43	0.25	0.44
Municipality ruled by PRI only	0.51	0.50	0.45	0.50
Political party coordinated with federal party	0.25	0.44	0.27	0.44
Sample size (N)	698		628	

Notes: σ refers to the standard deviation.

As the indicators show, children in schools face different environments depending on which municipalities they live in. The variable *Absolute Marginalization Index* refers to the poverty index made by CONAPO that combine and weight four aspects of poverty: illiteracy and lack of basic education, lack of a household that cover basic needs, rural distribution of the population, and lack of income. The higher the index, the more *marginalization* the municipality suffers. Federal remittances represent the annual amount, in million USD, that the municipality receives from the federal government as financial help. The marked difference between the two groups makes a straight comparison nonviable. They are not only influenced by the treatment stauts, the municipalities face different realities. Overall, the municipalities affected by drug-homicides have a more significant population, less rural, more prosperous and economically unequal, closer to the U.S., and more violent in 2005.

Section 6

Identification Strategy

The causal relationship of interest is the effect of drug-cartel violence on human capital accumulation.

Ideally, in experimental terms, cartel-violence and turf wars would be randomly distributed across Mexican municipalities and schools during the War on Drugs. While ideal, is not a valid assumption. For example, schools in the northern municipalities are closer to the North American border. Norther municipalities are more suitable for drug-cartel placement than southern municipalities, making them more worthy for the cartels to fight for the control of the smuggling points (*plazas*) in that municipalities.

I use Difference-in-differences Propensity score matching method proposed by Gutiérrez-Romero and Oviedo (2017) to sort the selection problem of cartel-violence into municipalities with certain characteristics. Firstly, Propensity Score Matching provides a sample of suitable municipalities in order to avoid selection into treatment based on observables (Dehejia, 2005). Then, Difference-in-difference is used to control for the unobservables characteristics. The primary assumption is that, while there is a bias from unobservable covariates, those are constant over time. In a recent paper, Ferraro and Miranda (2017) show that Difference-in-differences in combination with Propensity score matching are closer to identifying average treatment effects of a randomized control trial than any of the estimators alone.

Distance to the final drug-market, the U.S., and many other characteristics are different in the areas exposed to drug-homicides during the War on Drugs and the ones that did not. This self-selection of drug-violence into specific areas with certain attributes is observed in the Colombian traffickers' context (O. Dube and Vargas, 2013), and in the Mexican context (A.

Dube, O. Dube, and García-Ponce, 2013). It is argued as well that violent schools are more prompt to be in poorer municipalities and neighborhoods. Consequently, their alumni are not only affected by the exposure to violence, but also by having a more impoverished family background (Monteiro and Rocha, 2017).

In the case of the present thesis, the selection problem of schools into poor municipalities is attenuated by two factors. First, using Propensity score matching ensures that the violent and non-violent municipalities are similar in terms of socioeconomic conditions. Second, violent communities in Mexico were, in fact, more prosperous and have better overall school grades than non-violent communities before the War on Drugs. This evidence is aligned with the literature that explains that DTOs expansion in 2007 went through communities with enough economic infrastructure to continue their operations (Calderón, 2015). Hence, if the violence estimator is biased, the effect of violence would be downward-bias by those regions' better economic conditions.

6.1 Propensity Score Matching.

As stated, violent municipalities have different features than non-violent municipalities that affect the school's grades beyond the treatment status. To sort the selection problem of cartel-violence into treatment based on observables, I use Propensity score matching (PSM). The PSM algorithm rank municipalities in terms of how likely they are to have experienced drug-related violence from December 2006 to December 2010 (Treatment). This score is based on municipality baseline characteristics X stated in Section 5.7.

$$p(X) = Pr(Treat = 1|X) \tag{6.1}$$

Where $Treat = 1$ is experiencing at least one drug-related homicide from 2007 to 2010 but no cartel presence before, and X is a vector of covariates for the municipalities.

This vector of covariates tries to mimic the previous literature work of Gutiérrez-Romero and Oviedo (2017) on the specific topic of Mexican cartel presence. Hence, the variables selection is based on previous literature focusing on the municipal socioeconomic situation, previous violence, political ruling party, and the demographic/geographic setting. All the observations are collected before the Drug on Wars, so it is impossible that the variables are outcomes of the treatment. Appendix Table 10.1 in page 48 contain the detailed regressions applied to calculate the p-values, with a probit and a logit specification. High-order covariates and interaction terms are added to control the combination of factors that might affect cartels' appearances. Consequently, the propensity scores reflect the municipality's economic and social situation, making them more or less vulnerable to experience drug-homicides during the War on Drugs.

Following the standard in the literature, the probit version is used to calculate the propensity scores for the municipalities' pool. The estimates are only valid if it exists a region of common support for violent and non-violent municipalities. In Figure 6.1 is ploted the Propensity scores kernel density grouped by control (*non-violent*) and treated (*violent*) municipalities. The density distributions are similar to the propensity score results of Gutiérrez-Romero and Oviedo (2017), which can be seen in Appendix Figure 10.1.

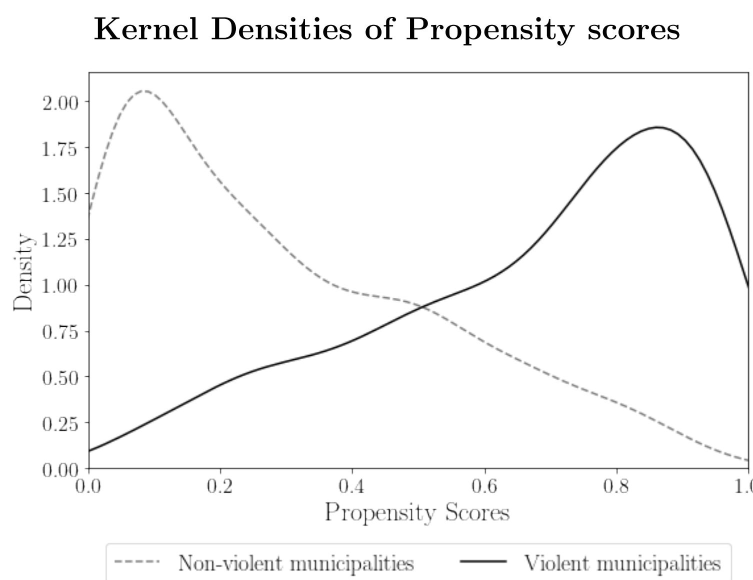

Figure 6.1: Kernel Densities of Propensity scores for Non-violent (Controls) and Violent (Treatment) municipalities

The matched municipalities will be the ones in the common support area, where the propensity score distributions of controls and treated municipalities overlap. Rosenbaum and Rubin (1985) show that it is not necessary to control for all the possible X variables to estimate the average treatment effect on Y. The estimate is unbias if the treatment status is correlated with observables, and the balancing property is satisfied. This is also known as the *Propensity Score Theorem* that states that PSM scores can be used when Condicional Independence Assumption (CIA) holds:

$$\text{Iff } Treat \perp (Y_1, Y_0) \mid X, \text{ then } Treat \perp (Y_1, Y_0) \mid p(X)$$

I implement the Nearest Neighbor algorithm (*NN-matching*) without replacement method to choose a comparable municipality in the treatment and the control pool. This version of NN-matching only chooses one control municipality for one treated municipality, and then the control gets out of the pool of possible choices for the next treated municipality. First, the algorithm calculates the probability of getting treated ($p(x)$) for all the municipalities, treated (i) and untreated (j). Then, it sorts all observations j in terms of the minimum Euclidean distance d with its neighbor i according to the centroid of the vector of covariates X:

$$d(x_i, x_j) = \sqrt{\sum_{p=1}^{p} (X_i - X_j)^2} \tag{6.2}$$

After the sorting, it chooses the neighbors with the lowest distance values, as they are "nearest neighbours". The main challenge of choosing NN-matching without replacement is the risk of bad matches and the arbitrary order of matching (Caliendo and Bonn, 2008). In a recent research study, King and Nielsen (2019) argue that this kind of pair matching can increase the initial panel imbalance. First, the matching can be weak if the closest neighbor is far away in the distribution. Second, the chosen observations depend on the order of the matching. This problem is also referred to as pruning (Smith and Todd, 2005; Abadie and Imbens, 2006). Those challenges are addressed by imposing a tolerance level on the maximum propensity score distance (also called *caliper*) and making the order in which the treatment units are matched randomly. This reduction in bias comes with a cost in terms of variance. The caliper width rules out some municipalities in the sample of controls and is treated, by setting a maximum distance threshold. Therefore, the results are contingent on the comparable municipalities - and not to all the municipalities affected by drug cartel-violence.

The caliper is set to 0.2 following Austin (2009), Austin (2011), and Wang et al. (2013). Using a wider caliper of 0.25 (Rosenbaum and Rubin, 1985) does not significantly change municipalities' selection. There is a trade-off between efficiency and bias: The more caliper, the more municipalities are allowed to match, and the sample size increase, but also it allows not-so-similar municipalities to be paired, increasing the bias. As far as I know, there is no golden rule for setting the caliper width. Selecting an extreme value of caliper would highly increase bias or variance. Most academic literature using NN-matching uses one of the mentioned widths. This match provides a comparable 666 municipalities based on socioeconomic development. Table 6.1 shows the descriptive statistics of the matched control and treatment before the start of the treatment in 2005.

Treated (Grey) and Control (Black) municipalities after the matching

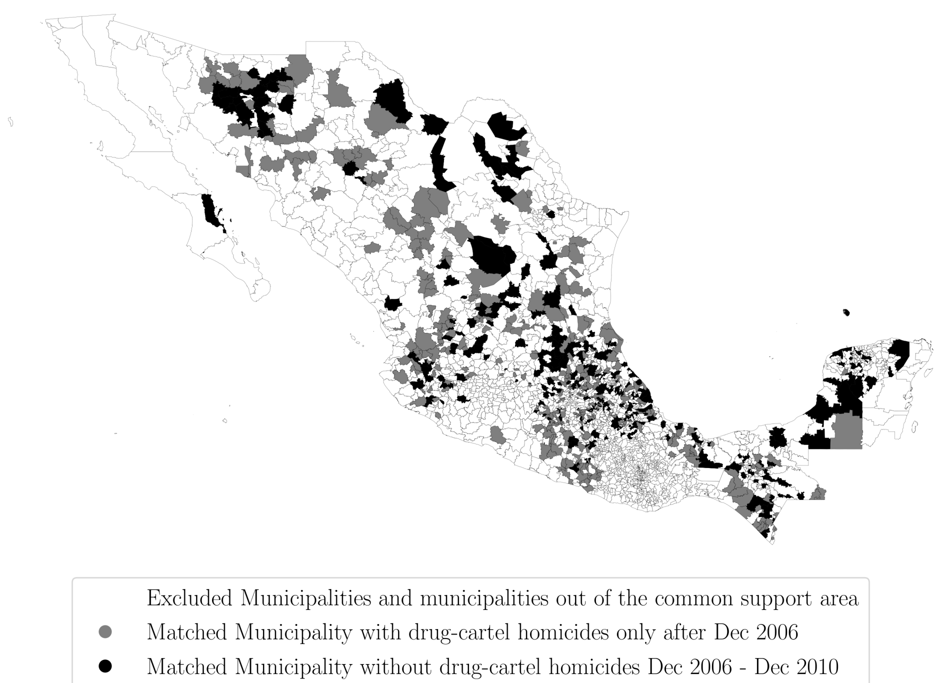

Figure 6.2: Mexican map signaling Matched municipalities based on Propensity score nearest neighbour matching

Table 6.1: Balance of selected municipal characteristics X_i. Matched Control versus Treatment

$Variable$	$E(X_{non-violent})$	$E(X_{violent})$	t
Absolute Marginalization Index in 2005	-0.04	-0.05	0.088
Percentage of inhabitants under patrimonial poverty in 2000	66.24	65.98	0.165
Political party coordinated with federal party (PAN-PAN)	0.27	0.2 8	-0.346
Rural municipality	0.15	0.13	0.673
Distance to the closest entry to U.S.	704.35	699.58	0.232
Log of total population in 2005	9.52	9.59	-0.830
Percentage of households without electricity in 2005	5.35	5.95	-1.015
Percentage of households without house access to drinking water in 2005	17.43	18.80	-0.899
Percentage of workers that earn at much 2 times the minimum salary in 2005	65.10	64.00	0.978
Gini Index in 2000	0.47	0.47	-0.372
Log of federal remittances in 2005	17.12	17.20	1.422
Homicide rate per 100.000 inhabitants in 2005	3.98	5.69	1.508
Average years of schooling of the population 15 years and over in 2005	6.06	6.12	-0.644
Municipality ruled by PAN only	0.26	0.26	0.088
Municipality ruled by PRI only	0.47	0.44	0.777
Sample size (N)	333	333	

Notes: t refers to a two-sample t-test. $t = (X_{\text{non-violent}} - X_{\text{violent}}) / \sqrt{s^2_{\text{non-violent}} + s^2_{\text{violent}}}$

In addition to establishing the overlapping common region, I checked the balance property using a two-sample t-test to measure the covariates mean differences of control and treated municipalities. The distribution of the variables is very similar. Two variables might raise identification concerns using Propensity score matching to estimate ATE: federal remittances and the homicide rate per 100.000 inhabitants in 2005. The effect in my variables of interest, children's educational outcomes, could be biased by the remaining differences between violent and non-violent municipalities. However, PSM is only used to select municipalities that ensure the Conditional Independence Assumption, and not to estimate ATE. Because of these concerns, I also performed a joint F-statistic regression to check that the variables are overall balanced. The joint-significance of the covaritates on the treatment status is insignificant (F-statistic = 0.5816, p-value = 0.8901).

6.2 Difference-in-differences.

The previous section explained the Propensity score matching (PSM) to control for cofounders that lead the treatment assignment. The second step of the identification strategy uses Difference-in-differences to estimate the average treatment effect (ATE) on the 666 comparable municipalities. Using Differences-in-difference will remove any remaining time-invariant pre-treatment, as the treatment effect would only reflect the changes over time. The pre-existing differences in the initial 2071 municipality sample made the Condicional Independence Assumption (CIA) over time impossible to sustain, the main reason I used PSM in the first place. As pointed out by Blattman and Miguel (2010), conflict-related studies that use Difference-in-differences rely on the assumption that the regional development of conflict-affected zones and peaceful areas follow similar trends, which is usually hard to believe.

To address this common problem, the Difference-in-differences only uses the resulting 666 municipalities from the PSM. These municipalities have parallel geographic, political, economic, inequality or poverty contexts (among other variables). I argue that similar socioeconomic municipalities before the treatment would have followed similar time-trends in 2007 if it was not by drug cartels' eruption in the area. The estimator is unbias as long as time-varying characteristics affect in equivalent ways to treated and control municipalities, and therefore to the schools and children in them. Therefore, the empirical setup holds based on the *parallel trends assumption*.

The sample "of interest" are municipalities characterized by not having cartel presence, alike socioeconomic levels, and similar criminal activity before December 2006. From this period on, the War on Drugs triggered the most significant increase in criminal expansion in Mexico's modern history (UNODC, 2019), affecting families and children's educational decisions.

When children make educational investment decisions, not only matters if the school is in violent municipality, but also how violent the cartels in municipality are. To isolate the effect of living in a drug-violent municipality on educational choices from the intensity of the violence, the regressions control for the firearm-homicides rate of the municipality as proxy for the intensity of the violence.

HC2 robust standard errors (MacKinnon and White, 1985) is used in all the regressions. The possibility of panel serial correlation drives the selection of the standard errors' type. In other words, it is plausible that the children's educational outcomes of the cohort at time t are correlated temporally with the previous cohort in time $t-1$: $Corr(y_t, y_{t-1}) \neq 0$. This correlation does not change the coefficient of the estimates, but would bias the standard errors. To control for this possibility, all the estimates include municipality fix effects and HC2 robust standard errors. The estimator is unbias as long as there are not time-varying characteristics that affect in different ways to treatment municipalities and control municipalities, and therefore to the schools in them. The possible bias has been mitigated by using Propensity score matching and selecting only the municipalities that satisfy the balancing property, as shown in Table 6.1.

The next section describes the results and includes the Difference-in-differences model specifications.

Section 7

Results

The current section describes the model used to estimate the causal effect of cartel-violence on human capital accumulation, and its results. Treated municipalities with cartel-violence are the ones that never had cartel presence before 2007, but experienced at least one drug-related homicide between December 2006 and December 2010. In contrast, control municipalities without cartel-violence had never had cartel presence before 2007 and did not experience any drug-related homicide afterward. I defined two proxies for human capital: average school grades and school attendance. In the first part, the dependent variable analyzed is the average scores in the national exam ENLACE for all the schools in the municipality. This metric is a proxy for the qualitative aspect of human capital learning. In the second part of the section, I describe the impact on childrens' school attendance as a second quantitative measure describing human capital accumulation.

The empirical strategy explained in the previous section is a combination of Propensity score matching, to select comparable municipalities, and Difference-in-Differences, to estimate the average treatment effect (ATE).

7.1 Effects on ENLACE exam scores

ENLACE is a nationwide exam across municipalities created to provide a homogeneous comparison of school performance. I have access to the exams conducted in 2006, 2007, 2009, 2010. The exam in 2006 was before Calderón presidency election, and the start of the War on Drugs, allowing to compare the before and after results. Figure 7.1 show the time-trends in the average

ENLACE exam grades before and after the treatment event. It is necessary to make sure that the treated municipalities with drug-related violence did not have downward education trends before War on Drugs that could explain worst results later regardless of the treatment effect.

Average of ENLACE Math and Language exam grades

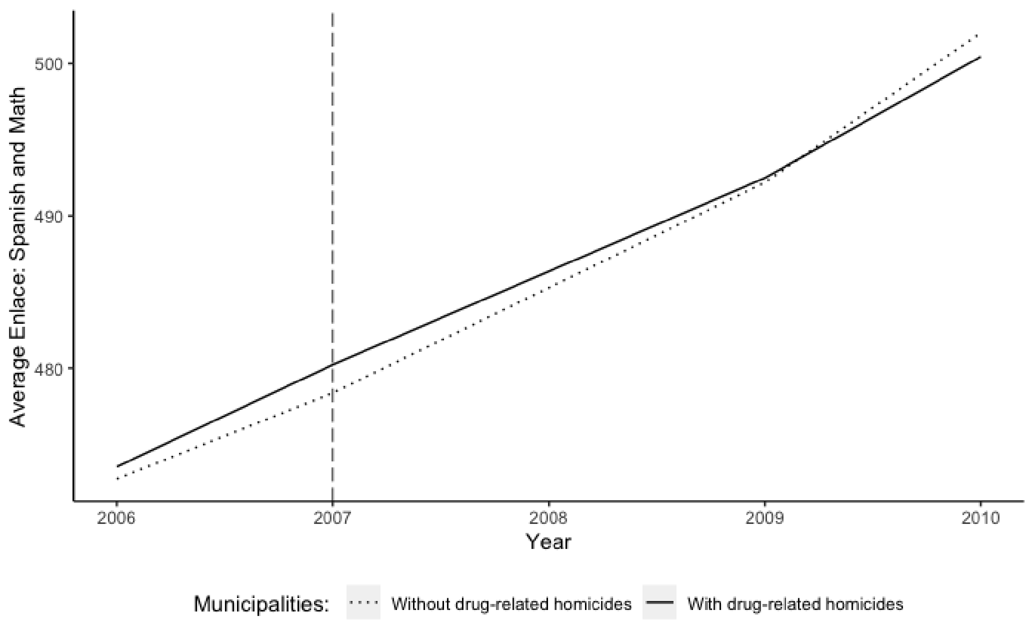

Figure 7.1: Average of ENLACE Math and Language exam grades for treated and untreated schools. It compares schools in municipalities that suffered cartel-violence with those without, according to the status treatment defined in Section 5.4. All the grades are grouped at municipal-level. Source: INEE for ENLACE data; ESOC and Coscia and Rios (2012) for treatment status.

As the gap in the average grades show in 2006, before the start of the 2007 War on Drugs, children in treated schools had better ENLACE grades than children in control schools. This gap increased in 2007, a relatively peaceful year. This result is consistent with the ENLACE results of Jarillo et al. (2016), in which violent municipalities also had better grades overall. After the 2008 escalation in violence depicted in Figure 5.2 (Section 5), the trends went in opposite directions. Control municipalities reach the same average level of grades than treated municipalities in 2009, and by 2010 they surpass them.

The Difference-in-Differences model is specified as follows:

$$\begin{aligned} y_{it} = \alpha &+ \beta_1 Post_t + \beta_2 Treat_i + \beta_3 (Post_t \times Treat_i) \\ &+ \beta_4 FH_{it} + \beta_5 FH_{it}^2 \\ &+ \mu_i + \phi_t + \epsilon_{it} \end{aligned} \tag{7.1}$$

where y_{it} is the municipal average ENLACE grades for the municipality i at the time t. $Post_t$ is a post-treatment dummy (2007-2010 $=$ 1), $Treat_i$ indicates if the schools were in a violent municipality i, and FH_{it} is the firearm-homicide rate per 100.000 inhabitants. It might be the case that, passing a threshold of firearms-homicides, children are motivated to study and do well in school tests as a vehicle to escape the violent environment. To control for this "quadratic effect" of violence on children grades, β_5 is included as well. Finally, μ_i and ϕ_t are municipality and year fix effects, followed by the residual ϵ_i . The DiD coefficient β_3 estimates the average treatment effect (ATE), while β_4 and β_5 only aim to control for the intensity of the violence episodes.

Table 7.1 indicates the effect on Mathematics, Language and both exam scores combined for primary (columns (1) to (3)) and secondary schools (columns (4) to (6)). I find no effect of cartel-violence on ENLACE average exam scores. One of the main limitations for this first part of the analysis is the absence of open-data at municipality-level for the given years that ENLACE tests were conducted. Therefore, it is not possible to control for possible time-varying observables that could make the estimation more accurate and significant.

The Difference-in-difference estimator shows no significant impact of cartel-violence. Therefore, the results do not support the Hypothesis I: *The escalation of violence in Mexico led to schools situated in drug-violent municipalities to attain lower (ENLACE) school grades.*

Table 7.1: Difference-in-differences estimator. Effect of cartel-violence on ENLACE average exam scores. Time period: 2006-2010.

	Primary school ENLACE scores. 6 to 11 years old children			Secondary school ENLACE scores. 12 to 14 years old children		
	Math	Language	Both exams	Math	Language	Both exams
	(1)	(2)	(3)	(4)	(5)	(6)
DiD	0.968	−0.469	0.250	−1.058	−1.730	−1.394
	(1.666)	(1.415)	(1.507)	(2.186)	(1.942)	(1.910)
Firearm-homicides rate	0.011	−0.013	−0.001	−0.039	−0.024	−0.031
	(0.043)	(0.025)	(0.034)	(0.037)	(0.029)	(0.027)
Firearm-homicides rate squared	0.00002	0.00003	0.00002	0.00004*	0.00002	0.00003
	(0.00003)	(0.00002)	(0.00002)	(0.00003)	(0.00002)	(0.00002)
Municipality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Robust HC2 SE	✓	✓	✓	✓	✓	✓
N	666	666	666	666	666	666

DiD represents the Difference-in-Differences Propensity Score estimator. It compares municipalities that suffered cartel-violence with those without, according to the status treatment defined in Section 5.4. All the grades are grouped at municipal-level. All the specifications include municipality and year fix effects, and HC2 robust standard errors. Significance given by: $^{***}p < 0.01$.$^{**}p < 0.05$.$^{*}p < 0.10$. Source: SNSP, INEE, ESOC, Coscia and Rios (2012).

7.2 Effects on school attendance

In this sub-section I concentrate on the effects of cartel-violence on school attendance. The periods are 2005 and 2010, before and during the Mexican homicide escalation, and the groups are the control and treated municipalities resulting of the Propensity score matching. I am able to control for socioeconomic conditions using census data from 2005 and 2010. The model has the same specification with the inclusion of a set of controls (X_{it}):

$$\begin{aligned} y_{it} = \alpha &+ \beta_1 Post_t + \beta_2 Treat_i + \beta_3 (Post_t \times Treat_i) \\ &+ \beta_4 FH_{it} + \beta_5 FH_{it}^2 \\ &+ \gamma X_{it} + \mu_i + \epsilon_{it} \end{aligned} \tag{7.2}$$

where y_{it} is the educational outcome of interest in the municipality i at the time t. $Post_t$ is a post-treatment dummy (2005 = 0, 2010 = 1), $Treat_i$ indicates if the schools were in a violent municipality i, FH_{it} is the firearm-homicide rate per 100.000 inhabitants.

X_{it} is a vector of the following time-varying socieconomic covariates at municipal level: i) *the % of the population living in a rural area within the municipality*; ii) *the % of inhabitants without access to a public health system*; iii) *the % of inhabitants without a fridge*. Finally, μ_i are municipality fix effects and ϵ_i the residual. The election of socioeconomic covariates is targeted to reveal the socioeconomic circumstances of the municipality. I have used none of the mentioned controls during the Propensity score matching, allowing variance both in 2005 and in 2010.

Table 7.2 presents the results for three quantitative educational outcomes: i) *% of children between 6 and 14 years old not attending school*; ii) *% of inhabitants without primary school completed*; iii) *average of years of education of the inhabitants of the municipality.* I find significant effects of cartel-violence, indicated by the treatment status, reducing children's attendance by 0.3%. The results are robust to the inclusion of a vector of controls X mentioned before and significant at 5% level. These findings support the Hypothesis 2, that states that *the War on Drugs in Mexico decreased children' attendance to schools situated in drug-violent municipalities.*

Table 7.2: Difference-in-differences estimator. Effect of cartel-violence on school attendance. Time period: 2005-2010

	% of children between 6 and 14 years old not attending school		% of inhabitants without primary school completed		Average of years of education	
	(1)	(2)	(3)	(4)	(5)	(6)
DiD	0.292** (0.132)	0.296** (0.130)	0.154 (0.158)	0.168 (0.147)	−0.021 (0.014)	−0.022 (0.014)
Firearm-homicides rate	−0.002 (0.003)	−0.002 (0.002)	0.003 (0.003)	0.0003 (0.003)	−0.0003 (0.0003)	−0.0002 (0.0003)
Firearm-homicides rate squared	−0.00000* (0.00000)	−0.00000* (0.00000)	−0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
% inhabitants in rural areas with the mun.		0.006 (0.006)		0.014** (0.006)		−0.001** (0.0005)
% inhabitants without access to health system		0.014 (0.004)		0.018*** (0.004)		−0.0001 (0.0004)
% inhabitants without fridge		0.001 (0.010)		0.117*** (0.016)		−0.007*** (0.002)
Municipality FE	✓	✓	✓	✓	✓	✓
Robust HC2 SE	✓	✓	✓	✓	✓	✓
N	666	666	666	666	666	666

DiD represents the Difference-in-Differences Propensity Score estimator. It compares municipalities that suffered cartel-violence with those without, according to the status treatment defined in Section 5.4. Socioeconomic controls used in even columns: (2), (4), (6). All the specifications include municipality fix effects and HC2 robust standard errors. Significance given by: $^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.10$. Source: SNSP, CONAPO, ESOC, Coscia and Rios (2012).

While the effect seems small, given the population size and demographics of Mexico, it is noteworthy. Mexico had a population of roughly 112 million people in 2010, with 22 million of them between 5 and 14 years old (INEGI, 2010). A reduction of 0.3% attendance means that 66,000 children in 2010 did not go to school as a result of drug-cartels violence. On the other hand, the effects are not significant for the dependent variable: *% of inhabitants without primary school completed* (Columns (3) and (4)). In relation to the previous section showing the effects on ENLACE exam grades, it appears to be unlikely that living in an area with drug-homicides affected children's grades or their ability to finish primary school. I find no effect on the qualitative or quantitative side of human capital accumulation in the early years of childhood (primary school). Furthermore, the last dependent variable: *Average of years of education* (Columns (5) and (6)) show negative but not significant estimates.

Is the Difference-in-differences parameter capturing poverty trends? The small difference in the *DiD* coefficients between odd and even columns in Table 7.2 suggest that the ATE estimation is robust to the poverty and socioeconomic X controls included. None of controls used have a obvious relationship with cartel-violence or drug-related homicides, but they are clearly correlated with the economic and institutional circumstances of the municipality. As expected, they are significantly correlated with educational attainment but do not influence the treatment effect. Therefore, it is unlikely that the *DiD* coefficient is over-estimating the effect of cartel-violence just because is capturing poverty.

Section 8

Robustness checks

8.1 Placebo test

Following the standard recommendations in policy evaluation, I conducted a placebo test manipulating the treatment's timing to see if the previous significant result is merely by chance. The dependent variable to be tested is *% of children between 6 and 14 years old not attending to school*. I will assume that the pre-treatment periods are previous to 2000, and the post-treatment period is 2005. I have no evidence of any major violence or cartel-violence escalation between 2000 and 2005 in Mexico, so it should be no effects of cartel-violence. The real event that separated the sample in violent and non-violent was the War on Drugs that started after 2007. The pool of treated and control municipalities is the same, explained in Section 5.4. I also use Propensity score matching to compare similar municipalities using the variables mentioned before to calculate the p-scores. If the treatment happened after 2007, the ATE given by the Difference-in-differences estimator should be statistically zero.

I find non-significant treatment effects of living in a violent municipality in 2007 on previous children's school attendance. The Table 8.1 show the results. Hence, the placebo test suggests that the early results are not coincidental.

Table 8.1: Placebo Difference-in-differences estimator. Time period: 2000-2005.

	% of children between 6 and 14 years old not attending to school	
	(1)	(2)
DiD	-0.219	-0.231
	(0.195)	(0.192)
Firearm-homicides rate	0.008	0.007
	(0.006)	(0.006)
Firearm-homicides rate squared	0.00002	-0.00003
	(0.001)	(0.001)
% inhabitants in rural areas		0.008
		(0.009)
% inhabitants without access to health system		-0.017^{***}
		(0.005)
% inhabitants without fridge		-0.031^{**}
		(0.015)
Municipality FE	✓	✓
Robust HC2 SE	✓	✓
N	666	666

DiD represents the Placebo Difference-in-Differences Propensity score estimator. Socioeconomic controls used in column (2).All the specifications include municipal fix effects and HC2 robust standard errors. Significance given by: $^{***}p < 0.01$. $^{**}p < 0.05$.$^{*}p < 0.10$.

8.2 Treatment Analysis

The argument of the thesis is sustained on violence escalating from the War on Drugs, affecting municipalities and schools. If I correctly identified treatment and control groups, one should expect that schools in treatment groups are located in municipalities where cartels are fighting each other. For example, it would be more probable to find the treated schools in municipalities in which the *Tijuana Cartel* and the *Sinaloa Cartel* operate, as they are confronting cartels. If there is no correlation between inter cartel conflict and my treated municipalities, the treatment status would be badly identified.

I have coded the inter cartel confrontations between the most important drug-cartels from Guerrero-Gutiérrez (2011) research work for every municipality and year from 2007 to 2010. From the municipalities without cartel presence before December 2006 and neither drug-related homicides afterward, only 7 contain DTOs that were in conflict with each other, according to the Guerrero-Gutiérrez (2011) work. That is 0.56% of the municipalities in the total controls pool (before the matching). From the municipalities without cartel presence before December 2006 and drug-related homicides after, 87 contain DTOs that were in conflict. It represents the 10.5% of the municipalities in the treatment pool. I find a positive correlation between inter cartel confrontations and the defined treatment status. The probability of finding cartels in conflict is 18.75 bigger in the municipalities in the treatment pool than in the control pool.

Intra and Inter Cartel Confrontations. Guerrero-Gutiérrez (2011, p. 109)

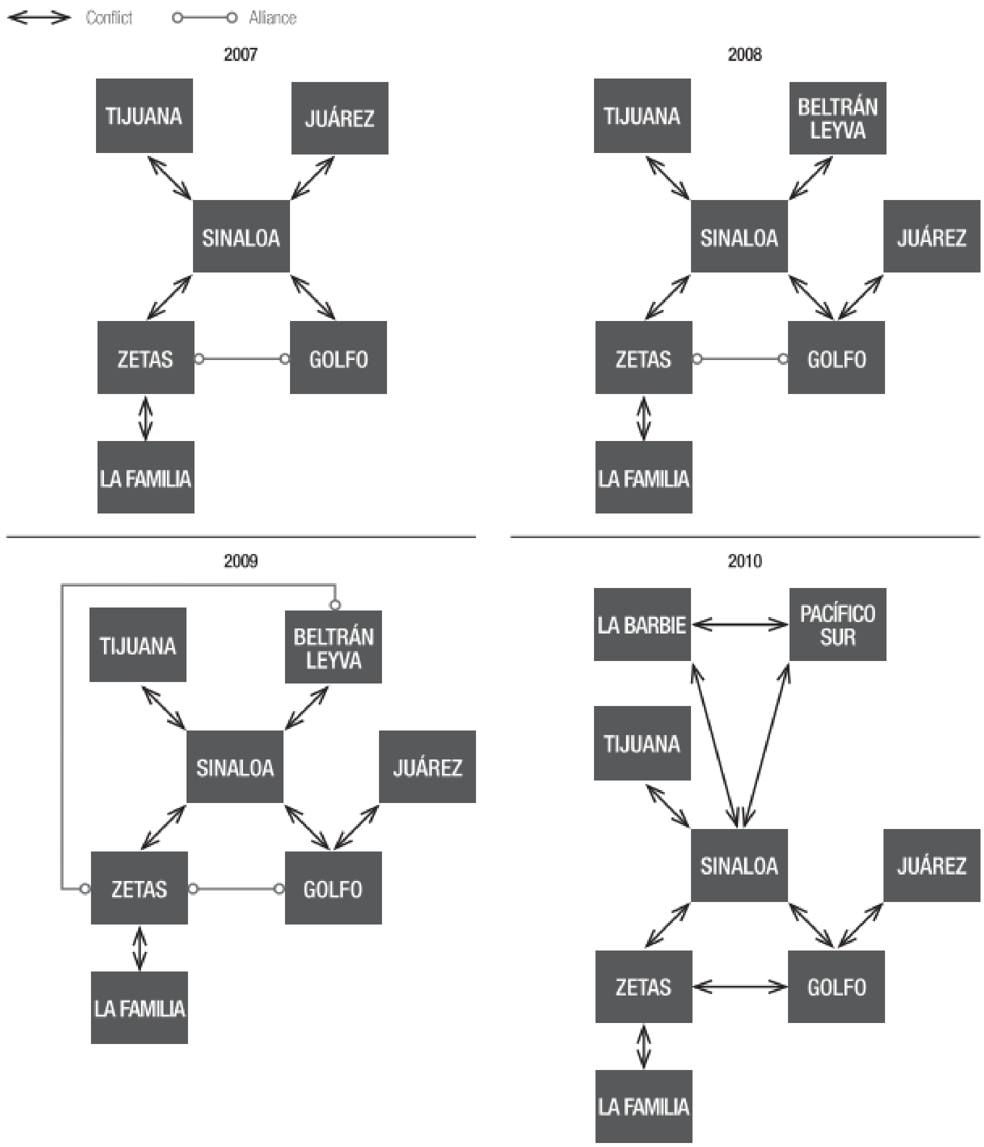

Figure 8.1: Alliances and confrontations between the most significant Mexican drug-cartels from 2007 to 2010. Source: Guerrero-Gutiérrez (2011).

Section 9

Conclusion

In this thesis, I studied the impact of drug-cartel violence on human capital accumulation in Mexico. The theoretical model developed provides a prediction equilibrium in which children spend less time accumulating human capital and the more time getting 'street capital' in violent municipalities. Possible mechanisms to justify this behavior can be the lack of safety that affects children's decision to go to school, or that cartel violence affects the local economies in such a way that diminishes education returns. To test the model, I have used a Differences-in-difference Propensity score matching empirical strategy, comparing schools and children living in Mexican municipalities with at least one drug-related homicide from December 2006 to 2010 with municipalities that remained peaceful during the War on Drugs. ENLACE national exam is taken as a measure of qualitative educational outcome, and the percentage of children between 6 and 14 who do not attend school represents a quantitative metric. According to the theoretical model, the escalation of violence in Mexico in 2007 would lead to schools situated in drug-violent municipalities to attain lower school grades and decrease school attendance.

The results show partial support to the model. I find that drug-cartel violence reduces children's school attendance by 0.3%. The results are robust to the inclusion of controls related to access to basic resources and a placebo test, supporting the idea that the municipality's violent context is the driver of the effect. Contrastingly, I find no statistical difference in the school grades between schools located in municipalities with drug-related crimes and the schools located in similar peaceful municipalities for the national exam ENLACE, differing from the previous literature.

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Section 10

Appendix

Gutiérrez-Romero and Oviedo (2017) Distribution of propensity scores between treatment and control groups.

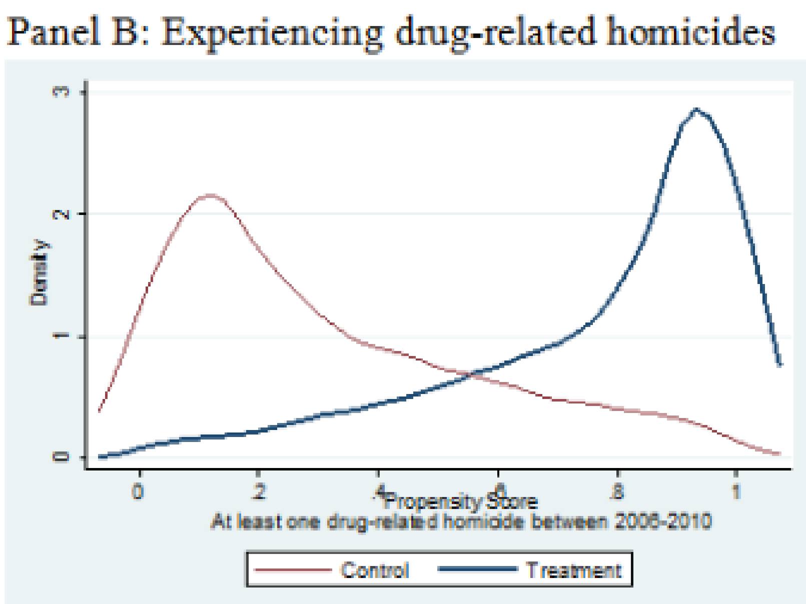

Figure 10.1: Gutiérrez-Romero and Oviedo (2017) Online Appendix, page 3, Fig. A.2 *Distribution of propensity scores between treatment and control groups.*

Table 10.1: Probit and Logit Regressions for Propensity score matching

Variable	*Probit*	*Logit*
Average years of schooling of the population 15 years and over in 2005	$-0.165^{**}(0.073)$	$-0.312^{**}(0.126)$
Percentage of households without electricity in 2005	$0.005(0.009)$	$0.011(0.015)$
Percentage of households without tap water in 2005	$0.008^{**}(0.003)$	$0.014^{***}(0.005)$
Percentage of inhabitants under patrimonial poverty in 2000	$-0.013^{***}(0.005)$	$-0.023^{***}(0.008)$
Absolute Marginalization Index in 2005	$0.003(0.179)$	$-0.044(0.307)$
Rural municipality dummy	$0.786^{**}(0.374)$	$1.305^{**}(0.637)$
Rural X Political party coordinated	$0.329(0.476)$	$0.604(0.816)$
Rural X Distance to the closest entry to U.S.	$0.001^{***}(0.0002)$	$0.001^{***}(0.0004)$
Homicide rate per 100.000 inhabitants in 2005	$0.031^{***}(0.006)$	$0.054^{***}(0.011)$
Homicide rate per 100.000 inhabitants in 2005 squared	$-2.272^{**}(0.989)$	$-3.890^{**}(1.677)$
Log of Total population in 2005	$0.144^{***}(0.052)$	$0.245^{***}(0.088)$
Log of Total population in 2005 squared	$-0.029^{***}(0.006)$	$-0.048^{***}(0.010)$
Percentage of workers that earn 2 times the minimum salary or less in 2005	$5.509^{**}(2.766)$	$9.792^{**}(4.854)$
Log of income transfers from the federal administration	$-0.153^{*}(0.080)$	$-0.272^{*}(0.141)$
Log of income transfers from the federal administration squared	$2.489^{***}(0.751)$	$4.189^{***}(1.291)$
Gini index in 2000	$-0.149(0.339)$	$-0.314(0.573)$
Municipality ruled by PAN only dummy	$-0.089(0.102)$	$-0.154(0.176)$
Municipality ruled by PRI only dummy	$-0.185(0.299)$	$-0.211(0.524)$
Political party coordinated with federal party (PAN-PAN) dummy	$-0.001^{**}(0.0004)$	$-0.002^{**}(0.001)$
Political party coordinated X Homicide rate	$-0.020^{**}(0.008)$	$-0.037^{**}(0.014$
Political party coordinated X Distance to the closest entry to U.S.	$-0.0004(0.0004)$	$-0.001(0.001)$
Municipalities (N)	1,326	1,326

Dependent variable: Having at least one drug-related homicide between December 2006 and December 2010. All the municipalities considered have not cartel presence before the War on Drugs. Sources: Municipal political party coordinated with Federal party is taken from electoral results. Distance to U.S. from own estimates. Other variables comes from CONAPO, SINAIS, INEGI and CONEVAL.