Throwing gasoline on cocaine production: the effect of a supply shock on violence

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Abstract

Does drug production lead to violence? In this paper, I exploit an exogenous supply shock in smuggled gasoline from Venezuela, an input factor needed to produce cocaine and analyze the effect on violence in coca-producing areas of Colombia. Using a difference-in-differences strategy, I compare areas closer and farther away from the border with Venezuela. The shock led to an increase in coca leaf cultivation and an increase of between 22 and 31 homicides per 100,000 inhabitants, corresponding to about 40% to 50% increase in the homicide rate. The main results are robust to various tests, such as controlling for immigration and the former territories of FARC. Hence, when it becomes cheaper to produce cocaine, production areas experience more violence. By focusing on the economic aspects of the drug market rather than enforcement measures, I demonstrate that price changes in the cocaine market can significantly impact violence levels. The paper also contributes to the literature by studying the interaction between two illegal markets: the smuggling of gasoline and cocaine production.

Keywords: illicit drugs, cocaine, gang violence, violence, Colombia, difference-in-differences

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1 Introduction

Latin America is the world's most violent region, not at war, with 45 of the 50 most murderous cities in the world and eight of the top 10 most murderous countries (Igarapé-Institute, 2017). In Colombia, interpersonal violence causes more premature deaths than heart disease and traffic accidents (Institute for Health Metrics and Evaluation, n.d.). One major mechanism thought to be behind the extensive violence is the prevalence of cocaine production throughout Colombia. The global production of cocaine has dramatically increased and more than doubled since 2015, leading to more cocaine availability. Only in the E.U. is it estimated that 18 million adults have tried cocaine during their lives (EMCDDA and Europol, 2019). Cocaine accounts for nearly one-third of the value of the illicit drug market, making it the second-largest after cannabis, and global consumption is increasing. Colombia is currently the most important cocaine producer (coca bush cultivation) in the world and the driver behind the increased production(UNODC, 2019).

In this article, I study the relationship between violence and cocaine production in Colombia. I hypothesize that a positive supply shock in the production of cocaine leads to more violence in the areas producing coca than in the ones that do not produce it. I use an exogenous price shock in the cocaine market to study the effect on violence in cocaine-producing areas. The decrease in international oil prices and Venezuela's poor monetary policy led to a fluctuation in the exchange rate between Venezuela's and Colombia's currencies in 2016. The resulting fluctuation caused a decrease in the price of a critical component in cocaine production: trafficked gasoline. This shock allows a quasi-experimental research design to study the impact on violence. I perform a difference-in-differences (DID) analysis between close and far away from the border with Venezuela and analyze areas with coca leaf production. I use data on coca cultivation and homicides, two reliable data sources in a field of research with many unknowns and a general lack of information. The positive supply shock leads to increased coca leaf production and leads to more violence in coca-producing areas closer to the border with Venezuela compared to producing areas further away from the border. The impact of the shock in the treatment group is an increase of 31.1 homicides per 100,000 inhabitants. Even for a violent country like Colombia, the number is relatively high. It is important to remark that these areas with coca production have a much higher level of violence. The average homicide rate in the treatment sample before the shock (2010 to 2015) was 58 homicides per 100,000 inhabitants, implying that the supply shock's effect is equivalent to a 53 % increase in the homicide rate. Furthermore, I find the results robust to various tests, such as controlling for immigration and territories formally controlled by Fuerzas Armadas Revolucionarias de Colombia (FARC).

Despite its importance, there is little research on cocaine markets (Storti et al., 2011). There is also little research on the causal mechanisms between drug markets and violence. As Mejía and Restrepo (2013) point out: "Anecdotal evidence linking cocaine production to violence is not enough to establish a causal relation". Despite the strong correlation, there is little research on the causal relationship between the cultivation, production, and trafficking of drugs in Latin America and violence. Evidence from Afghanistan suggests that violence can lead to more drug production; hence, the direction of causality is unclear (Lind et al., 2014). 95 percent of all scientific knowledge on effective violence prevention relates exclusively to the United States and wealthy European countries, where homicide rates are low (Eisner and Nivette, 2012). Thus, more research is needed in low- and middle-income countries to advance local knowledge on the causes of violence (Eisner, 2015).

This paper contributes to the literature by examining the effects of a pure economic shock and studying a supply shock instead of a demand shock in cocaine production. Most of the previous literature studies shocks that stem from law enforcement campaigns against drugs and studies changes in demand. Both Angrist and Kugler (2008) and Mejía and Restrepo (2013) have studied demand shocks in Colombian coca production as a consequence of drug enforcement campaigns. Abadie et al. (2014) have looked at the impact of drug eradication programs in Colombia. Castillo et al. (2020) have studied the effects of a negative supply shock from drug enforcement in Colombia and the impact of violence along Mexican trafficking routes. Dell (2015) has examined areas in Mexico with vigorous drug enforcement. Drug enforcement is violent, so it is challenging to distinguish the effect of violence from law enforcement campaigns from "pure" changes in demand. By looking at a pure economic shock on the drug market, instead of a drug enforcement intervention, one is more likely to establish a causal relationship where price changes affect the cocaine market, which in turn affects the level of violence. Furthermore, it is valuable to study a shock that does not dramatically change the market structure and to see whether less disruptive shocks have an effect. Another contribution to the literature is the study of supply shock. As drug production is a "black box" with limited information due to its illegal nature, predicting how it reacts to different types of shocks is not apparent, especially since it is an imperfect market without free competition. Therefore, the evidence in this paper that when it becomes cheaper to produce cocaine, there is more violence in production areas is valuable for policies. Avoiding available low-price input factors in drug production could prevent violence in production areas. Finally, the paper also contributes to the literature by studying the interaction between two illegal markets: the smuggling of gasoline and cocaine production, which helps further the understanding of the illegal sector.

The rest of the article proceeds as follows. First, I give background information on cocaine production in Colombia, violence in Colombia, and the exchange rate shock and gasoline import from Venezuela. Then, I look at related research and discuss the potential mechanism linking a price shock to cocaine production and violence. I argue that purely positive economic shocks to drug production will lead to more violence, even though no preexisting literature has studied it. Then, I describe the data before presenting my main analysis. Various robustness tests follow this. Finally, I conclude.

2 Background

2.1 Cocaine production in Colombia

Cocaine is a natural product extracted from the leaves of Erythroxylum coca and Erythroxylum novogranatese, better known as coca leaves (EMCDDA and Europol, 2019). Coca leaves are almost exclusively cultivated in Colombia, Peru, and Bolivia. Colombia is the major producer of the three countries, both in terms of coca leaves and cocaine production (UNODC, 2019). To produce cocaine, the coca leaves go through various chemical processes. First, the coca leaves are cultivated and harvested. It is important to note that the leaf is marketed in a fresh state and is a perishable good, as the leaf tends to rot about two days after harvest (UNODC and of Colombia, 2017). Then in the extraction process, the leaves are crushed with sulfuric, acid, calcium carbonate, and gasoline (EMCDDA and Europol, 2019). The leaves are soaked in barrels of gasoline and then drained, which creates the coca (base) paste. Coca (base) paste has about one-hundredth of the volume of coca leaves, and the transition from leaf to paste is where most of the weight reduction in cocaine production occurs (Angrist and Kugler, 2008). The first two stages, the cultivation and extracting, where the coca base paste is created, usually are taking place at the local farmer level (Mejía et al., 2010).[1] This article will focus on the second step, the extraction, where the gasoline is used. This process takes place close to the cultivation area for two reasons; the perishable nature of the leaves and the transportation cost. In order to produce the cocaine (base) paste, the quantity of coca leaves required is so large that transportation of the leaves becomes problematic.

There is no single method for producing cocaine, and many of the ingredients have substitutes (Mejía et al., 2010; EMCDDA and Europol, 2019). In the case of gasoline, the input of interest in this paper, it is possible to substitute with kerosene (paraffin) and oil.

[1] Approximately 2/3 of the peasant coca growers do not directly sell the coca leaf but transform it through a relatively simple and artisanal process into coca paste, and then sell it as an input to large-scale cocaine producers.

However, price and availability make gasoline the most common ingredient. Mejía et al. (2010) have estimated the economics of the supply chain for producing cocaine based on the different chemicals needed in the process. They estimate that about 70 % of the costs of these inputs stem from the gasoline.[2] As it is used in the first steps of production, it is an input for farmers with small and unstable incomes, making it a critical factor. Some estimations show that about a quarter of gasoline sold in Colombia is used for cocaine, about 70 million gallons per year (Collins, 2019; Loaiza, 2019).

2.2 Shock to gasoline prices

In neighboring country Venezuela, there is a highly subsidized gasoline market, intended for its inhabitants: everyone with a Venezuelan identity card can go to any gasoline station and buy gasoline for 1 bolivar/liter (ElPaisCali, 2017; BBC, 2018). An unintended consequence of the subsidy is that many Colombians either travel themselves across the border to buy gasoline or buy smuggled cheap gasoline from Venezuela (BBC, 2018; Collins, 2019). Part of this smuggled gasoline is then used in Colombia to produce cocaine (Mejía et al., 2010). Since the price of gasoline in Venezuela is fixed, the price for Colombians wanting to buy their gasoline will vary with the fluctuation in the currency between Colombian pesos and Venezuelan bolivars. When Venezuela was hit by hyperinflation, it became cheaper for Colombians to buy Venezuelan bolivars and gasoline from Venezuela. The closer to the Colombian border, the more expensive the gasoline becomes (ElPaisCali, 2017). The price differences remain important even though different actors require payments along the different smuggling routes.[3] In 2017, it was estimated that more than 400 million gallons of petrol were smuggled into Colombia from Venezuela (Collins, 2019). Venezuela is an oil-exporting and import-dependent economy

[2]Part of the gasoline used in the production is reusable, so for large-scale operations, there are efficiency gains. The estimations for gasoline are used with the prices from Colombia, not the smuggled gasoline.

[3]The Initiative for Investigative Journalism in the Americas, of the International Center for Journalists (ICFJ) has reported on the increase in illegal import of gasoline due to hyperinflation in Venezuela (ElPaisCali, 2017).

Source: Figure produced with data from the Central Bank of Colombia (2014-2018)

Figure 1: Exchange rate between Venezuelan Bolivar Fuerte Venezolano and Colombian Pesos

with repressed markets for foreign exchange and intermediate and consumption goods (Cerra, 2016). The oil export earnings cover the primary source of foreign exchange, which is used to import various foods and consumer goods. Venezuelan authorities tightly regulate foreign exchange rates, and its system for rationing foreign exchange creates a repressed goods market for import. When the international oil prices fell in 2014, this led to a drop in oil revenues, which again led to a massive reduction in the provision of foreign exchange to importers. This, in turn, led to a sharp decrease in the supply of goods to retail markets, driving the rise in inflation well beyond money growth. Together with a system that allowed different businesses to buy US dollars at different exchange rates, these factors led to a surge in inflation and the black market premium that led to hyperinflation in Venezuela in 2016. The inflation led to a dramatic fall of the Venezuelan bolivar compared to Colombian pesos (and other currencies), as shown in Figure 1. The depreciation of the Venezuelan bolivar to Colombian pesos makes illegal gasoline cheaper for Colombians, thus creating a shift in the cost of cocaine production in Colombia. As shown, the reduction in gasoline costs in Columbia was due to hyperinflation in Venezuela and was not related to the Colombian cocaine market. Therefore this can be considered an exogenous shock on gasoline prices in Columbia. This paper uses this exogenous price shock on the cocaine market to study the effect of the cocaine market on violence in cocaine-producing areas.

2.3 Violence in Colombia

Colombia has a long history of violence and civil wars since its independence in 1810 (Angrist and Kugler, 2008). There were high levels of violence in Colombia long before they started producing and trafficking drugs. The country experienced six major civil wars during the 19th century, and during La Violencia from 1948 to 1957, more than 200,000 Colombians were killed (Angrist and Kugler, 2008). Drugs did not cause all violence in Colombia, but it does not mean it did not perpetuate it. The incredibly high level of violence in the 1990s, when the homicide rate reached 70 homicides per 100,000 inhabitants, coincided with a shift in coca cultivation towards Colombia (Mejía and Restrepo, 2013). Most of the homicides in Colombia are committed with firearms coming from at least 20 countries (Democracy, 2017). Although the peace agreement in 2016 between Fuerzas Armadas Revolucionarias de Colombia (FARC) and the government forced FARC to hand in (some of) their weapons, there is no reason to believe that there is any shortage of firearms in the country (Rinaldi, 2019).

3 Previous literature and hypotheses

Most of the research on drugs and violence studies the relationship between legal enforcement of interventions against drugs that may lead to shifts in the market and their effects on violence. These are primarily studies that have a significant impact on the market structure. Law enforcement can contribute to increased violence by directly engaging with criminal organizations, sometimes necessitating force use. Additionally, it may influence the power dynamics among these groups, potentially sparking territorial conflicts or turf wars. Castillo et al. (2020) have studied the impact of a negative supply shock for cocaine from drug enforcement in Colombia and the effect of violence in areas in Mexico that were used for trafficking drugs into the U.S. They found that Mexican cartel violence increased in periods of reduced cocaine supply caused by Colombian government seizures. Dell (2015) shows that in areas with vigorous drug enforcement caused by a shift in political leaders, there was an increase in violence (homicide rate) in Mexico. Abadie et al. (2014) looked at the effects of drug eradication programs in Colombia and found that the eradication led to more violence in the short and long term. Both Angrist and Kugler (2008) and Mejía and Restrepo (2013) have studied demand shocks in Colombian coca production due to drug enforcement and its effect on violence and find that enforcement that leads to higher demand for coca leaves in Colombia generates more violence.

Mejía and Restrepo (2013) studied the effect of shifts in demand for cocaine in the U.S. on violence in Colombia. Similarly, Millán-Quijano (2020) studied the increase in prices for cocaine in the U.S. and European markets and its effect on violence in Colombian municipalities strategically placed to serve each international market. Both studies find a positive correlation between increased demand (prices) and violence.

Since there is little theory about the potential mechanisms between economic shocks and violence for illegal goods, it is relevant to investigate the literature on legal commodities and examine the link between price shocks and violence. Inside this literature, the focus is on cases where there is low legal enforcement, which is often the case far out in the countryside in developing countries with little state presence. In the last 10 to 15 years, this literature has changed from analyzing one homogenous effect at a country level to the micro-level and studying the underlying mechanisms, where research points out several competing mechanisms that might dominate under different circumstances (Rigterink, 2020). Therefore, there is no clear positive or negative correlation between price shocks, income, and violence. Dube and Vargas (2013) have examined how income shocks affect armed conflict and violence, focusing on Colombia. They show that two different mechanisms can lead to opposite effects. The first is the opportunity cost effect, which exhibits a negative relationship between income shocks and violence. The second is the rapacity effect, which shows a positive relationship between income shocks and violence. If prices for a labor-intensive natural resource increase, the wages for its workers should rise, which would lead to an upward shift in income for the households, which would increase the opportunity cost of conflict and recruitment to illegal activities (Dube and Vargas, 2013). However, the rapacity mechanism, also called "natural resources as a prize" or "greed" and related to the rent-seeking literature, would raise the return to conflict related to natural resources since there is more money to be earned (Rigterink, 2020). There are different theories on what makes the various mechanisms dominant (Dal Bó and Dal Bó, 2011; Dube and Vargas, 2013; Rigterink, 2020). However, the mechanisms should work in the same direction for an illegal good like coca, at least for a positive shock. Parallel to the opportunity cost effect, a positive shock to the coca market would increase the household income from coca and incentivize them to join these illegal activities, which can cause more violence. Here, it is essential to keep in mind that the farmers do the first step of the production where the supply shock occurs (see more detail about the production in section 2.1), and that these are imperfect markets where the criminal groups cannot necessarily extract all new surplus. For the rapacity effect, a positive shock to the coca market would increase the incentives to overtake production that belongs to others, either vertically (by taking over more of the production chain) or horizontally (by taking over coca leaves farms from others). The rapacity mechanism often leads to turf wars between gangs (Lessing, 2015). In conclusion, a positive supply shock resulting from cheaper gasoline should likely lead to more violence in the areas producing coca than in those not producing it. After the main analysis in Section 7 I try to disentangle the two effects by studying attacks by armed groups during this period and areas previously occupied by FARC guerrillas.

4 Data

My dataset includes data on the cultivation and production of coca and cocaine, data on violence, data on exchange rates between Colombia and Venezuela, data on time distance between municipalities and data on the violent present of armed actor.

Table 1: Summary statistics

	Mean	SD	Min	Max	N
Homicides per 100,000	55.64	44.79	0.00	385.40	715
Hectars of coca cultivation	857.58	1668.44	0.00	19892.71	715
Female homicides per 100,000	1.59	3.13	0.00	37.00	715
Shortest time to border (min)	1013.36	532.42	0.00	2166.37	715

Notes: Data from 2010 to 2020. Homicides were adjusted for the yearly population by gender. Shortest time to Venezuelan border in minutes. All data at the municipality level. The sample contains only municipalities with coca cultivation in the years before 2016. States bordering Ecuador and overseas municipalities are excluded.

4.1 Data on cultivation and production

To estimate the causal effect of cocaine production on violence, I would ideally use data on cocaine production; however, information on cocaine cultivation is not available since it is an illegal industry. Fortunately, I can use data on coca production, which is an indirect way to measure the effects of cocaine production. As mentioned in section 2.1, cocaine production in Colombia, the first stages of cocaine production take place physically close to cultivation areas. The data source on coca cultivation is the Integrated Monitoring System of Illicit Crops (SIMCI) of the United Nations Office on Drugs and Crime (UNODC). SIMCI is a satellite-based monitoring system that estimates the extension of coca crops annually (Abadie et al., 2014). It uses satellite imagery of Colombia, and based on these satellite pictures, SIMCI experts will geo-reference the area they interpret as coca-producing based on visual inspection. Then these areas interpreted as coca-producing are confirmed via high-definition photographs through helicopter flights.[4].

[4] I also tried to use the coca cultivation suitability index created by Mejía and Restrepo (2013) However, the correlation between the suitability index and actual coca leaves in 2015 is too small

As a robustness check, I also use seizure data. The problem with seizure data is that it might not be perfectly correlated with the actual cultivation data. The police might not always do significant seizures in areas with extensive cultivation because of fear of violent confrontation or other measurements of inaccessibility or corruption. Since Colombia has access to good-quality data on coca cultivation, it is still likely that the police do seizures regularly in areas with a high density of cultivation. I have verified that all the top-producing municipalities are part of the seizure data. A preliminary study of the geo-referenced data shows that nearly all municipalities in the treatment group had cultivation in 2016 and 2018. However, there are some considerable differences. The data I use is at a yearly level, and the data is at the municipality level. In Colombia, there are 1,123[5] municipalities grouped into 33 departments. Municipalities are analogous to counties in the U.S., whereas departments are analogous to states (Dube and Vargas, 2013).

4.2 Data on violence

My main dependent variable is the homicide rate per 100,000 inhabitants from 2010 through 2020, constructed from homicide data from National Police Statistical Contravention Crime and Operational Information System - SIEDCO. The data provide information on the cause, location (municipality), date, and gender. I use municipality-level population projections to compute death rates based on the National Census of 1985 and 2020 from the Colombian National Statistics Department (DANE). Homicides are often used as a proxy for violence because they are highly correlated with other violence and are accurately measured (Soares, 2004). I use the normalized variable, homicides per 100,000 inhabitants, as this is the most common practice and allows for comparison across time and space. The inverse hyperbolic sine of the homicide rate is also used as a robustness test.

(0.0343), which can be because other factors determine where the illegal crop can be grown, such as enforcement and new techniques. Thus making the index not suitable for this analysis.

[5]The three municipalities outside mainland Colombia are excluded from the analysis.

4.3 Data on distance to border with Venezuela

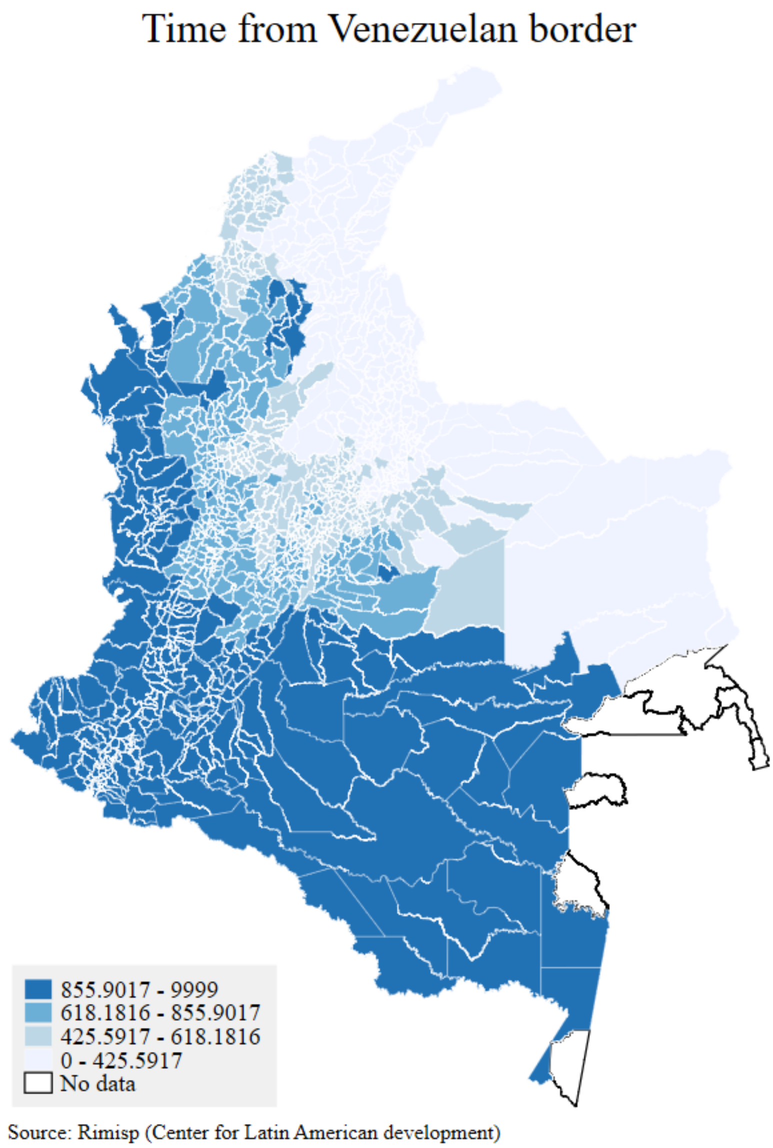


Figure 2: Time distances (min) to the border of Venezuela

To calculate the distance to the border of Venezuela, I use data from a database created by the National Planning Department (DNP) and Rimisp (Center for Latin American Development) with the calculated time needed to travel between each municipality, as seen in Figure 2. The database was created with the support of the German Cooperation Agency (GIZ) and the European Union. The methodology for classification is according to the typologies proposed by the OECD. Since the road quality can be poor in Colombia and there is a large variation in elevation in the country (there are several mountain ranges across Colombia), using time instead of distance is an advantage as it gives more accurate estimations. The estimations consider the different quality of roads and elevations.[6]

There are many illegal roads into Colombia from Venezuela called *trochas* due to the closure of the official borders between Colombia and Venezuela (Ramírez, 2022). Since there is no good information on all the trochas (since they are also illegal), the assumption will be that there can be trochas into Colombia across the border with Venezuela. Therefore all the frontier municipalities will be defined as a starting point. Then the minimum time from a frontier municipality plus the minim time to travel within this municipality will be chosen as an intensity indicator for gasoline smuggling.

4.4 Data on exchange rates

I use official currency data on exchange rates between Colombia and Venezuela from the Colombian Central Bank (Banco de la República Colombia 2020) to model the price shock. I use Colombian pesos for Colombia and Bolívar Fuerte Venezolano for Venezuela. Venezuela has several currencies due to its high inflation. I use Bolívar Fuerte Venezolano because it was the official currency from 2008 until August 2018. As shown in Figure 1, the price shock shows a massive devaluation of Bolívar Fuerte Venezolano to the Colombian peso in 2016.

4.5 Data on Violent Presence of Armed Actors

To study the heterogeneity of group present in Colombia, I use a database called the Violent Presence of Armed Actors [7] in Colombia, which maps all armed actors in Colombia between 1988 and 2019 (Osorio et al., 2019). The data presents an array of state and non-state armed actors clustered into five main types: Government forces, Insurgent organizations, Paramilitary groups, Criminal organizations, and FARC Dissidents. The

[6] Information on the classifications: https://www.invias.gov.co/index.php/informacion-institucional/2-uncategorised/2706-clasificacion-de-las-carreteras.

[7] The term Armed Actor refers to state and non-state armed entities that exercise the organized use of violence in a specific territory to achieve political or economic goals.

data indicates the Violent Presence of armed actors at the municipality-year level. Given the nature of the information source, this data reflects the location of armed actors involved in violent incidents, both lethal (e.g. assassinations) and non-lethal (e.g. threats, displacement). However, the main weakness of these data, by definition, is that they cannot observe armed actors who are present in a territory but exercise no violence. If one armed group has complete dominance or monopolistic control among armed actors, violence might not be unnecessary. Keeping this limitation in mind, the database can give valuable insights into how the dynamics of armed actors in areas with cocaine production affect violence when a price change occurs.

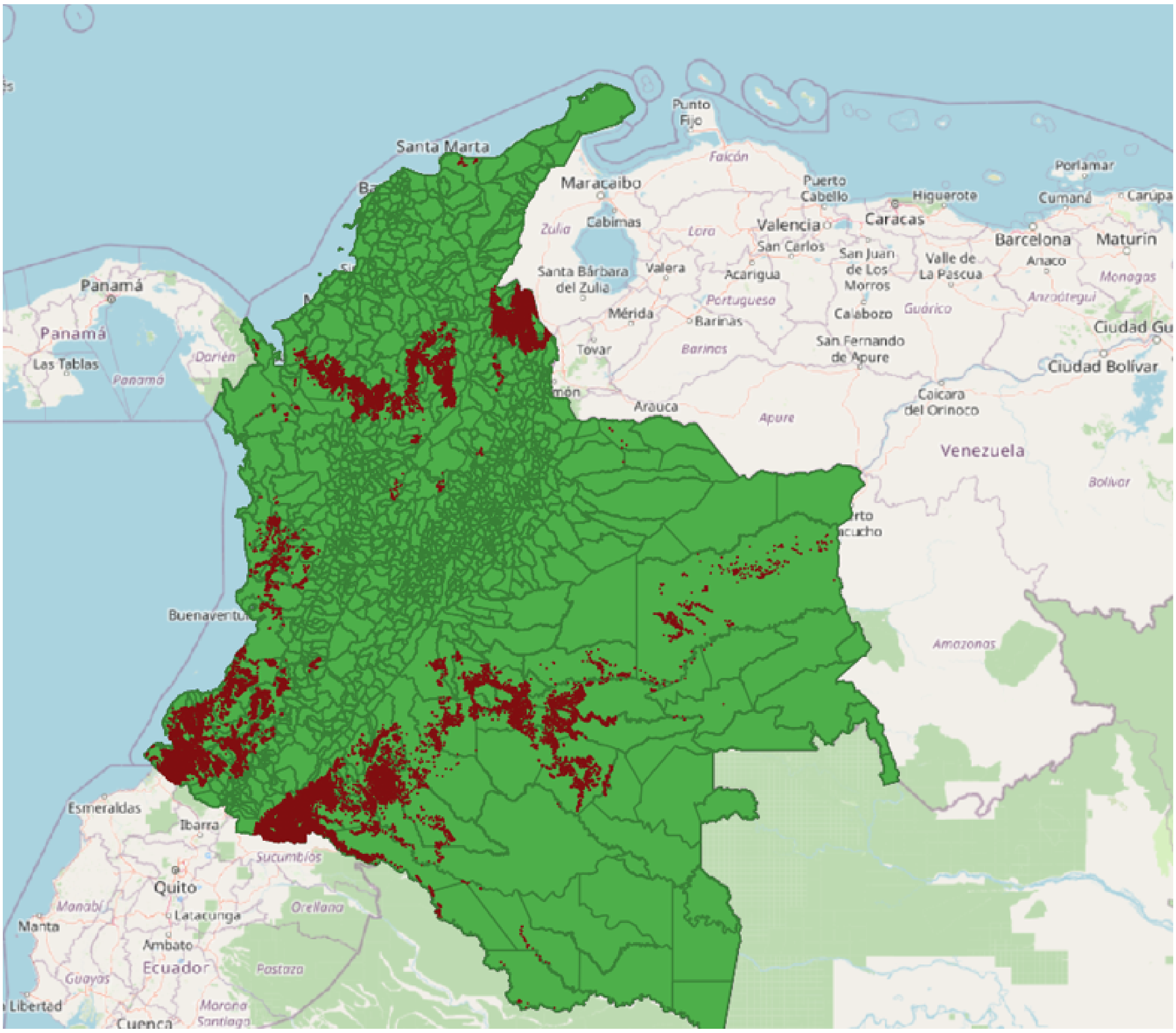
Using the dataset, I construct a measurement of exposure to FARC violence before the start of the ceasefire. Similar to Prem et al. (2021), I use the areas with violent attacks by FARC in 2011-2014 before the ceasefire during the peace negotiations.

I will use the competition of actors for each municipality in the year(s) before the price shock. In 2015, there were 2615 incidences reported across 45 different armed actors.

5 Empirical Framework

I will estimate the effect of the cocaine price shock on violence. However, it is challenging to estimate the causal effects of violence in a country like Colombia due to the high number of instability factors (war, peace processes, economic instability, and income inequality). Therefore, I use the difference-in-differences (DiD) design to exploit the geographic variation in coca cultivation intensity. I also exploit exogenous time variation in gasoline prices, an input in the cocaine production induced by a currency shock between Venezuela and Colombia. The strategy is similar to the one (Dube and Vargas, 2013) used to look at the effects of economic shocks and change in violence in Colombia for legal goods, and the one (Sviatschi, 2022) uses to estimate the impact of a demand shock for coca leaves on children's long-term outcomes in Peru.

There is a high concentration of coca cultivation within a few areas in Colombia, and this was also the case in 2016 when the gasoline price shock occurred (UNODC and of Colombia, 2017; UNODC, 2019).The concentration of cultivation is shown on the map 3. Therefore my sample will only consist of municipalities with coca leaf production.[8]



Source: Map produced with data from Observatorio de Drogas de Colombia. In light green, are the territories of mainland Colombia with the borders of the municipalities in dark green. In red, are all the areas with coca cultivation in 2016.

Figure 3: Coca cultivation in Colombia in 2016

Since the gasoline is smuggled over from Venezuela, a natural treatment variable is the distance to the border. The further the gasoline has to be smuggled into Colombia, the

[8]See Appendix A.2 for more details on the selection of sample.

more expensive and closer to official gasoline prices in Colombia it becomes (ElPaisCali, 2017). Therefore, the assumption is that municipalities close to the border with Venezuela should be more affected by the positive shock from Venezuela due to transportation costs (it takes time, money, and risk to transport illegal gasoline).

I first run a dichotomous treatment variable, where I define the treatment status based on belonging to a state (department) that borders Venezuela.[9] I also exclude the states (departments) that border Ecuador, as they are likely to get their gasoline from Ecuador.[10] I then also do the analysis with distance to Venezuela as a continuous variable. Looking at the road network in Colombia, it is not apparent how much the transportation time (and cost) increases in the different areas. As one can see from the map in figure 4, there are no main roads in the eastern part of the country, and therefore it is likely that the commodities from Venezuela arrive from the North and North East and will pass through the country to arrive in the South. Since the road quality can be poor in Colombia and there is a large variation in elevation in the country, I use the actual time distances (in minutes) between the different municipalities as the variable for the intensity of gasoline smuggling.

Formally, the difference-in-differences (DiD) is be expressed as:

$$y_{it} = \alpha_i + \alpha_2 * post_t + \beta * (treat_i * post_t) + \sigma_t + \epsilon_{it}$$

Where the subscript i specify the municipality, and t represents time measured in years. y_{it} is the homicide rate of municipality i in year t and is the outcome variable of interest. *treat* is the treatment variable taking the value 1 if the municipality is in the treatment group (with high cultivation of coca) and 0 if the municipality is in the control group (low cultivation of coca). Later the variable becomes a continuous variable. *Post* is a binary variable taking the value 0 if the year is 2010 to 2015 and the value 1 if the year

[9] Norte de Santander and Vichada

[10] Nariño, Amazonas and Putumayo

Figure 4: Road network by the Colombian Ministry of Transportation

is 2016 to 2020 since the shock happened in 2016. σ_t a vector of year-fixed effects, and α_i the municipality fixed effect. Like Dube and Vargas (2013), I employ the municipality fixed effects to control for time-invariant municipal characteristics that may be correlated with economic conditions that may affect the conflict outcome. ϵ_{it} is a time-varying error term. The coefficient of interest, β measures the average causal effect of the positive price shock in gasoline prices on the outcome variable, homicide rate. The identifying assumption is that the change in the outcome variable would have been the same in both the treatment and control group in the absence of the price shock. β, our parameter of interest, estimates the average change in violence for municipalities that produce coca compared with municipalities that do not produce coca.

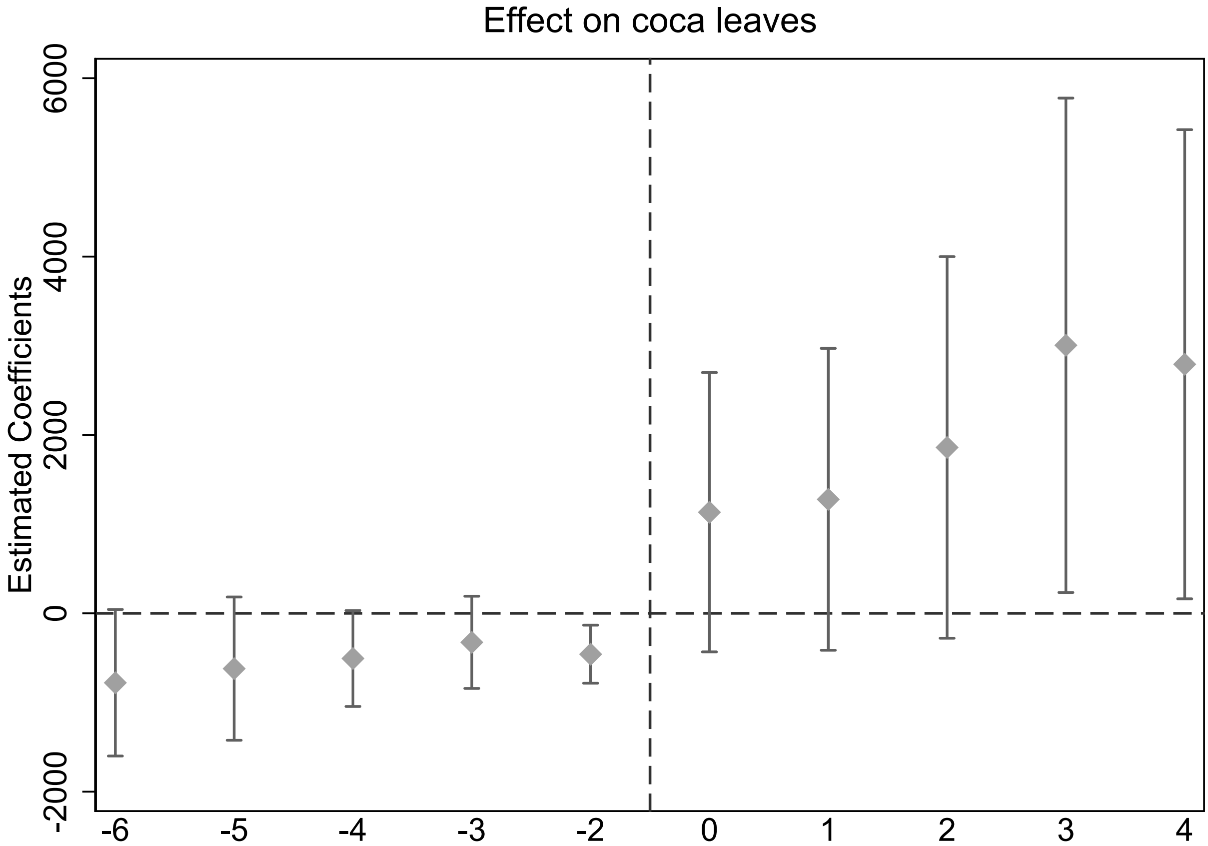
To avoid overstating the precision of the estimates, I cluster standard errors (Cameron et al., 2008).

I first cluster standard errors at the municipality level which is the level of treatment status.Then at department level (similar to Dube and Vargas (2013)) to account for potential serial correlation over time and across municipalities within a department in violence. Due to a low number of departments, to avoid potential downward bias with a small number of clusters (Cameron, Gelbach Miller 2008), I also use wild cluster bootstrap, a strategy that has been shown to perform well with small numbers of clusters.I also include municipality-specific time trends.

6 First stage

In this paper, I look at the effect of a decrease in the price of smuggled gasoline used in cocaine production on violence. Ideally, there would be a clear first stage, where I look at the effect of gasoline on the production of cocaine. Unfortunately, since this good is illegal, there does not exist good data on the actual production of cocaine at the municipality level. As a second-best option, I show the evolution in coca leaf production over time.

In figure 5, one can see an event plot of the evolution of coca leaves where the treatment is the areas close to the border with Venezuela (municipalities that belong to a state (department) that borders Venezuela). One can see that there is an increase in coca leaves after the shock in the areas closer to the border compared to the areas further away. The same result is shown in table 2 using a DiD analysis where one sees a large positive effect of 2200 to 860 hectares of coca leaves, which are statistically significant at a 0.01 level in some of the specifications. In table 3, one can see similar results but with a continuous treatment variable. Here, the variable is the time travel distance to the border with Venezuela. The effects are negative; the further away from the border, the smaller the effects.



Note: The treatment status is based on being close to the border with Venezuela. I define the treatment group as the municipalities that belong to a state (department) that borders Venezuela

Figure 5: Results: graphical representation of coca leaves

Table 2: First stage

	(1) Coca	(2) Coca	(3) Coca	(4) Coca	(5) Coca	(6) Coca
DiD	2196.3***	2196.3	2196.3***	2196.3	867.1***	867.1
	(560.7)	(1333.4)	(564.3)	(1341.9)	(149.5)	(810.9)
Control G	664.30	664.30	664.30	664.30	664.30	664.30
N	715	715	715	715	715	715
Cluster	Department	Municipality	Department	Municipality	Department	Municipality
Municipality-time	No	No	No	No	Yes	Yes

*Notes: Municipality-time: municipality-specific time trends. Wild cluster standard errors are in parentheses. Treatment group as the municipalities that belong to a state (department) that borders Venezuela. Sample are areas with coca production. *** p<0.01, ** p<0.05, * p<0.1*

Table 3: First stage with continuous distance to border

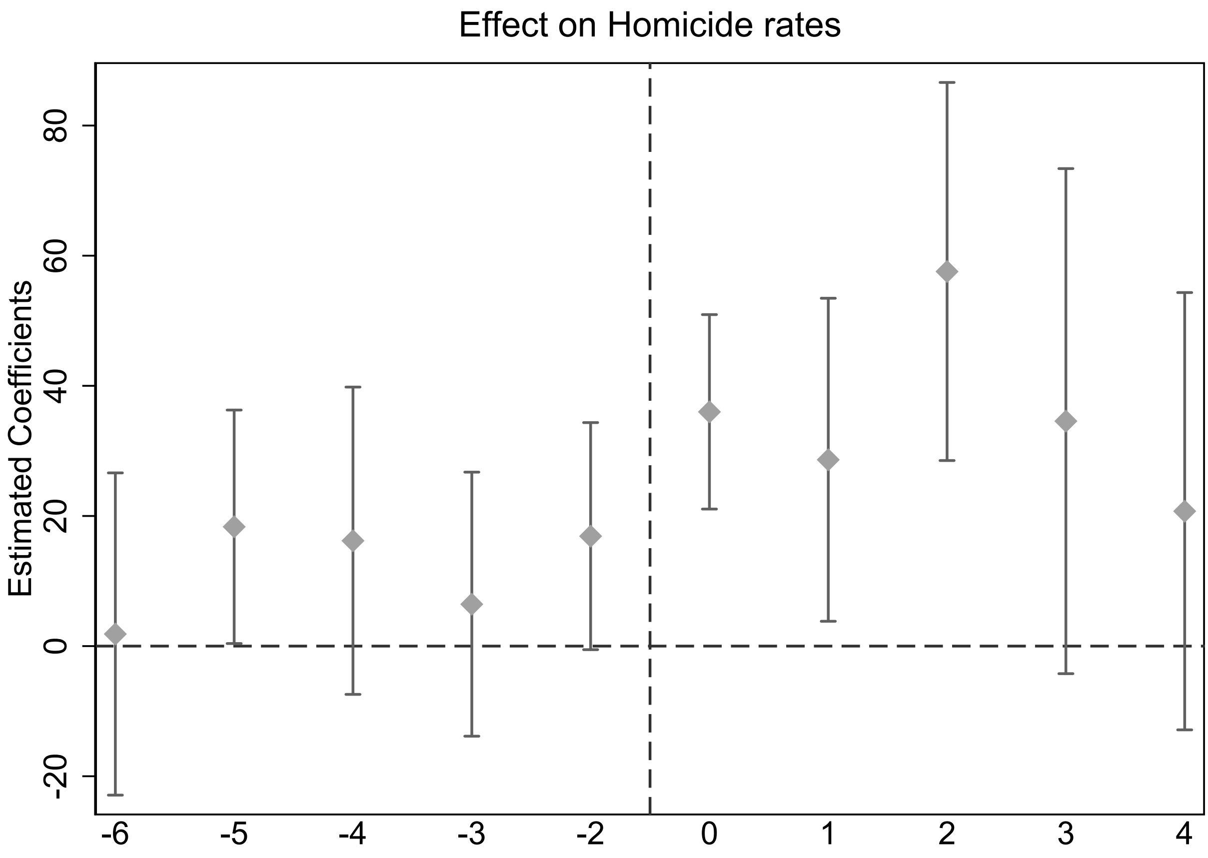
VARIABLES	(1) Coca	(2) Coca	(3) Coca	(4) Coca	(5) Coca	(6) Coca
DiD	-1.462**	-1.462**	-1.462**	-1.462*	-0.712***	-0.712
	(0.513)	(0.738)	(0.516)	(0.742)	(0.0994)	(0.466)
Observations	715	715	715	715	715	715
Number of muni	65	65	65	65	65	65
Municipality FE	NO	NO	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES	YES
Cluster	Department	Municipality	Department	Municipality	Department	Municipality
MSTT	NO	NO	NO	NO	YES	YES

*Notes: Municipality-time: municipality-specific time trends. Wild cluster standard errors are in parentheses. Treatment is a continuous variable with time distance to the border with Venezuela. Sample are areas with coca production. *** p<0.01, ** p<0.05, * p<0.1*

7 Effects on homicides

7.1 Graphical representations

In figure 6, an event plot is shown for the homicide rate, where the difference between control and treatment is plotted by year. Though slightly noisy results visually, the figure shows an increase in the homicide rate in the treatment group compared to the control group after the shock in 2016. This implies more homicides in the areas close to the border with Venezuela after the shock compared to areas further away.



Note: The treatment status is based on being close to the border with Venezuela. I define the treatment group as the municipalities that belong to a state (department) that borders Venezuela. Homicide rate per 100 000 inhabitants per year.

Figure 6: Main result

7.2 Main findings

In table 4, are the result from the main analysis. It shows the standard DID, an average treatment effect on the treated (ATT). The main result shows a positive statistically significant effect of 31.1, which is robust across all specifications. The result indicates that, on average, the impact of the shock in the treatment group (the areas close to the border with Venezuela) is an increase of 31.1 homicides per 100,000 inhabitants. Even for a violent country like Colombia, the number is quite high. It is important to remark that these areas with coca production have a much higher level of violence. The average homicide rate in the treatment sample before the shock (2010 to 2015) was 58 homicides per 100,000 inhabitants, implying that the supply shock's effect is equivalent to a 53 % increase in the homicide rate.

As a robustness test, I also log transform the main dependent variable, as shown in table A1 in the appendix. The results are smaller, with estimates of about 30% increase in homicide. I also make a synthetic difference in differences, which gives an estimate of about 25 homicides per 100,000 inhabitants, smaller than 31.1 homicides, but it is in the range of 22 to 31, estimated with the normal difference in differences.

In table 5, one can see similar results but with a continuous treatment variable. Here, the variable is the time travel distance to the border with Venezuela. The effects are negative; the further away from the border, the smaller the effects. Though it is a sign that the continuous and original treatment variables give consistent results, there might be some bias with using two-way fixed effects estimation with the continuous measurement, as Callaway et al. (2021) points out, and one should not rely on the point estimates to conclude about the effect size. I, therefore, try different definitions of treatment based on time distance to the border, as one can see in Table 6. One can see a larger effect in column 5 (which is 200 minutes or about 3 hours) compared to column 1 (which is 700 minutes or about 11 and half hours). Beyond 700 minutes, the variable starts to lose its significance. Unfortunately, I do not know how far into Colombia they smuggle the gasoline or where the smuggled gasoline is sold substantially cheaper than local gasoline.

7.3 Placebo test

I run a difference-in-differences placebo test. The idea with a placebo test is to pretend that the shock happened earlier than it happened. One can thus "test" the untestable parallel trend assumption, which is necessary for the DiD design (Gertler et al., 2016). The DiD design relies on the idea that in the absence of the shock (treatment), the treatment and control groups would continue to move in parallel. This assumption is impossible to test for, as we will never see the counterfactual (which in this case would be the absence of the price shock in 2016). It is still possible to test the validity of the parallel trend assumption with a placebo test.

A placebo test uses data from the pre-shock period between 2010 and 2015. For the different placebo estimations, I will assume that the shock happens in another year than the actual shock. In the first estimation, I assume the shock was in 2011. In the second estimation, I assume the shock was in 2012, and so forth. Commonly, the placebo test uses one point in time for the test; however, here, I have done a placebo test for all available time points.

If there were significant effects in the placebo test, the parallel trend assumption would not be valid. In Table 7, one can see the results of the placebo tests. The placebo tests show no statistically significant effects. In addition, in the last years before the

Table 4: Main results

	(1) Homicide rate	(2) Homicide rate	(3) Homicide rate	(4) Homicide rate	(5) Homicide rate	(6) homiciderate
DiD	22.6**	22.6*	22.6**	22.6*	31.1***	31.1***
	(9.20)	(12.0)	(9.26)	(12.1)	(6.44)	(7.47)
Control group mean	53.41	53.41	53.41	53.41	53.41	53.41
N	715	715	715	715	715	715
Cluster	Department	Municipality	Department	Municipality	Department	Municipality
Municipality-time	No	No	No	No	Yes	Yes

*Notes: Homicide rate per 100 000 inhabitants per year. Municipality-time: municipality-specific time trends. Wild cluster standard errors are in parentheses. Treatment group as the municipalities that belong to a state (department) that borders Venezuela. Sample are areas with coca production. *** p<0.01, ** p<0.05, * p<0.1*

Table 5: Results with continuous distance to border

VARIABLES	(1) Homicide rate	(2) Homicide rate	(3) Homicide rate	(4) Homicide rate	(5) Homicide rate	(6) Homicide rate
DiD	-0.0203**	-0.0203***	-0.0203**	-0.0203***	-0.0105	-0.0105*
	(0.00744)	(0.00731)	(0.00749)	(0.00736)	(0.0107)	(0.00601)
Observations	715	715	715	715	715	715
Number of muni	65	65	65	65	65	65
Municipality FE	NO	NO	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES	YES
Cluster	Department	Municipality	Department	Municipality	Department	Municipality
MSTT	NO	NO	NO	NO	YES	YES

*Notes: Homicide rate per 100 000 inhabitants per year. Municipality-time: municipality-specific time trends. Wild cluster standard errors are in parentheses. Treatment is a continuous variable with time distance to the border with Venezuela. Sample are areas with coca production. *** p<0.01, ** p<0.05, * p<0.1*

Table 6: Different treatment definitions

	(1) Homicide rate	(2) Homicide rate	(3) Homicide rate	(4) Homicide rate	(5) Homicide rate
DiD 700	26.7**	26.7***			
	(9.20)	(6.95)			
DiD 600			26.7***		
			(6.95)		
DiD 200				31.1***	31.1***
				(6.44)	(7.47)
Control group mean	53.41	53.41	53.41	53.41	53.41
N	715	715	715	715	715
Cluster	Department	Municipality	Municipality	Department	Municipality
Municipality-Time	YES	YES	YES	YES	YES

*Notes: Homicide rate per 100 000 inhabitants per year. Municipality-time: municipality-specific time trends. Wild cluster standard errors are in parentheses. Treatment groups are travel time to border with Venezuela. Sample are areas with coca production. *** p<0.01, ** p<0.05, * p<0.1*

shock, in 2013, 2014, and 2015, the effects were the opposite sign of the main findings. The negative sign reflects the drop in homicides for the treatment group before the price shock.

Table 7: Placebo test

VARIABLES	(1) placebo 2011	(2) placebo 2012	(3) placebo 2013	(4) placebo 2014	(5) placebo 2015
DiD	19.79	6.063	-10.07	-1.699	-16.38
	(13.05)	(17.65)	(15.62)	(15.02)	(11.81)
Observations	390	390	390	390	390
Number of muni	65	65	65	65	65
Municipality FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Cluster	Municipality	Municipality	Municipality	Municipality	Municipality
MSTT	YES	YES	YES	YES	YES

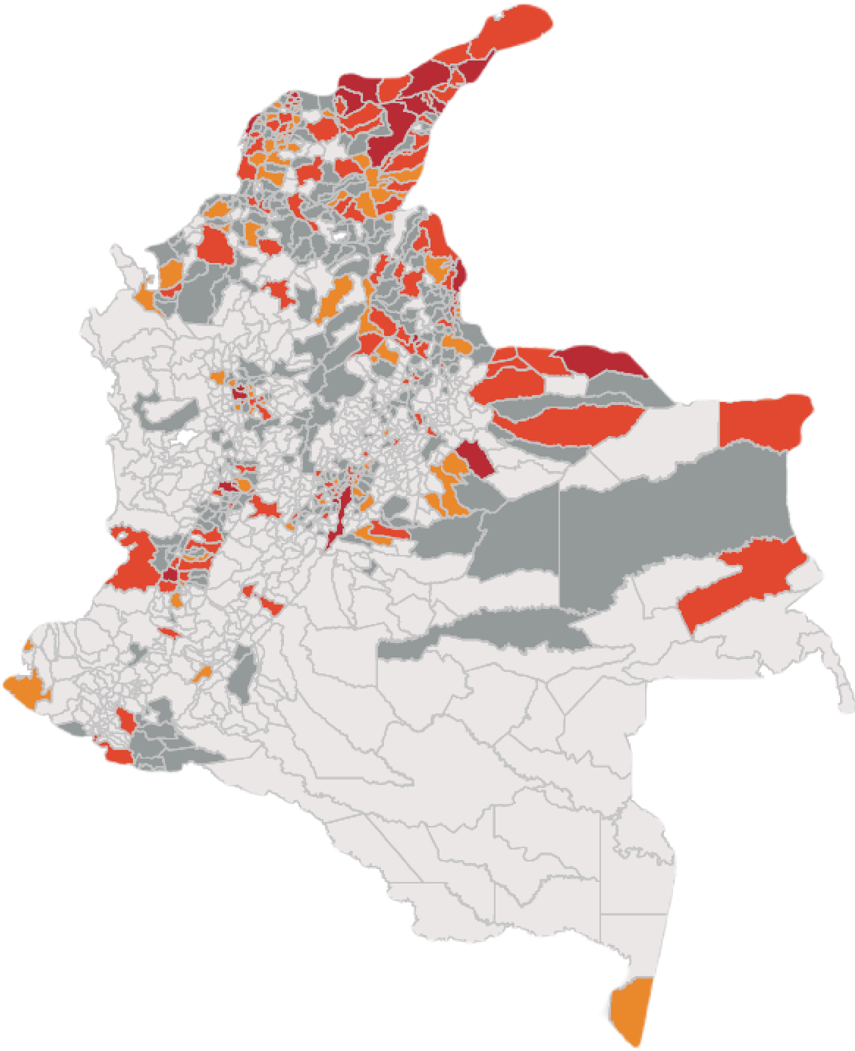
*Notes: Homicide rate per 100 000 inhabitants per year. Municipality-time: municipality-specific time trends. Wild cluster standard errors are in parentheses. Treatment group as the municipalities that belong to a state (department) that borders Venezuela. Sample are areas with coca production. *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

8 Potential threats to the difference-in-differences design

8.1 Immigration from Venezuela

One potential competing mechanism is the increasing immigration from Venezuela to Colombia. In the data, there is an increase in the number of Venezuelans who are victims of homicide. In 2010-2012, the number of Venezuelans killed was less than 20. In 2017, the number jumped to 80; in 2019, 439 were reported killed. The concern is not that these homicides would bias the results, as they constitute only 0.62 % of the murders, and removing them from the data is possible. The concern is that the Venezuelans might be crime victims and cause crimes since they are vulnerable, with little money, and escaping a difficult situation in their home country.

Knight and Tribin (2023) studied immigration and violent crime from Venezuela to Colombia during the time frame of interest in 2016. They do find an increase in homicides of Venezuelans close to the border; however, they do not find any increase in homicides of Colombians. If Venezuelan immigrants could disproportionately move to areas defined as treatment municipalities, this could bias the result. The homicides are also adjusted



From Colombian Immigrant Office. Colors by the number of Venezuelan immigrants: In dark red, more than 10.000, in light red between 10.000 and 1.000, in orange between 1.000 and 500, in dark grey between 500 and 100 and in light grey, less than 100

Figure 7: Intensity of Venezuelan immigrants by municipality.

for the population. Nevertheless, if there is a disproportional flow of Venezuelans that move the treatment areas, this could bias the estimations.

In 2014, only 23,573 Venezuelans lived in Colombia, while in 2019, 1,488,373 Venezuelans lived in Colombia (Colombia, 2020). The map 7 shows the estimations of the concentration

Table 8: Result excluding the municipalities with large portion of Immigrants

	(1) Homicide rate	(2) Homicide rate
DiD	29.5***	29.5***
	(6.80)	(7.73)
Control group mean	53.41	53.41
N	693	693
Cluster	Department	Municipality
MSTT	YES	YES

Notes: The top 65 municipalities in Colombia with Venezuelan immigration are excluded. Homicide rate per 100 000 inhabitants per year. Overseas municipalities excluded. Municipality-time: municipality-specific time trends. Wild cluster standard errors are in parentheses. Treatment group as the municipalities that belong to a state (department) that borders Venezuela. Sample are areas with coca production.

of immigrants from Venezuela at a municipality level in Colombia. The red color indicates more than 10,000 immigrants per municipality, dark orange indicates between 1,000 and 10,000 immigrants, light orange indicates between 500 and 1,000, dark gray indicates between 100 and 500 immigrants and light gray indicates less than 100 immigrants from Venezuela in the municipality. To test whether immigration could affect the DID analysis, I redo the analysis without the municipalities with many immigrants from Venezuela. I use the top 65 municipalities in Colombia with Venezuelan immigration and all the municipalities with noticeable migration and exclude them from the analysis. The result is shown in table 8 and shows a statistically significant effect of 29.5, which is quite close to the results in the main analysis 4 of 31.1. Therefore, immigrants do not seem to be the main driver of the results in the analysis. However, some of the immigrants from Venezuela go into the business of "raspachines", picking the coca leaves; this may lower the labor price for picking the leaves, which also could lower the cost of the production (Espinel et al., 2020; Monsalve, 2022).

9 Further analysis

9.1 Presence of FARC

As part of the Colombian peace agreement, another significant phenomenon in Colombia that happened in 2016 (UNODC & Government of Colombia 2017) was that FARC guerrillas had to give up the territories. On some of this territories they had used to produce coca and cocaine. The abandoning of territory might lead to violence in the competition over territories, either between the government and the illegal armed groups or between different illegal armed groups. I construct a measurement of exposure to FARC violence before the start of the ceasefire. Similar to Prem et al. (2021), I use the areas with violent attacks by FARC in 2011-2014 before the ceasefire during the peace negotiations.

In Table 9, one can see that the effects of the DID estimates are weaker in areas previously not attacked by FARC (columns 1 and 2) compared to areas with FARC (in columns 3 and 4). Compared to the main results of 31.1, the areas without FARC have a smaller but still statistically significant effect of 19.7 and the areas with FARC has a a larger effect of 33.9.

Table 9: Results: presence/no presence of FARC

VARIABLES	(1) Homicide rate 2011	(2) Homicide rate	(3) Homicide rate	(4) Homicide rate
DiD	19.65***	19.65**	33.87***	33.87***
	(7.064)	(8.086)	(9.051)	(3.169)
Control group mean	40.65	40.65	59.11	59.11
Observations	462	462	253	253
Number of muni	42	42	23	23
Municipality FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Cluster	Municipality	Municipality	Municipality	Municipality
MSTT	YES	YES	YES	YES
FARC	NO	NO	YES	YES

Notes: In columns 1 and 2, an analysis without municipalities that were exposed to FARC, 3 and 4 with only municipalities that were exposed to FARC. Exposure to FARC is defined as in the top—3 quartiles of the empirical distribution of the total number of FARC attacks (Normalized by 10,000 inhabitants) that took place from 2011 to 2014. Homicide rate per 100 000 inhabitants per year. Municipality-time: municipality-specific time trends. Wild cluster standard errors are in parentheses. Treatment group as the municipalities that belong to a state (department) that borders Venezuela. Sample are areas with coca production.

9.2 Attack by armed group

To further analyze if the increase in violence comes from the armed groups or the farmers, I study the number of attacks by the armed groups and the government. In Figure 8, one can see that the number of attacks by the government and the armed groups decreased in 2016 before it increased again in 2018 and then decreased again. Suggesting that the increase in violence seen after the shock in 2016 does not come from the armed groups attacking.

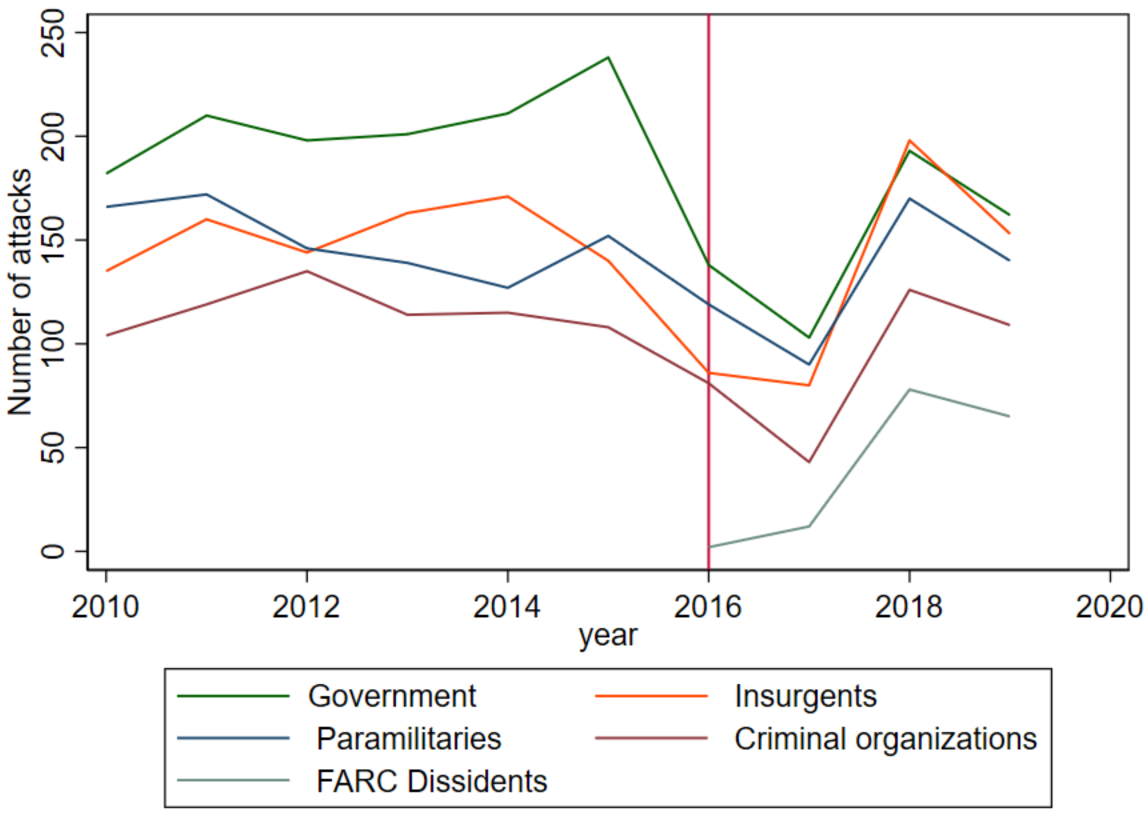


Figure 8: Results: graphical representation over the number of armed group attacks by group over time

10 Conclusion

In this article, I have studied the relationship between violence and cocaine production to investigate whether a positive shock to cocaine production leads to more violence. Using an exogenous price shock in the cocaine market, I have investigated the effect of violence in cocaine-producing areas. The price shock originates from a shock to the exchange rate between the currencies of Colombia and Venezuela, caused by hyperinflation in Venezuela due to oil shock and poor governmental manipulation of exchange rates. This shock affects the price of an input into cocaine production, the price of trafficked gasoline.

I employed a quasi-experimental research approach to assess the consequences of the supply shock on violence. Specifically, I conducted a difference-in-differences (DID) analysis, comparing high-intensity coca cultivation areas close to the border with Venezuela with areas father away. I merged data on coca cultivation from satellite images and homicide rates, drawing from two reasonably reliable data sources in a field characterized by substantial uncertainties and information gaps.

The impact of the shock in the treatment group is an increase of 31.1 homicides per 100,000 inhabitants. To put this into context, the average homicide rate in the treatment sample before the shock was 58 homicides per 100,000 inhabitants, corresponding to equivalent to a 50% increase in the homicide rate.

The results indicate that when it becomes cheaper to produce cocaine, there is more violence in the production areas. Furthermore, this violence does not seem to be driven by armed groups attacking each other, suggesting that the opportunity cost effect is driving the results. Since violence and drug production are both highly unwanted, the implication should be to ensure that it does not become cheaper to produce cocaine. One policy implication of doing this is by tightly controlling the input factors needed in cocaine production beyond the coca leaves. Most of the former efforts have focused solely on controlling the coca leaves; however, this has not been successful. The tight control of substances needed in production is most effective in the first part of the production done locally in Colombia. Both because it would be easier to control under a region than under the world in general. And secondly, since it can also improve local conditions.

The result can also be used to predict increased violence during positive price shocks for illegal substance production in similar situations where multiple illegal actors are fighting. Together with the work of Millán-Quijano (2020), we now know that positive supply and demand price shocks lead to more violence.

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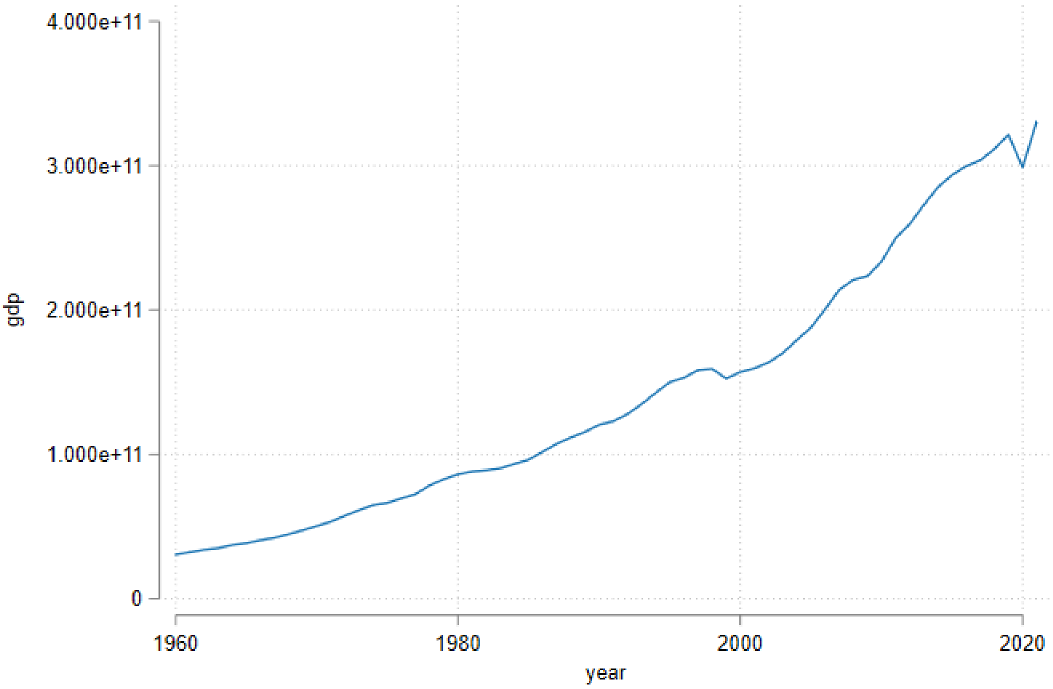
Appendix

A.1 Economic conditions in Colombia

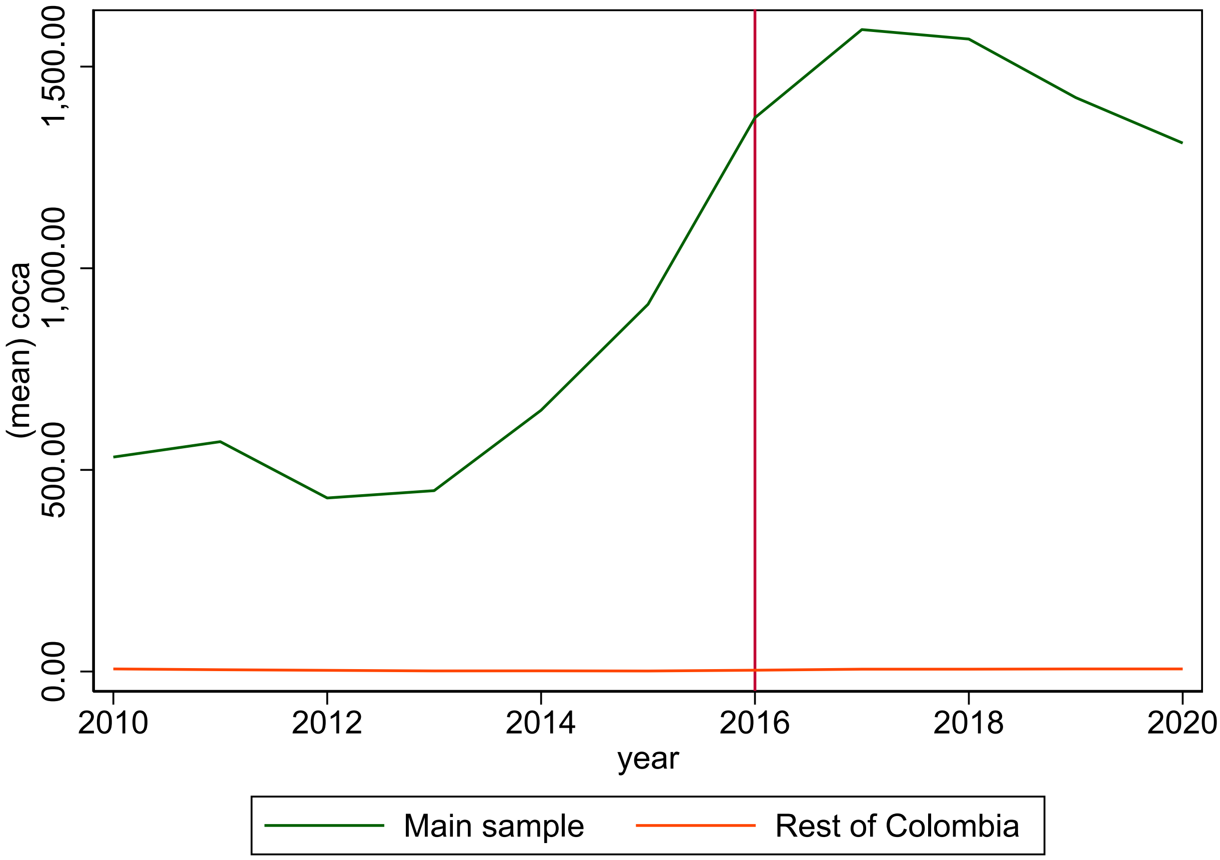


Source: Figure produced with data from the World Bank

Figure A1: GDP in constant 2015 $ in Colombia

A.2 Sample

I define the sample as the areas that had coca leaf production in the years before the shock. More specifically, the municipalities with more than 50 hectares per year per municipality in 2012, 2013, 2014, and 2015. As seen in Figure 3, coca cultivation is concentrated in some areas of the country. Below in Figure A2 we see the evolution of coca leaf in the sample and the rest of the country over the period of interest. One can see there is no large coca leaf production in the areas excluded from the sample. The increase in coca leaf cultivation starts before the shock. It is documented to be due to anticipation of the peace agreement, where farmers had the incentive to grow (more) coca to get more support with the self-eradication programs that were believed to be implemented with the peace agreement (Prem et al., 2023).



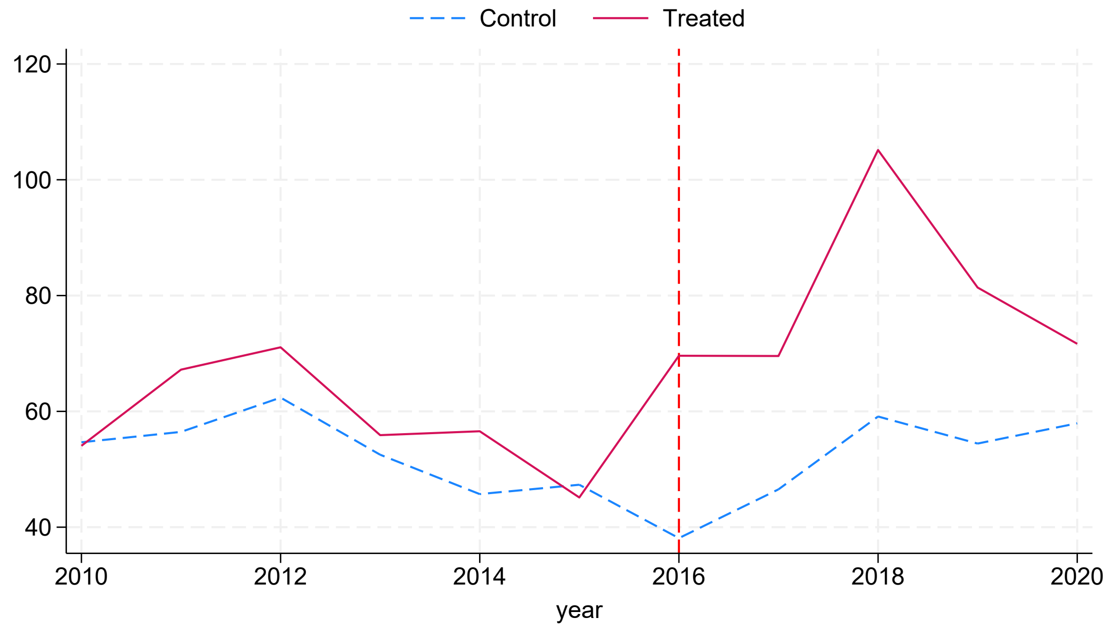
Source: In green is the main sample of the analysis, and in orange is the sample excluded from the analysis.

Figure A2: Coca cultivation in sample

A.3 Different treatment definitions

A.3.1 Log treatment

A.3.2 Synthetic difference in differences



Source: In pink is the treatment and in blue the synthetic control group

Figure A3: Synthetic difference in differences

Table A1: Results with log transformed outcome variable

	(1) Homicide rate	(2) Homicide rate
DiD	0.32**	0.32**
	(0.11)	(0.14)
Control group mean	3.69	3.69
N	715	715
Cluster	Department	Municipality
MSTT	YES	YES

*Notes: Homicide rate per 100 000 inhabitants per year. Municipality-time: municipality-specific time trends. Wild cluster standard errors are in parentheses. Treatment group as the municipalities that belong to a state (department) that borders Venezuela. Sample are areas with coca production. *** p<0.01, ** p<0.05, * p<0.1*

Table A2: Results with inverse hyperbolic sine (IHS) transformed outcome variable

	(1) Homicide rate	(2) Homicide rate
DiD	0.29**	0.29*
	(0.12)	(0.16)
Control group mean	4.34	4.34
N	715	715
Cluster	Department	Municipality
MSTT	YES	YES

*Notes: Homicide rate per 100 000 inhabitants per year. Municipality-time: municipality-specific time trends. Wild cluster standard errors are in parentheses. Treatment group as the municipalities that belong to a state (department) that borders Venezuela. Sample are areas with coca production. *** p<0.01, ** p<0.05, * p<0.1*

A.4 Female homicides

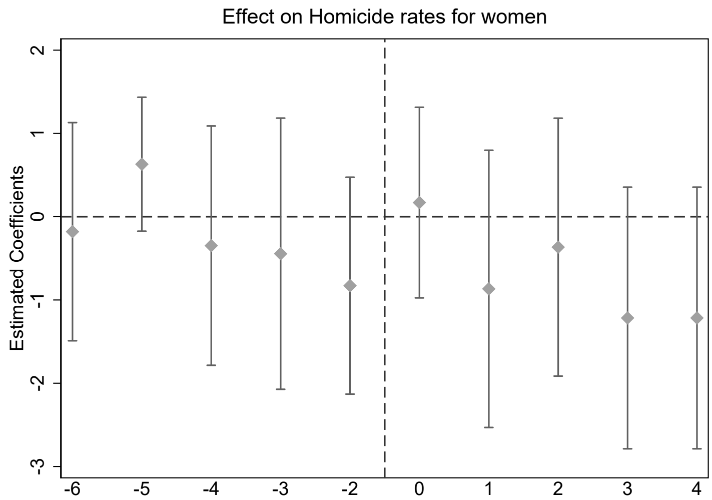


Figure A4: Results: female homicides

As a heterogenous analysis, I also study women, a sub-sample, and analyze the effect of the shock on them. The results are shown in Figure A4, and one can see no statistically significant effects. The effect sizes are also much smaller, 0.32, compared to 31.1 in the main analysis. The results are driven by homicide in men. The average homicide rate for women is 1.05, much smaller than the 24.60 for men in Colombia.

A.5 Geospatial spillover effects

As an extended analysis, I study the geospatial spillover effects of violence by studying the municipalities that border the coca treatment municipalities. First I do a DiD analysis where I include the original treatment sample as well as the border sample, the results as shown in table A3. I find a smaller effect for the main specification and no effects using the other specifications. This is expected as the spillover effects are generally weaker than the main effect.

Then, I study only the bordering municipalities as the treatment in a new DiD as shown in table A4. Here, the results are much smaller, 7.7 compared to 33.1 in the main analysis. They are also no longer statistically significant. However, in the main specification, they remain positive signed effects, which might indicate some small spillover effects.

Table A3: Spillover effects

	(1) Homicide rate	(2) Homicide rate	(3) Homicide rate	(4) Homicide rate
DiD	1.24	1.24	17.2	17.2**
	(14.4)	(7.42)	(11.1)	(7.02)
Control group mean	53.41	53.41	53.41	53.41
N	715	715	715	715
Cluster	Department	Municipality	Department	Municipality
Municipality-Time	NO	NO	YES	YES

*Notes: Municipality-time: municipality-specific time trends. Homicide rate per 100,000 inhabitants per year. Spillover treatment definitions are all the municipalities in states (departments) that border a state that borders Venezuela as well as these municipalities) *** p<0.01, ** p<0.05, * p<0.1*

Table A4: Only spillover effects

	(1) Homicide rate	(2) Homicide rate	(3) Homicide rate	(4) Homicide rate
DiD	-9.56	-9.56	7.69	7.69
	(11.6)	(6.17)	(7.69)	(7.27)
Control group mean	53.41	53.41	53.41	53.41
N	605	605	605	605
Cluster	Department	Municipality	Department	Municipality
Municipality-Time	NO	NO	YES	YES

*Notes: Municipality-time: municipality-specific time trends. Homicide rate per 100 000 inhabitants per year. Spillover treatment definitions are all the municipalities in states (departments) that border a state that borders Venezuela Here, the municipalities in the original treatment definition were excluded from the spillover treatment definition. *** p<0.01, ** p<0.05, * p<0.1*