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, an input factor needed to produce cocaine, and analyze the effect on violence in Colombia in coca-producing areas compared to non-producing areas using a synthetic difference-in-differences strategy. The shock led to an increase in coca leaf cultivation and an increase of 9.72 homicides per 100,000 inhabitants, implying that the supply shock's effect is equivalent to a 21% increase in the homicide rate. The main results are robust to various tests, such as controlling for immigration, distance from the border, and excluding big cities. Hence, when it becomes cheaper to produce cocaine, production areas have more violence. By looking at a purely economic effect on the drug market instead of a drug enforcement effect, I show that there is an effect of price changes on the cocaine market that goes beyond drug enforcement and that even more minor price shocks that do not disrupt the whole system have an impact. 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, synthetic 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 of the supply shock on violence. I perform a synthetic difference-in-differences (SDID) analysis between high-intensity and low-intensity coca cultivation areas. 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 is associated with increased coca leaf production and leads to more violence in coca-producing areas compared to non-producing areas.

The impact of the shock in the treatment group is an increase of 9.72 homicides per 100,000 inhabitants. Even for a violent country like Colombia, the number is relatively high. The average homicide rate in the treatment sample before the shock was 46.98 homicides per 100,000 inhabitants, implying that the supply shock's effect is equivalent to a 21% increase in the homicide rate. I discuss alternative mechanisms, and the violence does not seem to be driven by armed groups attacking each other, suggesting that the opportunity cost effect is driving the results. Furthermore, I find the results robust to various tests, such as controlling for immigration, distance from the border, and excluding big cities.

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 more minor shocks have an effect. Another contribution to the literature is to study a 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 not a free and perfect market with 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	24.60	31.30	0.00	471.07	12320.00
Hectars of coca cultivation between 2012 and 2015	233.21	1470.08	0.00	37600.24	12320.00
Female homicides per 100,000	1.06	5.45	0.00	141.00	12320.00
Shortest time to border (min)	694.95	625.72	0.00	9999.00	12243.00

Notes: Homicide data from 2010 to 2020. Homicides were adjusted for the yearly population by gender. Hectares of coca cultivation in the years before the shock. Shortest time to Venezuelan border in minutes. All data at the municipality level. Overseas municipalities 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

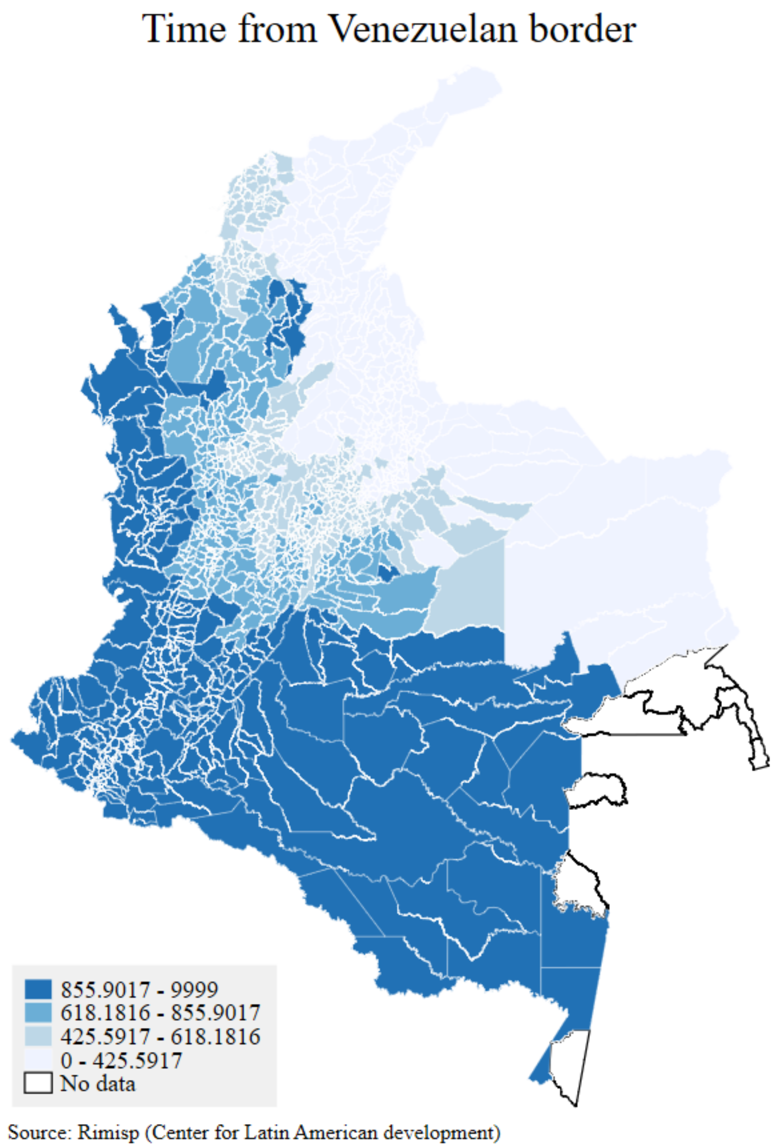


Figure 2: Time distances (min) to the border of Venezuela

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 on violence in a country like Colombia due to the high number of instability factors (war, peace processes, economic instability, and income inequality). Many factors can affect violence, and drugs do not cause all violence. Therefore, I use a synthetic difference-in-differences (SDID) design to exploit the geographic variation in coca cultivation intensity. The method is developed by Arkhangelsky et al. (2021) and builds on difference-in-differences (DID) and synthetic control group (SD).

The synthetic difference-in-differences (SDID) can be expressed as:

$$(1) \quad \left(\hat{\tau}^{\text{SDID}}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - D_{it}\tau\right)^2 \hat{\omega}_i^{\text{sdid}} \, \hat{\lambda}_t^{\text{sdid}} \right\}$$

Where the parameter τ identifies the average treatment effect on the treated, which is the 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 groups without the price shock. The outcome variable Y_{it} is the homicide rate. μ is the intercept. α_i and β_t represent the municipality and year-fixed effects. D_{it} is the binary treatment variable. It equals 1 if a municipality has coca cultivation, and it equals 0 otherwise. The standard errors are calculated by using the bootstrap algorithm with 400 repetitions recommended by the authors for large panels (Arkhangelsky et al., 2021). The synthetic difference-in-differences (SDID) (1) differs from a classic difference-in-differences (DID) (2) by including both time or unit weights:

$$(2) \quad \left(\hat{\tau}^{DID}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\alpha,\beta,\mu,\tau}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - D_{it}\tau\right)^2 \right\}$$

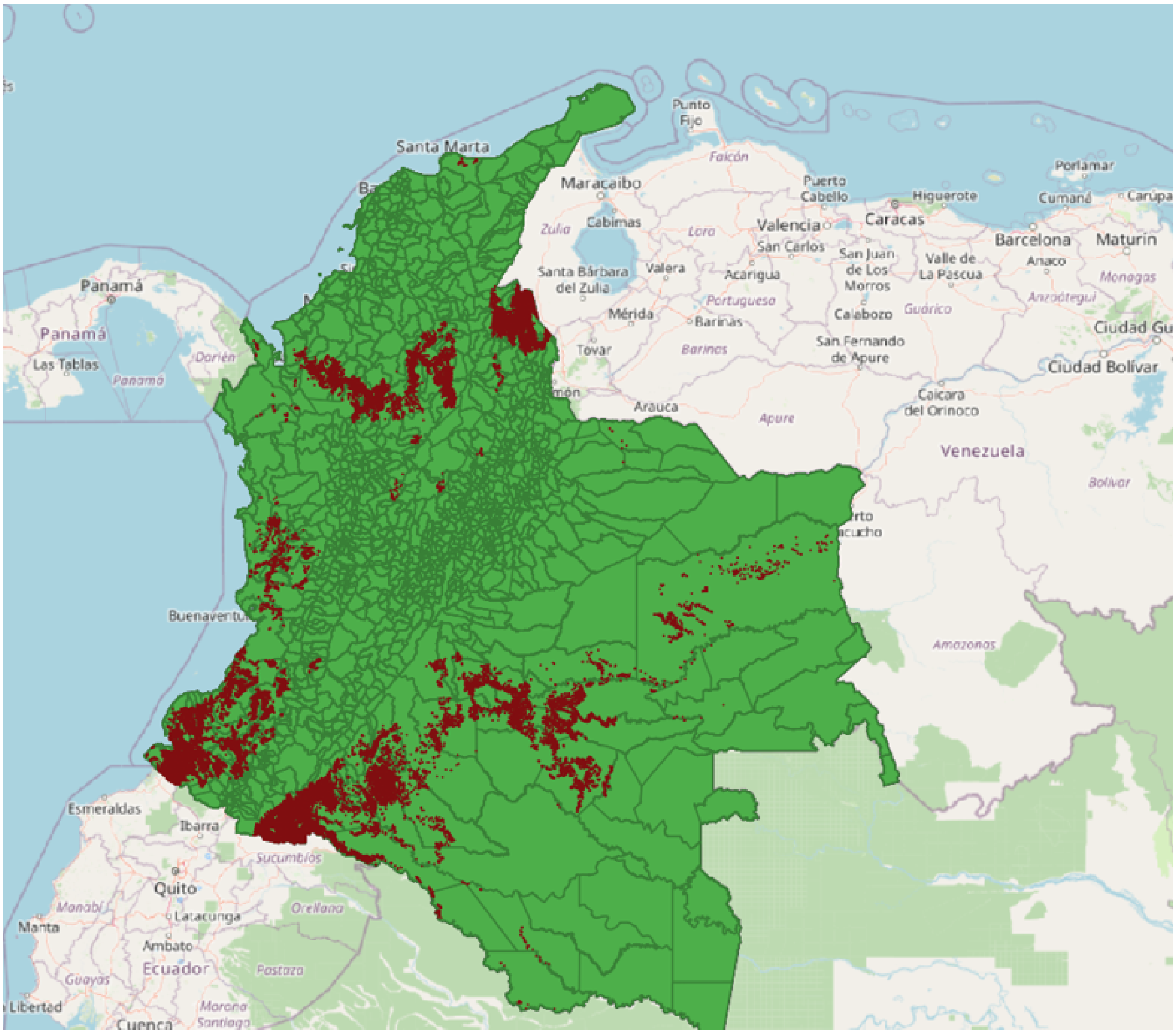
It reweights and matches pre-exposure trends to weaken the reliance on parallel trend-type assumptions. The use of weights in the SDID estimator effectively makes the two-way fixed effect regression "local" in that it puts more weight on units that, on average, are similar in terms of their past to the treated units, and it emphasizes periods that are on average similar to the treated periods.

The SDID (1) varies from the synthetic control group (SD) (3) by including time weights, which can both remove bias and improve precision by eliminating the role of time periods that are very different from the posttreatment periods. This makes the model more flexible and strengthens its robustness properties:

$$(3) \; \left(\hat{\tau}^{SC}, \hat{\mu}, \hat{\beta}\right) = \underset{\mu,\beta,\tau}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \beta_t - D_{it}\tau\right)^2 \hat{\omega}_i^{sc} \right\}.$$

Another reason for using a synthetic difference-in-differences (SDID) and not a difference-in-differences (DID) design is to account for the lack of parallel pre-trends in the difference-in-differences as one can see in figure A2.

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).



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

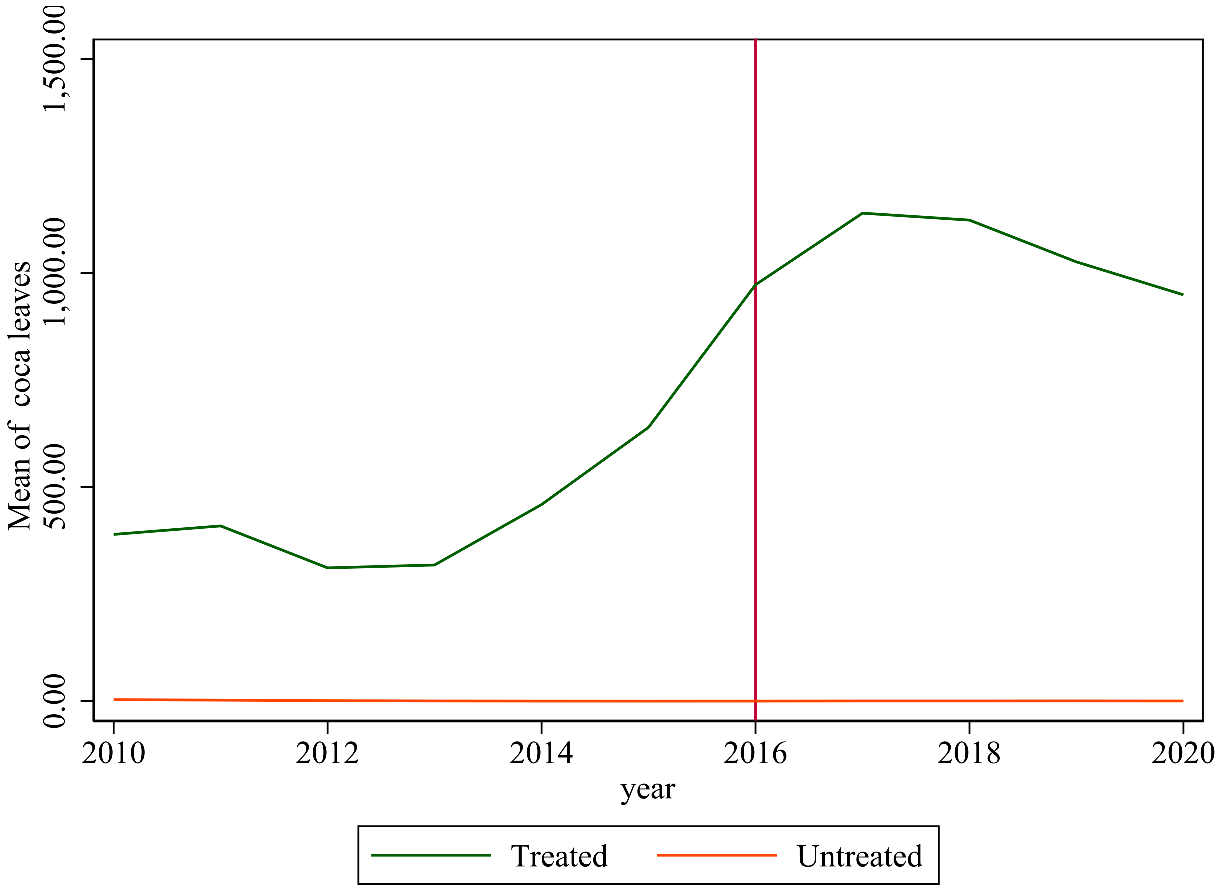
The concentration of cultivation is shown on the map 3. The map displays the coca cultivation where one can easily see a high concentration of coca crop cultivation in some areas. The high concentration of coca in a few areas makes the scenario suitable for a difference-in-differences analysis, where one compares the changes in violence in the "treated" areas with a high concentration of coca cultivation with the areas with low (or no) cultivation of coca. The areas with a high concentration of coca cultivation will be the treatment group that will be affected by the price shock, while the areas with low coca cultivation will be the control group. I create a dichotomous treatment variable where I define the treatment status based on coca cultivation status in the years before the shock in 2016. Map A3 shows which municipalities are in treatment and control groups (before SDID weighting). I define the treatment group as the municipalities that had registered coca cultivation all 4 years before the shock. More specifically, all municipalities that had more than 10 hectares of coca leafs per year in 2012, 2013, 2014, and 2015. This definition implies a treatment group of 150 municipalities, while the control group comprises 970 municipalities. After the main analysis, I will conduct a series of robustness checks with alternative definitions of the treatment variable.

As an alternative method for testing the robustness of the analysis, I run the SDID analysis for each municipality separately, and then I interact it with the distance to the border variable, to test whether municipalities closer to the Venezuelan border are more affected by the shock. The further the gasoline has to be smuggled into Colombia, the more expensive and closer to official gasoline prices in Colombia it becomes (ElPaisCali, 2017). Therefore, the assumption is that municipalities close to the Venezuelan border should be more affected by the positive shock from Venezuela due to transportation costs (it takes time, money, and risk to transport illegal gasoline). 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 travel time distances between the different municipalities as the intensity of smuggling of gasoline variable.

Figure 4: Road network by the Colombian Ministry of Transportation

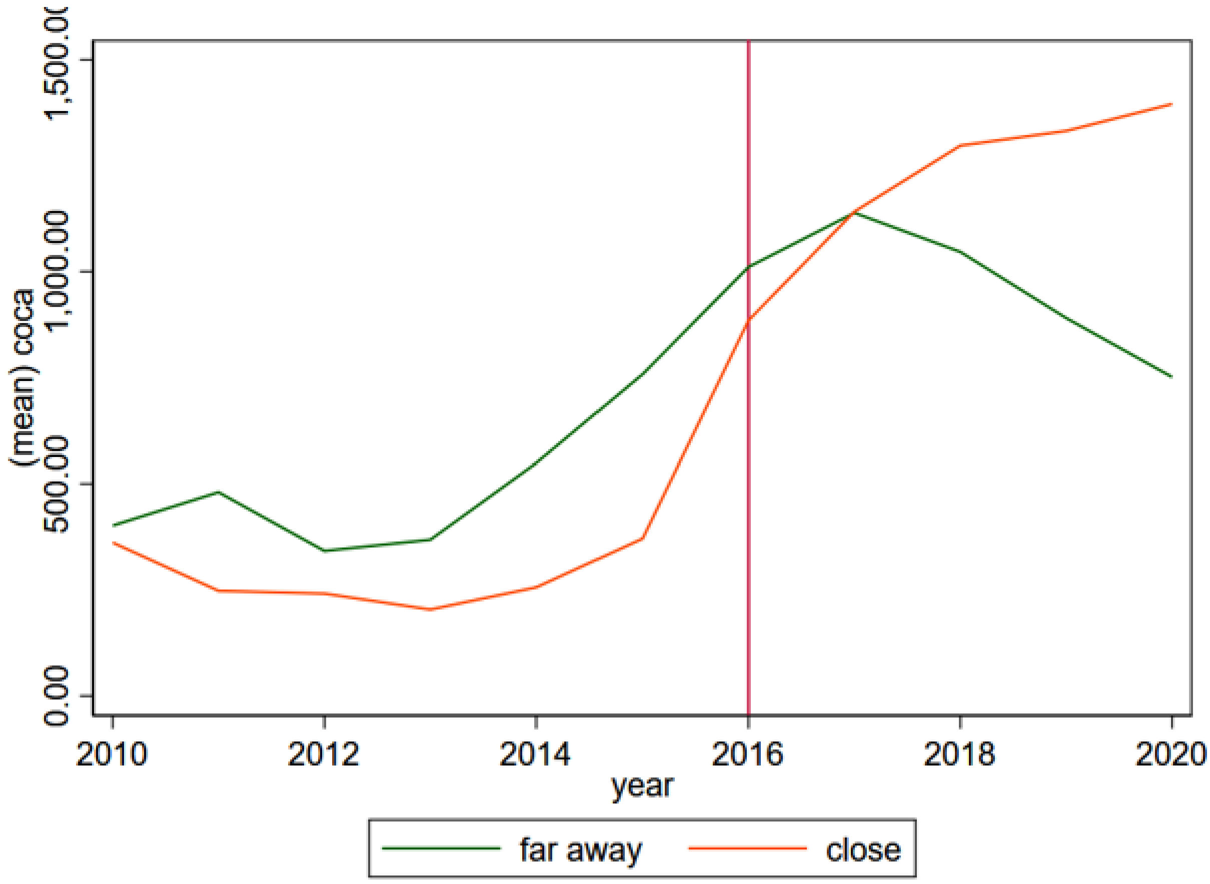
6 First stage

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 that there is a large and increasing cultivation of coca in the treatment group, and there is little coca cultivation in the control group (the control group is defined as the area with coca leaves cultivation in the years before the shock). 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). The same result is shown in table 2 using a DiD analysis where one sees a large positive statistically significant effect of 220 to 596 hectares of coca leaves. In Figure 6, we see only the treatment sample (only the areas with coca cultivation) divided into close and far away from the border. We see that the area far away from the border with Venezuela (in green) and the area close to the border with Venezuela (in orange) has a somewhat similar trend prior to the shock. The areas far away had higher production of coca until 2017 when the areas close to the border with Venezuela overtook in terms of production.



Note: The treatment status is based on coca cultivation status in the years before the shock in 2016. I define the treatment group as the municipalities that had registered coca cultivation all 4 years before the shock.

Figure 5: Results: graphical representation of coca leaves



Note: The sample is a sub-sample where each observation has treatment status, which is based on coca cultivation status in the years before the shock in 2016. I define the treatment group as the municipalities that had registered coca cultivation all 4 years before the shock.

Figure 6: Results: graphical representation of coca leaves by distance to border with Venezuela

Table 2: First stage

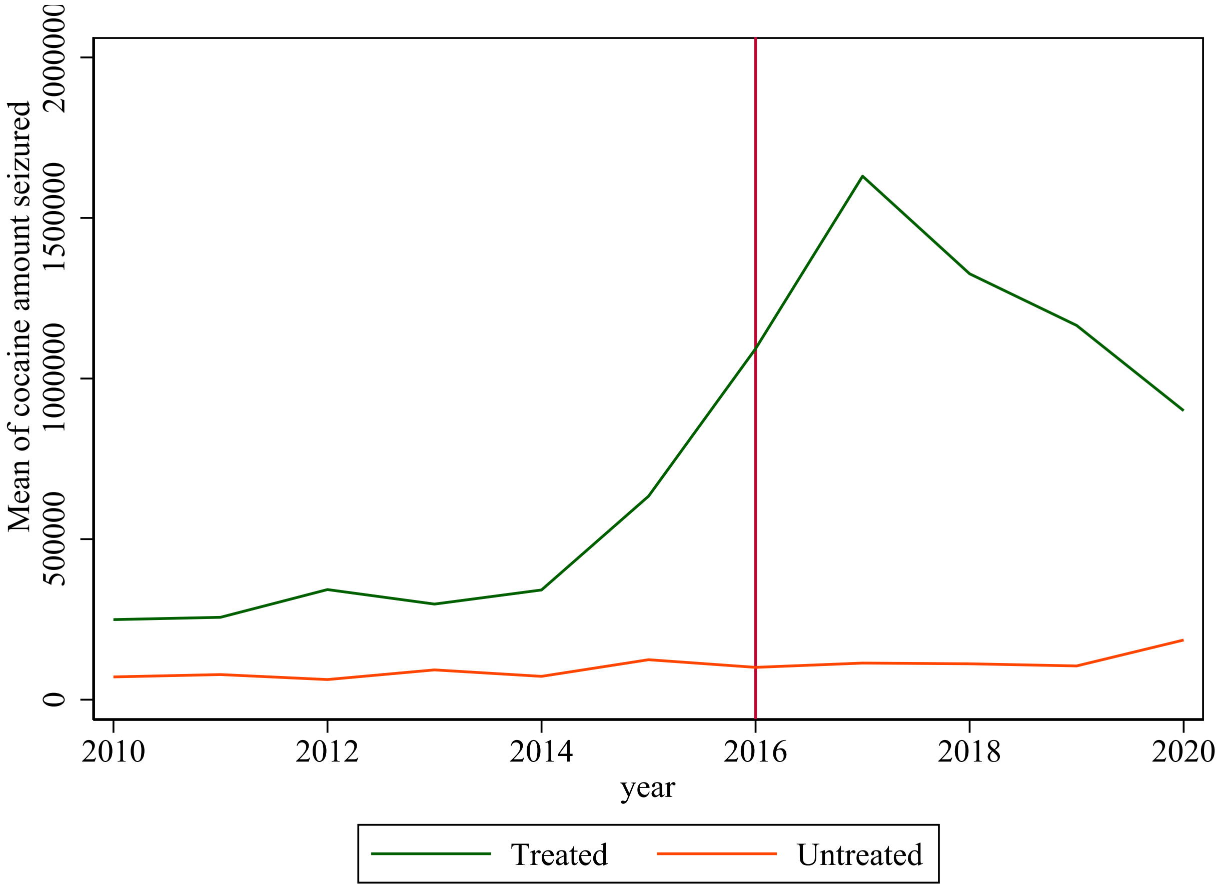
	(1)	(2)
	Coca	Coca
DiD	596.6***	220.7***
	(180.2)	(76.3)
Own group mean	0.96	0.96
N	12320	12320
Cluster	Department	Municipality
Municipality FE	NO	YES
Year FE	NO	YES
Municipality-Time	NO	YES

*Notes: Municipality-time: municipality-specific time trends. Homicide rate per 100 000 inhabitants per year. Overseas municipalities excluded. Treatment definition based on coca cultivation before the shock: All municipalities that had more than 10 hectares of coca leaves per year in 2012, 2013, 2014, and 2015. *** p<0.01, ** p<0.05, * p<0.1*

The second method is to study the seizure data of cocaine. There are issues with using seizure data mentioned more in detail in section 4.1. One particular issue might be that the area of the seizure might not be the area of production. Though there is some evidence at an international scale that the increase in production is captured in a scalable increase in seizure, there are large variations in these estimates, and they might be imprecise for picking up changes over a shorter time at a local level(UNODC, 2022). In figure 7, one can see the variation in the seizure of coca base over time, and in 8, one can see the variation in the seizure of cocaine over time. There are large variations in the coca base seizure over time, though it increased from 2016 to 2017 and again in 2019 and 2020. The cocaine data shows an increase up to 2017 and then a decrease. These graphs are to be taken cautiously; it is not because there is a decrease in cocaine seizures that there is necessarily a decrease in cocaine produced.

Note: The treatment status is based on coca cultivation status in the years before the shock in 2016. I define the treatment group as the municipalities that had registered coca cultivation all 4 years before the shock.

Figure 7: Results: graphical representation of coca base seizure



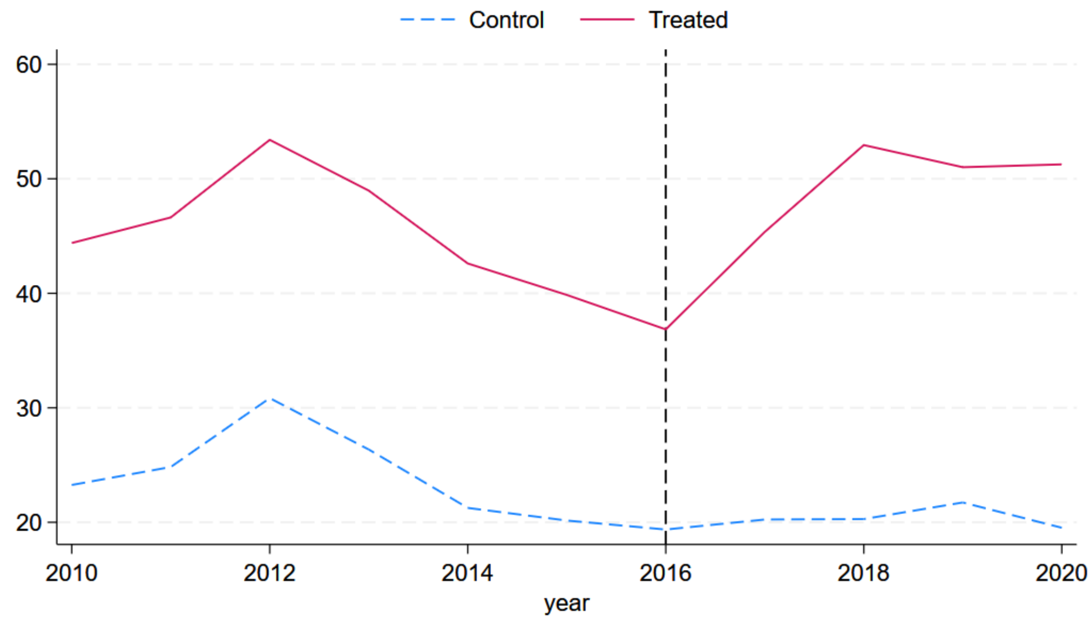
Note: The treatment status is based on coca cultivation status in the years before the shock in 2016. I define the treatment group as the municipalities that had registered coca cultivation all 4 years before the shock.

Figure 8: Results: graphical representation of cocaine seizure

7 Results

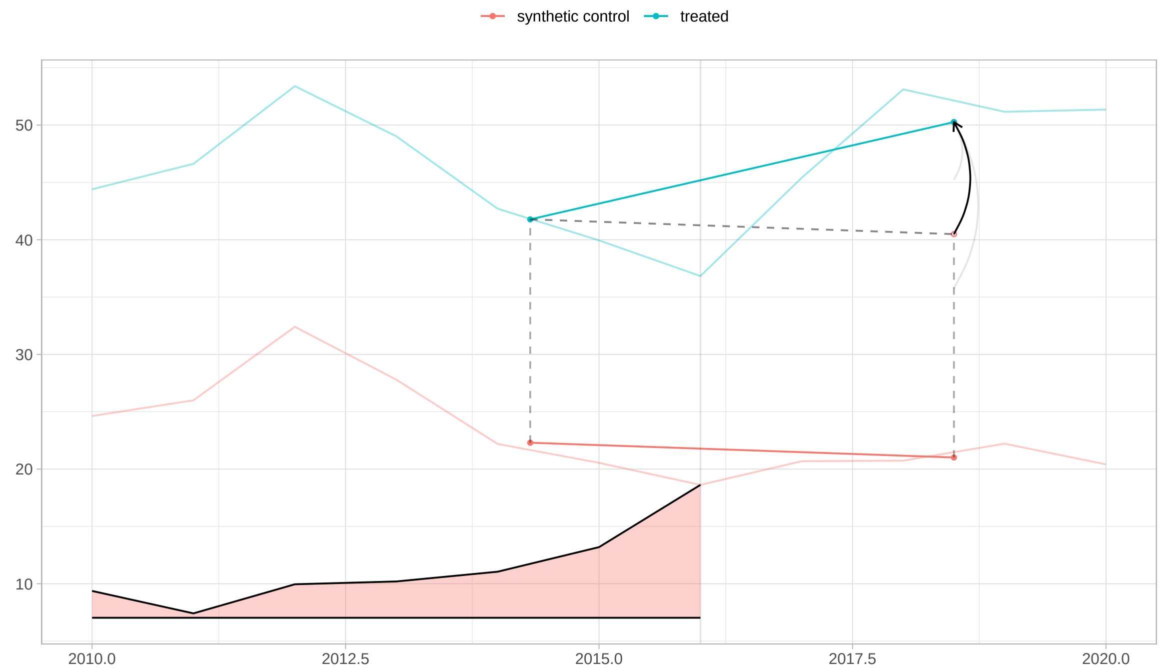
7.1 Graphical representations

In figure 9, an event plot is shown for the homicide rate, where the difference between control and treatment is plotted by year. The pink color indicates the treatment average, whereas the dotted blue line indicates the control average. Using SDID, the units in the control group are reweighted to get a parallel pre-trend. The figure shows an increase in the homicide rate in the treatment group compared to the control group after the shock in 2016. In figure 10 one can see more detailed the mechanisms behind calculating the SDID. In blue is the the treatment group trend and in red in synthetic control trend. In the shaded pink area on can see the time weighting in the pre-periods for the synthetic control groups: there is more weighting on the last periods before the shock. The lines on to of the trends and the arrow show how the SDID is calculated.



Note: The treatment status is based on coca cultivation status in the years before the shock in 2016. I define the treatment group as the municipalities that had registered coca cultivation all 4 y ears before the shock.

Figure 9: Results: synthetic difference-in-differences



Note: In blue the treatment group and in red in synthetic control. In the shaded pink area on can see the time weighting in the pre-periods for the synthetic control groups. The lines on to of the trends and the arrow show how the SDID is calculated.

Figure 10: Synthetic difference-in-differences explained

7.2 Main findings

In table 3, are the result from the main analysis. It shows the standard SDID, an average treatment effect on the treated (ATT), where the homicide rate in the control units is reweighted in pre-treatment periods to obtain pre-trends that are parallel. The main result shows a positive statistically significant effect of 9.72, which is robust across all specifications. The result indicates that, on average, the impact of the shock in the treatment group (the areas with high cultivation) is an increase of 9.72 homicides per 100,000 inhabitants. Even for a violent country like Colombia, the number is quite high. The average homicide rate in the treatment sample before the shock was 45.97 homicides per 100,000 inhabitants, implying that the supply shock's effect is equivalent to a 21 % increase in the homicide rate. Estimations from the UNODC find that cocaine production in Colombia increased by 54% between 2015 and 2016.[8] Since the treatment areas are the ones where the cocaine production are done, a very simplified calculation would imply that 1 % increase in cocaine production leads to 0.18 more homicides per 100, 000 per year or an average of 9 homicides per year in the areas where they are producing cocaine.[9] The parameter has a positive sign, suggesting that the positive supply shock to cocaine production (the drop in the price of imported gasoline) leads to more killings, as hypothesized.

As a robustness test, I also log transform the main dependent variable, as shown in table A2 in the appendix. The results do not change much, with estimates of between 21 % and 23 % increase in homicide.

[8] According to UNODC and of Colombia (2017), there was 1 007 ton potential cocaine production in 2016 in Colombia compared to 653 ton potential cocaine production in 2015. This is in percentage ((1007-653)/ 653) *100 = 54% increase in production.

[9] The effect size divided by the change in cocaine production between 2015 and 2016 : $9.72/54 = 0.18$ and the effect size multiplied by the population in the treatment area divided by the change in cocaine production between 2015 and 2016 $494/54 = 9.14$.

Table 3: Main results

	(1) Homicide rate
SDID	9.716***
	(7.55)
N	12320

*Notes: Homicide rate per 100 000 inhabitants per year. Overseas municipalities excluded. Treatment definition based on coca cultivation before the shock: All municipalities that had more than 10 hectares of coca leaves per year in 2012, 2013, 2014, and 2015. Column 1 shows the standard SDID where the homicide rate in the control units is reweighted in pre-treatment periods to obtain pre-trends that are parallel. *** p<0.01, ** p<0.05, * p<0.1*

8 Potential threats to the difference-in-differences design

8.1 Distance to border

To test whether municipalities closer to the Venezuelan border are more affected by the shock, I run the SDID analysis for each municipality separately, and then I interact it with the distance to the border variable. I exclude the department bordering Ecuador as they smuggle gasoline in from Ecuador and, therefore, have different patterns (the main analysis does not change when excluding these departments).

There is one major weakness with this testing, and it is that it is not known where the gasoline is smuggled across the border, and the border between Venezuela and Colombia is very long, 2,200 kilometers, which can lead to imprecision.

As one can see in Table 4, there is a negative sign of the estimate, so the further away from the border, the smaller the effect. However, this interaction has no statistically significant effect. One possible explanation is that the effects of distance are quite heterogeneous, where the municipalities close to the border will have effects, and the other municipalities further away, regardless of it being 5 hours or 24 hours, will have no effect. Therefore, I redo the analysis where I divide the sample according to the distance to the border, which is more or less than one standard deviation away from the border in time (1000 minutes or about 16 hours). The results are shown in Table 5 where column 1 is the sub-sample further away from the border, and column 2 is closer to the border. The results in the first columns are smaller than the last columns, 9.13 compared to 11.09; the municipalities close to the border have a larger effect. These results strengthen the hypothesis that the shock from gasoline in Venezuela caused the changes in homicide.

Test	Estimate	p_value
Interaction coefficient	-0.07	0.55

Table 4: Results with distance to border interaction

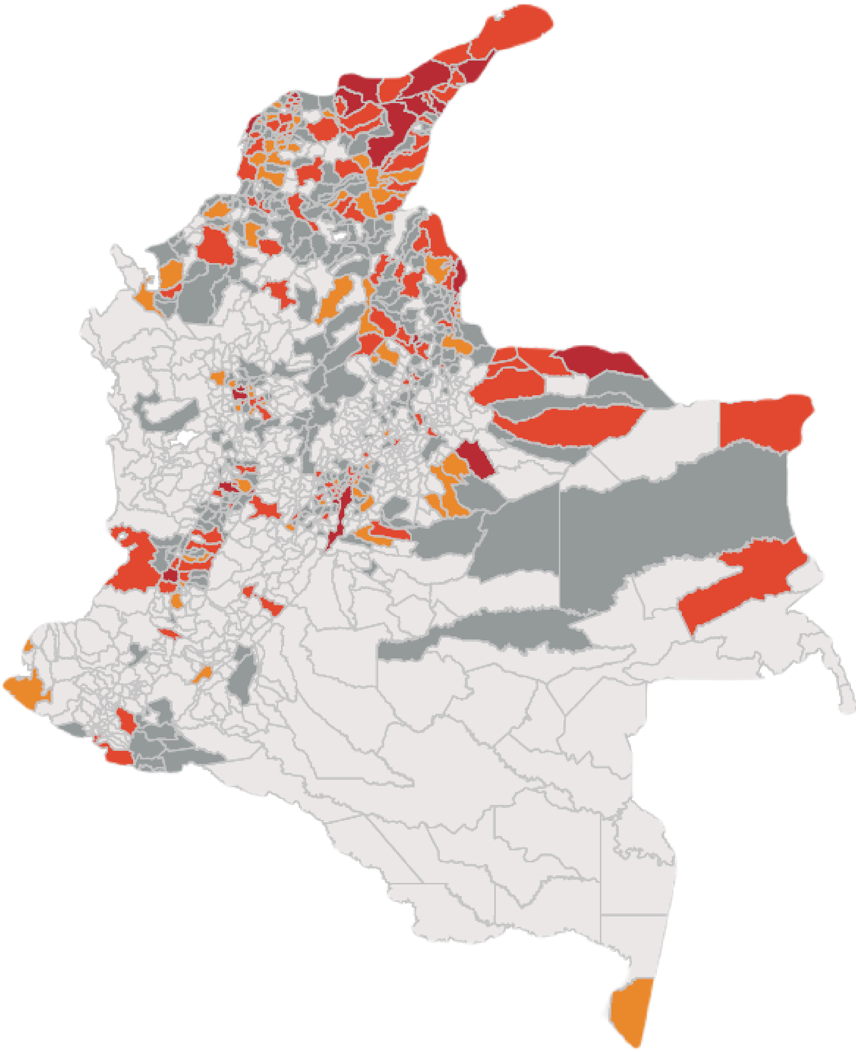
*Notes: SDID analysis for each municipality separately, and interacted with the time travel distance to the border variable. Overseas municipalities and department boarding Ecuador excluded. Treatment definition based on coca cultivation before the shock: All municipalities that had more than 10 hectares of coca leaves per year in 2012, 2013, 2014, and 2015. *** p<0.01, ** p<0.05, * p<0.1*

Table 5: Results with short/long distance to border

	(1) Far away from border	(2) Close to border
SDID	9.130**	11.087**
	(4.090)	(5.267)
N	1914	9449

*Notes: Column 1 is the sub-sample further away from the border, and column 2 is closer to the border. Distance to the border is defined as more or less than one standard deviation away from the border in time (1000 minutes or about 16 hours). Overseas municipalities and department boarding Ecuador excluded. Treatment definition based on coca cultivation before the shock: All municipalities with more than 10 hectares of coca leaves per year in 2012, 2013, 2014, and 2015. *** p<0.01, ** p<0.05, * p<0.1*

8.2 Immigration from Venezuela



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 11: Intensity of Venezuelan immigrants by municipality.

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,

Table 6: Result excluding the municipalities with large portion of Immigrants

	(1)
	Homicide rate
SDID	9.044***
	(2.247)
N	11605

*Notes: The top 65 municipalities in Colombia with Venezuelan immigration are excluded. Homicide rate per 100 000 inhabitants per year. Overseas municipalities excluded. Treatment definition based on coca cultivation before the shock: All municipalities that had more than 10 hectares of coca leaves per year in 2012, 2013, 2014, and 2015. *** p<0.01, ** p<0.05, * p<0.1*

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 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 11 shows the estimations of the concentration 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 SDID 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 6 and shows a statistically significant effect of 9.04, which is quite close to the results in the main analysis 3 of 9.72. Therefore immigrants does 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 7, one can see that the effects of the SDID estimates are weaker in areas previously attacked by FARC (column 1) compared to areas without FARC (in column 2), where the effect is nearly three times as big. When a FARC exposure is interacted with the SDID estimates in Table 8, there is a statistically significant effect between the FARC areas compared to the no FARC areas.

Table 7: Results: presence/no presence of FARC

	(1) Homicide rate (FARC area)	(2) Homicide rate (No FARC area)
SDID	5.916**	15.825***
	(2.666)	(5.110)
N	11011	1309

Notes: In column 1 an analysis with only municipalities that were exposed to FARC, and in column 2 an analysis without 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. Overseas municipalities excluded. Treatment definition based on the total coca cultivation before the shock: The standardization of the sum of all coca leaves per year in 2012, 2013, 2014, and 2015.

Table 8: SDID interacted with FARC presence

Coefficient	Estimate	Std.Error	t-value	p-value
Homiciderate	12.11	4.93	2.46	0.02

Notes: Each municipality regressed separately using SDID and then interacted with exposure 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. Overseas municipalities excluded. Treatment definition based on the total coca cultivation before the shock: The standardization of the sum of all coca leaves per year in 2012, 2013, 2014, and 2015.

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 12, 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. This one can be further seen in table 9 where one can see the results of SDID estimates studying the number of attacks by 10. 000 inhabitants per year by criminal organizations, government, and insurgents, respectively. They show no statistically significant results.

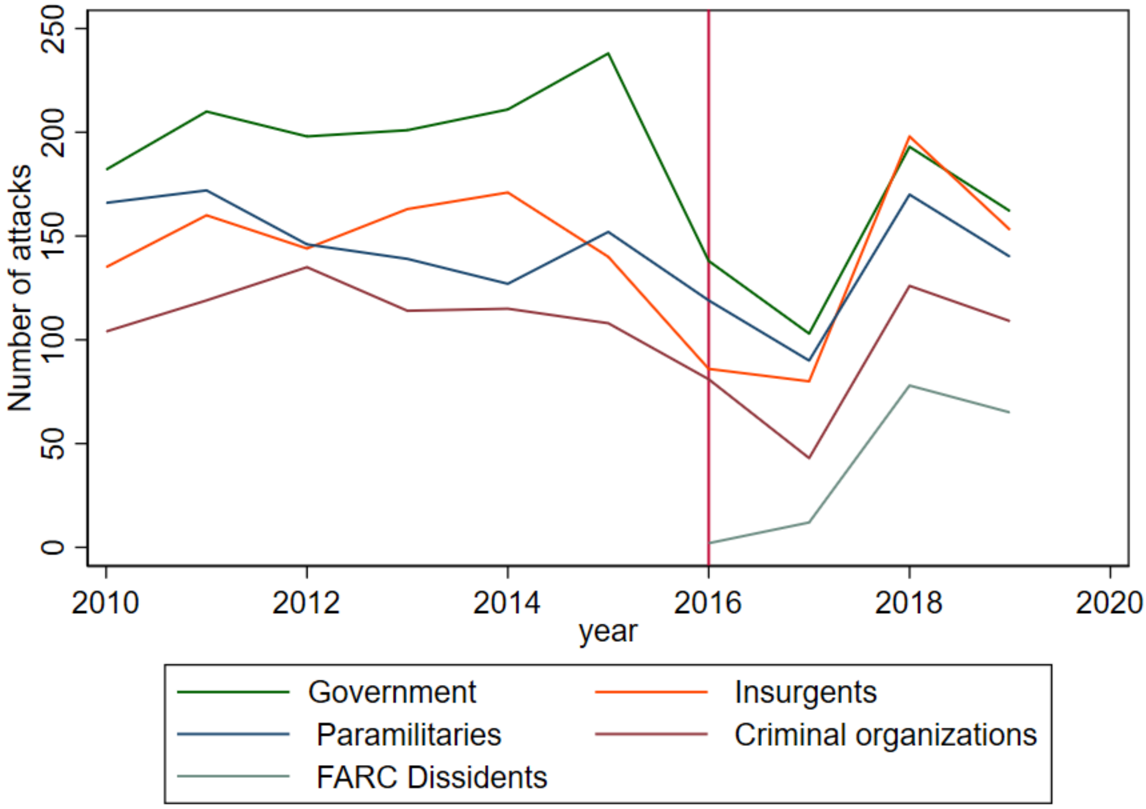


Figure 12: Results: graphical representation over the number of armed group attacks by group over time

Table 9: Number of attacks by different actors

	(1) Number of attacks	(2) Number of attacks	(3) Number of attacks
SDID	1.635	1.585	1.583
	(1.169)	(1.145)	(1.122)
N	11070	11070	11070

Notes: In column 1, number of attacks by criminal organizations. Column 2 shows the number of attacks by government organizations. Column 3 shows the number of attacks by FARC dissidents. The number of attacks is normalized as attacks per 10 000 inhabitants. Overseas municipalities and biggest cities excluded. Treatment definition based on the total coca cultivation before the shock: The standardization of the sum of all coca leaves per year in 2012, 2013, 2014, and 2015.

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 synthetic difference-in-differences (SDID) analysis, comparing high-intensity coca cultivation areas with low-intensity and non growing area. 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 9.72 homicides per 100,000 inhabitants. To put this into context, the average homicide rate in the treatment sample before the shock was 45.97 homicides per 100,000 inhabitants, implying that the supply shock's impact equates to a substantial 21% escalation 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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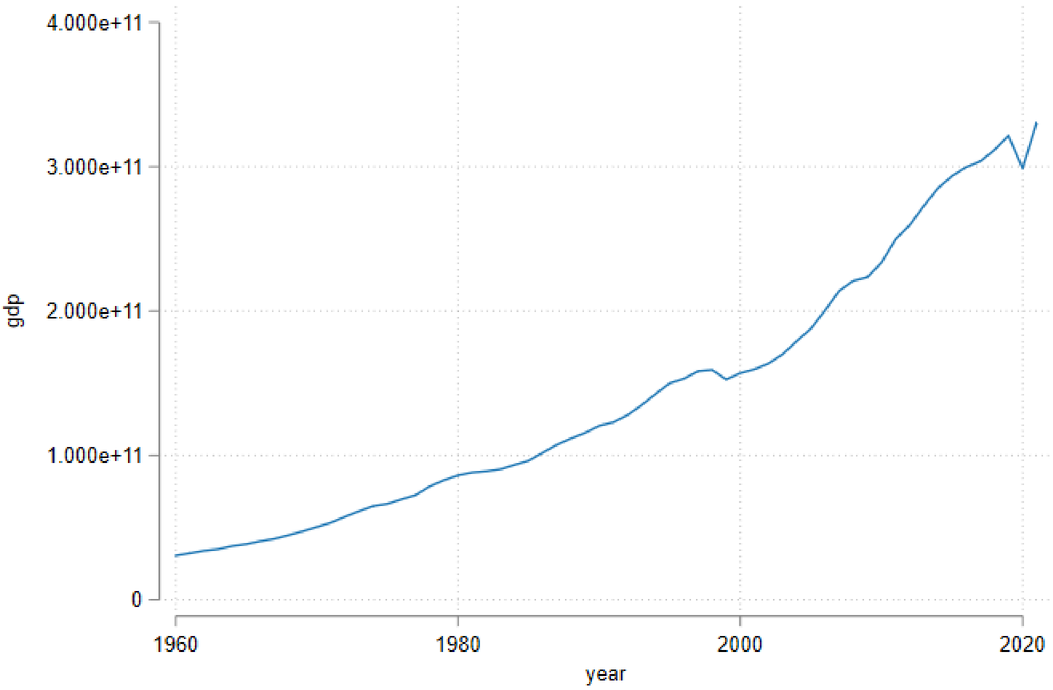
Appendix

A.1 Economic conditions in Colombia

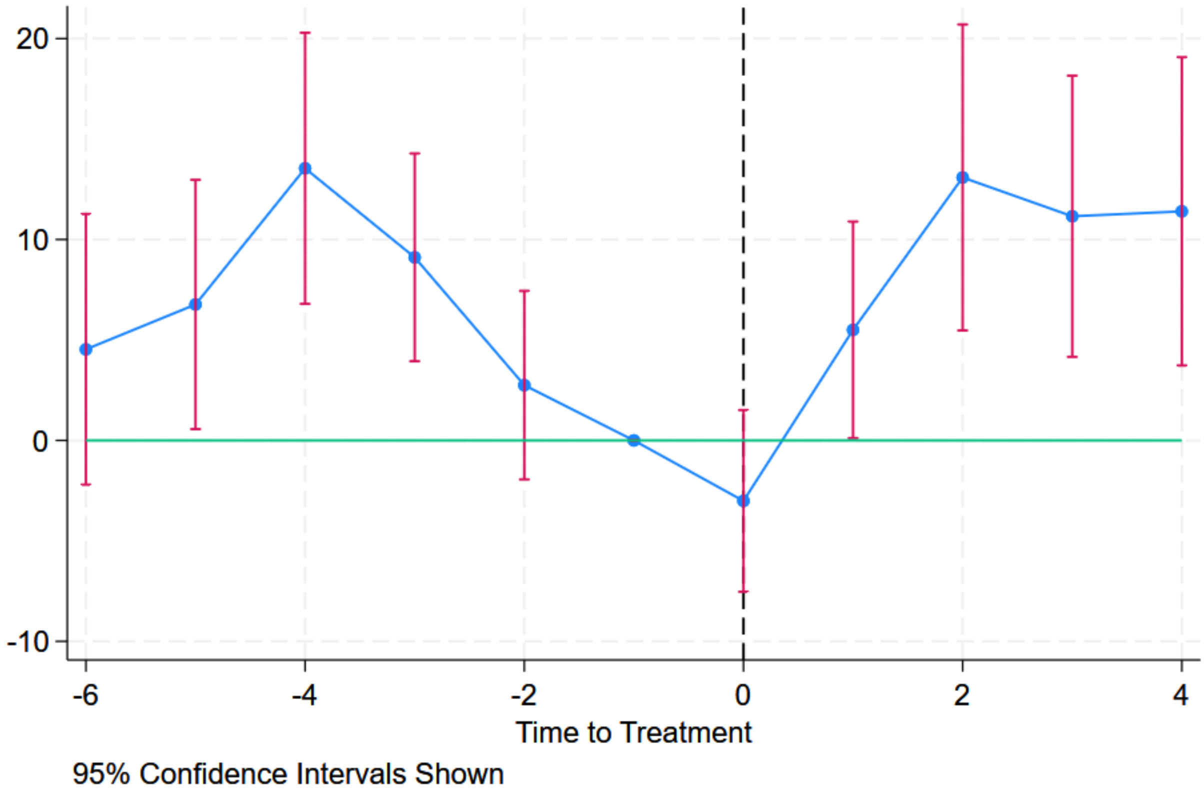


Source: Figure produced with data from the World Bank

Figure A1: GDP in constant 2015 $ in Colombia

A.2 Difference-in-Differences

A.2.1 Eventplot



Note: The treatment status is based on coca cultivation status in the years before the shock in 2016. I define the treatment group as the municipalities that had registered coca cultivation all 4 years before the shock.

Figure A2: Results: Event study

A.3 Different treatment definitions

A.3.1 Main treatment definition

I define the treatment status based on coca cultivation status in the years before the shock in 2016. I define the treatment group as the municipalities that had registered coca cultivation all 4 years before the shock. More specifically, all municipalities that had more than 10 hectares of coca leaves per year in 2012, 2013, 2014, and 2015.

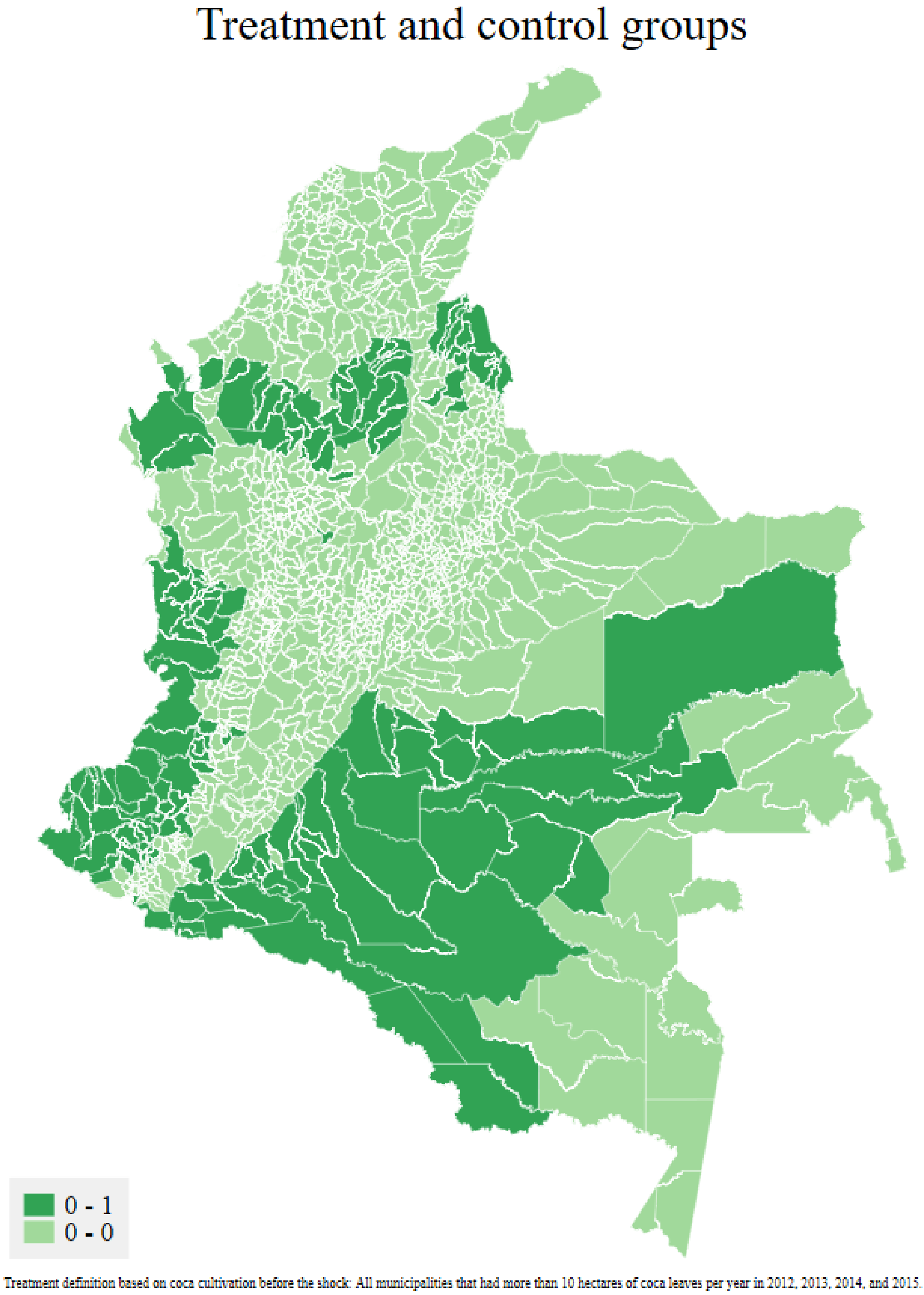


Figure A3: Main treatment definition

A.3.2 Definition of treatment

To test that the treatment status is not too sensitive to the cutoff of the treatment definition. I redo the analysis with slightly different definitions of treatment. First, I increase the treatment definition such that treatment is more than 50 hectares per year per municipality in 2012, 2013, 2014, and 2015. This implies 104 municipalities are treated, and 1016 are control. Then I decrease the treatment definition such that treatment is more than one hectare per year per municipality in 2012, 2013, 2014, and 2015. This implies that 192 municipalities are treated, and 928 are control. The visual results one can see in Figure A4 and A5. The results do not change much. Looking at the results in Table A1 are quite similar.

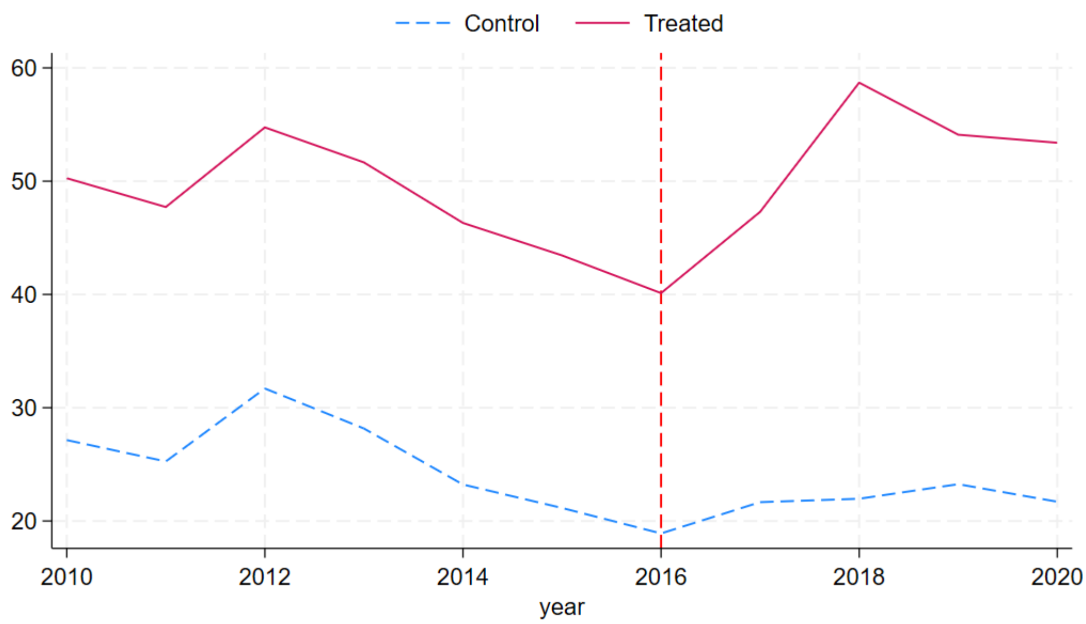


Figure A4: Results: graphical representation alternative treatment definition 1

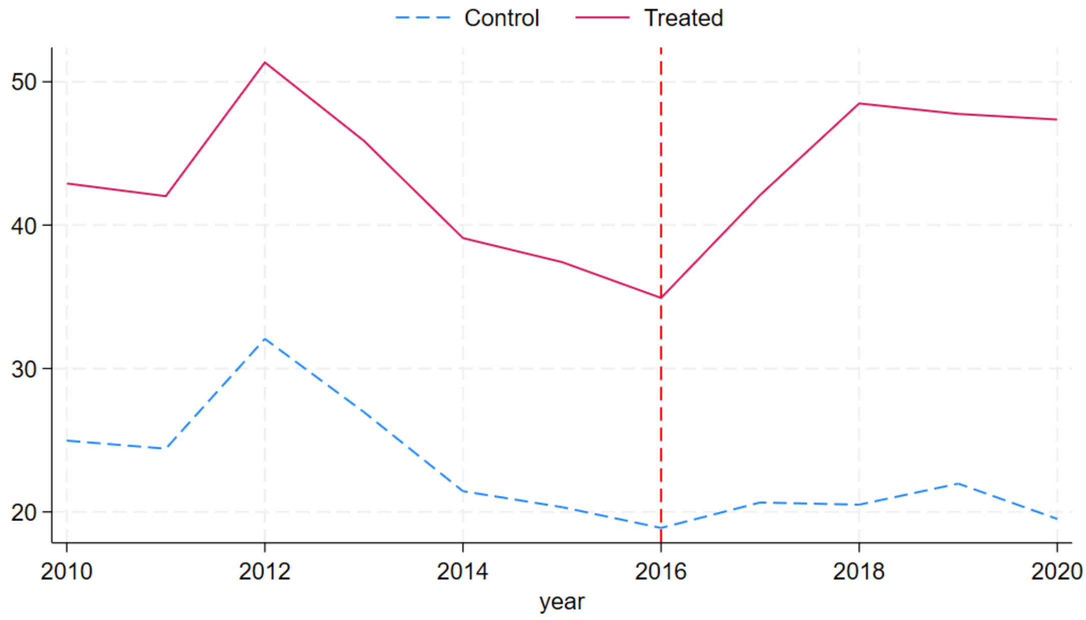


Figure A5: Results: graphical representation alternative treatment definition 2

Table A1: Alternative treatment definitions

	(1) Homicide rate	(2) Homicide rate	(3) Homicide rate
SDID	9.716***		
	(2.324)		
SDID2		8.893***	
		(2.776)	
SDID3			8.515***
			(1.972)
N	12320	12320	12320

*Notes: SDID analysis with alternative treatment definitions. Column 1 main definition: treatment is defined on coca cultivation before the shock: more than 10 hectares of coca per municipality per year in 2012, 2013, 2014, and 2015. Column 2: 50 hectares per municipality per year in 2012, 2013, 2014, and 2015. Column 3: more than one hectare per municipality per year in 2012, 2013, 2014, and 2015. Homicide rate per 100 000 inhabitants per year. Overseas municipalities excluded. *** p<0.01, ** p<0.05, * p<0.1*

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

	(1) Log homicide rate	(2) IHS homicide rate
SDID	0.207***	0.228***
	(0.054)	(0.061)
N	12320	12320

*Notes: Homicide rate per 100 000 inhabitants per year. Overseas municipalities excluded. Treatment definition based on coca cultivation before the shock: All municipalities that had more than 10 hectares of coca leaves per year in 2012, 2013, 2014, and 2015. *** p<0.01, ** p<0.05, * p<0.1*

A.4 Continuous treatment

An alternative specification to different treatment definitions is to use a continuous measurement of coca. As this is not possible with SDID design, I use the DID with continuous treatment. I try to implement this strategy by using the sum of the coca cultivation per municipality in the years before the chock (2015, 2014, 2013, and 2012) and then I standardize this measure as it is very heterogeneous as one can see in Figure A6. The result is shown in Table A3 and the effect of the standard deviation increase in coca cultivation is 3.850 homicides per 100, 000 inhabitants. However, there might be some bias with using two-way fixed effects estimation with continuous measurement as Callaway et al. (2021) points out.

Table A3: Results: continuous variable of coca

VARIABLES	(1) Homicide rate	(2) Homicide rate	(3) Homicide rate	(4) Homicide rate	(5) Homicide rate	(6) Homicide rate
did	0.718**	0.718	0.718**	0.718	3.298***	3.298***
	(0.308)	(0.597)	(0.308)	(0.597)	(0.514)	(0.899)
post*distance	3.683	3.683**	3.683	3.683**	4.471*	4.471
	(2.371)	(1.774)	(2.371)	(1.774)	(2.676)	(2.969)
distance*c.coca	8.363***	8.363***				
	(1.198)	(3.246)				
trippeldiff	12.77***	12.77***	12.77***	12.77***	7.311***	7.311**
	(1.486)	(3.305)	(1.487)	(3.306)	(0.890)	(3.571)
Observations	11,011	11,011	11,011	11,011	11,011	11,011
Number of muni	1,001	1,001	1,001	1,001	1,001	1,001
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: MSTT: municipality-specific time trends. Homicide rate per 100 000 inhabitants per year. Overseas municipalities excluded. Treatment definition based on the total coca cultivation before the shock: The standardization of the sum of all coca leaves per year in 2012, 2013, 2014, and 2015.

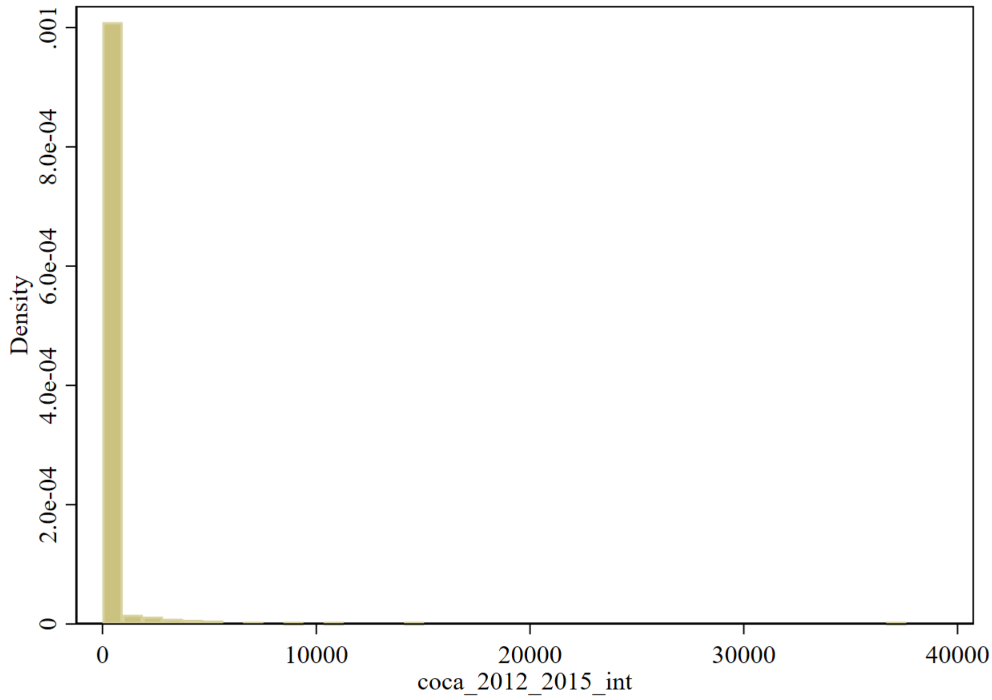


Figure A6: Density of coca

A.5 Excluding large cities with largest populations

The largest city in Colombia might have its unique patterns of violence. However, as seen in table A4 the results do not change when excluding the most populous municipalities.

Table A4: Result excluding the biggest cities

	(1) Homicide rate	(2) Homicide rate	(3) Homicide rate	(4) Homicide rate	(5) Homicide rate	(6) Homicide rate
DiD	10.7***	10.7***	7.78**	7.78***	11.8***	11.8***
	(3.48)	(2.44)	(3.39)	(2.42)	(2.80)	(3.14)
Post	-2.61*	-2.61***	-1.15	-3.19***	0.27	0.27
	(1.34)	(0.48)	(3.05)	(1.02)	(0.93)	(0.75)
Own group mean	21.08	21.08	21.08	21.08	21.08	21.08
N	12177	12177	12177	12177	12177	12177
Cluster	Department	Municipality	Department	Municipality	Department	Municipality
Municipality FE	NO	NO	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES	YES
Municipality-Time	NO	NO	NO	NO	YES	YES

*Notes: The eleven most populous municipalities are excluded. Municipality-time: municipality-specific time trends. Homicide rate per 100 000 inhabitants per year. Overseas municipalities excluded. Treatment definition based on coca cultivation before the shock: All municipalities that had more than 10 hectares of coca leaves per year in 2012, 2013, 2014, and 2015. *** p<0.01, ** p<0.05, * p<0.1*

A.6 Gold

Recent evidence suggests that gold mining in Colombia has been permeated by illegal organizations linked to the drug trade Rettberg and Ortiz-Riomalo (2016). Gasoline could be used in illegal gold mining as well if the same criminal networks that produce cocaine and that are in charge of the illegal mining. I, therefore, also study the areas of illegal gold mining. I dichotomously define a municipality as an illegal gold mining municipality if it had illegal gold mining in 2018 [10]. I then run difference-in-differences with illegal gold mining municipalities as a treatment. Around the period of the shock in gasoline prices, there were no large changes in the gold price [11]. The results are shown in table A5, and there are large and significant effects similar to the effect size of the main results. Then I run a triple difference-in-differences with the interaction between the original analysis and illegal gold mining. The results are shown in table A6 where in row 3, 13.62 is the effect in non-gold areas and it is -3 in gold areas.

A.7 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 table A7, and one can see no statistically

[10] 2018 is the earliest year I have data on illegal gold mining

[11] Between 2000 and 2020, the gold prices increased steadily until 2011, then they fell until they started to increase again in 2019 and 2020.

Table A5: Results: Illegal gold mining

	(1) Homicide rate
SDID	11.376***
	(2.836)
N	12188

*Notes: Illegal mining municipalities defined as all municipalities with illegal gold mining in 2018.Homicide rate per 100 000 inhabitants per year. Overseas municipalities excluded. *** p<0.01, ** p<0.05, * p<0.1*

Table A6: Results: interaction with illegal gold mining

VARIABLES	(1) Homicide rate	(2) Homicide rate
Treatment coca	-1,061	-1,061
	(1,049)	(1,061)
Post	-0.165	-0.165
	(1.138)	(0.717)
Treatment coca*Post	13.62***	13.62***
	(4.097)	(4.144)
Treatment illegal gold	-6,288***	-6,288***
	(2,257)	(1,765)
Treatment illegal gold*post	12.52	12.52*
	(8.814)	(6.894)
Trippeldifference	-16.02**	-16.02*
	(8.031)	(9.182)
Observations	12,320	12,320
Number of muni	1,120	1,120
Municipality FE	YES	YES
Year FE	YES	YES
Cluster	Department	Municipality
MSTT	YES	YES

*Notes: Illegal mining municipalities defined as all municipalities with illegal gold mining in 2018.Homicide rate per 100 000 inhabitants per year. Overseas municipalities excluded. Treatment definition based on coca cultivation before the shock: All municipalities that had more than 10 hectares of coca leaves per year in 2012, 2013, 2014, and 2015. *** p<0.01, ** p<0.05, * p<0.1*

Table A7: Results: female homicides

	(1) Female Homicide rate
SDID	0.028
	(0.102)
N	12320

*Notes: Female homicide rate per 100 000 female inhabitants per year. Overseas municipalities excluded. Treatment definition based on coca cultivation before the shock: All municipalities that had more than 10 hectares of coca leaves per year in 2012, 2013, 2014, and 2015. *** p<0.01, ** p<0.05, * p<0.1* significant effects. The effect sizes are also much smaller, 0.28, compared to 9.72 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.8 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 A8. The results are slightly lower than the main results but still robust. 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 A9. Here the results are much smaller, 0.19 to 3.76 compared to 7-11 in the main analysis. They are also no longer statistically significant. However, they remain positive signed effects, which might indicate that there are some small spillover effects.

Table A8: Spillover effects

	(1) Homicide rate	(2) Homicide rate	(3) Homicide rate	(4) Homicide rate	(5) Homicide rate	(6) Homicide rate
DiD	6.75***	6.75***	4.49**	4.49***	9.06***	9.06***
	(2.15)	(1.42)	(2.16)	(1.42)	(1.96)	(1.99)
Post	-3.22***	-3.22***	-3.58	-3.58***	-0.79	-0.79
	(1.18)	(0.48)	(2.90)	(1.01)	(1.18)	(0.75)
Own group mean	18.89	18.89	18.89	18.89	18.89	18.89
N	12320	12320	12320	12320	12320	12320
Cluster	Department	Municipality	Department	Municipality	Department	Municipality
Municipality FE	NO	NO	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES	YES
Municipality-Time	NO	NO	NO	NO	YES	YES

*Notes: Municipality-time: municipality-specific time trends. Homicide rate per 100 000 inhabitants per year. Overseas municipalities excluded. Spillover treatment definitions are all the treatment areas based on coca cultivation before the shock: All municipalities that had more than 10 hectares of coca leaves per year in 2012, 2013, 2014, and 2015, as well as the municipalities bordering a treatment municipality. *** p<0.01, ** p<0.05, * p<0.1*

Table A9: Only spillover effects

	(1) Homicide rate	(2) Homicide rate	(3) Homicide rate	(4) Homicide rate	(5) Homicide rate	(6) Homicide rate
DiD	1.13	1.13	0.19	0.19	3.76	3.76
	(2.15)	(1.49)	(2.15)	(1.53)	(3.86)	(2.38)
Post	-1.43	-1.43**	-2.30	-2.30**	1.26	1.26
	(1.40)	(0.56)	(3.10)	(1.07)	(1.48)	(0.81)
Own group mean	23.24	23.24	23.24	23.24	23.24	23.24
N	12320	12320	12320	12320	12320	12320
Cluster	Department	Municipality	Department	Municipality	Department	Municipality
Municipality FE	NO	NO	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES	YES
Municipality-Time	NO	NO	NO	NO	YES	YES

Notes: Municipality-time: municipality-specific time trends. Homicide rate per 100 000 inhabitants per year. Overseas municipalities excluded. Spillover treatment definitions are all municipalities that border the original treatment municipalities areas (based on coca cultivation before the shock: All municipalities that had more than 10 hectares of coca leaves per year in 2012, 2013, 2014, and 2015). Here, the municipalities in the original treatment definition were excluded from the spillover treatment definition.
**** p<0.01, ** p<0.05, * p<0.1*