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Abstract

How does violence affect social capital? I argue that its impact depends on two factors: i) the ability to identify the perpetrating group, and ii) the intensity of the violence. These factors help to reconcile the seemingly contradictory effects of violence on social capital presented in the literature. I study this question in the context of Colombia by exploiting changes in violence attributed to cross-border shocks on coca markets in neighboring countries interacted with a novel index of suitability for coca cultivation. This index uses satellite data from ecological conditions for growing coca. I document that violence has a negative effect on social capital measures such as trust, participation in community organizations, and cooperation. Notably, this effect is stronger when it is not possible to identify the enemy. The results are robust to a large number of controls that account for potential confounders. In particular, I show evidence that this effect is not related to the presence of drug cartels in Colombia during the Escobar and Cali era.

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Keywords: Causal effects of violence, social capital, coca production, instrumental variables, Colombia.

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"And how sad, because we were afraid of our friends. No one knew whether someone else was a crook. That screwed us up... I am still very afraid of people".[1]

1 Introduction

Conflicts have devastating effects on economic development. Each year, approximately 10% of the global GDP is spent on addressing and containing violence (IEP, 2019). In addition to their direct costs on society through the destruction of physical and human capital, conflicts can also lead to social and political disintegration (Collier *et al.* , 2009, Rohner *et al.* , 2013b). They are also more likely to occur in developing countries where, in absence of strong institutions, social capital is crucial for economic development. Indeed, a growing number of studies show that social capital –measured by trust, participation in community organizations, and cooperation– not only provides support in adverse situations, but also guarantees a more efficient provision of public goods, better outcomes in terms of fiscal capacity, governance, trade, and rapid diffusion of knowledge.[2] The effects of conflict-related violence on social capital have, however, been described as "the least understood of all war impacts" (Bauer *et al.* , 2016) and the evidence is mixed. Some studies document that the exposure to violence undermines trust, (Rohner *et al.* , 2013a Cassar *et al.* , 2013),[3] while another group of papers argues that violence enhances local cooperation (Bellows & Miguel, 2009; Voors *et al.* , 2012, Bauer *et al.* (2016)). Why there are instances of negative and positive effects of violence on social capital remains a puzzle.

Colombia provides an ideal setting for studying this question for a number of reasons. First, this country has one of the highest levels of violence worldwide. For the period of analysis, the homicide rate was 25 per 100,000 individuals. There is, moreover, substantial variation in violence over time and across the nation (UNODC, 2009).[4] Second, Colombia

[1]Testimony of a victim of conflict in Segovia, Antioquia (Colombia) (Centro de Memoria Historica, 2013, p. 274).

[2]See, for instance, Algan & Cahuc (2010); Foster & Rosenzweig (2001); Fafchamps & Lund (2003); Nannicini *et al.* (2013); Glennerster *et al.* (2013); Guiso *et al.* (2004); Cassar *et al.* (2013); Aghion *et al.* (2010); Conley & Udry (2010); Bandiera & Rasul (2006); BenYishay & Mobarak (2014).

[3]In a historical setting, Besley & Reynal-Querol (2012) find that precolonial conflict in Africa is negatively related to current levels of trust. Nunn & Wantchekon (2011) show that contemporary differences in trust levels within Africa can be traced back to the slave trade. Specifically, slaves were captured primarily through state-organized raids and warfare, but as trade progressed, the environment of ubiquitous insecurity caused individuals to turn on others—including friends and family members—and to kidnap, trick, and sell one another into slavery.

[4]For the same period, Brazil reported a homicide rate of 23, Mexico 14, the United States 5.3, and Sweden 1 (UN Office on Drugs and Crime's International Homicide Statistics database).

has collected data on social capital measures during times of conflict, whereas most of the currently available evidence is based on post-conflict settings. Third, armed groups largely rely on the production of coca to finance their fighting, such that exogenous shocks to the Colombian coca market can be used to identify the effect of violence on social capital. These exogenous sources of variation are given by cross-sectional variation in the ecological conditions for growing coca, and shocks in other coca-producing countries. I am thus able to combine rich data on conflict with different measures of social capital, with location fixed effects. Finally, the Colombian conflict is not driven by polarizations based on identifiable characteristics, such as religion or ethnicity, but rather offers a unified setting, where it is possible to distinguish between clashes where the perpetrators can, or cannot, be identified. In fact, this is a conflict without visibly marked divisions, and armed groups do not always wear uniforms or carry guns. In many cases, they dress civilian clothes, making it hard to differentiate who belongs to an armed group. I argue that this particular feature of the conflict allows to study the seemingly contradictory effects of conflict on social capital presented in the literature.

Specifically, I propose that the impact of violence on social capital depends on two factors: i) the possibility of identifying the enemy, and ii) the intensity of the violence. With regard to the former, the ability to distinguishing the enemy affects the certainty of whom people can trust. In municipalities in which violent attacks were perpetrated by difficult to discern militias, the effect is larger than when armed groups were clearly identifiable. Indeed, militias do not wear uniforms, bracelets with groups insignias, flags, or carry visible guns, and tend to mostly dress like the civilian population. As concerns the latter factor, very high levels of violence can be so disruptive that communities are unable to react, unlike for low levels of violence where the possibility of organizing to fight a common threat is greater. A failure to account for these two factors provides a tenable explanation for the mixed results found by different scholars.

Two main challenges arise in estimating the causal effect of conflict on social capital. On the one hand, social capital levels could affect the intensity of conflict, leading to reverse causality concerns. This is the case if well-organized communities protect themselves from violent attacks through neighborhood watch schemes (Kaplan *et al.* , 2010), or if armed groups target communities with low social capital so as to more easily take control. On the other hand, the correlation between conflict and social capital may be driven by omitted variables (i.e. the large variation in institutional performance), which could have a confounding effect rather than reflecting a causal impact. In either case, the measures of conflict on social capital will likely be biased.

I overcome these issues by exploiting the combination of a cross-sectional variation in violence and a plausible exogenous time-series variation in violence. The first source of variation regards the suitability for growing coca in Colombian municipalities, an important dimension given that armed groups largely finance their fighting with coca production. The second refers to external shocks to coca markets in Peru and Bolivia. Together with Colombia, these two countries are the main coca leaf producers in the world (UNODC, 2009). Thus, the eradication of coca plants in neighboring countries affects the demand for coca in Colombia, and in turn the intensity of violence. Mejia & Restrepo (2015) argue that the presence of coca plantations leads to violence, as property rights must be protected from other armed groups, and because violence is required to control municipalities for the planting of coca.[5] Since these shocks should affect coca-producing municipalities differently than non-producers, I use satellite data on ecological conditions to construct an exogenous index for coca cultivation at the municipal level. Using the interaction between cross-border shocks on coca markets and the coca index as an instrument has two main advantages: *i)* it provides conditionally random variation in violence over time, and *ii)* it allows for different trends of violence across municipalities.

[5]Similar examples can be found in the literature. Angrist & Kugler (2008), for instance, show that aerial interdiction campaigns in Peru and Bolivia led to an increase in the demand for coca cultivation in Colombia. Traditional coca-growing regions experienced a rise in coca cultivation and subsequently became more violent, by increasing the resources available to insurgent groups. Dube & Vargas (2013) exploit exogenous price shocks in international commodity markets. They find that a sharp drop in coffee prices in the 1990s lowered wages and increased violence differentially in municipalities cultivating more coffee, whereas a rise in oil prices heightened violence differentially in the oil region, by increasing the revenues to be appropriated by rebel groups. Rohner *et al.* (2013a) exploit an external political shock, namely when the US declared the main rebel movements of Uganda to be terrorist organizations, and document how the latter affected the intensity of fighting along the Sudanese border.

The validity of the instrument hinges on one critical assumption: cross-border shocks to the coca market did not affect municipalities that were more suitable for coca production in other unobservable dimensions. I address this concern by showing that the results are robust to the inclusion of controls for employment, pupils registered at school, tax collection, forced displaced population, suitability for growing coffee, and the possible legacy of the biggest drug lord in Colombia, Pablo Escobar. In addition, I present several checks that suggest that coca production has an effect on social capital only through the channel of violence. To this end, I digitized historical records on community organizations, an assessment of which indicates that the suitability for growing coca only affects social capital when the conflict is financed by coca, and not for previous political conflicts.

Broadly, this paper presents three sets of results. First, at the mean, violence has a negative and statistically significant effect on different measures of social capital. The estimated effect is quantitatively large and robust to alternative explanations of spillover effects and economic activity. A one standard deviation increase in the rate of violence is associated with a 38%, 22%, and 23% standard deviation decrease in trust, participation in community organizations, and contribution to solving problems, respectively. The magnitude of the effect is relatively large; taking trust as an example, this corresponds to the difference in trust levels between Germany and Colombia.[6] Second, these results seem to be driven by the fact that (as observed in other non-related conflicts) no basic cues were available to identify friend from foe, making people especially wary about whom they could trust. To this regard, I present evidence that individuals were afraid to interact with their communities. Indeed, they report a fear of running in local elections as well as of participating in community organizations as a result of non-identifiable perpetrators.

Finally, I document that the intensity of the exposure to violence matters as well. Low exposure to violence fosters social capital, possibly because local cooperation serves as a strategy to confront external threats. However, as violence becomes increasingly severe, social capital is negatively affected, consistent with the theoretical framework presented by Jennings & Sanchez-Pages (2017). My estimates imply that individuals living in a

[6] World Value Survey (2009).

Colombian municipality with the same level of violence as in the U.S., become more involved with their communities when experiencing violence, arguably a way of reacting in difficult times. This contrasts with an observed decrease in social capital in municipalities that have experienced levels of violence similar to Brazil or Mexico. Additionally, I show that when communities are able to identify the perpetrators, the decrease in social capital is less strong as compared to when it is not possible to identify the perpetrators. In Appendix C, I present a theoretical model that, when combined with empirical exercises, further helps to understand the apparently contradictory effects in the literature. The results of this study thus provide crucial insights for understanding the effects of conflict in other developing countries.

The remainder of the paper is organized as follows. The following section provides an overview of the Colombian conflict. Section 3 introduces the conceptual framework and Section 4 describes the data. Section 5 presents the identification strategy, and discusses the exclusion restriction of the instrument. Section 6 sets forth the results, robustness analysis, and possible mechanisms, as well as an extension on the potential consequences of low social capital on political participation. Section 7 concludes.

2 Background: The Colombian Conflict

2.1 Armed groups financed by coca production

The Colombian conflict dates back to the 1960s and, during the period of study, involved three illegal armed groups that competed for control of villages, natural resources, and strategic corridors of illegal markets. These non-state armed groups reigned over most of the territory. Two groups were left-wing guerrillas: the Armed Revolutionary Forces of Colombia (FARC) and the National Liberation Army (ELN). Both guerrilla groups fought with the stated aim of overthrowing the democratic government and claimed to represent the rural poor (Richani, 1997), and both were involved in the illegal cocaine business. After the demise of the Medellin and Cali cartels by the mid-nineties, armed groups started to participate in the production and commercialization of cocaine as a means of financing insurgent activities against each other and against the Colombian government (Suarez, 2000). Though revenues from underground economies are extremely difficult to measure, the guerrillas' income is estimated to have been about 1 billion dollars per year (Otis, 2014). The third actor consisted of a right-wing paramilitary group known as United Self-Defense of Colombia (AUC), which emerged as an anti-insurgent self-defense group organized by rural landowners and drug barons in response to guerrilla extortions.

In the late 1990s and early 2000s, much of the fighting between guerrillas and paramilitary forces was for control over coca plantations and trafficking routes for cocaine (Bagley, 2012). However, armed groups also participated in the production chain. In particular, they processed the leaf into cocaine in laboratories near plantations and sold it to international traffickers, obtaining profits from its trade.[7]

2.2 Armed Groups and their Relationship with the Civil Population

Beyond their engagement in drug trafficking, all the armed groups have been accused of human rights violations. The multi-party nature of the conflict and its intensity resulted in civilians being victims of threats, kidnappings, massacres, bombings, cross-fire, forced recruitment of minors, and extortion. Guerrilla bellicose activity primarily consisted of the disruption of the economic infrastructure (e.g, attacks on oil pipelines), attacks on government military positions, bombings, and roadblocks (Vargas, 2009), as well as kidnappings and extortions. In contrast, paramilitary forces assaulted civilians through selective killings, kidnappings of community leaders, and threats to peasant organizations whom they presumed to support rival groups. The paramilitary groups publicly claimed that at least two-thirds of the guerrilla members were civilian supporters rather than actual combatants, such that their priority was to block the "non-uniformed guerrilla" (Molina & Castaño, 2001). Civilians were often accused of aiding enemy groups were targeted and persecuted as a deliberate strategy of war (Morales, 2018).[8] Due to rumors, false

[7]See Mejia & Rico (2011) for a thorough description of the process of coca cultivation and cocaine production in Colombia, and Mejia & Posada (2008) for a description of the cocaine markets.

[8]Kaplan (2013) discusses the possibility of civilian collaborators in the Colombian conflict. However, data on suspects aiding armed groups is only available for one municipality in Colombia. Given that this

denouncements, and finger-pointing, people developed mechanisms of protection such as silence, distrust, and isolation from their community, and generally adopted a "low profile" strategy so as to be less visible to armed groups (Centro de Memoria Historica, 2013; de Memoria Historica, 2011). [9]

Similarly, prominent community members were victimized for being the spokespersons for collective claims. Over the last two decades, 1,227 local leaders, 1,496 politicians, 1,287 public servants, and 74 human rights defenders have been killed, and 8,000 leaders threatened (Department of Justice, 2017). In 2004, along the Caribbean coast, various female leaders were systematically attacked. Similarly, the guerrillas declared any state representative a military target, and many political candidates were forced to renounce or govern their towns from other cities (Centro de Memoria Historica, 2013).

3 Conceptual Framework

Social capital has been defined in the literature as the ability of a society to foster trust and cooperation among its members.[10] In this section, I discuss different reasons why one would expect violence to affect social capital. The first is rooted in neoclassical theory, by which greater cooperation arises from a high value of social insurance when violence decreases the returns from investments in other forms of capital. Violence destroys household assets and therefore victims become more dependent on local systems of risk-sharing in the absence of formal institutions. During wartime, investments in physical and human capital can be too risky, such that pro-social behavior becomes the optimal choice as a protection mechanism (Bauer *et al.* , 2016). Jennings & Sanchez-Pages (2017) formalize this idea in a theoretical model in which communities that face an external threat use social capital to protect themselves. Case studies by political scientists provide further evidence on the plausibility of this argument, as social cohesion enables civilians to overcome fear, implement collective

information is based on interviews, the lack of written records likely means some degree of measurement error. Nonetheless, the interviews suggest 67 cases of civilians helping armed groups in a village of 5,000 inhabitants.

[9] The Centro de Memoria Histórica is an official institution of the Colombian government whose purpose is to document testimonies related to the armed conflict.

[10] See, for example, Homans (1958), Coleman (1994), Putnam *et al.* (1993); Putnam (2020).

strategies for protection, and denounce aggressions (Kaplan *et al.* , 2010).[11]

A second possibility, set forth in the psychology literature, relates to a phenomenon called post-traumatic growth. Victims of traumatic experiences attach greater value to personal relationships. That said, other studies show that violence is linked to depression and distress, including a lack of desire to engage with people and difficulty maintaining close relationships (Ehlers & Clark, 2000). In line with these studies, Alesina & Ferrara (2002) document that a personal trauma such as a natural disaster or divorce, reduces social capital in the United States. For the Colombian case, Moya (2018) argues that traumatic conflict-related experiences can alter individuals' behaviors and deplete their ability to make economic decisions because of severe anxiety disorders.

Another explanation relies on the parochialism theories, which point to generosity towards insiders and selfishness towards outsiders who represent a threat (Choi & Bowles, 2007). The prediction from this viewpoint is that inter-group competition, including war, will promote individuals' pro-social behavior toward in-group members, compared to out-group members. The importance of the in-group's boundary relative to the out-group is underscored as a crucial feature in determining the consequences of conflict on social capital. Thus, the experience of a civil war that pits one group against another might strengthen within-group prosociality, while corroding the between groups' social capital (Cassar *et al.* , 2013).

Along these lines, homogeneity within ethnic groups allows individuals to find a common ground and a rational basis for coalition (Esteban & Ray, 2011). Ethnic boundaries based on physical differences are easier to police than boundaries based on non-visible differences. This makes such boundaries a low-cost sign of intentions, since they can be used as a marker to recognize potential infiltrators, and as an effective way of enforcing group membership (Caselli & Coleman, 2013; Chandra, 2007).

[11]For instance, organized communities in the Philippines stayed out of conflict between the military and rebels. In Guatemala, Communities of Populations in Resistance against conflict were created (Hancock & Mitchell, 2007). In Peru, the Peasant Rounds were originally formed as a protection force against theft (Starn *et al.* , 1999; Fumerton, 2001). In El Salvador, people tended to join and support rebel movements in response to government violence against them or their family (Wood, 2003).

However, for half of the conflicts around the world, making such a distinction is not possible as there is no polarization in terms of religious, regional, or ethnic divisions (Fearon & Laitin, 2003). This is true for the Colombian case as well, where 90% of the population does not identify as belonging to specific ethnic group (General Census of Population 2005). Further to this, armed groups did not always wear uniforms or carry guns. Instead, in many cases, they wore civilian clothes to try to blend with the local population (Centro de Memoria Historica, 2013). Dressing like the civilians allowed them to gather information on possible collaborators of enemy armed groups. It was thus not always possible to identify potential perpetrators. There are numerous examples of this "not readily identifiable" aspect of the conflict. Many victims later on reported that their perpetrators belonged to their community, reflecting the fact that a large part of the conflict took place within communities and that groups lived together (Centro de Memoria Historica, 2013).[12] Testimonies relating the difficulty of distinguishing criminals from civilians were common:

> *"Since they were in civilian clothes, many times we did not know who was a guerrilla member"*[13]

In light of the above observations, I hypothesize that the inability to distinguish friend from foe in a violent environment may have negatively impacted trust within communities. In the Colombian setting, there were insurgents among the civilian population, leading people to avoid involvement in the community so as to minimize their risk of being targeted. Appendix C presents a model in which social capital decreases when there is more uncertainty about allegiances in the community. The model furthermore shows that when levels of violence are lower, social capital can instead increase as a protective mechanism. These predictions are tested empirically in Section 6.

4 Data

In what follows, I describe the different data sets used in this paper. I first present the data on social capital, then that on armed conflict, and finally the information used to construct

[12] The New York Times wrote a piece in which tells the history of a town where neighbors were perpetrators.
[13] Testimony found in (Centro de Memoria Historica, 2013).

a suitability index for growing coca.

4.1 Social Capital

The measures of social capital come from the Latin American Public Opinion Project (LAPOP), specifically the Americas Barometer[14], a nationally representative survey of individuals over the age of 18 in rural and urban areas. It contains information on pro-social behaviors for approximately 12,000 individuals in 55 out of the 1,122 municipalities in Colombia for the period of 2004-2011, as a repeated cross-section (1,400 individuals per survey round on average). These municipalities were selected to be representative of the country based on socio-economic characteristics and population size.

Social capital includes features of social organization, such as social networks, norms, and trust that facilitate coordination and cooperation for mutual benefit (Putnam *et al.* , 1993). In this paper, I measure social capital as trust in other members of the community, and participation in community organizations. These measures are an indicator of collaboration within communities and the collective ability to respond to adverse situations (Durlauf & Fafchamps, 2005; Colleta & Cullen, 2000), and have been used in other studies on conflict. For instance, Rohner *et al.* (2013a) use the same survey design employed in this paper, but applied to the Ugandan case. Bellows & Miguel (2009) consider responses regarding interpersonal trust, community meeting attendance in the last year, membership in local groups, participation in elections, and political knowledge, such as the name of the local councilor. The main variables herein are constructed using the following questions from the LatinBarometer:

- *Trust*: "How much do you trust people from your community?". I code the variable as one if the respondent answers either "I trust them a lot", or "I trust them somewhat". Otherwise, the value assigned is zero, as in Rohner *et al.* (2013a). `(Question` *it*1`).`

[14] The Americas Barometer selects the samples as follows: each sample is a nationally representative cross-section of all citizens of voting age obtained by (a) strictly applying random selection methods at every stage and by (b) applying sampling with probability proportionate to population size. The sample is stratified by key social characteristics in the population such as sub-national area (e.g. region/department) and residential locality (urban or rural) (LAPOP, 2004-2011). This information is available for download here.

- *Participation in community organizations*[15]: "Did you attend community meetings in the last year?" I code the variable as one if the respondent reports having attended at least one community meeting in the last year and zero otherwise, as in Bellows & Miguel (2009). `(Question` *cp*8`)`.

- *Cooperation*: "Have you contributed to resolving a problem in your community or among your neighbors?" This takes a value of one if the answer is affirmative and zero otherwise. `(Question` *cp*5`)`.

In addition, LAPOP collects detailed information on the socioeconomic characteristics of surveyed individuals including their age, sex, household income, and years of education. The survey also asks about participation in local and national elections as well as media consumption (radio, TV, newspapers, and Internet). Descriptive statistics for these variables are displayed in Panels A and B of Table 1. On average, around 68% of individuals trust people from their community and 60% have participated in a community meeting during the last year. With regard to socioeconomic characteristics, half of the population are women, one quarter lives in rural areas, average age is around 37, and 6% are black.[16]

4.2 Armed Conflict

Data on the armed conflict come from the *Centro de Estudios sobre Desarrollo Económico* (CEDE) at the School of Economics at Universidad de Los Andes in Colombia. CEDE collects data from the Observatory of Human Rights of the Vice-Presidency and the National Planning Department. The original data consist of a compilation of reports drafted by the national police.[17]

The data set codes different violent events, by municipality location and groups involved. For this study, I construct a measure of violence that aggregates the number of attacks by

[15]The purpose of such organizations is to address general problems within the community (e.g., improving education, agriculture practices, security, or the provision of public goods).

[16]The descriptive statistics are consistent with those presented by the National Department of Statistics in Colombia, DANE, such that the sample is comparable to the averages for the main characteristics for the rest of the country.

[17]Martínez (2017) shows that these variables are consistent with a dataset produced by CERAC, a Colombian think-thank that collects information from national and local newspapers and complements the latter with reports from nongovernmental organizations working in remote areas.

rebel groups at the municipality-year level; the measure is normalized by population to create a rate of violence per 100,000 inhabitants for the period of 2004-2011.[18]

Descriptive statistics are presented in Panel C of Table 1. The mean of the violence rate that includes all types of attacks is equal to 49. To provide an idea of the magnitude of this rate, consider that the average homicide rate for the period 2004-2011 is 38.5, an already relatively high rate compared to other countries with similar levels of development. For instance, the average homicide rate in Latin American countries is 25 per 100,000 inhabitants. In Honduras, this rate is 58, in Brazil, 23, in the United States, 5, and in Sweden, 1.[19]

Regarding external validity, the sample of municipalities for which there is data on social capital exhibits a slightly lower rate of violence compared to the whole country. Figure 1 shows that the rates of violence for both samples (using the same source of data for the period of study) follow a similar pattern, increasing and decreasing over the same years.

5 Empirical Strategy

In this section, I first introduce the baseline estimating equation (Section 5.1). I then present the instrument for violence (Section 5.2) and finally, I provide evidence to support the identifying assumptions (Section 5.3).

5.1 Baseline Estimating Equation

The primary aim of this paper is to investigate the effect of conflict on social capital. To do so, I consider the following benchmark econometric model in a repeated cross-section

[18]Specifically I consider 18 types of events, used to construct the rate of violence: confrontations between illegal armed groups and the state military forces, explosive terrorist attacks, incendiary terrorist attacks, attacks on police stations, attacks on private property, attacks against institutions, general attacks, general confrontations, incursions into villages, roadblocks, air attacks on aircrafts belonging to the state military forces, ambushes on military/police cars, kidnappings of civilians, kidnappings of military forces, kidnappings of politicians, killings of civilians, killings of politicians, mass murders.

[19]UN Office on Drugs and Crime's International Homicide Statistics database.

setting:

$$P(SocialCapital_{imt} = 1) = \beta_0 + \beta_1 Violence_{mt} + \beta_2 X_{imt} + \beta_3 Z_{mt} + \gamma_m + \delta_t + u_{imt} \quad (1)$$

where $SocialCapital_{imt}$ is the outcome for an individual i, in municipality m, and year t. $Violence_{mt}$ corresponds to the rate of violence per 100,000 population. This variable includes 18 different types of violent attacks. X_{imt} includes a set of individual sociodemographic variables (gender, schooling, race, income, and media consumption).[20] Z_{mt} are time-varying municipality controls, including: employment rate, pupils registered at school, tax collection, forcibly displaced population, and suitability for growing coffee. γ_m and δ_t are municipality and year fixed effects, implying that β_1 is estimated from changes in the rate of violence within the same municipality over time, compared to other municipalities in a given year. Thus, any confounding variables that have a common effect on social capital across all municipalities in the same year –such as political changes or characteristics of municipalities that have a constant effect on social capital over time– are controlled for. Standard errors are clustered at the municipality level.

5.2 Instrument for Violence

When estimating the causal effects of conflict on social capital, two primary identification challenges emerge. First, it is possible that the levels of social capital in a municipality determine the intensity of violent attacks. This raises concerns regarding reverse causality, as violence would be the consequence rather than the cause of changes in social capital. The second challenge is related to omitted variables bias, where causation cannot be disentangled from correlation if unobservable variables determine both the exposure to conflict and social capital. For instance, armed groups might be present in areas considered strategic for political reasons or valuable resources (Acemoglu *et al.* , 2013). In either case, *OLS* estimates will likely be biased. A war strategy could be to attack areas without community organizations so as to avoid civilian resistance movements (Kaplan *et al.* , 2010), which would lead to overestimating the effect of conflict on social capital. Similarly, one would

[20] Olken (2009) documents that increased signal reception in Indonesia leads to more time watching television and listening to the radio, which is associated with less participation in social organizations and lower self-reported trust.

underestimate the impact of conflict if communities that are better organized are more likely to be attacked.

To address such endogeneity concerns, I use an Instrumental Variable (IV) strategy. In particular, I take advantage of the exogenous variation in Colombian violence attributed to the eradication of coca plants in Peru and Bolivia, combined with the suitability for growing coca in Colombian municipalities. The intuition behind the instrument is that changes in neighboring production of coca leaves –the raw input required for cocaine production– affect the demand for coca in Colombia, and in turn the violence, because traffickers have more incentives to grow coca (Mejia & Restrepo, 2015). Given that these external shocks affect violence disproportionately in municipalities with a potential for coca cultivation, I construct a suitability index. This index indicates which municipalities are more suitable for coca cultivation based on particular ecological and geographic conditions.

5.3 Coca Suitability Index and External Shocks to the Coca Market

This paper exploits the combination of two different sources of exogenous variation in violence. In what follows, I describe how these variations are constructed.

5.3.1 External Shocks to Coca Markets

External shocks to the Colombian coca market come from calculating the extent to which coca plantations have been eradicated from the total amount of coca planted in Peru and Bolivia in a given year. Coca cultivation data for Peru and Bolivia are obtained from satellite images available at the municipal level for the period of study from the United Nations Office on Drugs and Crime. Though the UN monitors coca cultivation by using various types of satellite images covering the entire national territory (equivalent to 1,142,000 square kilometers), the frequent cloud cover over the Colombian territory can make data acquisition difficult. To counter this, satellites with a frequent view and continuous recording are used (UNODC, 2009).[21] The equation reads as follows:

[21]The satellite has a 16-day repeat cycle, which enhances the chance for cloud free images (UNODC, 2009).

$$External\ shock_t = \frac{km^2\, of\, coca\, eradicated\, in\, Peru\, and\, Bolivia_t}{km^2\, of\, coca\, cultivated\, in\, Peru\, and\, Bolivia_t}$$

Figure 2 shows the rate of violence between 2004 and 2011, and the eradication efforts in Peru and Bolivia. Consistent with the narrative above, higher eradication efforts in neighboring countries are statistically positively correlated with higher levels of violence in Colombia, especially for municipalities that are more suitable for coca production.

5.3.2 Constructing the Coca Index

Coca plantations are sensitive to weather and environmental conditions, which makes coca cultivation exclusive to certain areas of Andean countries. For instance, if the temperature is too low, the plant does not grow, and if the temperature is too high, the leaves become very dry and lose their strength.

Data on ecological and geographic characteristics at the municipality level come from different sources. That on altitude was gathered from the U.S. Geological Survey Center, and soil pH from the Food and Agriculture Organization of the United Nations (FAO). Information on temperature, precipitation, humidity, and solar radiation were taken from the Global Weather and Climate Data (WorldClim). These measures are available at 30 seconds or a spatial resolution of 0.0083 degrees, which is equivalent to approximately one square kilometer and it is the finest possible grid cell disaggregation available. They correspond to their average value between 1970 and 2000.[22] I think of these variables as predetermined fixed municipality characteristics, determined mostly by ecological events unrelated to the rise of coca cultivation and production.

The ecological literature documents the most suitable conditions for growing coca. With respect to temperature, I rely on the findings of Acock *et al.* (1996), who show that the optimum average daily temperature for leaf growth ranges between 20°C and 30°C. Plowman

[22] Using the median value of this measure, the index does not change much; municipalities that were more suitable for growing coca continue to be more suitable for growing coca when using the median. Further information on the sources and construction of the variables is provided in Appendix B.

(1979) meanwhile finds that coca develops in humid tropical climates at altitudes between 300 to 2000 meters above sea level. Johnson *et al.* (1997) report that the relative humidity ranges between 55 and 85%, as well as provide evidence that coca plants grow better in soil with a pH level lower than 6. In addition, coca plants need a certain amount of daylight measured by the PPFD (Photosynthetic Photon Flux Density). These conditions are summarized in Table A1 and must be met in order to grow coca.[23] Based on these findings, the following equation is used to construct a novel measure for coca suitability:

$$coca\, index_m = \frac{\sum_{g=1}^{G_m} \mathbb{1}[300 \leqslant alt_{gm} \leqslant 2000 \wedge 20 \leqslant temp_{gm} \leqslant 30 \wedge 500 \leqslant precip_{gm} \leqslant 4000 \wedge 6 \leqslant PH \wedge 55 \leqslant Rh_{gm} \leqslant 85 \wedge PPFD \leqslant 400]}{G_m}$$

where $\mathbb{1}[\cdot]$ is an indicator function for the optimal conditions to produce coca. It takes a value of 1 when the grid cell g in municipality m satisfies the requirements established by the ecological literature, and zero otherwise. These values are added and divided by the total number of grid cells G in a given municipality, thus creating an index between 0 and 1 for each municipality and providing an estimate of the share of a municipality that is suitable for coca cultivation. A municipality with an index of 1 is entirely suitable while a municipality with an index of 0 is not at all suitable.[24] Figure 3 illustrates an example of how municipalities are divided into grids to calculate whether each fulfills the ecological conditions for coca cultivation, in which case the grid is shaded.

Figure 4 displays, on the left, the distribution of the index for the whole country and, on the right, for the sample of municipalities used in this paper. Overall, the shape of the index's distribution is comparable among samples. The main difference is in the tails, as the proportion of low suitable municipalities is slightly higher in the analyzed sample than it is for the country as a whole.[25] Figure 5 maps the coca index and shows that Colombia offers a good case for studying violence driven by illegal crops since coca suitability is not isolated to a particular region. In fact, 50% of municipalities in Colombia are classified as potential coca producers.

[23] When one of these conditions is not fulfilled, the coca index does not predict the presence of coca crops.

[24] In terms of external validity, though there is no other similar index available in the literature, I am able to show that it effectively predicts the actual coca cultivation.

[25] This is mainly due to the fact that I do not include the vast territories of the Amazon in my sample. That said, there are only a few remotes villages in these areas.

Finally, I demonstrate that this index is predictive of the location of coca crops during the period of interest. Specifically, Table A2 provides support that the ecological literature findings –namely, specific weather and soil conditions– indeed determine the availability of coca. The first three columns show different measures of the coca index for the whole country: *i)* the index described in this section that goes from 0 to 1, *ii)* as a dummy variable above the median and, *iii)* in terms of standard deviations above the mean. In all of the cases, the index positively predicts the amount of coca planted in a municipality. The last three columns present a similar story, but for the analyzed sample. The correlations are again positive but less statistically significant compared to the whole country. In particular, to facilitate the interpretation, a municipality that is one standard deviation above the coca index mean (column 6) cultivates two hectares more of coca plantation. By 2011, there were 64,000 hectares of coca planted in Colombia (UNO, 2012).

Therefore, $Violence_{mt}$ is instrumented with external shocks to the Colombian cocaine market ($ln\, External\, Shock_t$), interacted with a suitability index for producing coca $Coca\, Index_m$.[26] I can thus capture exogenous variation in violence across municipalities and time as follows:

$$Violence_{mt} = a + \alpha(ln\, External\, Shock_t) * Coca\, Index_m + \lambda_2 X_{imt} + \lambda_3 Z_{mt} + \gamma_m + \delta_t + v_{mt} \quad (2)$$

In particular, violence is identified from within municipality variation by comparing municipalities with different suitabilities in years with different external shocks to the coca market. Given this, the first stage is the differential impact on violence of external shocks for municipalities that are more suitable for coca production. Put differently, the suitability index determines the intensity of the treatment (violence), as the external shocks affect the whole country. Therefore, coefficient α should be interpreted as the differential effect of an increase of 1% in external eradication efforts. I discuss the validity of the instrument in the next section.

[26] The effect of the external shock is expected to be contemporaneous on violence, since coca bushes can be grown and harvested multiple times a year (minimum three and maximum eight, depending on the variety, and on average four) (Mejia & Posada, 2008). In addition, I use the logarithm of the external shocks because the effect can be interpreted as the increase on 1% in eradication efforts on the violence in Colombia. Using the linear form does not change the results.

6 Results

I first present the main results and provide evidence in favor of the exclusion restriction. I then show that the results are robust to concerns related to the instrument and spillovers. Next, I explore secondary outcomes, helping to shed light on potential mechanisms. Finally, I document that the effect of conflict on social capital also matters for institutions, such as participation in elections.

6.1 Baseline Estimates: The Effect of Violence on Social Capital

In Table 3, I study the effects of conflict on the different measures of social capital. The dependent variable is trust in other members of the community in Panel A, participation in community organizations in Panel B, and cooperation in Panel C. OLS estimations of equation (1) are reported in column 1,[27] while column 5 presents the 2SLS results. The 2SLS coefficients are larger than the OLS ones. Thus, a naive estimation of the effect of violence on social capital overestimates the true effect. One possible explanation is that places with more violence also have weaker institutions, and both have a direct effect on social capital and conflict. Therefore, when estimating the LATE – the effect of violence that is only driven by an external shock on the incentives to produce coca – the effect is smaller.

Table 3 also presents the reduced form estimates in column 2 without controls, which estimate the direct effect of the instrument on social capital. These coefficients show that the increase in eradication efforts in neighboring countries decreases social capital for people living in municipalities that are more suitable for coca production. In adding controls in columns 3 and 4, the estimates remain roughly unchanged, indicating that the effect is not driven by individual and municipality characteristics correlated with violence.[28]

Subsequent columns of Table 3 present the 2SLS results with and without adding individual and municipality controls. The coefficient of interest is stable across specifications

[27]The OLS coefficients are similar in magnitude to the corresponding marginal effects of a Probit model.

[28]When allowing, as in Conley (2010), for spatial correlation, the standard errors are larger though the results are still statistically significant at the 10% level.

even after additional covariates are included, suggesting only a small amount of selection on observables.[29] To discuss the magnitude of the results, I focus here on $Trust$ as this is the variable that has been broadly used in the literature of social capital. Trust has a sample mean of 0.68 and a standard deviation of 0.46. As shown in Table 3, Panel A, the point estimate in column 7 implies that a one standard deviation increase in the rate of violence produces a 38% standard deviation reduction in trust (corresponding to 17 percentage points). This magnitude corresponds to the difference in trust levels between Germany and Colombia, according to the World Value Survey (2009). Panel B documents that conflict decreases participation in community organizations by 22% of its standard deviation (10 percentage points). Panel C has the same structure but shows that the contribution to problem-solving decreases by 23% of a standard deviation (11 percentage points).[30] Finally, in an effort to control for possible confounders, I include municipality-level time trends, as well as province-level time trends instead of year-fixed effects. The estimates remain robust to these demanding specifications and, if anything, the effect is larger.[31]

6.2 Intensity of violence

Even if the effects are negative at the means, I investigate the impact of violence along its distribution. Figure 8 displays a local polynomial regression of social capital (trust) on the rate of violence. This figure reveals that a low incidence of violence induces higher levels of

[29] In Section 6.4, I discuss the potential role of omitted variables, following the approaches adopted by Altonji (2005) and Oster (2016).

[30] When including lags of violence in the main estimation, the coefficient for current violence remains significant and does not change in magnitude, whereas the lags are statistically insignificant. For robustness purposes, I conducted the same exercise with up to 4 lagged years.

[31] The main results presented in Table 3 show that the coefficient of interest is stable across specifications even after the inclusion of additional covariates, suggesting a small amount of selection on observables. However, it is not impossible that the latter explains the whole effect. I explore this possibility by following Altonji's (2005) omitted variable approach. Roughly speaking, the smaller the difference between the coefficients with and without controls, the less the estimate is affected by selection on observables, and so the larger the selection on unobservables needs to be, in order to explain away the entire effect of the variables of interest. This approach uses the degree of selection on observables as a guide for discerning the extent of selection on unobservables.[32] The value of the ratio indicates that selection on unobservables would need to be 10.5 times stronger than the selection on observables, which seems highly unlikely.[33] I also perform the Oster (2016) test to evaluate robustness to omitted variable bias. The basic idea is that the stability of the coefficient is not enough of a sign that the omitted bias is limited. The reason being that coefficients can appear stable after the addition of controls, but this may simply be because little of the outcome variable is explained by the observed variables. The δ obtained is equal to 5.7, which indicates that the unobservables would need to be more than 5 times as important as the observables to produce an effect of zero.

social capital, perhaps due to the latter's protective aspect. However, as the threat becomes severe, social networks are disrupted and social capital is likely to drop. In addition to this, in a back-of-the envelope calculation, I estimate the effect of violence on municipalities with rates of violence that are comparable to other countries. For instance, for the Colombian municipalities that have a rate of violence similar to that of the US (5.33 homicides per 100,000), conflict has a positive effect on social capital (Table 4, column 1).[34] One possible interpretation for this result is that investing in social capital is a protective mechanism adopted to face a common threat. Table A4 shows, in fact, that violence increases the likelihood of participating in protests, but only for those municipalities with low levels of violence.[35] As violence becomes intense, and more similar to countries like Mexico and Brazil, the effect becomes negative and significant (columns 2 and 3). These empirical findings thus help reconcile the seemingly contradictory results in the literature. The model presented in Appendix C furthermore shows that for low levels of violence, social capital proves useful in reducing losses from violent attacks; when, however, violence becomes severe, social capital losses its protective property and there is a decrease in its investment.

6.3 Inability to Distinguish "the Enemy"

Another possibility is that the effect of conflict on social capital depends on the extent to which the enemy is identifiable. In Colombia, and in many non-ethnic conflicts, there are often no basic cues that would allow to discern friend from foe within a community. As no comprehensive data on the observability of individual allegiances is available, I employ information on the use of camouflaged uniforms and insignias by armed groups as a proxy. Specifically, the Center for Investigation and Popular Education/Programme for Peace (CINEP/PPP) has collected data on human rights violations from victims of conflict that includes the name of the victim, the perpetrator, the geocoded place where the violent event occurred, and importantly, information on whether the perpetrator was from an identified armed group, or rather militia. The latter do not wear uniforms, bracelets with group insignias, flags, or carry visible guns, but instead dress like civilians (Centro de Memoria

[34] These municipalities correspond to the 8^{th} percentile of violence in Colombia.

[35] Most often, these protests demand greater human rights protection or better economic conditions. Unfortunately, there is no data available on the specific type of protest (LAPOP, 2004-2011).

Historica, 2013). As a result, I can test whether the observability of the enemy affects social capital. Table 5a estimates, in columns 1 and 2 respectively, the effect of conflict on social capital for municipalities in which violent attacks were perpetrated by identified armed actors, and for municipalities in which at least one event was perpetrated by militias. While the point estimates remain negative when armed groups were identified, the magnitude is even more negative and statistically different when the attacks were perpetrated by militias.[36] In addition, Table 5b shows that when there are more than two armed groups present in a municipality, the effect of violence on the different measures of social capital is negative and statistically significant, whereas when there is only one group, the effects are not different from zero. One possible explanation is that it is easier to identify members of armed groups when there is only one group; this interpretation aligns well with the model presented in Appendix C, in which social capital decreases when there is more uncertainty about allegiances in the community.

Consistent with this narrative, the conflict may have created a fear of engaging in community life. To test this idea, Table 6 investigates the impact of conflict on different variables that reflect apprehension over becoming involved in the community. These include: fear of participating in community organizations, fear of running as a local political candidate, and fear of voting in elections.[37] The structure of the table mirrors that of Table 3: column 1 reports results from the baseline specification for the OLS, while columns 2 to 7 show the reduced form and 2SLS estimations. The 2SLS estimates are positive and statistically significant, suggesting that a fear of interacting with neighbors who might be members of an armed group reduces the levels of social capital. In contrast, fear of voting does not appear significant, perhaps due to its secret character.

[36] Municipalities with and without militia did not have statistically different levels of violence.

[37] The precise questions used were: "Are you afraid to contribute to solving a problem in your community? Are you afraid to vote in elections within your community? Are you afraid to participate in a peaceful protest? Are you afraid to run for a political office in your community?". The variables take a value of one if the respondent answers yes and zero otherwise. (Questions $der1 - der4$).

6.4 Assessing the Instrument

I now discuss the identifying assumptions of the instrumental variable design, which uses the interaction between external shocks to the coca market at the year level and suitability for growing coca at the municipality level.

For this to be a good instrument, it must be relevant and valid. I begin with an intuitive and anecdotal justification of these assumptions. More formal tests are presented in Sections 6.4.1 and 6.4.2. Mejia & Restrepo (2015) provide evidence that coca plantations lead to violence for three reasons: first, property rights have to be protected from other armed groups. Second, violence is required to control vast territories and communities living in coca areas.[38] Finally, since cocaine production and trafficking are illegal, the high-profit margins create incentives for armed groups to grow coca trees. (Mejia & Posada, 2008).[39]

Thus, any shock to the Colombian coca market will generate changes in violence as cocaine demand is highly inelastic (Saffer & Chaloupka, 1999). A decrease in supply leads to a substantial increase in price, which in turn creates greater incentives for producing cocaine for municipalities where coca can be planted.[40] The relevance of this instrument is supported by the findings of Angrist & Kugler (2008), who show that aerial interdiction campaigns in Peru and Bolivia in 1994 led to an increase in the demand for coca cultivation in Colombia. Traditional coca-growing regions experienced an increase in coca cultivation and subsequently became more violent, by increasing resources available to insurgent

[38] Large expanses of land are needed for cocaine production. One hectare (10,000 m^2) of coca bushes produces, on average, between 1,000 and 1,200 kilograms of fresh coca leaf and 1 kilogram of cocaine (Mejia & Posada, 2008), whereas, for instance, between 600 and 1000 kg of coffee can be produced in the same area (FedeCafe).

[39] The main ingredient in the production of this drug is cocaine alkaloid, a chemical compound that can be extracted from the leaves of coca plants in a relatively simple process. The latter can be carried out in small local workshops and consists of three main steps: after being harvested and dried, coca leaves are converted into coca paste, then into a cocaine base, and then into the final product, cocaine hydrochloride. A few chemicals (precursors) such as sulfuric acid, potassium permanganate, hydrochloric acid, acetone, and ethylether, plus water, filters, and microwave ovens are necessary. The cost of the coca leaves required for producing 1 kilogram of cocaine ranges between \$300 and \$500, whereas that same kilogram can retail at $\$150,000$ in the United States at average street purity levels (Reuter & Greenfield, 2001).

[40] See Mejia & Restrepo (2015) for a detailed theoretical model. They show that the fully inelastic demand for cocaine guarantees that Colombian coca cultivation increases when Peru and Bolivia seize more cocaine, because traffickers substitute away from these sources. In the sample of municipalities used in this study, a 1% increase in Peruvian and Bolivian eradication activities increases the amount of coca planted in Colombia by 3.79%.

groups.[41] I use, however, the exogenous suitability for producing coca, rather than coca planted, since most of the cultivation takes place in areas that lack state infrastructure, leading to endogeneity concerns.[42] Moreover, because climatic shocks could potentially affect violence thRough mechanisms that also affect social capital, I focus on a suitability index that does not change over time.[43] For example, weather shocks could directly influence the feasibility of community gatherings. Such explanations can be ruled out given that local weather can be directly controlled for. The index is, for this reason, based on predetermined or historical weather conditions.

Furthermore, the benefit of this approach is that it relies on ecological expertise. These conditions are in turn determined by environmental interactions of temperature, humidity, solar radiation, soil nutrients, and vapor pressure that are captured in the coca index. Hence, given a set of time and municipality fixed effects, this measure combined with the exogenous shocks to the coca market is arguably an exogenous determinant of violence. Additionally, social capital measures are not likely to be affected by exogenous shocks to coca markets in neighboring countries, as these are determined by foreign policies.

6.4.1 Instrument Relevance: First Stage

The first stage of the instrumental-variable approach shows that external shocks to Colombian coca crops increase violence in high-suitability areas (Table 2). The coefficient in the second column, after including controls, indicates that for a 10% rise in eradication efforts in the neighboring countries, there is an increase of 10 violent events per 100,000 inhabitants for a municipality more suitable for growing coca. Robust (Montiel-Plueger) F-statistics accounting for clustered residuals at the municipality level are above the conventional

[41] Angrist & Kugler (2008) exploit a sharp change in the structure of the Andean drug industry: before 1994, most of the cocaine exported from Colombia was refined from coca leaf grown in Bolivia and Peru. Beginning in 1994, however, in response to an increasingly effective air interdiction by American and local militaries, the so-called air bridge that ferried coca paste from growers to Colombian refiners was disrupted. In response, coca cultivation and paste production shifted to Colombia's countryside, leading to high levels of violence.

[42] For instance, raw measures of coca could be related directly to social capital variables.

[43] In an experimental economic study, Castillo & Carter (2011) find that people who experienced extensive destruction from Hurricane Mitch shared a significantly larger portion of the pie with partners in a dictator game.

threshold for weak instruments.[44]

6.4.2 Instrument Validity

Although the exclusion restriction is not directly testable, I discuss its plausibility. This condition is violated if there are unobservable time-varying factors correlated with cross-border eradication efforts, for municipalities more suitable for coca production. In other words, if individuals in coca producer municipalities are less inclined to trust others or participate in community life due to unobserved cultural elements or a history of violence, these factors might have a direct effect on social capital. However, as long as their influence did not change with the external shocks in coca markets (other than due to the increase in violence), the instrument would be uncorrelated with the omitted variables conditional on municipality fixed effects. In contrast, concerns would arise if the error term includes time-varying factors that are correlated with the ecological variables. An example might be that whenever the demand for coca increases in high suitability areas, people start working together in coca fields raising the levels of trust. Therefore, for robustness purposes, I include municipal controls such as unemployment, the amount of taxes collected, and school attendance. These variables capture the fact that changes in incentives to grow coca might affect the local economy by displacing legal employment or school dropout in favor of illegal activities, which could directly affect social capital. The results are not, however, sensitive to the inclusion of these controls.

Placebo test.

In addition, I perform a placebo test to provide evidence for the exclusion restriction. Figure 6 plots the coca index (horizontal axis) and trust filtered by a set of municipality and time effects (vertical axis). The left panel shows municipalities characterized by a positive number of violent episodes, while the right panel displays those with no violent episodes. The relationship is negative and highly significant across municipalities experiencing violence, but it is insignificant across those that do not experience violence. Though not a

[44] The standard Stock-Yogo critical values for weak instruments are only valid under *i.i.d* assumptions on the residuals (Kleibergen & Paap, 2006). Montiel-Olea & Pflueger (2013) define weak instruments when the worst-case bias of two-stage least squares exceed 10% of the worst-case bias of the OLS. For a critical value of 5%, the null of weak instruments ranges from 9 to 11.52, and is thus always around to the Stock-Yogo rule-of-thumb cutoff of 10.

formal test for the exclusion restriction, this falsification analysis suggests that suitability for coca production has an effect on trust only through the channel of violence.

The effect is not related to the Escobar and Cali drug cartels.
Another concern is that coca cultivation in Colombia was first carried out by cartels before armed groups. The latter became involved in coca drug trafficking only after drug lord Pablo Escobar was killed by the government in 1993. Hence coca cultivation could have affected social capital through the presence of cartels, a powerful force that affected politics, economic growth in many cities, urban violence, and police presence. For instance, Escobar, head of the *Medellín Cartel,* largely monopolized the production of cocaine from Colombia and its distribution to the United States during the 1980s and 1990s. He was a controversial figure in that committed horrible crimes but also was a large provider of public amenities to the poor in Medellin. His philanthropic efforts included building an entire neighborhood for the indigent population, as well as soccer fields, sanitation systems, and hospitals (Salazar & Uribe, 1994)[45].

As a result, the coca index presented in this paper could have a direct effect on social capital through a channel other than violence even after controlling for municipality fixed effects. This would be the case if the suitability for growing coca was related to social capital before armed groups started to use coca to finance their fighting. To address this possibility, I control for the levels of social capital that existed at the time when cartels ruled; this should pick up the effects on social capital that Escobar may have generated. To this end, I digitalized historical records from community organizations created before armed groups joined the coca business. These community organizations were known as *Juntas de Acción Comunal (JAC)* and their purpose was to promote local development based on the initiative and voluntary participation of the community. Note that I consider not only the number of *JAC* per municipality during the time when cartels were growing coca, so as to account for the "Escobar" effect in the provision of public amenities, but also take

[45]For instance, Escobar launched his “Medellín Without Slums” program to rid the city of its slums and provide a “life of noble dignity” for the urban poor. He was also known as the “gentleman of football” because he invested in the local team, and provided funds to recruit foreigners and to retain the best players. As a result, they won the South American championship and were the pride of the region (Center for Latin American Studies, 2010).

into account records from the first *JAC* created in Colombia (in 1963), so as to address concerns that pre-existing levels of social capital might be driving the main effects (Archivo General de la Nación, 1963, 1993). Table A5, column 4 shows that the results do not change even after controlling for the number of *JAC*s per population during the Escobar era, suggesting that the possible long-term consequences of the cartel presence do not invalidate the instrument. Further to this, Table A5 column 5 shows that the findings are robust to the presence of historical *JAC*s created in 1963. Importantly, this exercise indicates that the coca index does not capture a historical predisposition for different levels of social capital.

In a further attempt to address concerns over how cocaine cartels might have shaped social capital before illegal armed groups became involved in coca drug trafficking, I restrict the main estimations to areas of Colombia that did not have a significant presence of drug cartels. In particular, I first exclude from the main estimations the Province of *Antioquia*, which was the territory controlled by Escobar. Second, I further restrict the sample by removing the province of *Valle del Cauca*, dominated by the other big cartel in Colombia —the *Cali cartel*. This cartel similarly committed atrocious crimes against the civilian population, though it was not well known for providing public amenities. Instead, the cartel may have directly affected local economic growth. Indeed, in order to launder the money from trafficking operations, the Cali cartel heavily invested in legitimate business (DEA, 1994). Table A6 shows that the results remain significant and of similar magnitude for the rest of the country when removing's domain. A similar picture emerges when further excluding the territory pertaining to the the Cali cartel (Table A7). Overall, these results suggest that the origins of the coca market in Colombia do not invalidate the point estimates presented in this paper.

Historical violence and coca suitability.

Finally, since the cross-sectional variation used to identify violence comes from the suitability for growing coca, I rule out the possibility that municipalities that are more suitable for growing coca are also inherently more violent than others. This might be a threat to identification if the coca suitability index creates violence that is not drug-related and that can have a direct effect on social capital. I consequently assess the relationship between the suitability coca index and different measures of historical violence before drug trafficking started in Colombia, when coca cultivation cannot be considered as being at the root of conflict. The intuition behind this exercise is that if the suitability index affects social capital only through incentives to fight over coca production, we should not see any correlation between the coca index and violence in the first half of the 20^{th} century. Such an outcome would indicate that the index is not related to pre-existing institutional characteristics after controlling for municipality fixed effects. Table A3 is consistent with this idea: the coca suitability index is not correlated with previous measures of conflict. In particular, columns 1 to 3 report the probability of having had a historical conflict given the suitability for growing coca.[46] The coefficients are not statistically significant for any of the historical land and political conflicts in Colombia.

Randomization of violence.

As the instrument is given by the interaction between the plausibly exogenous variation in the suitability for growing coca and shocks to the Colombian coca production, the first stage of the IV can be thought of as a form of a difference-in-difference (DiD) estimator. In this setting, even if including municipality-level time trends does not change the results, Barrett & Paul (2017) show that if the standard parallel trends assumption in the DiD is violated, the exclusion restriction underpinning the IV approach fails. In particular, it is possible that the results are driven by spurious correlations between the instrument, the dependent variable, and the outcome variable.

I accordingly perform an additional placebo test in the form of randomization inference. This test rests on the principle that introducing randomness into the endogenous explanatory variable of interest (a municipality's rate of violence), while holding constant the instrument, should eliminate, or at least substantially attenuate, the estimated causal relationship if indeed exogenous inter-annual shocks to the endogenous explanatory variable (violence)

[46] Historical conflicts are defined as in Férnandez (2012), who uses National Archives of Colombia to identify municipalities with different conflicts. During the period of 1901-1917 and 1918-1913, there were mainly disputes over land property rights. The period of 1948-1953 was instead characterized by political conflicts between Liberals and Conservatives.

drive the main outcome (social capital). Therefore, I randomly assign (without replacement) the rate of violence among the 55 municipalities for every year in the sample. This "new dataset" preserves the two sources of endogeneity highlighted as worrisome by Barrett & Paul (2017) –the time trend and selection into the treatment– but sweeps out the source of variation by randomizing the violence among municipalities. For instance, violence in town A cannot plausibly have caused violence in town B. This way, social capital can remain spuriously related to external shocks because neither the social capital nor the instrument is altered, but the causal mechanism has been rendered non-operational by randomization.

If true that the causal relationship between violence and social capital is negative and the identification is unaffected by selection bias and spurious time trends, the distribution of the coefficients would shift to the right relative to the original estimation, and if the share of municipalities in which violence causes changes in social capital is small relative to a large enough sample, it would center around zero, because the randomization of violence would attenuate the estimated relationship between violence and social capital. From the randomization, I obtain a mean of 0.007, and a median of 0.011. Neither lie on the confidence intervals of the observed effect (lower bound=–0.007, upper bound=0.0001, observed effect=–0.0031) (See Figure A1).

Finally, it is reassuring that the LIML (Limiting Information Maximum Likelihood) estimators are almost identical to the 2SLS (See Table A9), implying that there is no bias due to weak instruments. The LIML is an estimator that is less efficient, but also less biased by weak instruments (Angrist & Pischke, 2008). Furthermore, following Rohner *et al.* (2013a), I report the results of a specification where all variables are collapsed to the municipality level, allowing for the computation of the standard Cragg-Donald Wald F test. The F statistic is 16.38, which again suggests that weak instruments are not a problem (see Table A10).

6.4.3 Monotonicity

In this setting, the monotonicity assumption requires that municipalities that are little suited to growing coca and are violent, would also be violent if they were very well suited to growing coca, and vice versa for non-violent municipalities. This assumption ensures that the 2SLS identifies the local average treatment effect (LATE), i.e., the average causal effect among the subgroup of municipalities who might have had a different rate of violence because of their conditions for growing coca.

One testable implication of this assumption is that the first stage estimates should be non-negative for any subsample. Table A8 shows that for all quartiles of the coca index, the first stage estimates are positive and statistically different from zero, consistent with the monotonicity assumption.

6.4.4 Other concerns

Reverse causality may be a concern in the first stage because, for instance, eradication policies in Peru and Bolivia might respond to violence in Colombia, as a way of avoiding similar patterns of violence. I consequently first check whether in times of a generalized increase in violence in Colombia, there is still variation in violence at the municipal level, given that the identification comes from this variation. This is illustrated in figure 7, where the dots represent municipalities with different levels of violence across time. The idea being that even if cross-border shocks capture some variation caused by aggregate changes in the Colombian violence rates, this does not necessarily pose a problem for my identification strategy. As long as these aggregate changes are exogenous to a given municipality, I can use them in the spirit of a Bartik or shift-share instrument.

6.5 Extension: Effect on Voter Turnout

Finally, in an attempt to assess the economic impact of the collapse of social capital, I retrieve the estimates of the elasticity of institutional outcomes to trust. I hypothesize that if conflict destroys trust, it might also affect other outcomes, such as democratic institutions. Figure 9 shows that there is a negative correlation between voter turnout for the peace referendum of 2016 and the rate of violence during the period of study. When this relationship is analyzed in the IV context at the municipal level, I find an elasticity of -5.26. Given that by suggests that by 2016 most of the violent attacks had ceased, violence seems to have had a persistent impact on political institutions.[47] Violence has, in fact, been shown to effect not only informal institutions but also democratic institutions, which are proven to foster economic development (Daron Acemoglu & Robinson, 2019).

7 Conclusions

This paper estimates the causal effects of violence on social capital measures such as trust, participation in community organizations, and cooperation, by using individual and municipality data from Colombia. Specifically, I exploit municipalities' suitability for producing coca, interacted with cross-border shocks to the Colombian coca market.

My findings contribute novel insights to the literature by showing that, regardless of the specifics of a given conflict, the impact of violence on social capital depends on two factors: i) the ability to identify the antagonistic group, and ii) the intensity of violence. In particular, I document that when communities can identify the perpetrators, the decrease in social capital is not as strong as when they cannot be identified. Of no less importance, low levels of violence actually foster social capital, but when violence becomes severe, social capital is negatively affected, and this is the case for most Colombian municipalities. These results help to better understand the seemingly contradictory outcomes presented in the literature. For instance, in the conflict in Sierra Leone, the pitting of one ethnicity against another generated positive developments in collective action. Meanwhile in Uganda, violence decreased trust towards members from other ethnicities. The Spanish Civil War offers a similar case, where most of the killings were perpetrated by neighbors.

Finally, I observe that violence not only affects social preferences such as trust and

[47] This result could indicate that the impact on participation in community organizations was not simply a mechanical effect by which people did not attend community meetings because of the conflict. The reasoning being that in 2016 a peace deal substantially reduced the intensity of violence; if the mechanical argument was driving the results, then there should not be a significant effect on the referendum participation.

participation in community organizations, but also leads to the erosion of democratic institutions, which have in turn been shown to be relevant for economic development. From a policy perspective, my results suggest that the state of social networks in post-conflict settings should be taken in consideration. Indeed, it is not only physical and human capital that must be restabilized in the aftermath of conflict, but also social capital.

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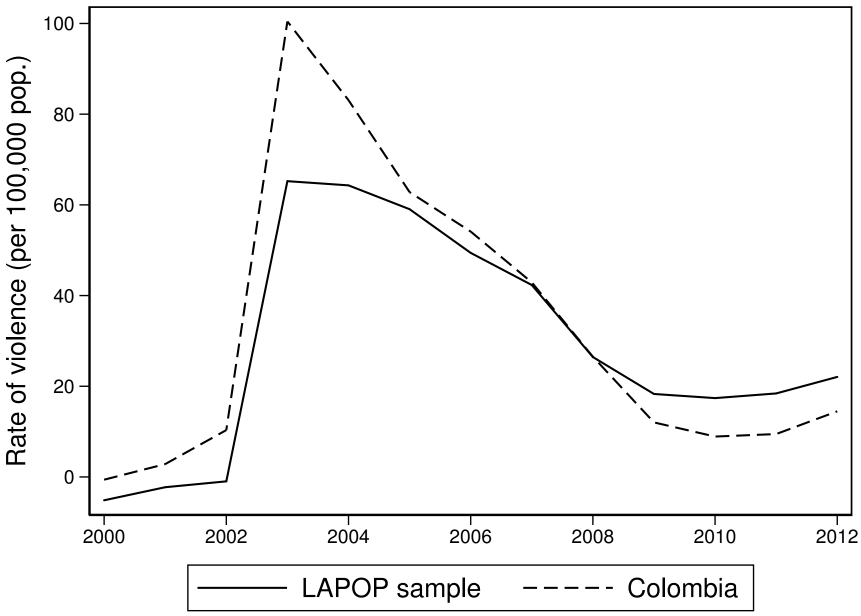
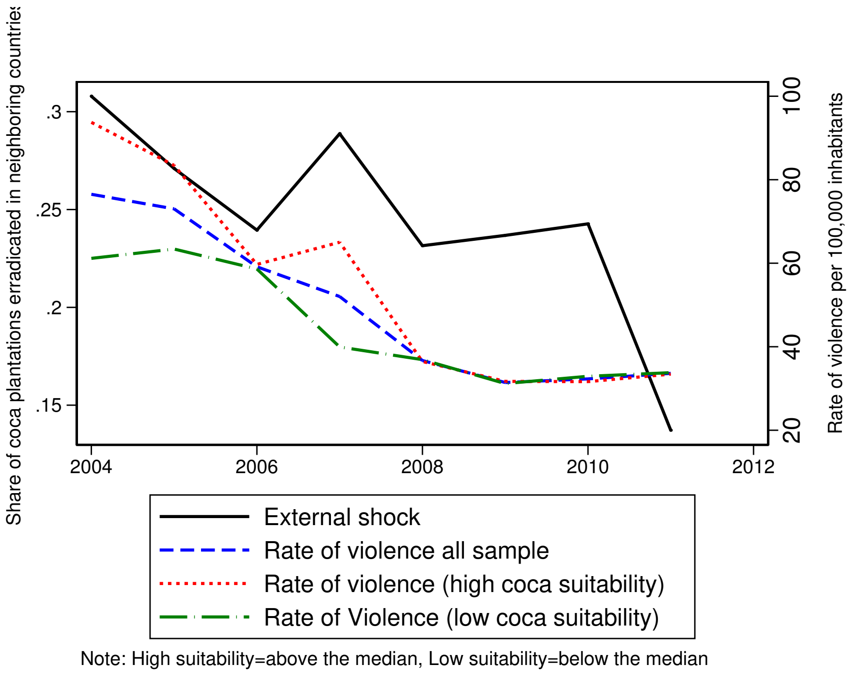
Figures

Figure 1: Comparison of the rate of violence between the sample of municipalities used in this study and the entire country



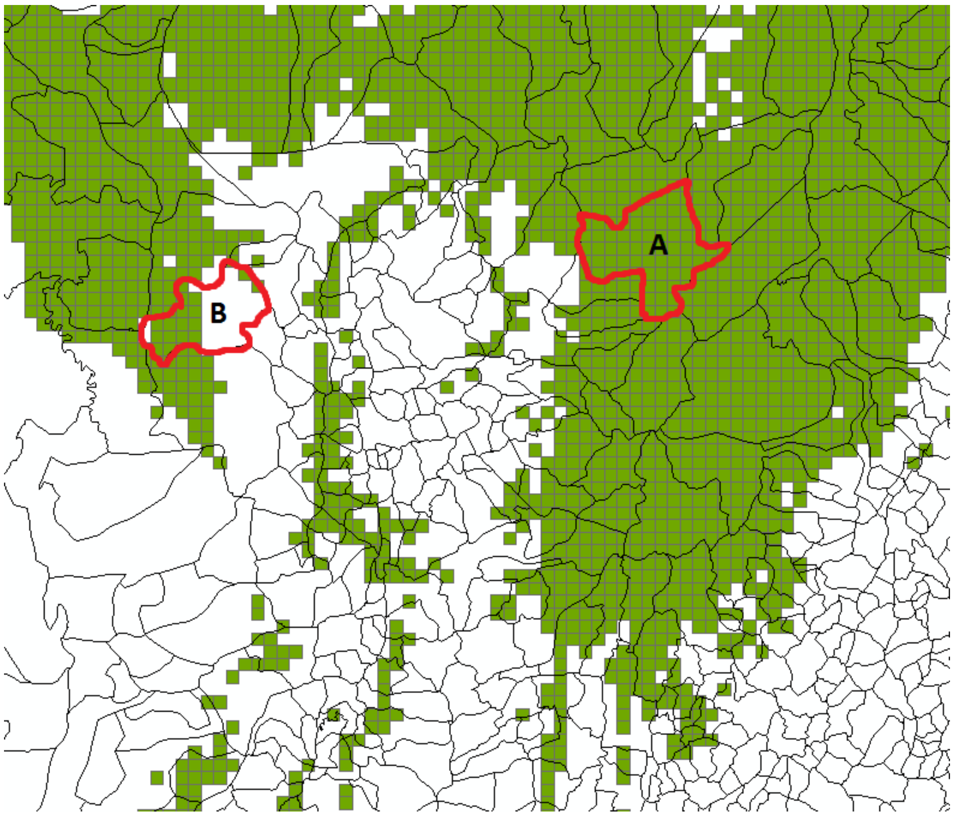
Note: The figure shows yearly averages of the rate of violence for the municipalities used in this paper (solid line), and for the entire country (dashed line). The sample contains 55 out of 1,121 municipalities in Colombia. They were selected by the LAPOP survey (Latin American Public Opinion Project) based on being nationally representative for both rural and urban areas in terms of socio-economic characteristics and population size. The rate of violence corresponds to the sum of 18 violent indicators divided by population from the Census records (which is the latest year available for the period studied). Data for violence come from CEDE.

Figure 2: Eradication in Peru and Bolivia is positively related to violence in Colombia



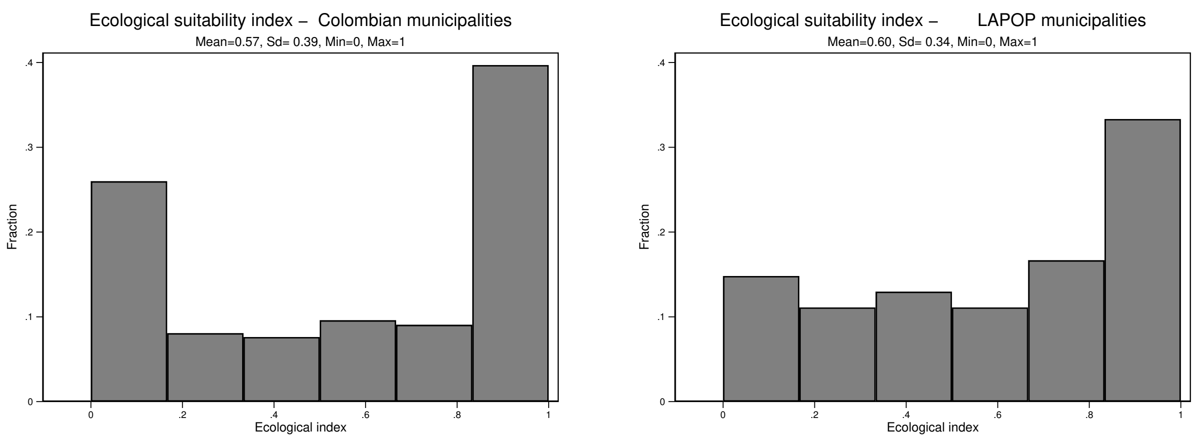
Note: The graph presents the yearly average rate of violence for municipalities with different suitability for coca production. The solid line depicts the amount of hectares that were eradicated in Peru and Bolivia across time. Violence is higher for municipalities with a high suitability for growing coca.

Figure 3: Example of how municipalities are divided into grids to calculate the share of land that is suitable for coca production



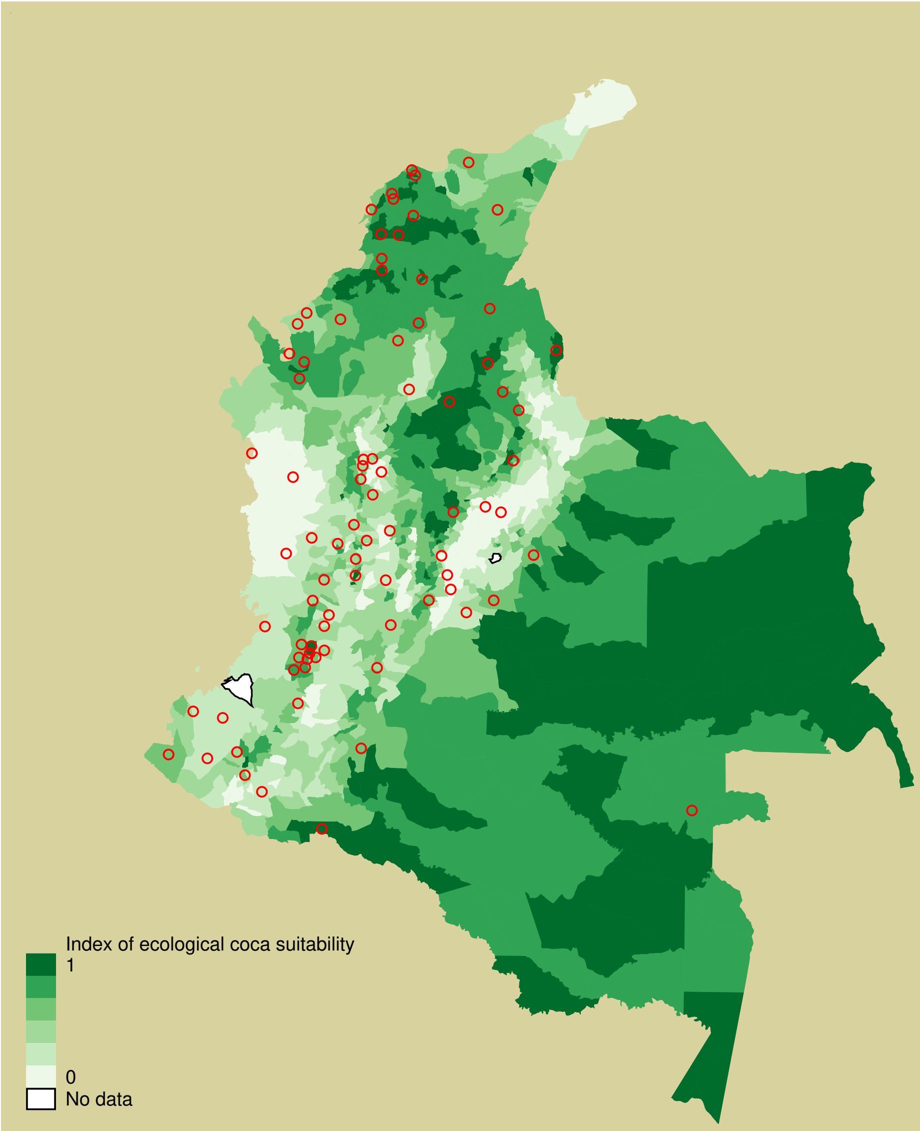
Note: each polygon represents a municipality. The figure gives an example of how municipalities are divided into grids to calculate the share of land that is suitable fo coca production. For instance, Municipality "A" is completely suitable for coca production, while only 0.5 of the municipality B is suitable because only half of the grids in the municipality fulfill the ecological requirements for coca cultivation. The coca index goes from 0 to 1, where 0 corresponds to a municipality that is not suitable for growing coca, and 1 is for a municipality entirely suitable for producing coca.

Figure 4: Distribution of the coca index (external validity)



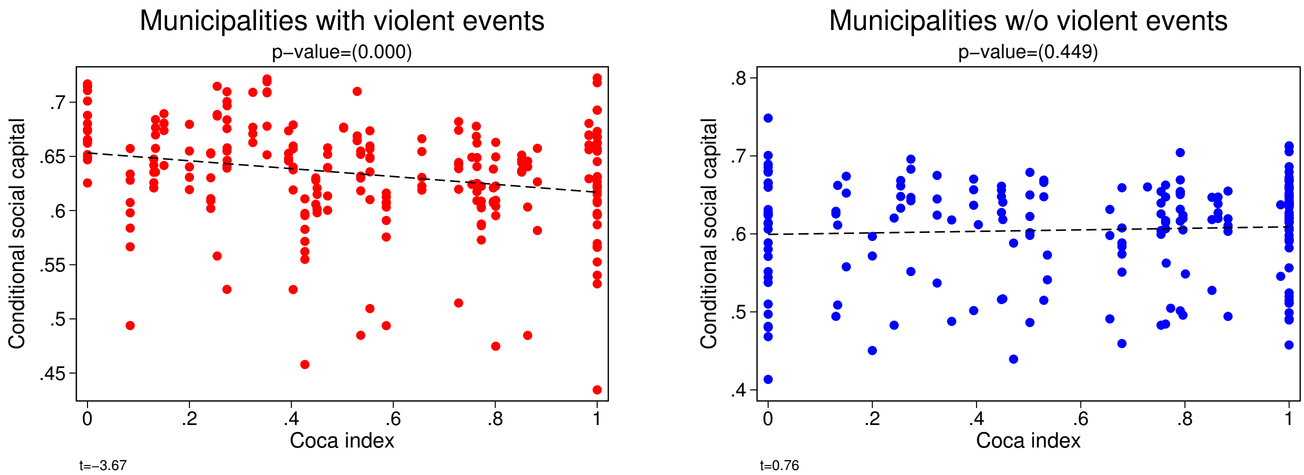
Note: The histograms show the distribution of the calculated coca suitability index. The left graph is for all the municipalities in Colombia. The graph in the right corresponds to the municipalities that are included in the sample used in this paper.

Figure 5: Map of coca suitability for Colombia. Darker municipalities are more suitable for coca production



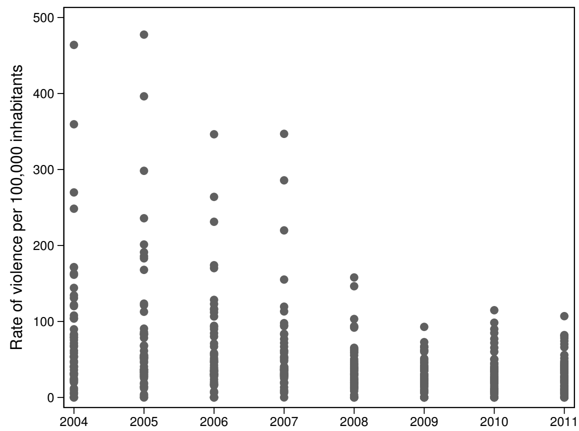
Note: The map presents the geographic distribution of the coca suitability index. The index goes from 0 to 1, where 1 corresponds to a municipality that it is completely suitable for growing coca. The circles represent the 55 municipalities in the studied sample. The figure suggests that the coca index is widely distributed throughout most of the country.

Figure 6: Placebo test for the exclusion restriction of the instrument



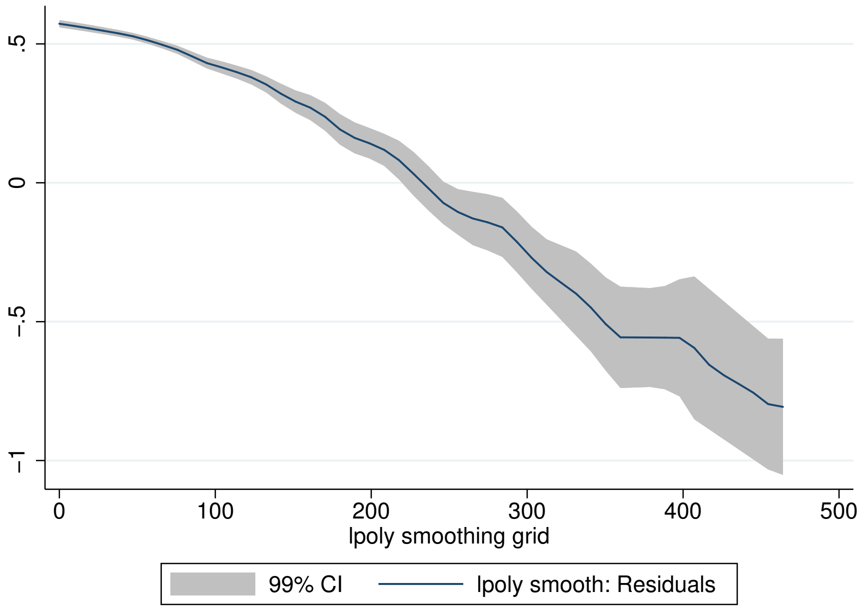
Note: The figures show the average trust filtered by a set of municipality and time effects. The right side presents the municipalities that have positive rate of violence. The left side displays municipalities with out violent events. There is only a negative statistically relationship between the instrument –coca suitability index– and the conditional main measure of social capital (trust), suggesting that the only way in which the instrument affects social capital is through the levels of violence.

Figure 7: Variation of violence within municipalities across time



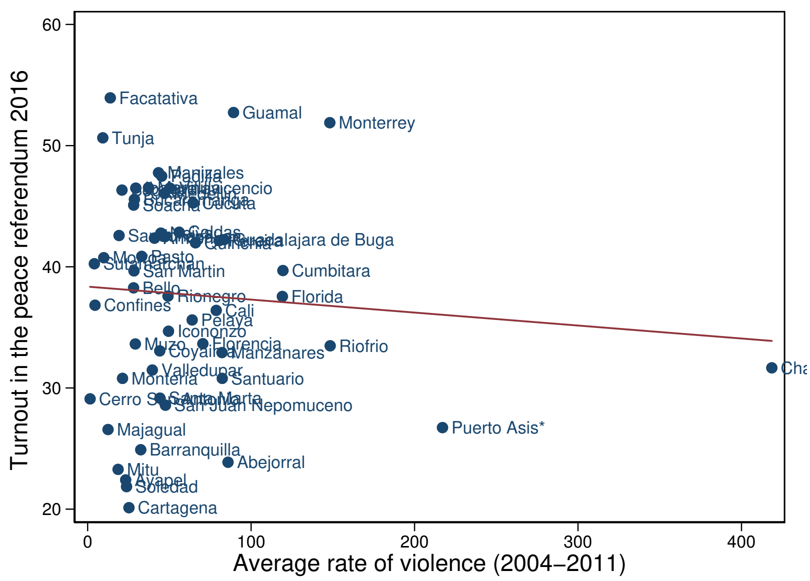
Note: The graph shows the yearly rate of violence for each municipality, which are represented by dots. The purpose of the graph is to show that there is municipality variation in the rate of violence across years as the identification strategy comes from variation in violence at municipal level.

Figure 8: Marginal effects across the distribution of violence



Note: Violence and residual trust, local polynomial with 99% confidence band. Residuals are calculated based on IV regression of trust rate of violence instrument with the coca suitability index and the external shock to the coca markets. I have included individual and municipal controls as well as year and municipality fixed effects.

Figure 9: Turnout in Referendum vs. Rate of Violence



Note: The graph plots the average rate of violence for the period 2004-2011 for all the municipalities included in the sample, against the turnout in the peace referendum in 2016.

Tables

Table 1: Descriptive Statistics

Variables	(1) N	(2) mean	(3) sd	(4) min	(5) max
Panel A: Social Capital					
Trust (=1)	11,682	0.687	0.464	0	1
Participation in community organizations (=1)	11,889	0.600	0.490	0	1
Cooperation to community problem solving (=1)	11,869	0.637	0.481	0	1
Fear to participate in community organizations (=1)	8,578	0.365	0.482	0	1
Fear to run for local elections (=1)	6,411	0.531	0.499	0	1
Fear to vote in local elections (=1)	8,002	0.154	0.361	0	1
Panel B: Individual controls					
Women (=1)	11,871	0.502	0.500	0	1
Years of education	11,871	8.877	4.350	0	17
Age	11,871	36.96	14.77	18	99
Black (=1)	11,871	0.0580	0.231	0	1
Rural (=1)	11,871	0.257	0.437	0	1
Media consumption (tv, newspaper, radio=1)	11,871	0.910	0.286	0	1
Close victim of conflict (=1)	11,871	0.320	0.467	0	1
Panel C: Municipality variables (2004-2011)					
Rate of violence (per 100,000 pop.)	11,871	49.26	56.61	0	477.6
Index for coca suitability (invariant)	11,871	0.508	0.373	0	1.000
Area of coca cultivated (ha.^{2})	11,871	36.12	273.0	0	4,531
N pupils registered at school	11,871	278,908	470,909	425	1.365e+06
Tax collection index	11,871	67.08	10.12	0	94.19
Forced displaced pop.	11,871	0.0126	0.112	0	1

Note: This table shows the summary statistics at individual and municipality level. Panel A presents the measures of social capital from the LAPOP survey at the individual level. Panel B displays the socio-economic characteristics of the sample which are also obtained from the LAPOP survey. Panel C presents variables measured at the individual level from the panel CEDE data. All the variables are presented as the average across years for the period 2004-2011.

Table 2: First stage results

Dependent variable in the first stage: Rate of violence	(1) *First Stage* Rate of violence	(2) *First Stage + Controls* Rate of violence
Coca index*Ln(External Shock)	96.43***	100.69***
	(27.70)	(28.97)
F test Cragg-Donald	218.67	227.67
F test Kleibergen-Paap	12.11	12.08
F test Montiel-Plueger	12.14	12.10
R2	0.65	0.65
N	11,682	11,682

Note: The table shows the results from the first stage of an instrumental variable regression. Standard error in parenthesis (robust clustered at the municipality level). All regressions include municipality and year fixed effects. The dependent variable is the rate of violence. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table 3: Main results of the effect of conflict on social capital

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	———Reduced form———			————-2SLS————-		
Panel A: Trust (mean=0.68)							
Coca index*Shock		-0.3322***	-0.3170***	-0.3172***			
		(0.0894)	(0.0886)	(0.0906)			
Rate of violence	-0.0002				-0.0034***	-0.0033***	-0.0031***
	(0.0001)				(0.0010)	(0.0009)	(0.0009)
Observations	11,682	11,682	11,682	11,682	11,682	11,682	11,682
R-squared	0.0247	0.0257	0.0454	0.0467			
Panel B: Participation in community organizations (mean=0.60)							
Coca index*Shock		-0.1829***	-0.1981**	-0.1896**			
		(0.0926)	(0.0915)	(0.0937)			
Rate of violence	-0.0004***				-0.0020**	-0.0019**	-0.0019**
	(0.0001)				(0.0010)	(0.0009)	(0.0009)
Observations	11,889	11,889	11,889	11,889	11,889	11,889	11,889
R-squared	0.0290	0.0287	0.0548	0.0552			
Panel C: Contribution to community problem solving (mean=0.63)							
Coca index*Shock		-0.2044**	-0.2062**	-0.2038**			
		(0.0875)	(0.0860)	(0.0881)			
Rate of violence	-0.0002				-0.0021**	-0.0021**	-0.0020**
	(0.0001)				(0.0009)	(0.0009)	(0.0009)
Observations	11,869	11,869	11,869	11,869	11,869	11,869	11,869
R-squared	0.0126	0.0129	0.0472	0.0477			
Indiv. controls	No	No	Yes	Yes	No	Yes	Yes
Muni. controls	No	No	No	Yes	No	No	Yes

Note: Column (1) presents the OLS results, Column (2) the reduced form, Column (3) the reduced form including individual controls, Column (4) adds municipal controls, Column (5) the 2SLS estimation, and Column (6) and (7) the 2SLS estimation with individual and municipality controls. Standard error in parenthesis (robust clustered at the municipality level). All regressions include municipality and year fixed effects. Individual control variables include: gender, schooling, age, race, income, media consumption on radio, TV and newspapers, dummy for rural area. Municipality controls: number of students attending to school, fiscal performance, forcibly displaced population and suitability for growing coffee. The dependent variable is the rate of violence per 100,000 population, which corresponds to the sum of 18 violent indicators divided by population. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table 4: Effect of conflict on social capital at different points of the distribution - Comparison with other countries

Dependent variable:	(1)	(2)	(3)
Trust	US	Mexico	Brazil
Percentile in Colombia	$P8^{th}$	$P16^{th}$	$P28^{th}$
	2SLS	2SLS	2SLS
Rate of violence	0.4093**	-0.0028***	-0.0058***
	(0.1937)	(0.0008)	(0.0018)
Observations	902	10,003	7,627

Note: The table shows the effect of conflict on different parts of the violence distribution, which corresponds to the average level of violence in other countries. The coefficients are estimated by using 2SLS. Individuals and municipality controls are included. Standard error in parenthesis (robust clustered at the municipality level). All regressions include municipality and year fixed effects. Individual control variables include: gender, schooling, age, race, income, media consumption on radio, TV and newspapers, dummy for rural area. Municipality controls: number of students attending to school, fiscal performance, forcibly displaced population and suitability for growing coffee. The dependent variable is the rate of violence, which corresponds to the sum of 18 violent indicators divided by population. The rate of violence in the US is 5.3, in Mexico 13, and in Brazil 23 for the period of study. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table 5a: Mechanism II: Inability to distinguish the enemy

	(1)	(2)
Sample	Armed group identified	Armed group not identified
Panel A: Trust (mean=0.63)		
Rate of violence	-0.0029***	-0.0045***
	(0.0008)	(0.0012)
Observations	11,531	358
Panel B: Participation in community organizations (mean=0.60)		
Rate of violence	-0.0015**	-0.0025**
	(0.0007)	(0.0012)
Observations	11,324	358
Panel C: Contribution to community problem solving (mean=0.63)		
Rate of violence	-0.0016**	-0.0023***
	(0.0008)	(0.0011)
Observations	11,511	358

Note: The fist column shows the estimates for the effects of violence on trust when perpetrators were identified. The second column shows the effect of conflict in municipalities in which perpetrators were not identified. Standard error in parenthesis (robust clustered at the municipality level). All regressions include municipality and year fixed effects. Individual control variables include: gender, schooling, age, race, income, media consumption on radio, TV and newspapers, dummy for rural area. Municipality controls: number of students attending to school, fiscal performance, forcibly displaced population and suitability for growing coffee. The dependent variable is the rate of violence, which corresponds to the sum of 18 violent indicators divided by population. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table 5b: Mechanism II: Inability to distinguish the enemy

	(1)	(2)	(3)
Sample	At least 2 armed groups	only 1 armed group (AUC)	only guerrillas
Panel A: Trust (mean=0.63)			
Rate of violence	-0.0037*	-0.0028**	-0.0021
	(0.0020)	(0.0014)	(0.0019)
Observations	2,743	4,116	4,345
Panel B: Participation in community organizations (mean=0.60)			
Rate of violence	-0.0048**	-0.0002	-0.0019
	(0.0020)	(0.0014)	(0.0019)
Observations	2,743	4,116	4,345
Panel C: Contribution to community problem solving (mean=0.63)			
Rate of violence	-0.0026**	-0.0020	-0.0008
	(0.0013)	(0.0019)	(0.0019)
Observations	2,743	4,116	4,345
Indiv. controls	Yes	Yes	Yes
Muni. controls	Yes	Yes	Yes

Note: The fist column shows the estimates for the effects of violence on trust when perpetrators were identified. The second column shows the effect of conflict in municipalities in which perpetrators were not identified. Standard error in parenthesis (robust clustered at the municipality level). All regressions include municipality and year fixed effects. Individual control variables include: gender, schooling, age, race, income, media consumption on radio, TV and newspapers, dummy for rural area. Municipality controls: number of students attending to school, fiscal performance, forcibly displaced population and suitability for growing coffee. The dependent variable is the rate of violence, which corresponds to the sum of 18 violent indicators divided by population. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table 6: Mechanism I: fear to get involved with the community

Dependent variable	(1) OLS	(2)	(3) Reduced form	(4)	(5)	(6) 2SLS	(7)
Panel A: Fear to participate in community org. (mean=0.36)							
Rate of violence	0.0001	0.5646***	0.5599***	0.4405**	0.0026***	0.0025***	0.0020**
	(0.0002)	(0.2068)	(0.2044)	(0.2117)	(0.0009)	(0.0009)	(0.0010)
Observations	8,578	8,578	8,578	8,578	8,578	8,578	8,578
Panel B: Fear to run in local elections (mean=0.53)							
Rate of violence	0.0003	0.8328***	0.8356***	0.7872***	0.0037***	0.0037***	0.0034***
	(0.0002)	(0.2440)	(0.2375)	(0.2465)	(0.0011)	(0.0011)	(0.0011)
Observations	6,411	6,411	6,411	6,411	6,411	6,411	6,411
Panel C : Fear to vote in local elections (mean=0.15)							
Rate of violence	0.0001	0.0036	0.0217	-0.0445	0.0000	0.0001	-0.0002
	(0.0001)	(0.1598)	(0.1583)	(0.1639)	(0.0007)	(0.0007)	(0.0007)
Observations	8,002	8,002	8,002	8,002	8,002	8,002	8,002
Indiv. controls	No	No	Yes	Yes	No	Yes	Yes
Muni. controls	No	No	No	Yes	No	No	Yes

Note: Column (1) presents the OLS results, Column (2) the reduced form, Column (3) the reduced form including individual controls, Column (4) adds municipal controls, Column (5) the 2SLS estimation, and Column (6) and (7) the 2SLS estimation with individual and municipality controls. Standard error in parenthesis (robust clustered at the municipality level). All regressions include municipality and year fixed effects. Individual control variables include: gender, schooling, age, race, income, media consumption on radio, TV and newspapers, dummy for rural area. Municipality controls: number of students attending to school, fiscal performance, forcibly displaced population and suitability for growing coffee. The dependent variable is the rate of violence, which corresponds to the sum of 18 violent indicators divided by population. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Appendix

A Figures and Tables

Table A1: Ecological conditions for growing coca

Variables	Optimum range	Units	Source
Altitude	300-2000	masl	Plowman (1979)
Temperature	20-30	C	Acock *et al.* (1996)
Precipitation	500-4000	mm year	Plowman (1979)
PH	<=6	pH	Johnson *et al.* (1997)
Relative humidity	55-85	%	Johnson *et al.* (1997)
Photosynthetic Photon Flux Density	<=400	$\mu mol\, m^{-}2s^{-}1$	Acock *et al.* (1996)

Note: This table summarizes the optimal conditions for growing coca according to the ecological literature. These characteristics are used to create the coca suitability index.

Table A2: The coca index predicts positively the coca cultivation for all the municipalities in the country and for the municipalities in the LAPOP sample

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Area of coca planted					
Coca index	1.4490***			3.2297**		
	(0.2123)			(1.3201)		
Coca index (=1 if above the median)		0.8864***			1.0131	
		(0.1679)			(0.9555)	
Coca index (1 sd. above the mean)			0.8260***			1.9997**
			(0.1210)			(0.8174)
Sample	Colombia	Colombia	Colombia	LAPOP	LAPOP	LAPOP
Observations	1,116	1,116	1,116	55	55	55
R-squared	0.0401	0.0243	0.0401	0.1032	0.0212	0.1032

Note: Robust standard errors in parenthesis. The area of coca planted is measured in hectares, which is equivalent to 10,000 km^2. Column 1, 2 and 3 shows the relationship between the coca index and the area of coca planted for the entire Colombia. Column 4, 5 and 6 presents the same information but for the sample used in this paper. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Coca index vs. historical measures of conflict

Dependent variable	(1) Land conflicts 1901-1917 (=1)	(2) Land conflicts 1918-1931 (=1)	(3) Political violence 1948-1953 (=1)
Coca index	-0.0163	0.222	0.0190
	(0.161)	(0.183)	(0.1256)
Constant	0.213*	0.188	0.1003
	(0.107)	(0.122)	(0.0839)
Observations	55	55	55

Note: The table includes as dependent variable dummies for whether there was a historic conflict in a municipality during different periods of time. All columns show that there is not a correlation between the coca index and the different measures of historical violence. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Effects of conflict on protesting activity by intensity of violence

Dependent variable: *Participation in protests*	(1) Low violence	(2) High violence
Rate of violence	0.2474*	0.0011
	(0.1438)	(0.0007)
Observations	902	10,942

Note: Column (1) presents the estimation of the basic specification (equation 1) for individuals living in municipalities with low levels of violence (United States levels of violence). Column (2) replicates the same estimation but for individuals living in municipalities with higher levels of violence (rest of the country). All regressions include municipality and year fixed effects. Individual control variables include: gender, schooling, age, race, income, media consumption on radio, TV and newspapers, dummy for rural area. Municipality controls: number of students attending to school, fiscal performance, forcibly displaced population and suitability for growing coffee. The dependent variable is the rate of violence, which corresponds to the sum of 19 violent indicators divided by population. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table A5: Results of the effect of conflict on social capital, controlling for historical social capital - 2SLS estimation

Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Trust (mean=0.68)						
Rate of violence	-0.0034***	-0.0033***	-0.0031***	-0.0031***	-0.0030***	-0.0030***
	(0.001)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
JACs – Escobar era				0.0002		0.0002
				(0.0002)		(0.0002)
JACs – Historical					0.0003*	0.0003*
					(0.0002)	(0.0002)
Observations	11682	11682	11682	11682	11682	11682
Panel B: Participation in community organizations						
Rate of violence	-0.0019**	-0.0021**	-0.0019**	-0.0019**	-0.0017**	-0.0017**
	(0.001)	(0.001)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
JACs – Escobar era				0.0001		0.0001
				(0.0001)		(0.0001)
JACs – Historical					0.0004*	0.0004*
					(0.0002)	(0.0002)
Observations	11889	11889	11889	11889	11889	11889
Panel C: Contribution to community problem solving						
Rate of violence	-0.0021**	-0.0022**	-0.0020**	-0.0020**	-0.0020**	-0.0020**
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
JACs – Escobar era				0.00015		0.00015
				(0.0001)		(0.0001)
JACs – Historical					0.0002**	0.0002**
					(0.0001)	(0.0001)
Observations	11869	11869	11869	11869	11869	11869
Indiv. controls	No	Yes	Yes	Yes	Yes	Yes
Muni. controls	No	No	Yes	Yes	Yes	Yes

Note: Column (1) presents the OLS results, Column (2) the reduced form, Column (3) the reduced form including individual controls, Column (4) adds municipal controls, Column (5) the 2SLS estimation, and Column (6) and (7) the 2SLS estimation with individual and municipality controls. Standard error in parenthesis (robust clustered at the municipality level). All regressions include municipality and year fixed effects. Individual control variables include: gender, schooling, age, race, income, media consumption on radio, TV and newspapers, dummy for rural area. Municipality controls: number of students attending to school, fiscal performance, forcibly displaced population and suitability for growing coffee. The dependent variable is the rate of violence per 100,000 population, which corresponds to the sum of 18 violent indicators divided by population. *JACs – Escobar era* corresponds to the number of community organizations *JAC* per population between 1980 to 1993. *JACs – Historical* accounts for the first community organizations created in 1963 Colombia. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table A6: Main results of the effect of conflict on social capital - Without Escobar area of influence

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	———Reduced form———			————-2SLS————		
Panel A: Trust							
Rate of Violence	-0.0002				-0.0037***	-0.0037***	-0.0037***
	(0.0001)				(0.001)	(0.001)	(0.001)
Coca Index*Shock		-0.3502***	-0.3502***	-0.3502***			
		(0.0914)	(0.0914)	(0.0914)			
Observations	10457	10457	10457	10457	10457	10457	10457
R-squared	0.0262	0.0274	0.0274	0.0274			
Panel B: Participation in community organizations							
Rate of Violence	-0.0004***				-0.0019*	-0.0019*	-0.0019*
	(0.0001)				(0.001)	(0.001)	(0.001)
Coca Index*Shock		-0.1758*	-0.1758*	-0.1758*			
		(0.0946)	(0.0946)	(0.0946)			
Observations	10621	10621	10621	10621	10621	10621	10621
R-squared	0.0299	0.0295	0.0295	0.0295			
Panel C: Contribution to community problem solving							
Rate of Violence	-0.0001				-0.0022**	-0.0022**	-0.0022**
	(0.0001)				(0.001)	(0.001)	(0.001)
Coca Index*Shock		-0.2077**	-0.2077**	-0.2077**			
		-0.0905	-0.0905	-0.0905			
Observations	10603	10603	10603	10603	10603	10603	10603
R-squared	0.0119	0.0123	0.0123	0.0123			
Indiv. controls	No	No	Yes	Yes	No	Yes	Yes
Muni. controls	No	No	No	Yes	No	No	Yes

Note: Column (1) presents the OLS results, Column (2) the reduced form, Column (3) the reduced form including individual controls, Column (4) adds municipal controls, Column (5) the 2SLS estimation, and Column (6) and (7) the 2SLS estimation with individual and municipality controls. Standard error in parenthesis (robust clustered at the municipality level). All regressions include municipality and year fixed effects. Individual control variables include: gender, schooling, age, race, income, media consumption on radio, TV and newspapers, dummy for rural area. Municipality controls: number of students attending to school, fiscal performance, forcibly displaced population and suitability for growing coffee. The dependent variable is the rate of violence per 100,000 population, which corresponds to the sum of 18 violent indicators divided by population. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table A7: Main results of the effect of conflict on social capital - Without Escobar area of influence

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	———Reduced form———			————-2SLS————-		
Panel A: Trust							
Rate of violence	-0.0002				-0.0034***	-0.0034***	-0.0034***
	(0.0001)				(0.0009)	(0.0009)	(0.0009)
Coca Index*Shock		-0.3613***	-0.3613***	-0.3613***			
		(0.0926)	(0.0926)	(0.0926)			
Observations	9274	9274	9274	9274	9274	9274	9274
R-squared	0.0288	0.0302	0.0302	0.0302			
Panel B: Participation in community organizations							
Rate of violence	-0.0003*				-0.0018*	-0.0018*	-0.0018*
	(0.0001)				(0.0009)	(0.0009)	(0.0009)
Coca Index*Shock		-0.1872*	-0.1872*	-0.1872*			
		(0.0957)	(0.0957)	(0.0957)			
Observations	9410	9410	9410	9410	9410	9410	9410
R-squared	0.0306	0.0306	0.0306	0.0306			
Panel C: Contribution to community problem solving							
Rate of violence	-0.0002				-0.0023***	-0.0023***	-0.0023***
	(0.0001)				(0.0009)	(0.0009)	(0.0009)
Coca Index*Shock		-0.2425***	-0.2425***	-0.2425***			
		(0.0926)	(0.0926)	(0.0926)			
Observations	9398	9398	9398	9398	9398	9398	9398
R-squared	0.0126	0.0131	0.0131	0.0131			
Indiv. controls	No	No	Yes	Yes	No	Yes	Yes
Muni. controls	No	No	No	Yes	No	No	Yes

Note: Column (1) presents the OLS results, Column (2) the reduced form, Column (3) the reduced form including individual controls, Column (4) adds municipal controls, Column (5) the 2SLS estimation, and Column (6) and (7) the 2SLS estimation with individual and municipality controls. Standard error in parenthesis (robust clustered at the municipality level). All regressions include municipality and year fixed effects. Individual control variables include: gender, schooling, age, race, income, media consumption on radio, TV and newspapers, dummy for rural area. Municipality controls: number of students attending to school, fiscal performance, forcibly displaced population and suitability for growing coffee. The dependent variable is the rate of violence per 100,000 population, which corresponds to the sum of 18 violent indicators divided by population. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table A8: Testing monotonicity assumption

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7
Slavery	Low rugged	High rugged	Low slave mortality	High slave mortality	Low dem vote vote	High democratic vote	No r
Cotton suitability	0.396***	0.448***	0.573***	0.666***	0.588***	0.768***	0.728
	(0.013)	(0.020)	(0.013)	(0.030)	(0.012)	(0.063)	(0.0
Constant	0.138***	0.295***	0.146***	0.209***	0.175***	0.044	0.0
	(0.011)	(0.016)	(0.012)	(0.023)	(0.011)	(0.036)	(0.0
Observations	2,476	4,738	5,739	1,475	6,842	372	3,6
R-squared	0.519	0.353	0.507	0.450	0.510	0.404	0.5

Note: The table shows the results from the first stage of an instrumental variable regression for the different subsamples. Standard error in parenthesis (robust clustered at the state level). The dependent variables is the intensity of slaverty. Controls include: county size (in acres), average farm value, the proportion of small farms, and a measure of land inequality. These variables proxy for the degree of workforce required for agriculture. In addition, I control for characteristics related to trade and commerce, including indicators for whether the county had access to rail and steamboat-navigable rivers or canals, and the ruggedness of the county terrain, which were crucial for agricultural markets. Finally I include proxies for racist attitudes as the percentage of votes for the democratic party in 1860, the relative mortality of slaves to whites, and the average occupant size of slave quarters in farms as a proxy for slave treatment. All regressions include county and year fixed effects. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table A9: LIML estimators

	(1)	(2)	(3)
Dependent variable	Trust	Participation	Contribution
Rate of violence	-0.0031***	-0.0019	-0.0020**
	(0.0011)	(0.0012)	(0.0010)
Observations	11,682	11,889	11,869
R-squared	0.0002	0.0584	0.1295

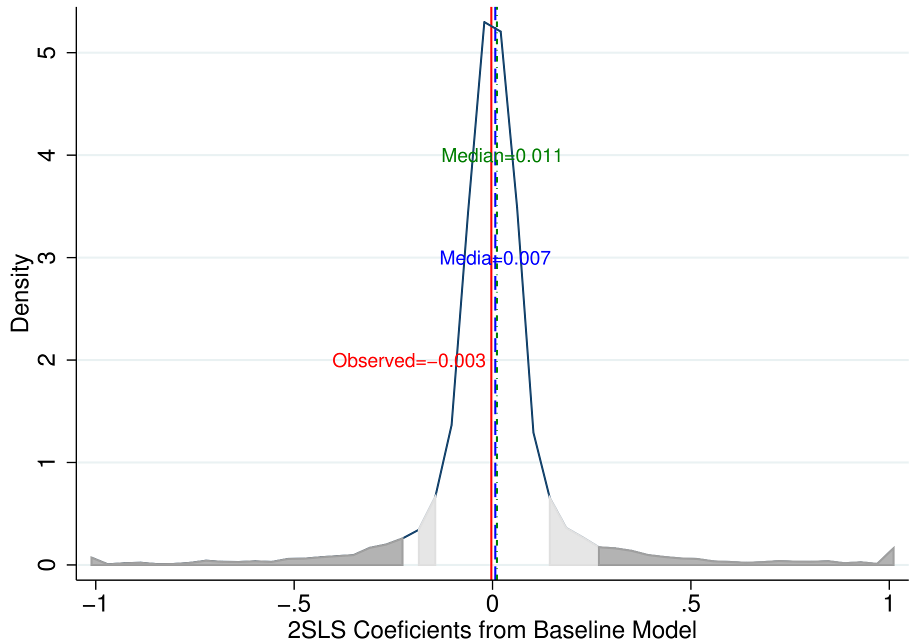
Note: This table replicates the results from Table 3, under LIML estimators (The LIML is an estimator that is less efficient, but also less biased to weak instruments (Angrist & Pischke, 2008)). Standard error in parenthesis (robust clustered at the municipality level). All regressions include municipality and year fixed effects. Individual control variables include: gender, schooling, age, race, income, media consumption on radio, TV and newspapers, dummy for rural area. Municipality controls: number of students attending to school, fiscal performance, forcibly displaced population and suitability for growing coffee. The dependent variable is the rate of violence, which corresponds to the sum of 18 violent indicators divided by population. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table A10: IV estimation with all variables collapsed to the municipality level

	(1)	(2)
Variables	Rate of violence	Trust
Coca index* Ln(External Shock)	57.66***	
	(14.42)	
Rate of violence		-0.0015**
		(0.0007)
F Cragg-Donald	16.38	
N	440	440

Note: Column (1) presents the first stage, and column (2) the 2SLS estimates for the sample collapsed at municipality level. So that the standard F Cragg-Donald can be computed as the errors are not clustered. Robust standard errors in parenthesis. p<0.01, ** p<0.05, * p<0.1.

Figure A1: Distribution of 2SLS Coefficient Estimates Using Randomized Conflict Allocations



Note: The density plot depicts the distribution of 2SLS coefficient estimates using the set of baseline controls with 10,000 draws of randomized allocation of violence among municipalities in Colombia. The dark shaded area indicates the bottom top 5%. The light shaded area shows the top and bottom 10%. The kernel density function and percentiles are estimated on the full set of 10,000 iterations.

B Data

1. Detailed individual controls

   - Age: Continuous variable are you? (question $q2$)
   - Rural: Dummy variable that varies on individual level. 1=Urban, 2=Rural (question ur)
   - Education: Continuous variable. Years of education (question ed)
   - Gender: 0=Male, 1=Female (question $q1$)
   - Black: Takes the value of 1 if individual report himself to be black. (question $cetid$)
   - Radio: "Do you listen the news in the radio? " Takes the value of 1 if individual report to listen the radio " Every day" or " at least once a week" , 0 if the answer is " seldom" or " never" (question $A1$)
   - TV: "Do you watch the news in the TV?" Takes the value of 1 if individual report to watch the TV " Every day" or "at least once a week", 0 if the answer is "seldom" or " never" (question $A2$).
   - Newspapers: "Do you read the newspapers?" Takes the value of 1 if individual report to read the newspapers " Every day" or "at least once a week", 0 if the answer is "seldom" or "never" (question $A3$).
   - Internet: "Do you read the news on the Internet?" Takes the value of 1 if individual report to read news on the Internet " Every day" or " at least once a week" , 0 if the answer is " seldom" or " never" (question $A4$).

   Imputation of missing data The method for imputing the missing data consists of calculating the mean value per year and municipality (Only 0.36% of the observations were missing values).

2. Data used for constructing coca suitability index
   Come form different sources and it is available at 30 seconds or 0.0083 degrees spatial resolution, which is approximate ($\sim 1\,km^2$)[48].

   Temperature

   - Mean temperature per year for period 1970-2000
   - Source: $CliMond$ (Version 2)
   - Freely available at: WorldClim - Global Climate Data (Free climate data for ecological modeling and GIS)
   - Variable used: $Bio001$

   Precipitation

   - Mean precipitation per year (mm) for period 1970-2000
   - Source: $CliMond$ (Version 2)

[48] For replication run program $Index - replication.py$ in $Python$ and $ArcGis$.

- Freely available at: WorldClim - Global Climate Data (Free climate data for ecological modeling and GIS)
- Variable used: $Bio012$

Relative Humidity

- This variable is estimated by using conventional formula for relative humidity (Unwin 1980)[49]:

$$Relative\, humidity = \frac{Vapor\, pressure * 100\%}{Saturated\, vapor\, pressure}$$

- information for $vapor\, pressure$ comes from $CliMond$ (Version 2). Freely available at: WorldClim. Whereas information for $Saturated\, vapor\, pressure$ is constructed by using temperature data and following formula (Mitchell et al. (2004))[50]:

$$Saturated\, vapor\, pressure = 6.107 * exp\left(\frac{17.38 * Temperature}{239 + Temperature}\right)$$

Altitude

- Meters above sea
- Source: U.S Geological Survey's Center for Earth Resources Observation and Science (EROS), with contribution of National Aeronautics and Space Administration (NASA), United Nations Environment Programme/Global Resource Information Database (UNEP/GRID), U.S. Agency for International Development (USAID), Instituto Nacional de Estadistica Geografica e Informatica (INEGI) of Mexico, Geographical Survey Institute (GSI) of Japan, Manaaki Whenua Landcare Research of New Zealand, and Scientific Committee on Antarctic Research (SCAR).
- Freely available at: GTOPO30

Ph Soil

- Measure for acidity and alkalinity of soil
- Source: Harmonized World Soil Database $v\,1.2$
- Freely available at: FAO Soil, created in 2004
- Variable used: $T_P H_H 20$

[49] More information here

[50] More information here.

C Theoretical Framework

C.1 Overview

I present a simple model to illustrate the mechanisms by which violence affects social capital. The model uses an insurance framework as a guide, and explains the key findings of Section 6, namely that conflict:

1. Fosters social capital for low levels of violence, but when the threat becomes severe social capital is negatively affected.

2. Has a stronger impact negative effect on social capital when perpetrators can not be identified.

C.2 Set-Up

Consider an individual who has to decide how much social capital to invest. The investment in social capital has two purposes: i) it enhances the benefits from wealth, and ii) protects individuals from violence. Formally she maximizes her expected utility by choosing the optimal amount of social capital in S[51]:

$$E(U) = (1-\pi)u(W - P(S)) + \pi u(W - P(S) - L(V,S) + S) \tag{1}$$

subject to:

$$W = (1 + \gamma S)W_e \tag{2}$$

$$P = pS \tag{3}$$

$$S \geqslant 0$$

$1 - \pi$ is the probability of having good neighbors. π is the probability of having neighbors that belong to an armed group and that attack them with V being the intensity of the attack. They are both exogenously given. Here I assume that the individual has a von Neumann-Morgenstern utility function $u(.)$ with the following properties:

1. Increasing. The first derivate is $u'(W) > 0$, so more wealth is always preferred to less

2. Strict concave. Second derivate is $u''(W) < 0$. This implies that the individual is risk-averse

Then I define the budget constraint. The individual's wealth is given by W. It depends on an initial wealth endowment and the investment in social capital as $W = (1 + \gamma S)W_e$. Intuitively, social capital can be thought as an investment that enhances wealth by a factor of γ. Different studies have proven the crucial role of social capital on economic outcomes.[52] Thus when there is no investment in social capital, wealth is given by W_e.

If the individual decides to "buy" insurance, or in this case to invest in social capital, she will receive a compensation S She pays P for this investment. The price of investing in social capital

[51] I assume that the individual can choose any vale of $S \geqslant 0$. The non-negativity restrictions says simply that the individual cannot offer a bet on to occurrence of a loss, and it is a realistic assumption on insurance markets

[52] See for instance Algan & Cahuc (2010), Rohner *et al.* (2013a), Guiso *et al.* (2006), Foster & Rosenzweig (2001), Fafchamps & Lund (2003), Nannicini *et al.* (2013), Glennerster *et al.* (2013), Guiso *et al.* (2004), Aghion *et al.* (2010), Cassar *et al.* (2013), Conley & Udry (2010), Bandiera & Rasul (2006), BenYishay & Mobarak (2014).

can be inferred from vales of P and S. The key point assumption is that $p = P/S$.

When the individual is attacked, a loss of size L occurs. This loss depends on the intensity of violence V, and social capital S. One can think of violence as increasing the portion of wealth that it is expropriated, and social capital as the tool that people have to protect themselves. In particular, it is given by the function $L(V, S) \in [0, 1]$. This loss function is twice differentiable, weakly increasing and concave on V, and weakly decreasing in S, and it satisfies $L(V, 0) = 1$ and $L(0, S) = 0$. This implies that all possible losses are realized when there is no investment in social capital, and there are no losses when violence is zero. This technology of protection takes the borrows the following functional form Jennings & Sanchez-Pages (2017):[53]

$$L(V,S) = \begin{cases} \left(\dfrac{V}{S}\right)^{\sigma} & \text{if } S > V \\ 1 & \text{otherwise} \end{cases} \tag{3}$$

This function has a constant elasticity $\sigma \geqslant 0$. Losses are complete when social capital is not enough to protect individuals from expropriation.

C.3 Comparative Statics

A representative individual maximizes her utility function subject to the budget constraint. Thus the simplest way to solves this is to substitute from the constrains into the utility function and maximize:

$$\max_S \qquad E(U) = (1-\pi)u\Big((1+\gamma S)W_e - pS\Big) + \pi u\Big((1+\gamma S)W_e - pS - L(V,S) + S\Big)$$

$$\frac{\partial E(U)}{\partial S} = 0$$

$$(\gamma W_e - p)(1-\pi)u'\Big((1+\gamma S)W_e - pS\Big) + (\gamma W_e - p + 1 - L'(V,S))\pi u'\Big((1+\gamma S)W_e - pS - L(V,S) + S\Big) = 0 \qquad (4)$$

we can name $(\gamma W_e - p) = A$ and expression (4) can be simplified to:

$$\frac{\pi}{1-\pi}\left(\frac{1}{A} + 1 - L'(V,S)\right) = \frac{u'\Big((1+\gamma S)W_e - pS\Big)}{u'\Big((1+\gamma S)W_e - pS - L(V,S) + S\Big)}$$

There is a $S^*(\gamma, W_0, P, \pi, V)$ that solves the above equation. Given the utility function assumptions the S^* depends on the parameters γ and π in the following way:

C.4 Predictions of the model

1. The probability that perpetrators can not be identified reduces the investment in social capital, as $\dfrac{\partial S^*}{\partial \pi} < 0$. If $\pi = 0$, there are no attacks and there is a positive investment in social capital. Thus the unobservability of individual allegiance will determine the level of participation. The fear of dealing with a neighbor that is a hidden member of the armed groups will drive social meetings out.

2. The intensity of the attack affects social capital. For low levels of violence ($S > V$), there is a positive investment in social capital that reduces the losses from the violent attack. However, for severe violence ($S < V$), the investment in social capital is reduced.

[53] Similar function forms have been used in Grossman & Kim (1995), Grossman & Kim (1995) and Robinson (2001).