THE ENVIRONMENTAL IMPACT OF CIVIL CONFLICT: THE DEFORESTATION EFFECT OF PARAMILITARY EXPANSION IN COLOMBIA

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Abstract

Despite a growing body of literature on how environmental degradation can fuel civil war, the reverse effect, namely that of conflict on environmental outcomes, is relatively understudied. From a theoretical point of view this effect is ambiguous, with some forces pointing to pressures for environmental degradation and some pointing in the opposite direction. Hence, the overall effect of conflict on the environment is an empirical question. We study this relationship in the case of Colombia. We combine a detailed satellite-based longitudinal dataset on forest cover across municipalities over the period 1990-2010 with a comprehensive panel of conflict-related violent actions by paramilitary militias. We first provide evidence that paramilitary activity significantly reduces the share of forest cover in a panel specification that includes municipal and time fixed effects. Then we confirm these findings by taking advantage of a quasi-experiment that provides us with an exogenous source of variation for the expansion of the paramilitary. Using the distance to the region of Urabá, the epicenter of such expansion, we instrument paramilitary activity in each cross-section for which data on forest cover is available. As a falsification exercise, we show that the instrument ceases to be relevant after the paramilitaries largely demobilized following peace negotiations with the government. Further, after the demobilization the deforestation effect of the paramilitaries disappears. We explore a number of potential mechanisms that may explain the conflict-driven deforestation, and show evidence suggesting that paramilitary violence generates large outflows of people in order to secure areas for growing illegal crops, exploit mineral resources, and engage in extensive agriculture. In turn, these activities are associated with deforestation.

JEL codes: D74, Q2
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1 Introduction

In the last few years there has been a growing interest on the effects of climate change and environmental deterioration on violent conflict. Social scientists have studied how global warming, climate volatility and water availability affect land use, economic growth and the relative scarcity of key commodities, and how these phenomena have fueled resource competition, social unrest and even violent conflict, especially in Sub-Saharan Africa. Several authors subscribe to a "Malthusian" view, arguing that the secular environmental damage coupled with population growth will necessarily produce social disruption and even conflict (e.g. Homer-Dixon, 1991)[1]. However – and surprisingly – despite theoretical reasons that suggest that conflict upsurges may also have environmental consequences, this opposite direction of causality has been much less studied.

Armed conflict generates large flows of refugees and internal migration either from the countryside to urban centers, or to unexploited frontier lands. In addition, while conflict often disrupts local economies, it also encourages the cultivation of illegal crops and the exploitation of natural resources. These examples illustrate the fact that forces associated with the dynamics of civil conflict may either encourage or reduce environmental pressures. But again, there is little empirical evidence as to whether conflict accelerates or decelerates environmental damage. Moreover, little is known about the channels linking the incidence and intensity of war with environmental outcomes.

Focusing on the recent experience of Colombia, this paper starts to fill these gaps in the case of deforestation. Using a satellite-based estimate of forest cover per municipality for 1990, 2000, 2005 and 2010, as well as detailed data on the longitudinal dynamics of civil conflict, we show that violence in Colombia has exacerbated deforestation. In particular, using a two-way fixed effects panel estimation we show that while conflict is more likely

[1] In 2012 the *Journal of Peace Research* published a 10-article special issue on the effect of climate change on conflict (Vol. 49, No. 1). Many of the contributing articles in the issue are sympathetic with this "environmental security" view. But this interpretation has been challenged by several scholars. Richards (1996), for instance, dismisses what he calls the "New Barbarism" theory of conflict, noticing that the process of forest conversion in Sierra Leone has taken place over many centuries, and that local land-users have responded in a sensible way to its different phases, with no evidence of environmental degradation spiraling out of control prior or around the years of civil war. He concludes that in Sierra Leone "war is a consequence of political collapse and state recession, not environmental pressure" (p. 124).

to occur in more densely forested areas, violence upsurges within municipalities produce deforestation. While this is true both for the activity of left-wing guerrillas and for that of right-wing paramilitary militias, in this paper we focus on the latter because we are able to confirm the panel findings using an instrumental variables approach. Such approach delivers a similar conclusion, suggesting that the effect of conflict on deforestation is unlikely to be driven by time varying omitted factors[2].

The instrumental variable approach exploits the creation in 1997 of a coalition of local right-wing militias was formed under an umbrella alliance called the United Self-Defense of Colombia (AUC). This alliance contributed substantially to the dramatic expansion of conflict activity during the late 1990s. This quasi-natural experiment allows us to instrument paramilitary activity with the distance from each municipality to the Urabá region, the epicenter of the paramilitary expansion. We do this for each of the available cross-sections of the deforestation data. The paramilitary expansion was characterized by the perpetration of selective massacres and by forcing large populations to flee in order to secure territory (Vargas, 2009). Paramilitaries displaced populations in part to grow illegal crops such as coca, and to expropriate the best land in order to develop a model of resource extraction and extensive agriculture (Goebertus, 2008). The resulting increase in land concentration and the implementation of such activities may have led to increased deforestation. We document the empirical relevance of these channels, and show that paramilitary attacks are correlated with forced displacement and subsequent coca cultivation, requests for extractive mining titles and growing oil-palm.

In the mid 2000s, following negotiation with the government of President Álvaro Uribe, the AUC paramilitaries largely demobilized. This historical episode allows us to conduct a falsification exercise. We show that after the AUC demobilization our instrument ceases to be relevant and, relatedly, that the deforestation effect of the paramilitary activity disappears.

Our results are of foremost policy relevance for a number of reasons. First, as a matter

[2]Unfortunately, we only have a good source of exogenous variation for the longitudinal patterns of paramilitary activity. The panel results of the effect of guerrilla-driven violence on deforestation are available upon request.

of general interest, but especially in Colombia in the context of an ongoing peace process, it is important to have a clear sense of the different ways through which conflict can cause economic and social costs. Valuing the potential dividends of peace is key to take a stand in terms of what society is willing to sacrifice in order to push the conflict to an end. Thus far, scholars studying conflict have been able to establish solid evidence on the long-term effects of violence in terms of the destruction of human and physical capital, often finding sizable effects (see Justino (2009) and Blattman and Miguel (2010)). However, some research has suggested that, at least in terms of physical capital, societies are able to recover from intense violence remarkably well in the long run (see, for example, Miguel & Roland, 2011).

Our findings suggest that conflict also has an effect on environmental degradation. To the extent that part of this damage is nonrenewable, or at least very costly to fix, our findings go against the idea that a full recovery from the consequences of violence is possible –even in the long run. This is a key finding, which policymakers should bear in mind when prioritizing efforts and public resources in the search for solutions to violent conflict. More specifically, our findings suggest that spending resources on ending violent conflict and building local institutional capacity (to prevent violence from displacing populations and enabling special interests to force economic activities that expand agricultural and mining boundaries) is even more socially profitable than previously recognized.

Second, our study not only provides evidence that conflict contributes to deforestation. It also sheds light on some of the mechanisms through which this occurs. Understanding these mechanisms is also important to designing strategies that attenuate the negative effect of conflict on the environment. Moreover, the key mechanisms also reveal the existence of strong economic interests that drive the connection between conflict and deforestation. These must be carefully taken into account. Also, in situations of post-conflict development, these groups likely become economic and political losers, as they formerly benefitted from violence and institutional disarray. Thus, policymakers should devise strategies to safeguard local communities from pressure from these interest groups.

Third, related to the previous point, we must recognize that economic development, even when orderly and legal, may still create deforestation. However, when deforestation occurs as a result of the interaction between violence and economic interests, it is more likely that institutions safeguarding the environment will be less able to take action. Therefore, identifying these economic interests and building institutional capacity (in particular, shielding them from being controlled by these vested interests) in places previously affected by violence is extremely important. Conflict often occurs in remote areas with scarce state capacity, in which public institutions are more easily controlled by militarily or economically powerful groups. Thus, the strengthening of institutions may require the mobilization of resources from national to local institutions. A considerable challenge in this regard is how to do this while also bolstering, rather than undermining, the development of local capacity.

While there is a large body of literature on the consequences of conflict, much of the empirical research relies on cross-country evidence, and typically does not adequately address issues of endogeneity. Indeed, Blattman and Miguel (2010) conclude in their survey of the literature that further cross-country regressions will only be useful to the extent that they can use credible methods to establish causality, and encourage more micro-level analysis relying on within-country variation in order to more credibly identify causal relationships. By relying on variation within Colombia and using an instrumental variables strategy, this paper joins an increasing body of work that follows such an approach, and identifies, for the first time, the effect of civil conflict on deforestation.[3]

Previous studies have looked at the connection between conflict and the environment (and deforestation in particular) in Colombia.[4] For instance, Dávalos et al. (2011) show that, in the south of the country, forest loss is more likely in areas with more coca plantations. Similarly, when comparing Colombia to Ecuador, Viña, Echavarria, and Rundquist (2004) find higher deforestation in Colombia and argue coca cultivation is one

[3]It is worth noting that the bulk of the literature that explores the effect of climate change on conflict suffers from methodological shortcomings that are similar to those mentioned in the case of the costs of conflict.

[4]And several studies examine patterns of deforestations, though not necessarily in connection to conflict. See, for example, Viña and Cavelier (1999), Etter, McAlpine, Pullar, and Possingham (2006) Etter, McAlpine, and Possingham (2008) Etter, McAlpine, Phinn, Pullar, and Possingham (2006a).

key driver of that phenomenon.[5] Armenteras, Rodríguez, and Retana (2009) examine the impact of roads and illicit crops on forests in the Colombian Guyana shield and find that both factors are important drivers of deforestation. Álvarez (2003) examines interesting sub-national variations in the policies of forest conversion applied by illegal armed groups; the study highlights the fact that the relationship between civil conflict and deforestation is not necessarily unique. On one extreme there is "gunpoint conservation", which refers to the fact that in some guerrilla-controlled areas, conservation is carried out by means of armed coercion.[6] On the other extreme, and much more frequently, armed groups lead a process of rapid conversion of forests and crops to cattle ranches and coca plantations. Finally, Etter, McAlpine, Phinn, Pullar, and Possingham (2006b) investigate the deforestation process in the state of Caquetá, during the period 1989–2002. They document the finding that the peace process between government and guerillas in 1999–2002 redirected the spread of deforestation and increased forest regeneration.

Another set of studies on the relation between conflict and the environment in Colombia is compiled in a volume edited by Cárdenas and Rodríguez (2004). As the editors emphasize, a key message stemming from the studies in this volume is that the relationship between the environment and violent conflict is extremely complex, with various directions of causality between all the intervening variables. In this sense, our effort to convincingly disentangle one of the directions of causality is an important contribution to the debate. The studies in this volume also shed light on the potential relevant channels linking violent conflict and environmental degradation in Colombia, underscoring in particular the role of illegal crops and that of natural resource exploitation by illegal armed groups.

Our paper builds on this literature and improves upon the way it has addressed endogeneity issues. We look at the entire country over a large period of time (1990–2010), and assess the causal effect of armed conflict on deforestation. We also explore

[5] See also Young (1996), who examines coca-driven deforestation in Peru, and Bradley and Millington (2008) who look at the case of Bolivia.

[6] For instance, the ELN guerrillas protect some forests in the Serranía de San Lucas "purportedly because of their role in the local hydrology. Their methods include placing landmines or posting signs that warn of landmines in patches of montane forests. In addition, these forests –el monte– have served as refuge from air surveillance by government forces" (p. 57).

the potential mechanisms mediating this relationship.

The rest of the paper is organized as follows. Section 2 presents the empirical strategy. Section 3 describes the data. Section 4 presents the main results, robustness checks and mechanisms. A few additional robustness exercises are relegated to the Appendix in the interest of brevity. Finally section 5 concludes.

2 Empirical strategy

2.1 Panel specification

To test the relationship between conflict upsurge and deforestation, we use the following reduced-from specification:

$$forest_{m,t} = \beta_0 + \beta_1 Para_{m,t} + \beta_2 X_{m,t} + \delta_m + \delta_t + \sum_t \kappa'_m \bar{\omega}_t + \epsilon_{m,t}, \tag{1}$$

where $forest_{m,t}$ is the ratio of forest to total area in municipality m at time t, for each of the approximately 1,000 Colombian municipalities and $t \in \{1990, 2000, 2010\}$.[7] To control for possible omitted variable bias, $X_{m,t}$ includes municipality-level time-varying controls like the municipal population (to account for the heterogeneity in the scale of the municipalities) and fiscal variables (to account for the economic conditions of the municipality). We also include time (year) fixed-effects, δ_t, that flexibly absorb any time trends affecting the rate of forest cover change in all municipalities in Colombia, as well as municipality fixed effects δ_m, that control for any fixed, municipality-specific characteristics which may influence forest cover. By including municipality fixed effects we focus on the effect of *changes* in paramilitary activity on *changes* in forest cover *within* municipalities. Thus, by design any fixed characteristics of municipalities cannot contaminate the estimation of the effect of paramilitary activity on forest cover. For further robustness, we also include differential trends depending on fixed geographical characteristics of municipalities. Thus, $\bar{\omega}_t = 1$ in year t and zero otherwise, and κ_m

[7] To follow the literature and for robustness we not only consider forest cover as the dependent variable, but also the log of forest cover.

are "time-invariant" geographical characteristics of municipality m described in Section 3. The inclusion of these controls is important as, having controlled for municipality fixed effects, the main remaining threat to our identification strategy is if deforestation in municipalities with more paramilitary attacks would have trended differentially, even without violence, for reasons other than the actions of paramilitaries. By directly allowing municipalities with different geographic characteristics to behave differently over time, we make sure that our results are not just driven by differential trends based on other municipal characteristics that could correlate with paramilitary activity.

$Para_{m,t}$ are paramilitary attacks in municipality m during the years leading up to period t. We check the sensitivity of our results against alternative time-windows to calculate $Para_{m,t}$. This is important as conceptually there is a difference between measures of armed actions (or presence) and proxies of "control" in a given municipality. In particular, while it is clear that the fact that we observe attacks by an illegal armed group in a given municipality is an indication of "presence" of that group, this fact does not necessarily imply that the group "controls" the area. It is moreover plausible that where armed groups have a sufficiently consolidated level of control there are actually less violent actions than in some other areas. Indeed, this idea has been suggested and extensively documented by Kalyvas (2006). Importantly, getting to this hegemonic type of control must necessarily involve some past violent actions. Hence, verifying different time windows to construct $Para_{m,t}$ is a useful exercise.[8]

In the specification in (1), therefore, the coefficient of interest is β_1, and it measures the relationship between prior violent activity by the paramilitary and levels of forest cover. This equation is a very demanding specification that arguably removes the most important sources of bias in estimating the impact of conflict on deforestation. However, even after the inclusion of all the controls, the fixed effects and the differential trends,

[8]Table A-1 provides evidence for the hypothesis that current hegemonic control (which involves little violence) is correlated with past violence in the case of the paramilitary. We use the dynamic panel data Arellano and Bond (1991) estimator to show that current paramilitary attacks are persistent in the short run (up to the third lag) but negatively correlated with past activity (starting in the fourth lag). Since theoretically both presence and control can have an impact on deforestation, in this paper we make no distinction between them, but check the sensitivity of our results against alternative time-windows and lags of paramilitary activity.

it is possible to raise the concern that the estimated impact of changes in violence in a given municipality is driven by other municipality-specific trends not accounted for by the two-way fixed-effects specification (for instance, by time-varying omitted factors). The ideal solution to this problem is finding an instrument for conflict activity, that is, a source of variation in violence that is otherwise unrelated to forest cover changes.

2.2 Instrumental variables

We use a geography-based measure of the distance of each municipality to the closest border of the region of Urabá as an instrument for paramilitary activity. Since this measure is time-invariant, for the instrumental variables specification we look at the cross-sections of the data on forest cover. That is, in each case we run the two-stage least squares (2SLS) specification:

$$Para_m = \gamma_1 Dist_m + \gamma_2 X_m + v_m \tag{2}$$

$$forest_m = \lambda_1 \widehat{Para_m} + \lambda_2 X_m + u_m \tag{3}$$

with equation (2) being the first stage and equation (3) the second stage of the 2SLS model.

In the first stage, $Dist_m$ is the Euclidean distance from municipality m to Urabá. While it might be preferable to use average travel time as the measure of distance, this information is not readily available in Colombia. However, as robustness we look at a distance measure that corrects for ruggedness of the terrain and for the presence of water courses, which are the two main drivers of differences in travel time across localities with similar linear distances. The predicted values of $Para_m$ from the first stage, $\widehat{Para_m}$, are used in the second stage to estimate the causal effect of paramilitary activity on forest cover in each cross section.

The basic rationale for the proposed strategy is that, while the distance to Urabá is a fixed municipality characteristic that is unlikely to have a direct effect on forest cover, it constituted an important determinant of paramilitary activity during the existence of the AUC, as this region was the epicenter of the nation-wide paramilitary expansion of the late 1990s. Indeed, the cattle-ranchers, landowners and large-plantation owners from Córdoba and northern Antioquia provided most of the initial funding necessary to sustain the expansion of the AUC from Urabá to the interior of the country. The famous banana producer Chiquita Brands International, for instance, was sued by family members of thousands of Colombians who were killed or who disappeared, for making payments to local paramilitaries.[9] Another example is the proved collusion of the Drummond Co. with paramilitaries to kill union leaders.[10]

This expansion was driven by massacres of alleged guerrilla supporters from the population in the areas that the paramilitaries went on to consolidate. At its peak of strength in 2002 the AUC had achieved a nation-wide presence and the bulk of the funding of their 30,000+ army had shifted from cattle ranchers and landowners to the growing and trafficking of illegal drugs. In December 2002 the AUC declared a unilateral ceasefire and in January 2003 the peace talks with the government of President Uribe began. These ended with the *de jure* demobilization of the entire AUC structure in 2005 and 2006. In this sense the distance to Urabá constitutes a good instrument for paramilitary activity during the six-year period of AUC existence. Indeed, it is strongly correlated with such activity and most importantly, being a fixed geography-based characteristic, is unlikely to be associated with the timing and intensity of deforestation. In addition, because the distance measure should not affect paramilitary activity after the 2002 ceasefire and posterior demobilization and dismantling of the armed group, the later cross-sections serve as a falsification exercise in which we expect the coefficient γ_1 not to be significant in the first stage.[11]

[9] "Colombians sue Chiquita over paramilitary payments," CNN, June 1, 2011. Available from: `http://edition.cnn.com/2011/WORLD/americas/05/31/colombia.chiquita.lawsuits/` (last accessed 12/7/2013).

[10] "Colombian judge convicts ex-contractor in Drummond union leader killing," FOX NEWS, February 6, 2013. Available from: `http://www.foxnews.com/world/2013/02/06/colombian-judge-convicts-ex-contractor-in-drummond-union-leader-killing/` (last accessed 12/7/2013).

[11] After the demobilization of the AUC members, our conflict database records as paramilitary violence the attacks by splintered AUC fronts that did not demobilize, and later in the sample period, activity by groups called "neo-paramilitaries" and "criminal bands."

3 Data

To econometrically examine the connection between armed conflict and measures of environmental degradation, we need data both on deforestation rates and the incidence of paramilitary activity.

3.1 Data on deforestation

Using standard GIS techniques we created a dataset on deforestation at the municipal level, taking advantage of detailed maps recently put together by the national agency IDEAM in partnership with the Moore Foundation. These maps portray forest/no forest information based on images with high spatial resolution for the entire country.[12] There are maps for the years 1990, 2000, 2005 and 2010. For consistency with the periodicity of the measures in the panel analysis described by equation 1 we use the years 1990, 2000 and 2010. However, the because the IV analysis (equations 2 and 3) looks at the cross-sections separately, then we use the 2005 satellite map of forest cover.

Panel A of Table 1 reports the descriptive statistics of the dependent variables used in the different specifications. The mean share of the municipal area covered with forrest averaged for the years 1990, 2000 and 2010 is 24%, with municipalities having no area covered with forest (mainly large urban centers) and municipalities featuring up to 99% of their surface with forrest. The mean figure decreases from 25% in 2000 to 21% in 2010.[13]

3.2 Data on paramilitary activity

Our data on paramilitary activity comes from a detailed event-based data from the Center for the Study for Armed Conflict (CERAC), and our own update of this data source. The data cover the period 1988-2009, which encompasses the four observations we have

[12] A "forest" is defined as a portion of land occupied primarily by trees (but that may also contain bushes, palm weeds, etc.) with a minimum canopy density of 30%, a minimum elevation of 5 meters (about 16ft) and a minimum covered surface of 1 hectare (about 2.5 acres). These characteristics help exclude commercial crops like oil palm.

[13] As explained in section 4.3, we do not look at the 1990 cross-section in the IV analysis and hence the descriptive statistics for this year are not reported on Table 1.

in the deforestation data. For every event the conflict dataset records its type, the date, location, perpetrator, and victims involved in the incident. The dataset, which is described thoroughly by Restrepo, Spagat, and Vargas (2004) and Dube and Vargas (2013), is constructed on the basis of events listed in the annexes of periodicals published by two Colombian human rights NGOs: CINEP and Justicia y Paz. Most of the event information in these annexes comes from two primary sources, a network of priests from the Catholic Church with representation in almost every municipality in Colombia, and over 25 newspapers with national and local coverage. The inclusion of reports from the Catholic priests, who are often located in rural areas that are unlikely to receive press coverage, broadens the municipality-level representation.

Based on these sources, the resulting data includes every municipality that has ever experienced a conflict-related action (either a unilateral attack or a clash between two groups). There is a stringent regime to guarantee the quality and representativeness of the data. As a first step a large number of events is randomly sampled and compared with the original source, to check for correct coding from the annexes. Second, a different random sample is searched for in press archives to confirm whether incidents should have been included in the annexes. This step checks the quality of the raw information provided by the NGOs, which turns out to be quite high. Third, the largest events associated with the highest number of casualties are carefully investigated in press records. Finally, without double-counting, the dataset is complemented by additional events provided in reports by human rights NGOs and by Colombian Government agencies.

We extract from this source the count of paramilitary attacks per municipality and year to construct the main independent variables used throughout the analysis. The descriptive statistics of these are reported on the Panel B of Table 1. As explained in section 2, we look at flexible lagged specification of paramilitary activity to assess the effect of the paramilitary expansion on deforestation. Further, we explore the extent to which our results are robust to accounting for potential spillovers of paramilitary activity on deforestation across municipalities. Thus we summarize in Table 1 all the cuts of the data on paramilitary activity used in the main analysis, its robustness and in the analysis of the mechanisms. This also help us compute the substantive effects of the coefficients reported in the regressions.[14]

3.3 Instrumental variable

Panel C on Table 1 reports the descriptive statistics of the main instrument, namely the Euclidean distance from every municipality to the Uarabá region, as well as of an alternative version of the instrument that penalizes such distance for the presence of mountains between the two points, and hence approximates better the actual travel time between them[15]. While the latter IV is used for robustness, we favor the most parsimonious specification for interpretation purposes as both yield equivalent substantive results.

The average distance from a municipality to the closest border of the Urabá region is 433Km (about 269 miles), with (neighboring) municipalities as close as 23Km (14 miles) and others as far as 1,524Km (947 miles). The roughness-penalized distance is, of course, larger on average as Colombia is a very hilly country.[16] The average roughness-corrected distance is 16,142Km (10,030 miles).

3.4 Data on potential channels

Informed by previous research on deforestation in Colombia[17], and by anecdotal evidence, we study several channels that are likely to mediate the relationship between conflict and deforestation. First, we confirm that conflict drives outflows of forced displacement, and check whether places that have experienced more displacement are more likely to witness deforestation afterwards. Indeed, Colombian armed groups are known for their strategy

[14]Note that since paramilitary violence is only available since 1988, in our panel regressions, for the 1990 cross-section we are forced to assume that the average violence two years prior 1990 is also a good approximation to violence for longer lags. In the case of the instrumental variable estimations, we instead exclude the 1990 cross-section to have full comparability in the lag structure.

[15]The penalized measure simply adds to the straight line calculation the additional kilometers required to travel up and down the rugged terrain in between two municipalities.

[16]The Andean cordillera breaks in three mountains chains when it enters Colombia from the south. Within Colombia, the three resulting cordilleras cover a large fraction of the country's surface.

[17]See, for example, Viña and Cavelier (1999), Etter, McAlpine, Pullar, and Possingham (2006), Dávalos et al. (2011), Viña et al. (2004) and Armenteras et al. (2009).

of forcing via violent means the migration of local leaders and peasants, in order to secure territorial dominance to put in place their (legal and illegal) investments. The data on forced displacement comes from *Acción Social*, the government agency in charge of social policy (it was replaced in 2011 by the *Departamento de Prosperidad Social*).

Second, we look at whether conflict upsurges are correlated with the subsequent appearance of coca fields, and check if these reduce the share of forest cover at the municipal level. Data on the amount of land used to grow coca bushes is calculated using satellite imagery of the entire territory of Colombias mainland by the Integrated Monitoring System of Illicit Crops (SIMCI, in its Spanish acronym) of the United Nations Office on Drugs and Crime (UNODC).

Third, in addition to (illegal) coca growing we look at (legal) exploitation of natural resources and extensive agriculture. These two activities are in turn likely to affect the share of land covered with forests. To this end we use data obtained from the Ministry of Mines and Energy on the allocation of mining titles and from the Ministry of Agriculture on the cultivation of African oil-palm.

Not all these sources are available for the entire period for which we have forest cover information. However, all of them overlap in the four-year period 2002-2005. Hence, when examining mechanisms, we focus on the average of each channel for this period, how is it affected by lagged paramilitary activity, and how it correlates with the change in forest cover over between the 2000 cross section and the 2005 one. Panel A of Table 2 reports the descriptive statistics of each mechanism, averaged over the period 2002-2005 and across the 1,118 Colombian municipalities.

3.5 Other data

In addition to the time and municipality fixed effects, we include a battery of municipal-level controls. First, as a scale control, we include both the municipal population and the share of population settled in the urban part of the municipality. These two variables, for which we report descriptive statistics in Panel B of Table 2, are under the vector called *Population* in all the tables, and their source is DANE, Colombia's national statistics office.

Second, in accord with the empirical literature suggesting that conflict is correlated with geo-ecological conditions like rainfall and the roughness of the terrain (e.g. Miguel, Satyanath, and Sergenti (2004) and Fearon and Laitin (2003)), under the label *Geography* in the tables we include various (time-invariant) geographical characteristics: the municipal surface area, its elevation, the average rainfall and the availability of water (rivers and lakes), the erosion and quality of the soil and the distance to the department's capital.[18,19] Importantly, because the satellite-based measure of forest cover tends to underestimate the forested area in cloudy regions, we also control for the share of the municipal surface shaded by clouds at the time each cross-section of forest was computed. With the exception of the clouds data, which is taken from the satellite-maps of the national agency IDEAM and the Moore Foundation, all the geo-ecological controls come from IDEAM and IGAC (another national agency), in charge of the climate and geographic analysis respectively. It should also be noted that, while the geographical characteristics are time-invariant, in the specifications that include the municipality fixed effects we include those interacted with the time dummy. This allows flexibility in controlling for differential time trends common to municipalities that have similar geo-ecological conditions. Descriptive statistics for these characteristics are reported on Panel C of Table 2.

Third, under the label *Rents* we include both the mining royalties received by the municipality and the municipal income tax revenue (per 100,000 inhabitants). Both controls are very important. On the one hand, by controlling for the amount of royalties obtained from the exploitation of natural resources like oil, coal or gold, we are accounting for the availability of legal economic rents that can be captured by illegal groups. On the other hand, in the absence of municipal-specific GDP data in Colombia, the income tax revenue is a good proxy for the municipality's economic activity, which is one of the most robust correlates of the incidence of conflict in the cross-country literature (e.g. Fearon

[18] In Colombia's political division, the 1,100+ municipalities of Colombia are equivalent to US counties. In turn, the departments, of which there are 33, are like the US states.

[19] The distance to the department's capital, as well as our instrument (the distance to the closest border with the Urabá region), are computed using standard GIS software with a shape file provided by IGAC.

& Laitin, 2003 and Collier & Hoeffler, 2004). The fiscal data is summarized in Panel D of Table 2 and comes from the National Planning Department.

4 Results

4.1 Baseline results

To empirically assess the effect of conflict on deforestation outcomes we start by estimating the baseline model in (1).

Our measure of conflict is the number of attacks perpetrated the paramilitary in a given municipality. As mentioned, it is important to check the sensitivity of the results to alternative time-windows and lags of this measure, the reason being that the "presence" of a non-state actor is not equivalent to that group's "control". Indeed, when a territory is no longer contested by two factions, the winning group may no longer need to conduct armed actions, as it now rules the territory (Kalyvas, 2006). However, for the same reason this type of control is often preceded by a contestation stage in which armed activity is intense.

Panels A through D of Table 3 report the OLS results. Each panel aggregates lags of increasing lengths. Hence, Panel A averages attacks two to one years prior to the measurement of forest cover, Panel B four to one, and so forth, up to panel D which averages attacks from year -1 to year -8. That is, Panel D looks at the effect on forest cover of the average paramilitary activity in the eight years before forest cover is measured. In every panel, the first column includes no controls. Column 2 uses the municipal population as scale control and the proportion of urban population to account for how urbanized the municipality is. This is important as, everything else equal, deforestation should be greater in more urbanized areas. Because our dependent variable is measured in 1990, 2000 and 2010, in order to flexibly control for aggregate temporal shocks in Column 3 we add time fixed-effects. Columns 4 and 5 include, respectively, the geo-ecological and the fiscal controls described in Section 3.5, which account for geographical confounders of both conflict activity and forest cover and for the municipal general economic activity and the activity related to the exploitation of natural resources.

Columns 1-5 exploit differences in conflict incidence *between* municipalities to study how these correlate with municipal differences in forest cover. However, given the likely influence of conflating factors that may affect both municipal forest cover and conflict, we emphasize the point that while the results in these columns serve as a useful reference point, they cannot be interpreted causally. In contrast, by adding municipality specific fixed effects that flexibly control for any fixed, municipality-specific characteristic that may influence changes in forest areas, Column 6 focuses on the effect of changes in violence on changes in forest cover within municipalities. In this column we continue to control for time-varying municipal characteristics. Moreover, we interact time-invariant characteristics (like the geographical controls) with the time fixed effects. As noted in Section 2, this allows us to control for potentially common trends among municipalities with similar geographic characteristics.

As apparent from the above explanation, each one of the coefficients reported in Table 3 is an estimate of the effect of interest (β_1), coming from a different regression.[20] According to Columns 1 to 5, in all panels, violence perpetrated by the paramilitary increases the share of land covered by forest across municipalities. If these estimates were to be believed, it might be thought that not only deforestation is not a cost of armed conflict in Colombia, but instead, that the reverse is true, i.e. that violence is a force that favors re-forestation. Taking as a benchmark the coefficient reported in the fifth column of Panel B, which includes all the controls but the municipality fixed effects, a one standard deviation increase in the two-year cumulative lagged paramilitary attacks (= 0.3, see ninth line of Panel B of Table 1) increases the municipal share of forest cover in 1.02 percentage points ($= 0.3 \times 0.034 \times 100$).

However, as noted, the results reported in Columns 1 to 5 should be interpreted as a correlation. Column 6, moreover, suggests that the causal relation points in the opposite direction: once all time-invariant municipal-specific heterogeneity is accounted for by the fixed effects, and the focus is placed on the effect of violent surges on changes in

[20]The estimates of the controls, omitted for simplicity, are available upon request.

forest cover within municipalities, the is effect is negative. Focusing on the estimated coefficient of the sixth column of Panel B, which in addition to the entire set of controls includes municipal fixed effects, a one standard deviation increase in the two-year cumulative lagged paramilitary attacks decreases the municipal share of forest cover in 0.34 percentage points ($= 0.3 \times -0.0113 \times 100$). Although the magnitude of the effect is rather small, the figure is somewhat misleading. The paramilitary expansion made municipalities go from experiencing no attacks to experiencing at the very least one of them. In this case the interpretation of the same estimated coefficient is different: A municipality that goes from zero to one attack decreases the municipal share of forest cover in the two subsequent years in 1.13 percentage points. This effect, equivalent to 4.3 standard deviations of forest cover in the sample period of Table 3, is in contrast quite substantive. Moreover, a municipality that goes from zero to five attacks (the maximum of the average two-year cumulative lag) decreases the municipal share of forest cover in 5.7 percentage points ($= 5 \times -0.0113 \times 100$).

Hence, we conclude that while conflict tends to occur in places with more forest cover (Columns 1 to 5), the effect of conflict on forest cover is negative, as upsurges in conflict-related activity within municipalities produce deforestation (Column 6).[21]

We end this section by emphasizing that the intuitive nature of the interpretation of why the coefficient of interest flips the sign once the fixed effects are included. Armed conflict is correlated with rough terrain as illegal rebel groups find it easier to hide and establish their safe-heavens in forests, jungles, and rough geography as these territories are harder to access by the state.[22] Thus there is a positive cross-sectional correlation between the presence paramilitaries and the proportion of forest. However, in a given municipality an *increase* in paramilitary activity leads to a reduction in the forest cover, even after controlling for trends in deforestation among regions with similar geographic characteristics. The latter is indeed the interpretation of the coefficient of Column 6 of Table 3, which includes municipal fixed-effects and trends parametrized as functions of

[21] The negative estimated coefficient of Column 6 ceases to be significant when we look at the average eight-year lag (Panel D of Table 3).

[22] See Fearon and Laitin (2003) and Collier and Hoeffler (2004) for cross-country evidence of this positive correlation.

observable municipal variables.

4.2 Robustness

Before looking at the instrumental variables estimates, we estimate alternative specifications of the baseline panel regression. The corresponding tables are reported in the Appendix.

As a first robustness check we repeat the baseline results, but use as the dependent variable the logarithm of the proportion of forest cover, rather than the untransformed proportion. This measure is commonly used in environmental economic literature, and hence for comparison purposes it is important to show that our results are robust to this transformation. The results are reported in Table A-2 and indeed the results are qualitatively unchanged. For comparability, focus again on the sixth column of Panel B: A municipality that goes from zero to one attack decreases the municipal share of forest cover in the two subsequent years in 0.68 percentage points ($= 1 \times -0.00675 \times 100$).

This robustness to functional form dependence, by estimating the impact of conflict on percentage rather than absolute changes in forest cover, also reveals that our results are not simply an artifice of differences in the levels of forest cover for municipalities with and without paramilitary violence.

For the second robustness check we add to the most demanding baseline specification, which included all the controls and the time and municipal fixed effects (as reported in Column 6 of Table 3), spatial lags of the conflict measure. By doing this we account for the potential spatial diffusion and spillovers of conflict: The share of the municipal land covered with forest is likely to be affected not only by the violence that takes place within the municipal boundaries, but also in neighboring regions.

Table A-3, shows the results of estimating model (1) with all the controls plus spatial lags of paramilitary attacks. We keep the same lag structure of the conflict variable in Panels A through D, and include three columns that look cumulatively at different spatial lags: in Column 1 the main independent variable is average paramilitary attacks of a given municipality and all its neighbors (that is, the municipalities that share borders with a specific town). Column 2 computes this average, also taking into account the municipalities that are neighbors (have a common border) with the neighbors of order one (included in Column 1). Column 3 aggregates an additional layer of neighbors. The estimated coefficient is not only still negative (and significant up to four years of cumulative lag) but also larger in magnitude than the coefficient estimated without spatial lags (Table 3, Column 6). This indeed implies that failing to account for the geographical spillovers of violence underestimates the effect of conflict on deforestation. Take for comparability the average of the cumulative two-year lagged paramilitary attacks up to the third order neighborhood of a given municipality (Column 3 of Panel A of Table A-3). A municipality surrounded by a neighborhood that experiences at least one paramilitary attack decreases its share of forest cover in the two subsequent years in 4.96 percentage points.

One additional robustness check repeats the baseline specification but, instead of exploring different cumulative lag structures of the conflict variable, looks at the non cumulative lags. The reasoning behind this is that it may be the case that what affects current environmental outcomes is the lagged conflict activity only, and not the current-plus-lagged activity, as implied by the cumulative lags. These results are reported in Figure 1. We plot a (dark) line connecting the estimated coefficients of all the lags from the first up to the eighth, together with the 95 percent confident bounds. The estimates come from the specification that includes all controls as well as the municipal and year fixed effects. The figure suggests that the estimates of lagged paramilitary violence are generally not significant, which implies that what produces deforestation is the cumulative history of paramilitary violence.

4.3 Instrumental variables results

Even with fixed effects and additional controls, it may still be the case that there are omitted municipal time-varying characteristics that are correlated both with past activity of the illegal armed groups and with current deforestation. To account for such a potential source of bias, we propose an exogenous source of variation during the years in which the AUC was active. The distance of every municipality to the region of Urabá is a plausible instrument because it is a source of variation of paramilitary activity that, being a geography base time-invariant measure, is arguably otherwise unrelated to changes in forest coverage overtime.

Because of the lack of a time-varying instrumental variable, we here look at the 2000, 2005 and 2010 cross-sections of forest cover separately. The odd columns of Table 4 estimate the effect of paramilitary activity for different cumulative lags on forest cover using OLS. The entire set of controls (excluding, of course, fixed effects) is included in all the specifications. The estimated coefficients are generally either not significant or positive and significant. The positive sign is consistent with the panel results presented in the first five columns of Table 3.

The even columns estimate the 2SLS model given by equations (2) and (3). Consistent with the findings of the entire panel and adding the municipality fixed effects for the 2000 cross section of forest cover, the causal effect of paramilitary attacks on forest cover (given by the second stage) is negative, implying that paramilitary violence induces deforestation. This is true for the different lags reported from Panel A to Panel D and the magnitude of the coefficient increases across specifications that add additional lags structures. In addition, the fist stage results validate the relevance of the instrument. The distance from every municipality to the closest border of Urabá is a significant predictor of paramilitary activity in this cross-section. Moreover the F-statistic is greater than the rule-of-thumb figure of 10 used to identify strong instruments in all cases.

As for the size of the effect in 2000, a municipality that goes from zero to one attack in the two year prior to 2000 experiences a reduction in its share of forest cover of 69 percentage points (Panel A, Column 2). Note that this year is the peak of the AUC paramilitary expansion and thus it is likely to have produced the highest effect of deforestation.

The 2005 cross-section provides a very similar picture, with the exception that the distance to Urabá does not explain paramilitary activity in the two years preceding 2005. Consistent with this lack of exogenous source of variation we find no effect in the second stage (see Panel A, Column 4). Longer lags however have a significant first stage and the causal effect of paramilitary attacks on forest cover is negative and significant.

Notice that rather than going against the story that paramilitary violence increases deforestation, this last result provides a validation of it. As explained before, in December 2002 the AUC declared a unilateral cease-fire when initiating the negotiations with the government. Clearly, from this point onward the dynamics of paramilitary violence changed: the number of AUC actions fell, and whatever violence persisted, it was no longer strongly associated with distance to Urabá. Thereafter, paramilitary activity was perpetrated by splintered former AUC fronts, which did not demobilize and thus became scarce. This is why there is not reason to expect *a priori* any effect of the distance to Urabá on paramilitary activity. One should not expect an effect of paramilitary violence on deforestation in the last cross section (2010) either. Column 6 of Table 4 confirms this intuition by showing that neither the first stage nor the second stage are significant. Moreover, focusing on the 2005 cross-section, as noted we do find a significant first and second stage result when looking at long lags of paramilitary activity. Again, this provides further validation of the approach as the AUC demobilization began in 2002 and the peace deal was signed in 2005. For long lags prior to 2005, however, the Urabá remained an important epicenter of paramilitary activity.

Table A-4 in the Appendix shows that the IV results are robust to a refinement of the instrument, so that instead of using the Euclidean distance from every municipality to Urabá, we approximate the actual travel distance by weighting the Euclidean distance by the roughness of the terrain located between each municipality (outside Urabá) and this region. Again, for the 2000 cross section the first stage shows a good explanatory power of the instrument and the second a negative causal relationship between paramilitary attacks and the proportion of land covered by forest in each municipality. However, neither of these facts is true for the 2005 cross-section and the second stage is not significant in the 2010 cross section. This is consistent with the demobilization of the AUC in the mid 2000s. The size of the effect in 2000 is smaller than in the case that does not correct the instrument for the roughness of the terrain: A municipality that goes from zero to one attack in the two year prior to 2000 experiences a reduction in its share of forest cover of 27 percentage points (Panel A, Column 1).

4.4 Mechanisms

To explore the mechanisms mediating the effect of paramilitary violence on deforestation, we look at three potential channels plus one intermediate outcome. The channels are the amount of land cultivated with illicit coca crops (used, among other things, to finance the expansion of many AUC fronts), the municipal area requested for the exploitation of underground minerals, and the land cultivated with oil palm. In turn, the intermediate outcome is the number of internally displaced people who abandon a municipality. The idea is that paramilitaries forcibly displace local leaders and peasants in order to secure the control of valuable land, and this land is subsequently used to carry out economic activities that may be legal (mining, extensive agriculture) or illegal (coca growing)[23].

Tables 5 to 8 test these mechanisms with the following structure: consistent with the lags structure of Table 3, columns 1 through 4 look at the effect of different cumulative lags of paramilitary violent activity, from the average two year lag up to the average eight year lag, on the average observed channel from 2002 to 2005. This is to corroborate that paramilitary violence affects each mechanism in the expected direction, and that this is robust to different lag structures, as showed in the previous tables.[24] Column 5 looks at the effect of each outcome (mechanism) on the inter-period change in the proportion of forest cover, from the 2000 to the 2005 cross-section. This second specification is used to corroborate whether the channel produces deforestation.

Table 5 starts with the intermediate outcome. It shows that paramilitary attacks in the years preceding 2002 exacerbate the average outflow of IDPs in the period 2002-2005. In turn, the higher the level of outgoing forced displacement in this period, the larger the drop in forest cover between 2000 and 2005.

Table 6 concludes the same as Table 5 for coca growing: pre-2002 paramilitary attacks

[23]Illegal mining is also common, but we do not have reliable data on this activity.

[24]Because most of the channels explored are available for a period starting after 2000 (generally 2002) and before 2010 (generally 2005) we cannot test the mechanisms for the entire sample period, and hence we focus on their 2002-2005 value.

are associated with more area cultivated with coca in the 2002-2005 period (Columns 1 to 2), though this effect is only significant for the average paramilitary attacks in the four years preceding 2002. In turn, these areas experienced a larger drop in forest cover (Column 5).

Table 7 reports a similar story for the case of coal mining: One the one hand, more titles are allocated in areas that had experienced more violence in the years prior to 2002 (especially up to four years before, as only Columns 1 and 2 are statistically significant). On the other, places with more mining activity witnessed a larger drop in forest cover (Column 5).[25]

Finally, Table 8 suggests that paramilitary attacks are followed by the introduction of African oil palm crops, which in turn produce deforestation (though this last relationship is short being significant).

These results are consistent with the anecdotal evidence and journalistic accounts that portray the paramilitary militia as a violent group that clears valuable areas through displacement, thus allowing legal and illegal economic interests to buy the vacated lands at very low prices in order to establish profitable activities. In turn, this process ends up linking the violent territorial expansion of armed groups with deforestation.

5 Conclusion

Despite the growing literature on the effects of climate change and environmental deterioration on violent conflict, little research has been done on the opposite direction of causality, namely the effect of conflict on environmental outcomes. This paper starts to fill this gap by looking at the effect of conflict on deforestation across municipalities in Colombia.

Our subnational level approach contrasts with the cross-country literature and facilitates the solution of the empirical challenges that are common in that literature. In particular we take two complementary approaches to deal with potential issues of endo-

[25]We found no significant effects in similar regressions using requests for exploitation of other minerals: gold on the one hand, and an aggregation of copper, iron, aluminum, silver and platinum, on the other.

geneity and omitted variable bias. First, we estimate a fixed-effects model that allows us to look at the impact of conflict surges on deforestation rates within a municipality over time, thereby accounting for any municipal-specific unobserved heterogeneity that is time-invariant. Second, we instrument paramilitary violence with the distance to the region that constituted the epicenter of the paramilitary expansion in the late 1990s. We exploit this source of exogenous variation to estimate the causal effect of paramilitary attacks on deforestation.

The results from both specifications point to the same conclusion, namely that violent conflict in Colombia has been a force that has driven and continues to drive deforestation. This is robust to different lag windows of the measurement of violent conflict.

Moreover, we explore the mechanisms that may explain the deforestation effect of conflict. Our results are consistent with the idea that paramilitary militias use the following modus operandi: first, valuable territories are cleared through violent intimidation, which induces forced displacement; second, the vacated land is purchased at very low prices; and third, legal and illegal investments are instituted in those areas. Examples of end products of this process are coca crops, mineral exploitation and oil palm agriculture.

These findings have important policy relevance as, in the context of an ongoing peace process, it is important to have a clear sense of what the costs of conflict are, in order to evaluate the potential dividends of peace and take a stand as to what society is willing to sacrifice in order to drive the conflict to an end. Knowing the mechanism is also important in order to design strategies that attenuate the negative effect of conflict on the environment. Moreover, the key mechanisms also unveil the existence of strong economic interests driving the connection between conflict and deforestation. Of course, economic development, even when orderly and legal, may create deforestation. But when deforestation occurs as a result of the interaction between violence and economic interests, it is more likely that institutions safeguarding the environment are less able to take action. Identifying these vested interests and building institutional capacity in places affected with violence is therefore of the utmost importance, both to attenuate these costs during conflict and to prepare for potential actions of these groups in a post-conflict scenario.

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Table 1: Descriptive statistics: Main variables

	Obs	Mean	Stdv.	Min.	Max.
Panel A: *Deforestation Outcomes*					
Share of mun. area with forest (1990, 2000, 2010)	3363	0.24	0.26	0	0.99
Share of mun. area with forest (1990)	1121	0.27	0.26	0	0.99
Share of mun. area with forest (2000)	1121	0.25	0.26	0	0.98
Share of mun. area with forest (2005)	1121	0.23	0.25	0	0.98
Share of mun. area with forest (2010)	1121	0.21	0.25	0	0.98
Panel B: *Paramilitary Attacks (PA)*					
PA t-1 − t-2 (t={1990, 2000, 2010})	3253	0.07	0.3	0	5
PA t-1 − t-4 (t={1990, 2000, 2010})	2196	0.06	0.24	0	3.25
PA t-1 − t-6 (t={1990, 2000, 2010})	2179	0.07	0.22	0	2.67
PA t-1 − t-8 (t={1990, 2000, 2010})	2167	0.07	0.21	0	3
PA t-1 − t-2 (t={1990, 2000, 2010}) - spatial lag 1	3280	0.08	0.2	0	3
PA t-1 − t-4 (t={1990, 2000, 2010}) - spatial lag 1	2236	0.08	0.17	0	2
PA t-1 − t-6 (t={1990, 2000, 2010}) - spatial lag 1	2244	0	0.01	0	0.11
PA t-1 − t-8 (t={1990, 2000, 2010}) - spatial lag 1	2244	0	0.01	0	0.08
PA t-1 − t-2 (t={1990, 2000, 2010}) - spatial lag 2	3280	0.07	0.14	0	1.06
PA t-1 − t-4 (t={1990, 2000, 2010}) - spatial lag 2	2236	0.07	0.12	0	0.82
PA t-1 − t-6 (t={1990, 2000, 2010}) - spatial lag 2	2244	0	0	0	0.04
PA t-1 − t-8 (t={1990, 2000, 2010}) - spatial lag 2	2244	0	0	0	0.03
PA t-1 − t-2 (t={1990, 2000, 2010}) - spatial lag 3	3280	0.07	0.11	0	0.65
PA t-1 − t-4 (t={1990, 2000, 2010}) - spatial lag 3	2236	0.07	0.1	0	0.7
PA t-1 − t-6 (t={1990, 2000, 2010}) - spatial lag 3	2244	0	0	0	0.02
PA t-1 − t-8 (t={1990, 2000, 2010}) - spatial lag 3	2244	0	0	0	0.02
PA t-1 − t-2 (t=2000)	1095	0.14	0.45	0	5
PA t-1 − t-4 (t=2000)	1078	0.1	0.31	0	3.25
PA t-1 − t-6 (t=2000)	1061	0.08	0.22	0	2.17
PA t-1 − t-8 (t=2000)	1049	0.07	0.19	0	2.13
PA t-1 − t-2 (t=2002)	1117	0.19	0.58	0	6.5
PA t-1 − t-4 (t=2002)	1117	0.17	0.45	0	4.75
PA t-1 − t-6 (t=2002)	1117	0.13	0.35	0	3.67
PA t-1 − t-8 (t=2002)	1117	0.11	0.28	0	3
PA t-1 − t-2 (t=2005)	1118	0.07	0.28	0	3.5
PA t-1 − t-4 (t=2005)	1117	0.12	0.35	0	5.25
PA t-1 − t-6 (t=2005)	1105	0.14	0.37	0	5.17
PA t-1 − t-8 (t=2005)	1088	0.13	0.33	0	4.25
PA t-1 − t-2 (t=2010)	1122	0.03	0.18	0	3
PA t-1 − t-4 (t=2010)	1118	0.03	0.14	0	2
PA t-1 − t-6 (t=2010)	1118	0.06	0.22	0	2.67
PA t-1 − t-8 (t=2010)	1118	0.07	0.22	0	3
Panel C: *Instrument*					
Distance to Urabá	1122	433.32	200.2	23.45	1523.83
Roughness-corrected distance to Urabá	1122	16142.79	10359.88	380.11	50203.32

Notes. PA t-i (t={1990, 2000, 2010}) refers to the cumulative lags of number of paramilitary attacks i years prior to each of the reference dates in the panel regressions, namely 1990, 2000 and 2010. Where it says "spatial lag 1", the calculation of paramilitary violence considers the municipality and its neighbors, for "spatial lag 2" the neighbors of the neighbors, and so on. Note that since paramilitary violence is only available since 1988, for the 1990 cross-section we are forced to assume that the average violence two years prior 1990 is also a good approximation to violence for longer lags. PA t-1 − t-n (t=year) refers in turn to the average cumulative violence n years leading up to each of the cross sections in the instrumental variables regressions, namely year 2000, 2005, and 2010. This is also computed for year 2002 for the mechanism regressions.

Table 2: Descriptive statistics: Controls and mechanisms

	Obs	Mean	Stdv.	Min.	Max.
Panel A: *Mechanisms*					
Palm produced (2002-2005)	1118	0.03	0.3	0	5.82
Share of land cultivated with coca (2002-2005)	1118	0.34	1.41	0	18.09
Number of expelled IDPs (2002-2005)	1118	249.92	582.5	0	7140.25
Requested titles for coal exploitation (2002-2005)	1118	0.64	2.99	0	36
Panel B: *Population*					
Total population (1990, 2000, 2010)	3280	36565.6	217395.45	156	7363782
Share urban pop. (1990, 2000, 2010)	3280	0.39	0.24	0	1
Panel C: *Geography*					
Municipality area	1114	1018.74	3206.86	15.39	65618.92
Average elevation	1061	1180.26	1162.33	2	25221
Average rainfall	1053	119.69	97.2	0	600
Water availability index	937	1978.09	1071.12	160	9200
Erosion index	1061	1.91	1.07	0	5
Quality of soil index	1061	2.67	1.22	0	8
Distance to the state's capital	1061	3327776.5	552067.68	0	5625773
Area with no satellite info. (1990, 2000, 2010)	3363	0.03	0.07	0	0.79
Panel D: *Rents*					
Log royalties per 100K people (1990, 2000, 2010)	3218	2.06	3.43	0	13.2
Log tax income per 100K people (1990, 2000, 2010)	3218	8.99	2.82	0	13.55

Table 3: Effect of paramilitary activity on forest cover: 1990-2010

	Ordinary least squares regression					
Dependent variable: *Forest cover*						
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average Two Year Lag						
Paramilitary Attacks	0.0447***	0.0645***	0.0631***	0.0148	0.0158	-0.00755**
	(0.0117)	(0.0111)	(0.0114)	(0.0101)	(0.0101)	(0.00320)
Observations	3,247	3,247	3,247	2,692	2,686	2,686
R-squared	0.003	0.063	0.066	0.360	0.358	0.569
Panel B: Average Four Year Lag						
Paramilitary Attacks	0.0755***	0.108***	0.106***	0.0312**	0.0340**	-0.0113**
	(0.0180)	(0.0176)	(0.0182)	(0.0146)	(0.0146)	(0.00476)
Observations	3,247	3,247	3,247	2,692	2,686	2,686
R-squared	0.004	0.065	0.068	0.361	0.359	0.569
Panel C: Average Six Year Lag						
Paramilitary Attacks	0.0597***	0.116***	0.120***	0.0332*	0.0381**	-0.00879*
	(0.0198)	(0.0201)	(0.0205)	(0.0174)	(0.0176)	(0.00521)
Observations	3,209	3,209	3,209	2,690	2,684	2,684
R-squared	0.002	0.063	0.067	0.361	0.359	0.568
Panel D: Average Eight Year Lag						
Paramilitary Attacks	0.0519***	0.117***	0.124***	0.0375**	0.0422**	-0.00819
	(0.0199)	(0.0209)	(0.0213)	(0.0184)	(0.0185)	(0.00554)
Observations	3,197	3,197	3,197	2,683	2,677	2,677
R-squared	0.002	0.062	0.066	0.361	0.360	0.568
Controls						
Population		Yes	Yes	Yes	Yes	Yes
Year fixed effects			Yes	Yes	Yes	Yes
Geography				Yes	Yes	Yes
Rents					Yes	Yes
Municip. fixed effects.						Yes

Notes. Robust standard errors are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. Geographic characteristics include the municipality's area, average elevation, average rainfall, distance to the state's capital, an index of water availability, and the percent of no information on forest cover due to clouds. Rents include royalties and tax income per capita. Average two year lag is the average of the independent variable one and two years before the dependent variable is measured, and so on. In Column 6 time-invariant controls are interacted with time dummies.

Table 4: Effect of paramilitary activity on forest cover in cross sections

Dependent variable: *Forest cover*						
Year:	2000		2005		2010	
Estimator:	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average Two Year Lag						
Second stage						
Paramilitary Attacks	0.0103	-0.692***	0.0138	7.474	0.0545*	12.08
	0.0107	(0.207)	(0.0199)	(13.06)	(0.0287)	(35.76)
First stage						
Distance to Uraba		-0.000410***		3.16e-05		1.74e-05
		(9.75e-05)		(5.57e-05)		(5.20e-05)
F-Stat		14.93		1.52e-05		0.0321
Panel B: Average Four Year Lag						
Second stage						
Paramilitary Attacks	0.0198	-0.757***	0.0384***	-1.479*	0.1229***	13.23
	(0.0168)	(0.199)	(0.0138)	(0.801)	(0.0418)	(32.22)
First stage						
Distance to Uraba		-0.000374***		-0.000160**		1.59e-05
		(6.92e-05)		(7.69e-05)		(3.93e-05)
F-Stat		23.69		6.202		0.0292
Panel C: Average Six Year Lag						
Second stage						
Paramilitary Attacks	0.0259	-0.972***	0.0367***	-0.802***	0.0524*	2.717
	(0.0243)	(0.242)	(0.0114)	(0.291)	(0.0298)	(1.755)
First stage						
Distance to Uraba		-0.000291***		-0.000295***		7.72e-05
		(4.88e-05)		(8.00e-05)		(4.93e-05)
F-Stat		41.09		15.53		0.885
Panel D: Average Eight Year Lag						
Second stage						
Paramilitary Attacks	0.0235	-1.159***	0.0414***	-0.773***	0.0618**	65.32
	(0.0294)	(0.287)	(0.0137)	(0.258)	(0.0280)	(926.0)
First stage						
Distance to Uraba		-0.000248***		-0.000306***		3.21e-06
		(4.18e-05)		(7.16e-05)		(4.60e-05)
F-Stat		27.86		20.44		0.231
Controls						
Population	Yes	Yes	Yes	Yes	Yes	Yes
Geography	Yes	Yes	Yes	Yes	Yes	Yes
Fiscal	Yes	Yes	Yes	Yes	Yes	Yes

Notes. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. Robust standard errors are shown in parentheses. Geographic characteristics include the municipality's area, average elevation, average rainfall, distance to the state's capital, an index of water availability, and the percent of no information on forest cover due to clouds. Rents include royalties and tax income per capita. Average two year lag is the average of the independent variable one and two years before the dependent variable is measured, and so on.

Table 5: Effect of paramilitary activity on forest cover through IDPs expelled

Dependent variable:	IDPs expelled 2002-2005				ΔForest cover
Average lag	Two years	Four years	Six years	Eight years	(2000-2005)
	(1)	(2)	(3)	(4)	(5)
Paramilitary Attacks	432.6943***	608.4927***	809.2290***	$1.0e+03$***	–
	(55.7843)	(69.8653)	(85.5826)	(114.0589)	
IDPs expelled					-0.0109**
					(0.0050)
Observations	901	901	901	901	901
R-squared	0.3026	0.3332	0.3424	0.3432	0.4050
Controls					
Population	Yes	Yes	Yes	Yes	Yes
Geography	Yes	Yes	Yes	Yes	Yes
Rents	Yes	Yes	Yes	Yes	Yes

Notes. Robust standard errors are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. Geographic characteristics include the municipality's area, average elevation, average rainfall, distance to the state's capital, an index of water availability, and the percent of no information on forest cover due to clouds. Rents include royalties and tax income per capita. Average two year lag is the average of the independent variable one and two years before the dependent variable is measured, and so on.

Table 6: Effect of paramilitary activity on forest cover through coca cultivation

Dependent variable:	Coca cultivation 2002-2005				ΔForest cover
Average lag	Two years	Four years	Six years	Eight years	(2000-2005)
	(1)	(2)	(3)	(4)	(5)
Paramilitary Attacks	0.2417	0.3688*	0.3815	0.4489	–
	(0.1468)	(0.2020)	(0.2349)	(0.2938)	
Coca cultivation					−12.7197***
					(4.3841)
Observations	901	901	901	901	901
R-squared	0.1234	0.1275	0.1220	0.1205	0.4674
Controls					
Population	Yes	Yes	Yes	Yes	Yes
Geography	Yes	Yes	Yes	Yes	Yes
Rents	Yes	Yes	Yes	Yes	Yes

Notes. Robust standard errors are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. Geographic characteristics include the municipality's area, average elevation, average rainfall, distance to the state's capital, an index of water availability, and the percent of no information on forest cover due to clouds. Rents include royalties and tax income per capita. Average two year lag is the average of the independent variable one and two years before the dependent variable is measured, and so on.

Table 7: Effect of paramilitary activity on forest cover through mining

Dependent variable:	Coal mining titles 2002-2005				ΔForest cover
Average lag	Two years	Four years	Six years	Eight years	(2000-2005)
	(1)	(2)	(3)	(4)	(5)
Paramilitary Attacks	0.2963*	0.5202*	0.6114	0.7544	–
	(0.1609)	(0.3042)	(0.3996)	(0.4980)	
Coal mining titles					−0.6915**
					(0.3019)
Observations	901	901	901	901	901
R-squared	0.0784	0.0840	0.0817	0.0809	0.3955
Controls					
Population	Yes	Yes	Yes	Yes	Yes
Geography	Yes	Yes	Yes	Yes	Yes
Rents	Yes	Yes	Yes	Yes	Yes

Notes. Robust standard errors are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. Geographic characteristics include the municipality's area, average elevation, average rainfall, distance to the state's capital, an index of water availability, and the percent of no information on forest cover due to clouds. Rents include royalties and tax income per capita. Average two year lag is the average of the independent variable one and two years before the dependent variable is measured, and so on.

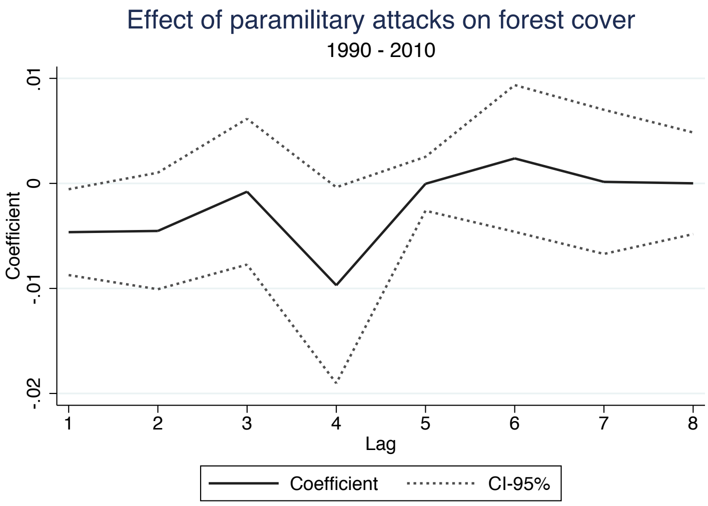
Table 8: Effect of paramilitary activity on forest cover through African oil-palm cultivation

Dependent variable:	Palm produced 2002-2005				ΔForest cover
Average lag	Two years	Four years	Six years	Eight years	(2000-2005)
	(1)	(2)	(3)	(4)	(5)
Paramilitary Attacks	0.0182	0.0560*	0.0979**	0.1181*	–
	(0.0210)	(0.0297)	(0.0498)	(0.0611)	
Palm produced					−3.1205
					(4.1163)
Observations	901	901	901	901	901
R-squared	0.0262	0.0314	0.0365	0.0351	0.3952
Controls					
Population	Yes	Yes	Yes	Yes	Yes
Geography	Yes	Yes	Yes	Yes	Yes
Rents	Yes	Yes	Yes	Yes	Yes

Notes. Robust standard errors are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. Geographic characteristics include the municipality's area, average elevation, average rainfall, distance to the state's capital, an index of water availability, and the percent of no information on forest cover due to clouds. Rents include royalties and tax income per capita. Average two year lag is the average of the independent variable one and two years before the dependent variable is measured, and so on.

A Appendix

Figure A-1: Effect of paramilitary activity on forest cover using non-cumulative lags



Note: The figure plots the coefficient of paramilitary attacks on forest cover for different (non-cumulative) lags measured on the X axis. The coefficients come from a specification that includes all the controls as well as year and municipality fixed effects. The 95 percent confidence interval of the estimate is also included.

Table A-1: Effect of past paramilitary activity on current activity

Arellano and Bond (1991) estimator	
Dependent variable:	*Paramilitary attacks*
$Attacks_{t-1}$	0.134***
	(0.0254)
$Attacks_{t-2}$	0.0597**
	(0.0257)
$Attacks_{t-3}$	0.0206
	(0.0158)
$Attacks_{t-4}$	-0.0362**
	(0.0178)
$Attacks_{t-5}$	-0.0517**
	(0.0226)
$Attacks_{t-6}$	-0.0608***
	(0.0215)
$Attacks_{t-7}$	-0.0469**
	(0.0205)
$Attacks_{t-8}$	-0.0739***
	(0.0208)
Constant	0.238
	(0.224)
Observations	13,884
Municipalities	1,114

Notes. Robust standard errors are shown in parentheses. The controls include year fixed effects, municipalities fixed effects and population. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. Data from 1997 to 2009.

Table A-2: Effect of paramilitary activity on log forest cover: 1990-2010

Ordinary least squares regression						
Dependent variable: *Log forest cover*						
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average Two Year Lag						
Paramilitary Attacks	0.0388***	0.0535***	0.0525***	0.0162**	0.0169**	-0.00437**
	(0.00878)	(0.00837)	(0.00862)	(0.00748)	(0.00748)	(0.00215)
Observations	3,247	3,247	3,247	2,692	2,686	2,686
R-squared	0.004	0.064	0.068	0.348	0.347	0.586
Panel B: Average Four Year Lag						
Paramilitary Attacks	0.0637***	0.0876***	0.0862***	0.0305***	0.0325***	-0.00675**
	(0.0136)	(0.0133)	(0.0137)	(0.0111)	(0.0111)	(0.00322)
Observations	3,247	3,247	3,247	2,692	2,686	2,686
R-squared	0.005	0.067	0.071	0.349	0.347	0.586
Panel C: Average Six Year Lag						
Paramilitary Attacks	0.0517***	0.0940***	0.0971***	0.0327**	0.0362***	-0.00514
	(0.0149)	(0.0152)	(0.0155)	(0.0133)	(0.0135)	(0.00357)
Observations	3,209	3,209	3,209	2,690	2,684	2,684
R-squared	0.003	0.065	0.070	0.349	0.348	0.585
Panel D: Average Eight Year Lag						
Paramilitary Attacks	0.0473***	0.0961***	0.102***	0.0371***	0.0404***	-0.00530
	(0.0149)	(0.0156)	(0.0159)	(0.0140)	(0.0141)	(0.00387)
Observations	3,197	3,197	3,197	2,683	2,677	2,677
R-squared	0.002	0.064	0.069	0.349	0.348	0.585
Controls						
Population		Yes	Yes	Yes	Yes	Yes
Year fixed effects			Yes	Yes	Yes	Yes
Geography				Yes	Yes	Yes
Rents					Yes	Yes
Municip. fixed effects.						Yes

Notes. Robust standard errors are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. Geographic characteristics include the municipality's area, average elevation, average rainfall, distance to the state's capital, an index of water availability, and the percent of no information on forest cover due to clouds. Rents include royalties and tax income per capita. Average two year lag is the average of the independent variable one and two years before the dependent variable is measured, and so on. In Column 6 time-invariant controls are interacted with time dummies.

Table A-3: Effect of spatial lag of paramilitary attacks on forest cover

Ordinary least squares regression			
Dependent variable: *Forest cover*			
Spatial Lag:	1	2	3
	(1)	(2)	(3)
Panel A: Average Two Year Lag			
Paramilitary Attacks	-0.0120^{***}	-0.0194^{***}	-0.0235^{**}
	0.0044	0.0071	0.0093
Observations	2692	2692	2692
R-squared	0.5687	0.5689	0.5685
Panel B: Average Four Year Lag			
Paramilitary Attacks	-0.0327^{***}	-0.0465^{***}	-0.0496^{***}
	0.0100	0.0147	0.0180
Observations	1802	1802	1802
R-squared	0.5909	0.5906	0.5882
Panel C: Average Six Year Lag			
Paramilitary Attacks	-0.1069	0.4784	0.7503
	0.1353	0.3091	0.5465
Observations	1802	1802	1802
R-squared	0.5837	0.5847	0.5845
Panel D: Average Eight Year Lag			
Paramilitary Attacks	-0.1450	0.7270^{*}	1.0911
	0.1626	0.3840	0.6628
Observations	1802	1802	1802
R-squared	0.5837	0.5853	0.5848
Controls			
Population	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Geography	Yes	Yes	Yes
Rents	Yes	Yes	Yes
Municip. fixed effects.	Yes	Yes	Yes

Notes. Robust standard errors are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. Geographic characteristics include the municipality's area, average elevation, average rainfall, distance to the state's capital, an index of water availability, and the percent of no information on forest cover due to clouds. Rents include royalties and tax income per capita. Average two year lag is the average of the independent variable one and two years before the dependent variable is measured, and so on. In column 1 these average paramilitary attacks add those of a given municipality and all its neighbors (that is, the municipalities that share borders with a specific town). Column 2 also takes into account attacks in municipalities that are neighbors (have a common border) with the neighbors of order one (included in Column 1). Column 3 aggregates an additional layer of neighbors.

Table A-4: Effect of paramilitary activity on forest cover in cross sections (IV is distance to Urabá weighted by roughness of terrain)

Instrumental variables regression			
Dependent variable: *Forest cover*			
	2000	2005	2010
	(2)	(3)	(4)
Panel A: Average Two Year Lag			
Second stage			
Paramilitary Attacks	-0.272**	1.270	-0.0611
	(0.123)	(1.296)	(0.294)
First stage			
Distance to Urabá Mount.	-6.80e-06***	1.14e-06	-2.25e-06***
	(1.60e-06)	(1.06e-06)	(5.35e-07)
F-Stat	20.38	0.538	15.78
Panel B: Average Four Year Lag			
Second stage			
Paramilitary Attacks	-0.278**	-0.458	-0.0984
	(0.120)	(0.285)	(0.478)
First stage			
Distance to Urabá Mount.	-6.65e-06***	-3.16e-06***	-1.40e-06***
	(1.20e-06)	(1.16e-06)	(4.98e-07)
	31.85	9.221	8.371
F-Stat			
Panel C: Average Six Year Lag			
Second stage			
Paramilitary Attacks	-0.380**	-0.251*	-0.554
	(0.165)	(0.134)	(3.527)
First stage			
Distance to Urabá Mount.	-4.79e-06***	-5.76e-06***	-2.48e-07
	(8.26e-07)	(1.23e-06)	(8.53e-07)
F-Stat	34.78	23.94	0.248
Panel D: Average Eight Year Lag			
Second stage			
Paramilitary Attacks	-0.445**	-0.248*	-0.131
	(0.199)	(0.130)	(0.653)
First stage			
Distance to Urabá Mount.	-3.96e-06***	-5.84e-06***	-1.05e-06
	(6.80e-07)	(1.12e-06)	(7.94e-07)
F-Stat	35.10	29.04	0.216
Controls			
Population	Yes	Yes	Yes
Geography	Yes	Yes	Yes
Fiscal	Yes	Yes	Yes

Notes. Robust standard errors are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. Geographic characteristics include the municipality's area, average elevation, average rainfall, distance to the state's capital, an index of water availability, and the percent of no information on forest cover due to clouds. Rents include royalties and tax income per capita. Average two year lag is the average of the independent variable one and two years before the dependent variable is measured, and so on.