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Summary

This study offers evidence on the relationship between armed conflict and its environmental impacts. For the case of Colombia, using a unique annual municipality panel dataset (from 2004 to 2012) and an instrumental variable approach to control for possible endogeneity between forest cover and forced displacement, there is evidence that the armed conflict is a force for forest *protection and growth. In December 2016, the Colombian government concluded the negotiations with the Revolutionary Armed Forces of Colombia (FARC) to end South America's longest-running internal conflict. Forest degradation often increases in post-war situations. These findings highlight a need for increased protection of Colombia's forests in the wake of the peace settlement.*

Keywords: forest cover, forest change, reforestation, deforestation, armed conflict, violence, forced displacement, land abandonment, coca crops

JEL codes: C01, C23, Q33.

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The findings, interpretations and conclusions expressed in this paper are entirely those of the authors and do not necessarily represent the views of the University of Sussex, at Brighton, United Kingdom, or the National Planning Department (DNP), at Bogotá, Colombia, part of the Colombian Government.

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1.1 Introduction

The toll of civil conflict goes well beyond human suffering and the damage to physical infrastructure. Conflicts may also cause the degradation and destruction of local environments and biodiversity. This paper offers evidence on the relationship between armed conflicts and forest cover for the case of Colombia.

Little attention has been given to the impact of conflicts on the environment. In fact, most conflict studies investigate the effects of conflict on socioeconomic and institutional outcomes, such as a country's' macroeconomic performance, human capital and asset accumulation, or civil political participation. For example, from a macroeconomic perspective Collier (1999) using a cross-country dataset (92 countries, 1960 to 1992) estimates a GDP per capita annual decline of 2.2% for a country that experienced a civil war relative to its counterfactual, on average. Likewise, Hoeffler and Reynal-Querol (2003) using a global dataset (211 countries, 1960 to 1999) report that civil wars that last five or more years reduce the country's average annual growth rate by 2.4% on average.

Regarding human capital accumulation Justino *et al*. (2013) examine the impact of violence in Timor Leste using data from 1999. In the short term, the authors found supporting evidence that school attendance was reduced. In the longer-term, primary school completion declined particularly for boys exposed to peaks of violence during the 25-year conflict. Similarly, Shemyakina (2011) for the case of Tajikistan, found that girls aged between 7-15 years old in 1999 are about 11 percentage points less likely to be enrolled in school if their household's dwelling was damaged during a conflict period (1992-1998).

In terms of asset accumulation Deininger (2003), using household data from Uganda, found that the conflict negatively affected investment and non-agricultural enterprise formation between 1992 and 1999. The household income decision on investment was affected by the imposition of war taxes by the rebel forces.

On the subject of civil political participation, Bellows and Miguel (2006) investigate the socioeconomic and institutional outcomes in 2004 and 2005 in Sierra Leone, some years after the civil war period (1991-2002) had ended. The empirical evidence shows that political mobilization measures became higher in areas that experienced more violence.

Understanding how conflict affects forest cover could provide insights on the need to promote natural resource conservation with the corresponding governmental engagement in structural forest governance regulations particularly important in preventing the escalation of conflict.

The 2016 peace deal was intended to end the 60 years of conflict with the FARC. Apart from reducing victimization, it is anticipated to generate immense economic benefits for the country. For example, a National Planning Department (DNP)[1] study suggests that Colombia's GDP will grow between 1.1 and 1.9 percentage points more with the arrival of peace. However, it is important to clarify that the 'environmental' peace dividend would not necessarily be positive. In particular, in Colombia the effect of the conflict on forest cover is often regarded as ambiguous.

On the one hand, the presence of illegal armed groups[2] in protected areas restricts colonization trends and assist these areas to remain free of environmental damage (Álvarez, 2003; Dávalos et al. 2011). In fact, guerrilla groups often served as the local environmental protection authority, taking explicit decisions on nature conservation, enacting and enforcing unofficial laws limiting hunting, fishing, and deforestation (Dávalos, 2001; Sánchez-Cuervo and Aide, 2013).

[1] This is based on DNP (2015), "Dividendo económico de la paz".

[2] During the period covering this study the armed conflict comprised mainly two guerrilla organizations known as the Revolutionary Armed Forces of Colombia (FARC) and the National Liberation Army (ELN). In addition, there exists in the shadows a third actor, a right-wing paramilitary group known as the United Self-Defence Forces of Colombia (AUC), which even though signing a demobilization agreement in 2003 remains active in criminal and drug-related activities.

The environmental friendly attitude of the guerrilla movement in Colombia is usually linked to their prevailing economic and military interests in the area. Conserving the forests helps rebel forces conceal their activity and establish safe-havens with transit corridors for troops, military supplies, drugs, or illegally extracted natural resources such as timber or minerals (Álvarez, 2003; Dávalos et al. 2011).

On the other hand, in other areas, illegal armed groups have caused devastating effects on the ecosystem, destroying oil pipelines, engaging in illegal mining, and clearing forests to acquire land for the cultivation of illicit crops. The war on drugs has exacerbated this situation. Chemically or manually, coca eradication automatically causes localized deforestation in the area in which it is conducted. In response, coca producers tend to move to even more remote locations such as national parks or other protected areas where chemical fumigation is prohibited. New coca plantations are then established which ultimately lead to a cycle of deforestation (Dávalos et al., 2011).

This paper complements and enhances the existing literature by identifying the direction of the relationship between armed conflicts and forestation in Colombia. The identification strategy used relies on exploring the causal effect that forced displacement exerts on forest cover at the municipal level.

According to official figures more than 5.2 million persons were forcibly internally displaced between 1990-2012. This represented 11.2% of the population. Illegal armed groups are the main implicated parties. In fact, it well known that violence against civilians has not been random. Instead, it has been a deliberate strategy of war. Illegal armed groups have displaced peasants in order to secure control of valuable land rich in natural resources. This enables the armed groups to engage in legal or illegal economic activities such as mining or planting illicit crops, or use the land to establish camps for troops, or store illegal drugs and weapons. Selective killings, massacres, death threats, disappearances, forced recruitment and property damage are consequences of attacks perpetrated by these groups to frighten and intimidate local inhabitants, which eventually leads to forced displacement (Roche-villarreal, 2012; Moya, 2012; Ibáñez, 2009).

The research presented here provides an important contribution to the existing literature on conflict. In particular, the scope of existing studies has been limited by data restrictions regarding the availability of forest cover and conflict statistics at the sub-national level. Thus, while some studies have focused on examining a conflict's environmental impacts, others exclusively deal with the impacts generated by a single conflict actor. In addition, few studies employ appropriate econometric techniques to tackle this research question. Therefore, this study goes beyond others studies by using a unique annual Colombian panel dataset of forest cover satellite imagery at the municipal level over the period from 2004 to 2012. Furthermore, the research also investigates and tests for the endogeneity problem between forest and conflict presence using an array of appropriate econometric techniques. Specifically, a fixed effects (FE) Instrumental Variable (IV) approach is used to address the potential endogeneity problem between forest cover and forced displacement. In exploiting forced displacement as the main conflict-specific explanatory variable we not only capture the effect of multiple perpetrators of violence, but also its link or relationship to land use. This allows us to explore the conflict's impact on forest coverage given armed conflicts invariably induce large flows of displaced persons either from the countryside to urban centres, or to unexploited frontier lands elsewhere.

The main finding of this study is that the armed conflict has been a beneficial force for forest protection and growth in Colombia, but the estimated effect of the conflict on forestation is found to be small in magnitude. Consequently, the positive yield of conflict conservation is overwhelming offset by the negative consequences of violence which involve, for example, a high number of deaths in the fighting, the destruction of human capital and physical infrastructure, educational and health outcomes and market disruption, and the increments of drug production which undermines governance, among other things. Hence, the major achievement of the 2016 peace deal that ended 60 years of conflict with the FARC was reducing victimization. Yet, since forest degradation frequently increases in post-conflict situations the government may need to play an active role in developing conservation policies in those developing areas currently under the control of the guerrillas when the peace finally arrives. Otherwise, the peace dividend for the environment will not emerge.

The paper is structured as follows. The next section presents a literature review which is followed by a section describing empirical modelling issues. A fourth section describes the data and some descriptive statistics. A fifth reports the empirical results, while a sixth section examines the role of a set of time-invariant variables on explaining forest cover. A final section offers some concluding remarks and the policy implications for the analysis.

1.2 Literature review

Most of the literature linking conflict and the environment emphasizes the connection between abundant natural resources, armed conflict, and underdevelopment. This is generally known as the “resource curse” which makes reference to a situation in which the natural resources are mismanaged by a certain interest group (See, for example, Auty (2004); Ross (1999); Collier and Hoeffler (1998)[3]; and Sachs and Warner (1995))

The findings are somehow mixed in terms of the duration of conflicts and the presence of forests. For example, Collier *et al*. (2004) investigates the causes of civil war, exploiting a database of 161 countries over the period 1960-1999 (79 civil wars) and reports that the extent of forest cover is not statistically associated with longer conflicts. In contrast, De Rouen and Sobek (2004) exploit a database containing information on 114 civil wars in 53 countries between 1944 and 1997, and find that highly forested countries are associated with a significantly decreasing probability[4] of the civil war ending.

[3] In the Collier and Hoeffler (1998) paper on the economic causes of conflicts, countries experiencing civil wars were found to have marginally lower forest cover (29%) than their counterparts who did not experience civil war (31%).
[4] In this study, a logit model is used to explain what determines the probability of civil war outcomes (i.e., government victory, rebel victory, truce, or treaty), whereas a hazard analysis identifies the factors that determine the time to reach such an outcome.

However, studies that use cross-country data are subject to criticism. Often the forest cover is calculated for the whole country, but it is likely that only some parts of the country experienced the conflict. Hence, Lujala (2010) shows that the location of the natural resources are key determinants of conflict durations using a dataset known as PETRODATA[5], which contains the geographic coordinates on the location of hydrocarbon (i.e., crude oil and natural gas) reserves for 111 countries. According to the author's research, if these resources are located inside the actual conflict zone, the duration of the conflict actually doubles.

There is also a growing literature that tries to explicitly link the relationship between civil war and forest cover. In particular, progress has been made in terms of incorporating spatially explicit forest cover in to empirical analysis given the evolution and development of user-friendly satellite data. Once again, these studies offer mixed results regarding the direction of the impact of conflicts on forests and are usually subject to the inherent mechanics of country conflicts, which demonstrate the need for more focused research.

Focusing on the experience of Colombia, Fergusson *et al*. (2014) is one of the few studies that addresses the endogeneity problem between conflict and forests. In particular, the authors focus on examining the deforestation impact of the paramilitary expansion, which was characterized by the perpetration of selective massacres and by forcing large populations to flee in order to secure territory during the late 1990s. They instrument paramilitary attacks with the distance to the Urabá region, the epicentre of the paramilitary activity. The forestation data were based on satellite images for the years 1990, 2000, 2005 and 2010. The authors detected a negative effect of the paramilitary expansion on forest cover using cross-sectional models controlling for, among other things, municipality fixed effects,

[5] This dataset includes 890 onshore and 383 offshore locations with geographic coordinates and information on the first oil or gas discovery and production year. PETRODATA allows researchers to control for both the spatial and temporal overlap of regions with hydrocarbon reserves and armed conflict. PETRODATA is available at http://www.prio.no/CSCW/Datasets/Geographical-and-Resource .

Dávalos *et al*. (2011), examining the case of Colombia, use forest cover maps at 1-km grid[6] spatial resolution to quantify forest changes in the northern Andes, Chocó and the Amazon regions. These represented the largest coca leaf producing zones between 2002 and 2007. The authors use logistic regressions and control for the grid distance to the closest newest coca fields and the area of coca cultivation around 1 km^2, and the population, road accessibility and climate controls, among other things. The study finds that the cell probability of transition from forest to no forest increases with shorter distances to the newest coca fields and with the area of coca cultivated in its boundaries. This paper suggests that establishing larger protected areas could help reduce deforestation and preserve biodiversity.[7]

Viña *et al.* (2004) concentrate their analyses on the region along the Colombia-Ecuador border using satellite data between 1973 and 1996. The authors compare images to calculate the rates and patterns of land-cover changes along the border. Their comparison suggests that forest cover loss is higher on the Colombian side of the border with 43% on that side compared to 26% on the Ecuadorian side. They do not use an econometric model to identify specific factors driving these results. However, they suggest that the illegal coca production, occurring mainly along the Colombian side, might explain the differences in deforestation rates.

Álvarez (2003) using information obtained through semi-structured interviews with local civilians and members of the guerrilla groups situated in the main forested regions of Colombia (e.g., the Macarena mountains, Munchique National Park, Tambito Nature Reserve, the San Lucas mountain range, and the Churumbelos mountains) emphasize that the relationship between conflict and forest cover is ambiguous. On the one hand, the author finds evidence of ‘gunpoint’ conservation in some sites, which means that the guerrilla groups, such as the ELN in the San Lucas mountain range, undertook conservation activities. In this particular case, this was done by placing landmines[8] or

[6] These comprise a network of lines that cross each other to form a series of squares.
[7] Fjeldså (2005) report similar results, concluding that the eradication campaigns lead to a constant relocation of drug dealers, thus making illicit crops one of the main causes of deforestation.
[8] Landmines are in effect a ‘negative capital stock’ that society accumulates during a conflict. They continue to kill and mutilate people long after the actual fighting has ended (see Hoeffler & Reynal- Querol, (2003)).

posting signs that warn of landmines in patches of the forests. In turn, the forests served the guerrillas as cover from government surveillance and air strikes. On the other hand, guerrilla groups have also expedited deforestation. For example, in the Choco Department lowlands, forests were actually converted into cattle ranches or coca plantations.

Among the international studies on this subject that are of relevance is Stevens *et al*. (2011). Their paper investigates the forest cover changes on two sites, with a total area of circa 160,000 hectares located along the Atlantic Coast of Nicaragua over a period covering the civil war (1978 to 1993). Based on a forest and non-forest image pixels[9] classification detection methods[10], the authors find that in the first five to 7 years of the conflict, reforestation was greater than deforestation due to forced displacement. However, once the conflict terminated people returned to their lands and the level of deforestation was almost double the level of reforestation that had occurred during the conflict.

Hecht and Saatchi (2007), using a visual interpretation of satellite imagery data of forest cover between 1990 to 2007 for El Salvador, highlight the expansion of woody vegetation, especially in the northern provinces, in mountainous zones at the edge of agricultural frontiers, and in regions that had been under the control of the Farabundo Martí Front for National Liberation. They conclude that woodland resurgence is positively correlated with the occurrence of the civil war. They note that many people fled the country to avoid being killed in the conflict.

Nackoney et al. (2014) for the Democratic Republic of Congo, comparing satellite imagery data across two decades (1990–2010) with an algorithm that uses surface reflectance to detect image changes, report that primary forest loss and degradation rates occurring during the conflict decade (1990–2000) were over double the rates of the post war decade (2000–2010). This suggests pressure on the forests during periods

[9] Pixels are the smallest elements of an image that can be individually processed in a digital screen.
[10] Based on a classification scheme, the pixel classes were divided into specific land cover categories, which included forests (deciduous, mixed, secondary) and non-forest (agriculture, rangeland, and barren land) types.

of conflict. Despite the fact that their images do not consider forest regrowth, the authors note that after the end of the war in 2003, the rate of primary forest loss taking place within the agricultural zones increased, meaning that in the post-war era people returned from remote forested areas to their homes, and cleared forests in order to regenerate food production activity.

Table 1.2.1 Selected studies on the relationship between conflict and forests

Author	Published Journal	Sample coverage	Methodology	Conflicts impacts on forests
Collier et al (2004)	Journal of Peace Research	Cross-country overtime (1960 - 1999) 161 countries	Probability model (logit)	No impact
Fergusson et al (2014)	Working paper CEDE series, Universidad de los Andes, Colombia	Colombia overtime (1990, 2000, 2005 and 2010)	Cross-sectional and instrumental variables models	Negative (due to paramilitary activity expansion)
Dávalos (2001)	Environmental science technology	Colombian regions (Northern Andes, Chocó and the Amazon) overtime (2002 - 2007)	Probability model (logit)	Negative (due to coca production)
Viña et al (2004)	Journal of the Human Environment	Colombia & Ecuador border region overtime (1973 - 1996)	Satellite imagery analysis	Negative (due to coca production)
Alvarez (2003)	Journal of Sustainable Forestry	Colombia main forested regions (Macarena mountains, Munchique National Park, Tambito Nature Reserve, the San Lucas mountain range, and the Churumbelos mountains) 2003	Not Econometrics (interviews)	Ambiguous (due to "gunpoint" conservation)
Stevens et al (2011)	Biodiversity and Conservation	Nicaragua's Atlantic Coast (160,000 ha) overtime (1978-1993)	Satellite imagery analysis	Positive (due to displacement)
Hecht and Saatchi (2007)	BioScience	El Salvador overtime (1990 - 2007)	Satellite imagery analysis	Positive (due to displacement)
Nackoney et al (2014)	Biological Conservation	Democratic republic of Congo overtime (1990-2010)	Satellite imagery analysis	Negative (due to pressure on natural resources)
Burgess et al (2015)	Environmental Research Letters	Sierra Leone overtime (1990 and 2000)	Log linear regressions	Positive (due to displacement)

In contrast, Burgess *et al.* (2015) for Sierra Leone, merged satellite imagery of forest cover with chiefdom-level conflict incidents (151 observations) for the years 1990 (prior to the civil war) and 2000 (just prior to the end of the civil war) and found that conflict prevented local deforestation. In particular, conflict-ridden chiefdoms experienced significantly less forest loss relative to their counterparts due to forced displacement.

Table 1.2.1 provides a short summary of the research done in this topic reviewing data sources, methodologies and key findings. The major constraint on research progress on this topic have been a lack of data on both conflict and forest cover at the sub-national level. Some studies concentrate their analysis only on particular biomass areas (eco-regions), while others are confined to the effects of a single perpetrator of violence. Very few adopt a clear or clean identification strategy and address the endogeneity problem between the conflict and forestation or deforestation. Although, it is acknowledged the potential problem may not be present in the current application since, as we have found, it depends on the choice of the conflict variable used in the empirical analysis. The aim of this paper is to fill these lacunae.

1.3 Empirical and identification strategy

The research question is addressed empirically by using instrumental variables and panel data methods. The variation of the dependent and explanatory variables over time and across municipalities is exploited to identify the effects of the armed conflict on forest cover. Equation (1.1) outlines the specification to be estimated:

$$Forest_{i,t} = \gamma FD_{i,t} + \beta X_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t} \tag{1.1}$$

where $Forest_{i,t}$ is the share of municipality *i*'s area covered by forest in year *t.* The conflict variable is the forced displacement rate per 1000 of the municipal population ($FD_{i,t}$). Following the literature review, the main reason as to why forced displacement was chosen as a variable to measure the impact of the armed conflict on forests is because it not only represents a deliberate[11] strategy used in war, but also is linked to land use and conservation trends.[12] Similar to areas with harsh environmental conditions[13] that may experience agricultural abandonment and a subsequent spontaneous ecosystem recovery, productive areas abandoned by humans due to

[11] According to Ibáñez (2009) violence against civilians is not a random act.
[12] Forced displacement is the conflict consequence most connected to forestation trends.
[13] Environmental variables can explain the patterns of forestation because they can restrict or encourage different land uses.

conflict may experience a reduction on land pressure, which leads to forest regrowth (See Sanchez-Cuervo and Aide, 2013).

CNMH (2015), using statistics from the Central Registry for Victims Office (RUV) (1985-2014), suggest that 62.5% percent of the victims of forced displacement declared that the perpetrator was an illegal armed group (41.4% of which were guerrillas and 21.1% paramilitaries, respectively). The emergent criminal bands (known by the name of Bacrims in Spanish) accounted for 4% of the total displacement, while various state forces were found to be directly responsible for only 0.8%. Unfortunately, the remainder of the victim statements (32.7%) contained in the RUV do not offer a detailed description of the actors identified by the victims as the displacement perpetrators.

In Colombia, illegal armed groups promoted forced displacement often to reduce the offensive capacity of the "enemy", expropriate and concentrate land, exploit and usufruct the dispossessed territory, or to establish and sustain illegal economies (e.g., money laundering, planting of illicit crops, development of drug trafficking routes). Forced displacement is not an unintended result of the internal conflict. Instead, groups attack the civil population to strengthen territorial strongholds, expand territorial control, weaken support for the opponent, and accumulate valuable assets (Ibáñez and Vélez, 2008).These actions are the standard modus operandi of a warlord who seeks territorial control and appropriation of the revenues of the territory (CNMH, 2015; Duncan, 2004). Thus, forced displacement is provoked by any threats or direct attacks by an armed group, regional indiscriminate violence, or even the mere presence of armed groups. Civilians are displaced to avoid direct victimization, or, simply as a way of preventing a confrontation (Ibáñez, 2009a).

In particular, Engel and Ibáñez (2007) and Ibáñez and Vélez (2008) investigate displacement determinants using logistic regression models for a sample of 376 households conducted during the year 2000. The data cover displaced households (200) from the departments of Antioquia and Cordoba (the expulsion zones) which migrated to Bogota, Medellin and Cartagena, and others (176) that remained at their place of origin. The probability of displacement is determined by variables capturing the strategies pursued by armed groups, state presence, income generation possibilities, and household characteristics. For example, the study finds that a household is significantly more likely to opt for displacement if there were violent acts committed in its surrounding area, the presence of a subversive group (either paramilitary or guerrilla), if it owns larger landholdings or high levels of livestock[14], it is far from economic markets, or it is located in a region with a high index of basic needs. On the contrary, the probability of household displacement is reduced when there is an active presence of military forces and the national police, there is access to social services (education and health), and when the age of the household head and the level of education is high.

Dueñas et al. (2014) present similar results based on fixed effects panel data estimation for the period 2004–2009. In particular, the authors show that the rate of expulsion of a displaced person is positively and strongly correlated with the conflict intensity (attacks undertaken by illegal armed groups), the presence of coca crops, royalties (which is a proxy for the presence of natural resources) and low economic and security conditions at the municipal level.

In summary, violence and security perceptions are the major determinants of displacement and are, therefore, viewed as the key levers in preventing displacement (Ibáñez and Vélez, 2008).

Authors such as Aide and Grau (2004) and Meyerson et al. (2007) have shown that rural–urban forced displacement promotes ecosystem recovery due to the reduction of human pressure on land. The research findings in this thesis is in line with that hypothesis. Despite the fact that rural to rural displacement might also increase forest degradation, in Colombia most of the forced displacement is actually rural to urban in nature. In other words, it goes from forested areas and most often to the larger cities. According to official figures during the study period (2004-2012) around 60% of the total

[14] Livestock can be transformed into cash relatively easily (more easily than land). Thus, it provides financial resources that help to cover the costs of displacement and provide a basis for a new start in the receiving location.

displaced people were expelled from a “strictly”[15] rural municipality, and around 75% of the displaced was received by a “strictly” urban municipality.

In Equation (1.1), γ is the primary parameter of interest in the empirical analysis. In order to identify the causal effect of forced displacement on forest coverage, the error term ($\varepsilon_{i,t}$) needs to be uncorrelated with the forced displacement rate per population (i.e., the main variable of interest ($FD_{i,t}$) must be exogenous). The standard econometric literature suggest that there are at least three possible reasons why the $FD_{i,t}$ may be endogenous (i.e,. correlated with the error term): i) measurement error, ii) simultaneity, and iii) omitted variables. Yet, in this particular case it should be noted that one cannot rule out the possibility that the measurement error bias dominates the other two endogeneity causes.

First, it is expected that **measurement error** may play a role in the estimation of γ due to data on $FD_{i,t}$ may be subject to underreporting. In particular, precise statistics for the number of people who have been internally displaced in Colombia are unavailable.

The government Registry for Displaced Populations (RUPD) consolidates forced displacement statistics. The RUPD objective is to legally recognize displaced households, and, therefore, quantify the demand for public aid. Displaced persons approach local government authorities to declare, under oath, the circumstances of their displacement. Then, public servants confirm whether or not this is truthful. According to Ibáñez (2009) approximately 30% of the displaced population is believed not to be registered.

Displacement is not confined to remote or isolated municipalities as it extends throughout the whole of Colombia. Underreporting in displacement is due to a person’s

[15] The municipal urban and rural classification follows the theoretical framework developed by the “National Mission for Rural Transformation of Colombia” led by the National Planning Department during 2014-2015, which defined four categories of municipalities according to its degree of “rurality” (cities and agglomeration, intermediate, dispersed rural, and rural) based on three variables: the number of inhabitants, the population density per square kilometre, and the share of people that reside in their main cities. In particular, whilst the categories “cities and agglomerations” and “intermediate” are assumed “urban”, the “dispersed rural” and "rural" are assumed “rural”.

unwillingness to become registered in the official registration system for reasons including a fear it places on an individual's personal and household security at risk, the desire of anonymity because of the situation of displacement, reticence or mistrust towards the state and its institutions, the lack of information on the existence of the registration system, or unawareness about the system registration benefits, among other factors (Ibáñez, 2009; Silva and Sarmiento, 2013).

On the other hand, there are registration inefficiencies and bureaucratic procedures that could vary regionally. For example, it can be the case of refusal to register by an official in charge of feeding the system in a region due to the non-recognition of certain causes of displacement (e.g., due to a state-caused displacement through the aerial fumigation of coca crops in the region). Finally, depending on the case, the regional authorities may not record the number and the reasons for the rejection. Similarly, there aren't records about the number of appeals or of the responses to appeals (See Rivadeneira, 2009). In conclusion, under-registration makes the true extent of displacement impossible to quantify with certainty. All of these explanations are random and municipality case-specific. Therefore, although the levels of registrations may be affected, we do not believe that the variation in registrations are affected given the random nature of under-reporting. Hence, we believe it is a reasonable assumption to make that measurement error in the forced displacement variable is likely to be random in nature. Furthermore, we believe that the IV estimation procedure used would address the issue of measurement error if it were systematic (rather than random) in nature.

Bottom-line, measurement error may conceal the true impact of $FD_{i,t}$ on forest cover. Since underreporting is likely to be negatively correlated with the $FD_{i,t}$ the estimate of γ is likely to be downward biased if estimated by OLS.

Second, **simultaneity** issues may also bias the parameter estimate of γ. $Forest_{i,t}$ and $FD_{i,t}$ are possibly determined simultaneously. On the one hand, $FD_{i,t}$ may be particularly widespread in forested regions. The illegal armed groups are profit-driven actors and therefore, natural resources such as faunae, timber, minerals, and tree crop booms attract them to the forests for harvesting purposes. These groups often then enter into conflict with the local people or with each other causing civilian displacement. For example, it is well known that the FARC and other criminal gangs, known locally as “Bacrims”, have sought control of illegal mining activities in the more remote forest lands. In the department of Choco illegal armed groups have violently secured control of territories, which are used by locals to carry out illegal gold mining. The FARC then charges the miners a gold production tax and a fee for using each unit of machinery (i.e., excavators).[16]

On the other hand, the presence of illegal armed groups affects forest conservation efforts. Historically, the Colombian government has often neglected remote regions and their inhabitants. As a result, local populations have limited loyalty to local governments, and look to other groups to perform traditional government functions. Thus, the guerrillas have taken advantage and have performed natural resource management and conflict resolution to legitimize their role as a local political actor in these regions. For example, it has been well documented that the ELN protected forests in the Serranía de San Lucas, a forested massif located in the department of Bolívar, northern Colombia, because of their major role in the local hydrology (See Álvarez, 2003; and Dávalos et al., 2011). In the Serranía de la Macarena, a set of mountains located in the Department of Meta, eastern Colombia, FARC violently enforced environmental protection. A noteworthy example is a ban they established on yellow catfish harvesting, a threatened species, especially when it is migrating up rivers and streams to spawn.[17]

Therefore, if there is a simultaneity bias one could expect a negative correlation between the unobservables determining $Forest_{i,t}$ and $FD_{i,t}$, ($\varepsilon_{i,t}$) and ($\mathrm{u}_{i,t}$), respectively, that might explain a downward bias in the estimate of γ if OLS is used in preference to an appropriate IV estimation procedure. However, looking for

[16] For example, see the article entitled “El medio ambiente: la víctima olvidada” an online special edition of Semana Magazine retrieved from: http://sostenibilidad.semana.com/medio-ambiente/multimedia/medio-ambiente-conflicto-colombia/33709
[17] Ibid.

unobservables and also a convincing narrative that leads to this particular result is hard. In fact, it is more likely that the correlation between unobservables is weak.

Third, **omitted variables** could also potentially affect the estimate for this key parameter as well. The set of controls ($X_{i,t}$) may neglect some time-varying factors that are difficult to capture but are also correlated with forest cover and forced displacement. For example, Acevedo (2015) argues that in coca areas the increase in coca yield is associated with a decrease in forced displacement mainly due to the establishment of 'coercive' institutions enforced by illegal actors. Thus, forced displacement only occurs when farmers are able to escape safely from the coca-farming contract entered into with the guerrillas and local drug barons. The negative correlation between the establishment of coercive institutions by guerrillas and forced displacement could potentially downward bias the OLS estimate of γ, though the direction of bias cannot be known a priori. However, the inclusion of municipal fixed effects may attenuate this particular bias in this circumstance.

It is likely that the measurement error bias dominates the other two endogeneity sources due to a presence of increased underreporting found in the forced displacement variable. First, even if the simultaneity and measurement error act in opposite directions, the correlation between unobservables determining $Forest_{i,t}$ and $FD_{i,t}$ is likely to be weak, which means that simultaneity bias is largely offset by the measurement error bias. Second, since inclusion of municipal fixed effects controls for permanent unobserved heterogeneity, the omitted variable problem is attenuated.

In order to tackle these endogeneity concerns, an instrumental variable (IV) technique is employed. Therefore, Equation (1.1) represents the structural model and comprises the second-stage equation in a two-stage estimation procedure.[18] The IV estimation seeks

[18] One alternative way to bypass the endogeneity problem is to use the lag of the $FD_{i,t}$ variable. It could be argued that this might solve the simultaneity problem as it could be argued that today's forest cover will not influence armed conflict activity in the past. However, the weakness of this approach is that if there is any inertia in the variables, the lags will not necessarily resolve the endogeneity problem. In any event, exogeneity, in its most stringent form, requires the unobservables to be independent of past, present and future values of the conflict variable. In general, this condition is rarely satisfied.

to separate the exogenous part of the total variance of the variable of interest from a part that is endogenous and thus correlated with the error term in Equation (4.1). Under the assumption that this separation is undertaken correctly, the final least squares estimates will be unbiased and consistent. In practice, it is necessary to find a set of variables, known as instruments, which are independent wither respect to forest cover, but strongly correlated with the variable of interest (i.e., displacement). The three important features of a good instrument are that: i) it should be correlated with the endogenous variable (i.e., relevance); ii) it should be uncorrelated with the error term (orthogonality); and most importantly iii) there should be a persuasive narrative about the use of the instrument(s). The first two of these requirements can be investigated empirically.

Thus, the first-stage Equation (1.2) is defined as:

$$FD_{\mathrm{i,t}} = \pi Z_{i,t} + \delta X_{i,t} + \alpha_i + \lambda_t + u_{i,t} \qquad (1.2)$$

where (Z_{it}) is the set of instruments that includes the lagged values of the victims of massacres per 100,000 inhabitants and the number of conflict kidnappings per 100,000 inhabitants. Exploiting various valid instruments can improve precision, hence, the use of a third instrumental variable is also explored. In particular, it is considered the percentage of the agricultural frontier with coca crops fumigated[19] and manually[20] eradicated; or expressed as the percentage of the municipal area with coca fumigated and manually eradicated. The vector $X_{i,t}$is comprised of exactly the same set of variables assumed exogenous in Equation (1.1). The key point here is that the predicted variable $\widehat{FD_{\mathrm{i,t}}}$, by construction, is independent of $u_{i,t}$ and thus the estimation yields unbiased and consistent estimates. The $u_{i,t}$ is an error term assumed to be identically independently distributed with zero mean and a constant variance.

The rationale underlying the "relevance" of these instruments is now discussed. First,

[19] Aerial spraying is undertaken using an herbicide called glyphosate, commercially sold as Roundup. It kills the plants inhibiting their ability to produce amino acids. The herbicide is sprayed from small aircrafts as closely as possible to the coca crops.

[20] Manual eradication is performed by a group of men who destroy coca crops by hand.

forced displacement is usually preceded by an escalation of violence, driven by exposure to more than one type of violence. In such instances, displacement becomes the last resort to survive. One of the main reasons driving people to flee their homes is the occurrence of massacres. Massacres are defined as those events in which four or more people are murdered at once. Usually, illegal armed groups have conducted massacres as a deliberate tool to instil fear and intimidate the civilian population in order to seize assets, disintegrate entire communities, and appropriate territory (Calderón-Mejía and Ibáñez, 2015; Roche-villarreal, 2012).[21] According to Ibáñez (2009a) the occurrence of massacres account for about one fifth (21.1%) of the total forced displacements.

Forced displacement and massacres are strongly linked at the municipal level in Colombia. In particular, high incidences of displacement and massacres coincide in 66.2% of Colombian municipalities; conversely, municipalities with low incidences of forced migration also exhibit a low incidence of massacres (Ibáñez and Vélez, 2008).

Second, kidnappings, just like other acts of violence, serve to remind the local inhabitants that coercive threats are real, and that a violent event could happen to anyone within the community boundaries (See Moya (2012)). According to Ibáñez (2009a) kidnappings explain 7.6% of the total forced displacements.

Third, there is evidence of a positive effect of the drug trade on violence (Dell, 2015; Dube and Vargas, 2013; and Angrist and Kugler, 2008). The presence of coca has fuelled Colombia's long enduring civil conflict. Despite the fact that coca production appears to improve crop producers' income, violence increases sharply in the coca-growing regions. Guerrillas derive substantial income by taxing coca-growers. Violence, or the threat of violence, is regularly used to enforce coca farming contracts in this illegal industry, which ultimately leads to displacement (See Acevedo, 2015; Rabasa and Chalk, 2001).

[21] Most massacres were committed during the time of the right-wing paramilitary activity between 1999 and 2003, rendering this armed group responsible for 58% of these cases.

In particular, coca leaf production and forced displacement are potentially related. According to Ibáñez (2009,a) the growth in illicit crop areas adds pressure on land and displacement not only because of the acquisition of lands for cocaine and poppy crops by illegal armed groups but also due to the importance of establishing transport routes for drugs. This is tested empirically by Dueñas et al. (2014). The authors, using fixed effects municipal panel data estimation for the period 2004–2009, report that the rates of expulsion of the forced displaced is positively correlated with the higher areas under coca cultivation.

Angrist and Kugler (2008) explain that coca crops generate only modest economic gains by farmers, mostly in the form of increased self-employment earnings[22] , and increased labour supply provided by teenage boys. However, rural areas which experience accelerated coca production subsequently become more violent due to an increase in the economic resources available to illegal armed actors. This in turn leads to increased forced displacement. In contrast, Acevedo (2015) suggests that coca production by farmers in some situations is not a voluntary choice. Instead it is forced by the illegal armed groups. In particular, coca planting, harvesting and processing into cocaine are activities that may be enforced with violence or the threat of violence. This is consistent with some anecdotal evidence that suggests that the economic benefits of coca growing are largely taxed. This kind of reasoning postulates that an increase in coca productivity should be associated with expansion efforts by the coercive non-state armed groups and a decrease in forced displacement. The Acevedo (2015) results confirm that an additional millimetre of precipitation above the municipality mean, which positively affects the yield of the crops, decreases forced displacement by 1.22% in coca-suitable areas with rich harvest data. An inference to be drawn from this is that forced displacement occurs only when farmers are able to leave “safely” the coca farming contract (and the region) thus mitigating the risks of retaliation.

[22] Coca cultivation *per se* may do little to enrich the cultivators. The price of raw coca leaf makes up a small fraction of the price of cocaine.

Finally, programs to eradicate illicit crops may also produce displacement. According to Engel and Ibáñez (2007) aerial fumigation of illicit crops destroys farmer assets, generating a negative income shock. This exacerbates violence in coca crops regions. Especially, the Forced Eradication Anti-Drug Programs in Colombia is one of the most aggressive programs in the world.[23] Data from the Colombian Anti-narcotics Police (DIRAN) suggest that in 2014 these programs treated around 68,050 hectares (UNODC, 2015). According to Rozo (2013), when the share of municipality area sprayed increased by 1%, the homicide rates increased by 4.56 per 100,000 inhabitants, the number of armed engagements increased by 1.69 per 100,000 inhabitants and the number of displaced people increased by around 41.6 per 100,000 inhabitants in the municipality.

In regard to the “orthogonality” of these instruments, which imply that they are independent of forest cover, all three instruments are as good as randomly assigned. First, the massacres reflect a complex interaction between gangs, paramilitaries, guerrillas and drug trafficking interests, which together have created several cycles of extreme violence in different geographies independently of forest cover presence. Second, forest cover has nothing to do with kidnappings. Kidnap victims are frequently targeted for their political beliefs or their wealth, and even others due to being in the wrong place at the wrong time. Today kidnapping is becoming not as lucrative as drug trafficking, is riskier and requires more resources than other crimes like extortion. And, third, the monitoring of coca crops cultivation in Colombia is based on the interpretation of satellite images and the validation of the data obtained through aerial or terrain reconnaissance each semester. Hence, eradication depends on detection. It can also be said that the cultivation of coca occurs in agricultural hubs, which means that it is not necessary to clear forests to plant coca bushes (See Dávalos et al., 2011)

The vector $X_{i,t}$ represents the municipal characteristics that affect forest cover. In

[23] Aerial spraying was first implemented in Colombia in 1978. Manual eradication programs began in 2007 and are modest in size given its high cost in terms of human lives. Reports from the Anti-narcotics National Police estimate that since its implementation, 135 men have been killed through explosions of mines hidden in the ground to prevent the eradication (Gaviria and Mejía, 2011).

particular, Equation (1.1) controls for the legal[24] extraction of valuable minerals such as gold, silver or platinum in municipality i in year *t.* Due to the potential bias that its inclusion might cause through a potential simultaneity problem with the dependent variable, the lag of the mining presence variable is used. In particular, mining is expected to have a negative environmental impact. It involves increased erosion, loss of biodiversity, and the contamination of soil, ground and surface waters by chemicals. Mining also often requires the clearance of large areas of forest, both for the mine itself, but also to create space for the storage of the created debris, and for the roads and other required infrastructures. Mining can be interpreted as part of the mechanisms enhancing conflict driven deforestation. For example, when the prices of minerals increase, and/or national security policies reduce the incomes of the guerrilla groups and/or criminal gangs (e.g., the illegal incomes earned from kidnapping and drug trafficking), these illegal actors frequently finance themselves through mining. For example, it is well known that FARC controls mines legally or illegally either through having direct stakes in operations or through extortion, respectively.[25]

Mining usually occurs in those municipalities rich in environmental resources - from the Pacific lowlands and rivers of the Amazon to the coffee-growing regions. Around 18%[26] of Colombia's territory has been licensed to national and multinational corporations in order to develop mining projects. This fact reflects the government's objective to turn the country into a mining powerhouse. Some mining requests have even been granted in protected forested areas such as national parks, indigenous territories and collectively held lands occupied by communities of African heritage.[27]

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[24] There are only official statistics for the legal extraction of minerals. At the moment, the government is trying to formalise the status of traditional miners who operate without licenses, while concurrently cracking down on those which serve the rebel groups and criminal gangs.

[25] According to governmental estimates around 80% of all gold in the country is mined illegally, and as much as 20% of the profits from these illegal activities go to the FARC, ELN and other criminal organizations. See also the article entitled "El medio ambiente: la víctima olvidada" in an online special edition of Semana Magazine retrieved from: http://sostenibilidad.semana.com/medio-ambiente/multimedia/medio-ambiente-conflicto-colombia/33709

[26] This is according to statistics from the Mining and Energy Planning Unit (UPME, acronym in Spanish). This share corresponds to the current and potential mining areas estimates. See also the article entiled "En sus 130 años, la U. Externado entrega estudio sobre minería" in El Tiempo newspaper retrieved from: http://www.eltiempo.com/estilo-de-vida/educacion/universidad-externado-entregara-estudio-sobre-mineria/16510296.

[27] See the article "Fiebre minera se apoderó de Colombia" in Semana magazine retrived from http://www.semana.com/nacion/articulo/la-fiebre-minera-apodero-colombia/246055-3

In Equation (1.1), the additional time varying controls included are the municipal population and municipality urbanization levels. Both variables account for the pressure of human activities on forests, capturing the increased demand for food products and timber which leads to both the need for converting forests into land for agriculture and an over-exploitation of forests.

The income tax revenue per inhabitant, which mirrors the heterogeneity in the overall economic activities at the municipality level, is also included as a control variable. Due to the high degree of fiscal decentralization, Colombian municipalities differ in terms of their fiscal abilities. There is significant dispersion in terms of a municipality's ability to raise local taxes or to invest tax revenues generated locally (Cardenas et al., 2016).

A potential question is whether any of the explanatory variables in the model, might also be affected by the presence of conflict. Although there is a link, the yearly effect of the conflict on population and urbanization is not sizeable when compared to the more standard natural drivers of population such as births and deaths. Thus, according to official statistics during the study period (2004-2012) the average yearly rate of reception[28] of displaced people is 8.6 per 1000 inhabitants (8.0 per 1000 inhabitant in urban municipalities). On the other hand, while the average yearly birth rate is 15.7 per 1000 inhabitants (16.1 per 1000 inhabitants in urban municipalities), the average yearly deaths rate is 4.3 per 1000 inhabitants (4.5 per 1000 inhabitants in urban municipalities). Hence, the rate of natural increase of the population (and urban populations) is greater than the rate of reception of displaced people (also with respect to urban municipalities). Migration, which is not necessarily directly related to conflict in many cases and is difficult to quantify, is likely to have an effect on urban population growth. In any event, the key purpose of the variables relating to population and urbanization are to act as controls. There is no research interest in this study to causally identify the impact of conflict on municipal population and urbanization levels.

[28] It corresponds average number of displaced people that arrived to municipalities divided by its population per 1000 inhabitants in the study period.

That represents a different research question and is not the primary one investigated here.

Finally, the inclusion of municipality fixed effects (α_i) controls for any municipality-specific characteristics that are assumed constant over time. The time fixed effects (λ_t) control for aggregate time trends in forest cover, and thus potentially capture macroeconomic shocks and outcomes to any shifts in deforestation policies that may have occurred in particular years. The standard errors are clustered at the municipality level and are thus robust to the presence of both autocorrelation and heteroscedasticity (Stock and Watson, 2008).

1.4 Data

The panel dataset used consists of annual municipal-level observations from 2004 to 2012 (inclusive). Colombia has a total of 1,123 municipalities. However, we use only 859 of these municipalities given the requirement around the availability of satellite data to compute the forest coverage variable. The forest cover variable calculations were done by research staff at the International Centre for Tropical Agriculture (CIAT) using satellite images (at 30-meter resolution) compiled by the Department of Geographical Sciences at the University of Maryland partnering with other major research centres[29] in the United States (Hansen et al., 2013). For 265 of the municipalities, the forest cover estimates using satellite images were either not available at all, or only available for one or, in some exceptional circumstances, just two years. The criterion used here for the empirical analysis is that the data panel requires observations on forest cover must be available for a minimum of three continuous years.

Although this may be viewed as a limitation, we present three reasons why we believe this should not be a major concern for the empirical analysis undertaken here. First, the **Figure 1.10.1** in the Appendix **1.10**, which presents the final sample map, reveals that

[29] Google; the Department of Forest and Natural Resources Management, State University of New York; the Woods Hole Research Center; the Earth Resources Observation and Science, United States Geological Survey; and the Geographic Information Science Center of Excellence, South Dakota State University.

the location of the municipalities excluded *are in fairly remote parts of the country.*[30] *In particular, some are situated in the Amazon Jungle, South East Colombia bordering Brazil, while others are in the C*hocó Department, Northwest Colombia, which borders Panama, and is also a jungle area and rich in natural resources. The other missing areas included are in the Orinoquía Region, East Colombia, which borders Venezuela, also known as the “Eastern Plains” (“Llanos Orientales” in Spanish), where traditionally raising beef cattle and oil exploitation occurs; the Cesar Department, North Colombia, part of the Caribbean regions with valleys; and in Norte de Santander Department bordering Venezuela, with a mixed geography comprising mountainous areas, deserts, plateaux, plains and hills.

Second, in order to examine the relationship between the conflict and the forestation impacts using relevant maps, **Figure 1.10.1** in Appendix **1.10** presents a map of the main locations of forced displacement in Colombia for the last decade[31], which reflects visual testimony of where in Colombia the armed conflict has had an incidence. The considerable overlay between maps, **Figure 1.10.2** (which proxies the presence of conflict) and **Figure 1.10.1** (which maps the final sample locations), both reported in the Appendix **1.10**, suggest a plausible correlation between the conflict locations and the forest cover areas that are available to us for analysis. We highlight that we do not know a priori the sign of the direction of a causal relationship. However, since the municipalities excluded from the analysis *are fairly remote, we can say with some degree of confidence that their exclusion is unlikely to affect the sign of the correlation that we are trying to disentangle empirically in the econometric analysis.*

Third, Table 1.4.1 presents the summary statistics for the final sample. In addition, **Table 1.10.1** and **Table 1.10.2** reported in Appendix **1.10** reports the mean statistics for the key variables for the omitted municipalities, and the means statistical differences t-test between both samples. The mean values for the direct conflict kidnappings per 100.000 inhabitants (lagged one year), the percentage of the agricultural frontier with

[30] The final sample includes municipalities with prominent economic *activity*.
[31] 2005-2014.

coca crops fumigates and manually eradicated (lagged one year), the percentage of the municipal area with coca fumigated and manually eradicated (lagged one year), mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year), and the income tax revenue per inhabitants are broadly similar between samples. The sample mean values of the share of municipality area with forest coverage [0-100], the forced displacement per 1000 inhabitants, victims of massacres per 100,000 inhabitants (lagged one year), the percentage of urban population, and the municipal population are statistically different between these samples. Overall, the variable means are not necessarily similar for these two sets of municipalities.[32] It should be stressed that these comparisons are likely to be unreliable given the significant presence of missing values in the set of remote and excluded municipalities.

However, given the differing geographical and socio-economic nature of the included and excluded municipalities, the detection of differences in observables is to be anticipated. Our argument is that the econometric results are conditional on the sample used. We acknowledge the data that we are employing may not be representative of the country. This does not vitiate the analysis, nor does it undermine our attempt to identify the size and the sign of the effect of conflict on forest cover in those areas where conflict has had the most pervasive effect.

Table 1.4.1, as mentioned, presents the descriptive statistics employed in the regression analysis for coefficients interpretation purposes. Note that the sample period is adjusted to start at year 2005. This is because the 2004 observations are “lost” when the set of instruments are lagged one year. As noted above, the primary outcome is the share of municipality area covered by forest. Between 2005 and 2012, the average share of the municipality area covered with forest is more than half (58.4%) the land size of Colombia.

[32] This result is not surprising, as mentioned, due to the absence in the final sample of a significant part of the Amazon Jungle and the forests of Chocó Department.

Table 1.4.1 Summary statistics

Variable	Mean	SD	Min	Max
Share of municipality area with forest [0-100%]	58.40	25.85	0.67	98.93
Forced displacement per 1000 of the municipal population	10.09	22.87	0.00	702.72
Victims of massacres per 100,000 inhabitants (lagged one year)	0.43	4.98	0.00	187.62
Direct conflict kidnappings per 100.000 inhabitants (lagged one year)	1.04	5.56	0.00	185.56
Hectares of coca fumigated and manually eradicated (lagged one year)	173.23	1091.46	0.00	34432.53
Percentage of the agricultural frontier with coca crops fumigates and manually eradicated [0-100%] (lagged one year)	0.12	0.75	0.00	27.63
Percentage of the municipal area with coca fumigated and manually eradicated [0-100%] (lagged one year)	0.11	0.68	0.00	24.81
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	0.16	0.36	0.00	1.00
Population	32027.15	80091.16	885	1200513
Log Population	9.58	1.10	6.79	14.00
Percentage of urban population [0-100]	43.10	23.79	1.68	99.89
Income tax revenue per inhabitants (COP[33])	86762.13	126009.15	385.47	2749220
Log income tax revenue per inhabitants	10.93	0.97	5.95	14.83

Statistics refer to N = 6826 observations for 859 municipalities over the period 2005-2012.

Satellite images issues such as persistent cloud cover in the tropics, shadows from the tree canopy, and the complexity of forest structure can all lead to (random) small errors in forest cover calculations. Furthermore, the ambiguity in the concept “forest” leads to different assessments of the extent of forest cover. For example, geographers and ecologist have long called for the definition to be more standardized. One scientist could consider that the area is forested if 30 percent of the land is covered with trees (the definition employed here by CIAT), while another could argue that a forest exits when there is 10 percent tree cover and excluding areas of intermediate tree cover, such as savannahs, scrublands, mountain ridge forests, and boreal taiga. Thus, many researchers currently claim that there should be either a single, unambiguous definition of forest/non-forest that can be used globally or, preferably, that the research community should shift to the use of measureable ecological characteristics such as tree cover, canopy height, and/or biomass.

The use of satellite images for forest cover is not free from critics. However, if the estimation manages to yield statistically significant coefficients with an apparent mis-measured dependent variable, this is actually good news. Measurement error in the

[33] Colombian peso.

dependent variable does not cause the slope coefficients to be biased, but it does cause the standard error for the slope coefficients to be larger, which suggests that in this case a statistical significant coefficient is way more significantly different from zero.

The primary conflict variable is the forced displacement rate per 1,000 of the population ($FD_{\mathrm{i,t}}$) and is calculated based on estimates from the Information System of Displaced Population (SIPOD, its Spanish acronym), the Central Registry for Victims Office (RUV)[34], and the Observatory of the Presidential Human Rights and International Humanitarian Law of the Vice Presidency of Colombia. As discussed in Section 3, the main drawback on displacement statistics is under-reporting. In the dataset, an average of 10.09 people per 100,000 inhabitants were forcibly displaced due to violence at the municipal level. One municipality experienced a displacement of 702.7 people per 100,000 of its population in one year (see Table 1.4.1).

Regarding the data sources for the identifying instrumental variables, the victims of massacres per 100,000 inhabitants are based on data from Colombia's National Centre of Historical Memory. The statistics on the direct conflict kidnappings[35] per 100,000 inhabitants are taken from a conflict panel dataset constructed by the Centre of Development Economics Studies (Centro de Estudios sobre Desarrollo Económico, CEDE in Spanish), Universidad de los Andes, Bogotá, Colombia.

The number of hectares of coca fumigated and manually eradicated in the municipalities is calculated using satellite-based information from the Integrated Monitoring System of Illicit Crops of the United Nations Office of Drugs and Crime (SIMCI[36]-UNODC) and the Anti-Narcotics Directorate of the Ministry of National Defence in Colombia. The municipal agricultural frontier area corresponds to the sum of agricultural, agroforestry, animal husbandry and forest vocation areas calculated by the Geographic Institute Agustin Codazzi (IGAC, in Spanish).

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[34] This registry, established under Act 1448 of 2011, contains the number of registered victims of human rights violations during the armed conflict and over the period from 1985 to the present.
[35] Bear in mind that these types of kidnappings mainly target businessmen, political leaders and senior members of the army.
[36] This is known as the Integrated System for Monitoring Illicit Crops (SIMCI, according to its Spanish acronym).

In the municipality dataset used in the regressions, around 0.43 people per 100,000 of the population were killed in massacres, with a maximum reported of 187.6 per 100,000 inhabitants. Armed groups kidnapped one person 1.04 per 100,000 inhabitants and the military fumigated and manually eradicated a total of 173.2 hectares of coca plants on average, which corresponds to circa 0.12% and 0.11% of the average municipal agricultural frontier and municipal area, respectively (see Table 1.4.1).[37]

A dichotomous variable [Yes=1; No=0], representing the extraction of elements such as gold, silver or platinum, is constructed using data on municipal mining records from the Colombian Mining Information System (SIMCO, its Spanish acronym). About 16% of the municipalities have mining activities, producing gold, silver or platinum (see Table 1.4.1).

The information on socioeconomic and geographic covariates such as the municipal population, the percentage of urban population, and the income tax revenue per inhabitant was provided by the National Administrative Department of Statistics (DANE, according to its Spanish acronym) and the National Planning Department (DNP, according to its Spanish acronym). The municipality average population is 31,846 inhabitants and almost half of these (43.1%) live in cities, and their inhabitants pay yearly on average COP 82,389.69 in income tax.

1.5 Empirical results

1.5.1 Validity of the instruments

The first stage regression results employing initially two instruments are presented in Table 1.5.1 with the standard IV-diagnostic tests presented in the bottom panel of this table.

[37] Not all municipalities of the country produce coca. In fact, only 16% of municipalities produce coca, on average.

Table 1.5.1 First stage reduced form results (two instruments)

Dependent variable: Forced displacement per 1000 inhabitants
Two instruments: a) Victims of massacres per 100,000 inhabitants (lagged one year); and b) Direct conflict kidnappings per 100.000 inhabitants (lagged one year)

	(1) 1st Stage FE
Victims of massacres per 100,000 inhabitants (lagged one year)	0.19**
	(0.083)
Direct conflict kidnappings per 100.000 inhabitants (lagged one year)	0.15**
	(0.070)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-1.69
	(1.69)
Log Population	-22.2**
	(10.4)
Percentage of urban population [0-100]	-1.21**
	(0.53)
Log income tax revenue per inhabitants	-0.57
	(0.75)
Year 2006	1.39*
	(0.74)
Year 2007	2.8***
	(1.05)
Year 2008	1.51
	(0.95)
Year 2009	-3.51***
	(0.99)
Year 2010	-5.32***
	(1.14)
Year 2011	-3.89***
	(1.37)
Year 2012	-4.03**
	(1.59)
Observations	6826
Cragg-Donald Wald F statistic	16.99
Hansen J statistic	0.000
Hansen p-value	0.999

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

The IV estimator is based on asymptotic properties. Thus, it is subject to finite sample bias which can only be reduced through using stronger and more relevant instruments. In addition, using stronger instruments ensures that the estimator follows a normal distribution. That's why the relevance condition is so important.[38]

The Cragg and Donald (1993) test yields a value 16.99, indicating that the instruments

[38] It is possible to attempt to bypass the endogeneity issue by using explicitly the lagged values of $FD_{i,t}$ (See Table 1.10.3 in the Appendix), however, the correct method of estimation is IV.

are relevant. However, the result comfortably passes the 'rule-of-thumb'[39] value of 10. The Hansen (1982) J-test provides a p-value of 0.999. Thus, the null hypothesis of zero correlation between the instruments and the error term is upheld at the conventional significance levels, though the prob-value is acknowledged to be on the high side.

We now turn to an interpretation of the estimates for the selected identifying instruments. The individual significance of these identifying instrument imply that the military strategies adopted by the illegal armed groups and forced displacements are strongly correlated. Indirect violence, including massacres and directly related conflict kidnappings, play a strong role in determining civilian displacement. If the number of victims of massacres per 100,000 municipality inhabitants in the previous year increases by 1, which is a sizeable increase relative to the mean, approximately 1.9 persons per 10,000 of the population are forced displaced, on average and *ceteris paribus*. The empirical estimates also reveal that an increase in 1 conflict-related kidnapping in the previous year per 100,000 inhabitants, which is effectively a doubling relative to the sample mean, is associated with an increase of 1.5 displaced persons per 10,000 of the municipal population, on average and *ceteris paribus*.

In order to improve IV models efficiency, the use of a third instrumental variable related to drug production in municipality *i* is explored as well. The first stage regression results including the percentage of the agricultural frontier with coca crops fumigated and manually eradicated; or the percentage of the municipal area with coca fumigated and manually eradicated, along with the standard IV-diagnostic tests are presented in Table 1.5.2 and Table 1.5.3, respectively. In both cases, the estimated coefficient associated with the instrument with coca crops presence is borderline statistically significant with a t-ratio of 1.6. However, overall all three instruments are jointly statistically significant with a F-test of 14.26 and 14.34, respectively, which exceed the conventional 'rule-of-thumb' of 10.

[39] This rule-of-thumb means that we are tolerating a 10% finite sample bias in the IV estimator relative to the OLS estimator.

Table 1.5.2 First stage reduced form results (Three instruments A.)

Dependent variable: Forced displacement per 1000 inhabitants
3rd instrument: Percentage of the agricultural frontier with coca crops fumigates and manually eradicated (lagged one year)

	(1) 1st Stage FE
Victims of massacres per 100,000 inhabitants (lagged one year)	0.18**
	(0.082)
Direct conflict kidnappings per 100.000 inhabitants (lagged one year)	0.15**
	(0.070)
Percentage of the agricultural frontier with coca crops fumigates and manually eradicated (lagged one year)	1.19
	(0.74)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-1.62
	(1.68)
Log Population	-22.1**
	(10.3)
Percentage of urban population [0-100]	-1.21**
	(0.53)
Log income tax revenue per inhabitants	-0.59
	(0.75)
Year 2006	1.31*
	(0.75)
Year 2007	2.68***
	(1.04)
Year 2008	1.41
	(0.95)
Year 2009	-3.59***
	(0.99)
Year 2010	-5.35***
	(1.14)
Year 2011	-3.89***
	(1.36)
Year 2012	-4.03**
	(1.59)
Observations	6826
Cragg-Donald Wald F statistic	14.26
Hansen J statistic	0.0883
Hansen p-value	0.957

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.5.3 First stage reduced form results (Three instruments B.)

Dependent variable: Forced displacement per 1000 inhabitants
3rd instrument: Percentage of the municipal area with coca fumigated and manually eradicated (lagged one year)

	(1) 1st Stage FE
Victims of massacres per 100,000 inhabitants (lagged one year)	0.18**
	(0.082)
Direct conflict kidnappings per 100.000 inhabitants (lagged one year)	0.15**
	(0.070)
Percentage of the municipal area with coca fumigated and manually eradicated (lagged one year)	1.32
	(0.83)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-1.62
	(1.68)
Log Population	-22.1**
	(10.3)
Percentage of urban population [0-100]	-1.21**
	(0.52)
Log income tax revenue per inhabitants	-0.59
	(0.75)
Year 2006	1.31*
	(0.75)
Year 2007	2.68***
	(1.04)
Year 2008	1.41
	(0.95)
Year 2009	-3.59***
	(0.99)
Year 2010	-5.35***
	(1.14)
Year 2011	-3.88***
	(1.36)
Year 2012	-4.02**
	(1.59)
Observations	6826
Cragg-Donald Wald F statistic	14.34
Hansen J statistic	0.0923
Hansen p-value	0.955

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

The disruption of drug production and forced displacement are also correlated. If a municipality is subject to a one percentage point increase of the agricultural frontier with coca crops fumigates and manually eradicated, or a one percentage point increase in the municipal area with coca fumigated and manually eradicated, both in the previous year (and representing substantial increases of circa 8.3 and 9 times their mean, respectively), this leads to an increase of 11.9 and 13.2 forced displaced persons per 100,000 municipality inhabitants, on average and *ceteris paribus*. If the scale of disruption activities is correlated with the scale of drug production activities, this result is consistent with the literature indicating that coca production is associated with the establishment of coercive institutions governed by the illegal armed groups. Thus, forced displacement only occurs when farmers are able to escape safely from the region (Acevedo, 2015).

The instruments related to victims of massacres and conflict kidnappings maintain their expected sign, size and statistical significance.

1.5.2 IV Estimates of the Causal Effect

Table 1.5.4 provides evidence on the relationship between the armed conflict and forest coverage in Colombia using initially two instruments. In particular, it provides estimates based on treating forced displacement per 1000 of the municipal population endogenously and instrumenting it (FE-IV). Under this context the results are a causal effect and, in some sense, a Local Average Treatment Effect (LATE). The treatment effect estimate is local, because it only applies to the subset of municipalities who are exposed to the treatment and experience forced displacement, because of variation in the instruments.[40] The model also includes the controls described in Section 1.3.

[40] The IV estimate can be interpreted under weak conditions as a weighted average of LATEs, where the weights depend on the elasticity of the endogenous variable to changes in the instruments. This means that the effect of a variable is only revealed for the sub-populations affected by the observed changes in the instruments, and that sub-populations which respond most to changes in the instruments will have the largest effects on the magnitude of the IV estimate.

Table 1.5.4 Forest cover FE-IV equation estimates (two instruments)

Dependent variable: Share of municipality area with forest [0-100]
Two instruments: a) Victims of massacres per 100,000 inhabitants (lagged one year); and b) Direct conflict kidnappings per 100.000 inhabitants (lagged one year)

	(2) 2nd Stage FE-IV
Forced displacement per 1000 of the municipal population	0.012
	(0.0074)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.076
	(0.056)
Log Population	-2.89^{***}
	(0.51)
Percentage of urban population [0-100]	-0.035
	(0.025)
Log income tax revenue per inhabitants	0.054^{*}
	(0.029)
Year 2006	-0.20^{***}
	(0.017)
Year 2007	-0.43^{***}
	(0.030)
Year 2008	-0.60^{***}
	(0.033)
Year 2009	-0.81^{***}
	(0.051)
Year 2010	-0.96^{***}
	(0.066)
Year 2011	-1.17^{***}
	(0.069)
Year 2012	-1.40^{***}
	(0.077)
Observations	6826
R-Squared	0.536
F-stat	105.0
Exogeneity test statistic	2.027
p-value (Ho: Regressor is exogenous)	0.155

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

On the basis of the instruments used, the exogeneity assumption for the forced displacement variable is not rejected by a Hausman test (p-value of 0.155), thus, confirming there is no need to use IV techniques in the application using two instruments. The same happens when employing a third instrument related to drug production in the municipality. In particular, the Hausman test p-values are 0.12 and 0.13, respectively (See Table 1.5.2 and Table 1.5.3).

Table 1.5.5 Forest cover FE-IV equation estimates (three instruments A.)

Dependent variable: Share of municipality area with forest [0-100]
3rd instrument: Percentage of the agricultural frontier with coca crops fumigates and manually eradicated (lagged one year)

	(2) 2nd Stage FE-IV
Forced displacement per 1000 of the municipal population	0.011*
	(0.0063)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.077
	(0.055)
Log Population	-2.90***
	(0.50)
Percentage of urban population [0-100]	-0.036
	(0.024)
Log income tax revenue per inhabitants	0.054*
	(0.029)
Year 2006	-0.20***
	(0.016)
Year 2007	-0.42***
	(0.028)
Year 2008	-0.60***
	(0.032)
Year 2009	-0.81***
	(0.049)
Year 2010	-0.97***
	(0.063)
Year 2011	-1.17***
	(0.066)
Year 2012	-1.41***
	(0.075)
Observations	6826
R-Squared	0.541
F-stat	105.5
Exogeneity test statistic	2.314
p-value (Ho: Regressor is exogenous)	0.128

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.5.6 Forest cover FE-IV equation estimates (three instruments B.)

Dependent variable: Share of municipality area with forest [0-100]
3rd instrument: Percentage of the municipal area with coca fumigated and manually eradicated (lagged one year)

	(2) 2nd Stage FE-IV
Forced displacement per 1000 of the municipal population	0.011*
	(0.0063)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.077
	(0.055)
Log Population	-2.91***
	(0.50)
Percentage of urban population [0-100]	-0.036
	(0.024)
Log income tax revenue per inhabitants	0.054*
	(0.029)
Year 2006	-0.20***
	(0.016)
Year 2007	-0.42***
	(0.028)
Year 2008	-0.60***
	(0.032)
Year 2009	-0.81***
	(0.049)
Year 2010	-0.97***
	(0.063)
Year 2011	-1.17***
	(0.067)
Year 2012	-1.41***
	(0.075)
Observations	6826
R-Squared	0.541
F-stat	105.5
Exogeneity test statistic	2.260
p-value (Ho: Regressor is exogenous)	0.133

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

1.5.3 The OLS fixed effects (FE-OLS)

The OLS fixed effects (FE-OLS) estimation are presented in Table 1.5.7. The downward bias of the OLS fixed effects (FE-OLS) of γ (0.0028) relative to the IV models (0.012 and 0.011, using two and three instruments, respectively) estimates suggests that measurement error is a probable source of the downward bias reported, which dominates the simultaneous reverse causality problem. Note that the use of municipal fixed effects is likely to attenuate the omitted variable bias problem here. Nonetheless, the more appropriate method to make inferences is the OLS fixed effects (FE-OLS) model, in the light of the Exogeneity tests involving the selected set of instruments used.

Table 1.5.7 Forest cover FE-OLS equation estimates

Dependent variable: Share of municipality area with forest [0-100]	
	FE-OLS
Forced displacement per 1000 of the municipal population	0.0028**
	(0.0011)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.090*
	(0.051)
Log Population	-3.07***
	(0.48)
Percentage of urban population [0-100]	-0.046**
	(0.023)
Log income tax revenue per inhabitants	0.048*
	(0.029)
Year 2006	-0.19***
	(0.012)
Year 2007	-0.40***
	(0.023)
Year 2008	-0.59***
	(0.031)
Year 2009	-0.84***
	(0.041)
Year 2010	-1.01***
	(0.050)
Year 2011	-1.21***
	(0.059)
Year 2012	-1.44***
	(0.067)
Observations	6826
R-Squared	0.571
F-stat	108.6

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

We now focus, therefore, on the FE-OLS model estimates for our discussion of the causal estimate of interest. The estimate in column two is well determined statistically and suggests that an increase in one forced displaced person per 1,000 of the municipal population, which represents a 9.91% increase with respect to the sample mean, increases the share of the municipality covered by forest by 0.0028 of a percentage point, on average and *ceteris paribus*. This represents a small effect relative to the mean forest coverage rate of 58.4%. In other words, an approximate 10% increase in displaced person per 1,000 of the population leads to a 0.003% increase in forest cover.

Although the estimated effect is economically small in terms of its magnitude, the explanation for this is straight-forward. The presence of armed groups means that large rural areas become inaccessible and thus are preserved and protected from the economic forces and rural production activities that encourage deforestation. In this case, the armed conflict appears to be a force that favours forest protection and growth, albeit in extremely modest terms. As mentioned previously, this is because some of the armed groups practice a form of forest conservation, although one situated within a highly localized and coercive framework and entirely to the benefit of such groups rather than the environment.

Regarding the other municipality-level characteristics that are statistically significant, the presence of mining, as expected, has a negative environmental impact. A municipality in which there was extraction of elements such as gold, silver or platinum compared to another that did not experience extraction, in the previous year, exhibits a reduction of 0.09 percentage points in the share of municipality area covered by forest, on average and *ceteris paribus*.

On the other hand, a 10 percent increase in the municipality population is associated with a 0.307 percentage points decrease in the share of municipality area covered by forest. This effect is anticipated as it reflects the impact of population pressure on forest resources and their conservation. The population effect could be easily interpreted as an increase of one person per 1,000 of the municipal population, which is equivalent to a 3.12% increase in the population. This increase is associated with a 0.096 percentage point reduction in the share of municipality area covered by forest. Population pressure reduces the forest cover thirty-four times (34.2) more than the effect induced by forced displacement when using the same metric (i.e., one person per 1,000 increase of the municipal population). This confirms the relatively small magnitude of the forced displacement effect on forest cover compared to conventional demographic pressures on forestation.

An increase of 10 percentage points in the percentage of urban population is related to a 0.46 percentage point decrease in the share of municipality area with forest cover, on average and *ceteris paribus*.

In addition, an increase of 10 percentage points in the income tax revenues per inhabitant is associated with a 0.0048 percentage point increase in the share of municipality area covered with forest. This may reflect the fact that revenues are being used to conserve forests. The estimate may also reflect the role of governance and the rule of law. However, revenues are mainly generated in major cities reflecting the strength of local economies already in place. The concentration of people in cities leaves room for nature. It is likely that major cities do not have large sized forests left to clear. Large industrial farms have already taken over rural areas and expanded further into the nearest forests.

Finally, the estimated time dummy effects reveal sizeable annual reductions in forest coverage. The average effects per year are about one-fifth of a percentage point, *ceteris paribus*. This does suggest a secular trend in deforestation, the magnitude of which is sizeable compared to the estimates corresponding to the other regressors included in this specification.

1.6 Are coca crops to blame for forest cover loss?

In this section, we explore some alternative expressions of the conflict to test the sensitivity of the IV results obtained in the last section. Often when exposed to high levels of violence, farmers tend to reduce the allocation of land devoted to legal crops. Illegal crops are planted instead and additional forest clearing occurs (Ibañez et al., 2013). Between 2001 and 2014, it is estimated that planting coca has caused the deforestation of around 290,992 hectares of forest, which is equivalent to a little over twice the area of Bogotá city (UNODC, 2015). Therefore, we use the presence of coca crops to re-estimate Equation (1.1) with the presence of coca crops replacing the forced displacement variable.

The conflict variable in Equation (1.1) is now represented by the presence of coca crops in the municipalities. The selected set of instruments that meet the econometric requirements for valid instruments are the lagged number of dismantled coca crystal laboratories and the confiscation of cocaine paste base (tons).[41] In particular, both measures are taken to reflect the government's capacity to counteract criminal activity in the municipalities and are also highly correlated with the armed conflict. In addition, it is difficult to argue they are correlated with forest cover.[42]

Table 1.6.1 Summary statistics when the presence of coca crops is used as an explanatory variable

Variable	Mean	SD	Min	Max
Presence of coca crops [Yes=1; No=0]	0.16	0.37	0.0	1.0
Dismantling of coca crystal laboratories (number, lagged one year)	0.22	1.34	0.0	45.0
Confiscation of cocaine pasta base (tons, lagged one year)	0.052	0.420	0.0	18.72

Statistics refer to N = 6826 observations for 859 municipalities during 2004-2012.

[41] The "extraction" laboratories called "kitchens", "Chagres", "Chongos, "Saladeros", "Picaderos" are basic constructions at the farmers houses for the extraction of coca paste base by processing raw materials (plant material) using organic solvents. Thus, the coca pasta base is an extract of the leaves of the coca bush. It contains coca alkaloids, and its purification yields cocaine. Then, the coca crystal laboratories are those in which the cocaine is obtained through the chemical processes.

[42] Camacho and Rodriguez (2013) provide support for these instruments. In their study, the authors used an instrumental variable approach, in which contemporaneous armed conflict was instrumented with lagged government deterrence measures.

Around 16% of the municipalities report the presence of coca crops. Regarding the set of instruments, the police dismantled 0.22 coca crystal laboratories and confiscate 0.052 tons of cocaine paste base on average[43] (see Table 1.6.1). The data source for these variables is the Anti-Narcotics Directorate of the Ministry of National Defence of Colombia.

Table 1.6.2 First stage results when the presence of coca crops is used as an explanatory variable

Dependent variable: Presence of coca crops [Yes=1; No=0]	(1) 1st Stage FE
Dismantling of coca crystal laboratories (lagged one year)	0.0098*
	(0.0050)
Confiscation of cocaine paste base (lagged one year)	0.014*
	(0.0081)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	0.0091
	(0.011)
Log Population	0.091
	(0.073)
Percentage of urban population [0-100]	0.0024
	(0.0035)
Log income tax revenue per inhabitants	-0.0058
	(0.0065)
Year 2006	0.0078
	(0.0065)
Year 2007	0.0026
	(0.0071)
Year 2008	0.0096
	(0.0086)
Year 2009	0.015
	(0.0091)
Year 2010	0.0079
	(0.010)
Year 2011	0.012
	(0.011)
Year 2012	0.0085
	(0.012)
Observations	6826
R-Squared	0.89
Cragg-Donald Wald F statistic	13.87
Hansen J statistic	0.0372
Hansen p-value	0.847
Exogenity test statistic	0.021
Exogeneity p-value (Ho: Regressor is exogenous)	0.885

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.6.2 presents the first stage results. Both instruments signal the municipality's potential of producing coca. The strength of the instruments is assessed using the Cragg-Donald Wald F statistic (1993). The hypothesis of weak instruments is rejected, though again the relevance of the instruments is not strong with the Wald-transformed

[43] The confiscation of cocaine paste base obviously is quite low in most of the municipalities, however, more than 90 experienced one ton or more up to a maximum of 18.72 tons.

F-test for exclusion of instruments 13.87, only marginally above the threshold of 10. The Hansen (1982) J-test p-value is 0.84, hence, instruments are orthogonal to the error structure in the structural equation. However, the proposition that the presence of coca crops is exogenous cannot be rejected in this case. Therefore, the use of IV is not required. This indeed is confirmed by the exogeneity test, which yields a p-value of 0.885.

Table 1.6.3 Effect of the presence of coca crops on forest cover

Dependent variable: Share of municipality area with forest [0-100]

	FE-OLS
Presence of coca crops [Yes=1; No=0]	0.027
	(0.073)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.095*
	(0.052)
Log Population	-3.13***
	(0.49)
Percentage of urban population [0-100]	-0.049**
	(0.023)
Log income tax revenue per inhabitants	0.046
	(0.029)
Year 2006	-0.19***
	(0.012)
Year 2007	-0.40***
	(0.022)
Year 2008	-0.59***
	(0.031)
Year 2009	-0.85***
	(0.041)
Year 2010	-1.03***
	(0.050)
Year 2011	-1.22***
	(0.060)
Year 2012	-1.45***
	(0.068)
Observations	6826
R-Squared	0.568
F-stat	107.3

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.6.3 present the FE-OLS model results which is the more efficient method of estimation. Thus, the FE-IV results can be found in **Table 1.10.4** in the Appendix **1.10**.[44] Consistent with FE-OLS model results, the presence of coca crops has no effect on forest cover, on average. These results are plausible since coca crops account for only a small percentage of total deforestation rates. In addition, compared to a root vegetable like cassava, which requires a lot of space and effort to harvest but brings in a relatively small amount of money, the coca plant has a dense leaf cover and fetches

[44] The coefficients and the standard errors from the FE-IV estimates are almost identical to those from FE.

high prices. This means that coca farmers obtain higher value per areas cultivated.

1.7 An Analysis of the forest cover OLS fixed effects estimates

Forests play a crucial role in biodiversity conservation. It helps to purify the air, sustain the quality and availability of freshwater supplies, and provide essential services to local populations. Furthermore, forest preservation has been attracting increased attention in the fight against climate change. The FE-OLS model cannot accommodate time-invariant variables. Thus, any time-invariant variables are absorbed within the fixed effects. However, understanding which time-invariant factors potentially influence forest coverage is of considerable interest and may provide some insights that aid the design of policy interventions.

Equation (1.3) describes the model that examines the determinants of the estimated fixed effects retrieved from the estimation reported Table 1.5.7. These fixed effects are regressed on a set of time-invariant covariates and thus provide insights on the impact of time-invariant factors on municipality forest cover. The model is specified as:

$$\hat{\alpha}_i = \mathrm{c}_i + \delta_i \mathrm{W}_i + \mathrm{v}_i \text{, with } i = 1; \dots, \mathrm{n}. \qquad (1.3)$$

$\hat{\alpha}_i$ is the estimated municipality i specific fixed effect estimate corresponding to the coefficient on the municipality dummy variables in Equation (1.1). W_i is a vector of time-invariant covariates assumed to affect forest cover, which for the purposes of the analysis here include the municipality's degree of elevation, average monthly precipitation, the distance to the department capital, and a soil quality index. The variable c_i is the constant and the term v_i represents the error assumed to satisfy the standard assumptions. The analysis is conducted using only 848 (of 859) municipalities for which forest coverage and the other time-invariant covariates data is available.[45]

[45] In particular, we lost 11 data points due to the presence of missing values in the soil quality index. This index is calculated by the Geographic Institute Agustin Codazzi (IGAC, in Spanish) based on georeferenced information

Table 1.7.1 Time-invariant covariates summary statistics

Variable	Mean	SD	Min	Max
Municipality elevation (m)	1225.8	1221.9	2.0	25221.0
Avg. precipitation monthly (mm)	176.1	85.6	52.8	712.0
Distance to the department capital (km)	76.6	54.3	0.0	376.1
Soils quality index [1-8]	2.7	1.2	0.0	8.0

N=848 municipalities during 2004-2012.

The data source for the time-invariant covariates is the Centre of Development Economics Studies (Centro de Estudios sobre Desarrollo Económico, CEDE in Spanish), Universidad de los Andes, Bogotá, Colombia, which treasures official statistics produced by the National Administrative Department of Statistics (DANE, in Spanish), the Geographic Institute Agustin Codazzi (IGAC, in Spanish) and the National Planning Department (DNP, in Spanish). Table 1.7.1 above reports the summary statistics.

An average municipality has an elevation of 1,229.4 meters and the precipitation levels reach 173.5 millimeters (mm)[46]of rain monthly. The soil quality index measures the suitability of the land for agricultural activities depending on land topography and soil type. It ranges from 1.0 (not suitable for agriculture) to 8.0 (fully suitable for agriculture). The average municipality has a soil quality index value of 2.73.

Table 1.7.2 reports the estimates for a regression of the fixed effects estimates from the FE-OLS model (Section 1.5.3) on this set of time invariant variables using a Weighted Least Squares (WLS) method.[47] The weights are proportional to the estimated standard errors from the FE-IV model. Thus, the fixed effects that are more precisely estimated secure a higher weight in the WLS estimation procedure. Since each weight is inversely

regarding topography types, drainage presence, municipality climates, and others fundamentals that affect soils quality.

[46] The standard instrument for the measurement of rainfall is the 203mm (8 inch) rain gauge. This is a circular funnel with a diameter of 203mm which is kept in an open area, so that it collects the rain into a graduated and calibrated cylinder. The measuring cylinder can record up to 25mm of precipitation. The precipitation value in mm is referring to the amount of rain per square meter in one hour. One millimeter of rainfall is the equivalent of one liter of water per square meter.

[47] See
Table 1.10.5 for the determinants of forest cover fixed effects using the OLS model.

proportional to the standard error variance, it reflects the information contained in that fixed effect.

Table 1.7.2 Determinants of forest cover fixed effects

Dependent variable: Estimated municipal fixed effects

	WLS
Municipality elevation (m)	0.0015*
	(0.00078)
Avg. precipitation monthly (mm)	0.14***
	(0.011)
Distance to the department capital (km)	0.028*
	(0.015)
Soils quality index [1-8]	-3.70***
	(0.70)
Constant	72.3***
	(3.58)
Observations	848
R-Squared	0.244

Robust (heteroscedasticity correction) std. err. (in parentheses)
WLS model weighting proportional to the u_i Std.Err.
* $p < .10$, ** $p < .05$, *** $p < .01$

Most of the regressors have strong explanatory power.[48] This is confirmed by the R-squared indicating that the regressors explain almost a quarter (24.4%) of the variation in the FE-OLS coefficients. Fluctuations in temperature and rainfall levels are due mainly to changes in elevations. Elevation also affects biodiversity. The lowlands are often more easily accessible and thus more suitable for agriculture. Thus, according to Table 1.7.2 , an increase in elevation of 100 meters is associated with a 0.15 percentage points increase in the share of the municipality covered by forest. Forests are often located in tropical climates where precipitation is high and occurs all year-round. Therefore, an increase in 10 millimetres of average monthly precipitation (which represents about a 5.7% increase in monthly precipitation relative to the sample mean) is associated with a 1.4 percentage point increase in the share of the municipality covered by forest.

[48] We also included in the regression a land concentration measure based on a Gini coefficient. We found no impact of land holding inequality on deforestation. The estimated effect for the land concentration index is not found to be well determined at a conventional level.

There is more pressure to convert forest land to non-forest uses particularly when forest land is located near main cities. In contrast, remote forest land tends to be less valuable and, therefore, more likely to be conserved. The estimates above confirm this dichotomy. Thus, an increase of 10 km in the distance to the department capital is associated with a 0.28 percentage points increase in the share of municipality area covered by forest, on average and *ceteris paribus*.

On the other hand, agriculture is identified as a key factor implicated in forest degradation. This is likely to be exacerbated by poor agricultural technologies, which means that more land is cleared for agriculture. Areas with soil quality more suited to agricultural activity are likely to be associated with greater levels of deforestation. There is nothing wrong with deforestation due to agriculture production provided it is well planned and managed. The estimates reported here suggest that an increase of 1 unit in the soil quality index (approximately an increase of over 1/3 relative to the sample mean and implying better soil suitability for agriculture) is associated with a 3.7 percentage point decrease in the area of a municipality covered by forest.

Overall, the foregoing estimates suggest considerably stronger effects on deforestation mediated through elevation, precipitation, and soil quality compared to the magnitude detected for displacement effects due to conflict.

1.8 Conclusions

The literature on the impact of conflict and violence on forestation is ambiguous and many studies fail to address the endogeneity issue of the empirical relationship. On the one hand, violence could lead to more deforestation as armed groups exploit natural resources. On the other, the presence of armed groups also means that large rural areas become inaccessible and thus are preserved and protected from deforestation. So, the impact could go in either direction in theory and, therefore, the direction as well as the magnitude of the effect remains an empirical question.

A major challenge for this study was obtaining accurate estimates of the share of municipality area covered by the forest. However, the availability of satellite-based information on forest coverage for not less than three years in the period of the study restricts the panel data we use here to 859 municipalities, which represents about 76.6% of all municipalities in Colombia.[49]

The final sample used for the analysis excluded the more remote municipalities. Using suggestive mapping, the spatial distribution overlaps fairly well with the Colombian conflict locations. Hence, the main challenge of this study is to disentangle the sign of the direction of a plausible causal relationship using econometric analysis. In addition, the summary statistics comparing mean outcomes between the included and excluded municipalities reveal that the mean values are not necessarily similar for some key variables. However, a summary analysis of differences in mean statistics between samples is fraught with difficulty. For example, the extent of missing values for some variables in the sub-set of municipalities excluded is large. Nevertheless, it is difficult to argue that the set of municipalities used for our analysis is not subject to some degree of selection bias. However, the problem of missing values in the end dictates the sample we focus down on.

In addition, our main and preferred econometric specifications are influenced by the work of Fergusson et al. (2014), which sets the framework for our research question. This framework is primarily concerned with how the presence conflict affects the changes in the level of forest coverage in Colombia. However, since only a number of models are presented and discussed in this study, there obviously exists space for further research on this topic. For example, a different research approach could try to identify the determinants of the rate of growth of deforestation. This can be done using the change in (log of) forest cover (or the log differences) as a dependent variable. The deforestation growth is not necessarily explained by the structural drivers (e.g., the role of population or urbanization) as captured by the explanatory variables used in our estimation. Instead, the deforestation growth is closely linked to market forces and

[49] Accounting for 62.4% of the population.

policy incentives (e.g., changes in food prices, the presence of taxes, or conservation laws, etc.) and may be viewed short-run in nature. Often, econometric deforestation growth models include the market forces or policy incentives variables expressed in terms of their changes. In addition, deforestation growth models often encounter significant econometric problems since market forces and policy incentives are potentially endogenous to decisions of deforestation. Finally, their estimation includes a lag of the dependent variable (log of forest cover) which by construction is an endogenous variable in a panel setting. Therefore, GMM and dynamic panel data models estimations are required (for example, see, for example, Hargrave and Kis-Katos, 2013). Overall, this represents an agenda for future research and is not one that is pursued in this study.

Our empirical analysis attempted to causally identify the impact of civilian displacement through violence (or the threat of violence) on forestation. We believe the identifying instruments used are valid and provide us with some confidence that the estimated effect is causally identified. Our estimates suggest there is evidence that the armed conflict is indeed a force for forest conservation. In particular, the alignment between rural underdevelopment and the rural–urban displacement as a result of the violence contributed to the protection of forests. The estimated effect suggests that an additional person displaced per 1,000 inhabitants increases the percent of forest covered by 0.0028 of a percentage point at the municipality level.[50] The magnitude of this effect is relatively small, and even more so when compared to more conventional forestation drivers such as the effects associated to average precipitations monthly (0.14), the distance to the department capital (0.028) and the soils quality index (3.7). In addition, based on the same metric of one person per 1,000 increase of the municipal population, the population pressure reduces the forest cover thirty-four times (34.2) more than the effect in which forced displacement increases it.

[50] According to the sample used in the regressions, the average share of the municipality area covered with forest is more than half (58.04%), which corresponds to 51,168.57 hectares (511.7 km2). The estimated effect suggests that one person displaced per 1,000 inhabitants increase the municipality covered by forest by 1.43 hectares (0.0016% of the total municipality area), on average and ceteris paribus.

A naïve view of the result of this study may interpret the armed conflict as something good for the country since it brought a positive environmental yield. However, it is important to emphasize the fact that the major achievement of the 2016 peace deal that ended 60 years of conflict with the FARC was reducing victimization. According to official figures during the study period (2004-2012) at least 150,164 people were killed in the fighting, 6016 killed and permanently 1476 wounded by landmines, 4,990 people kidnapped, and approximately 2.6 million forcibly internally displaced. All of this reflects an immense human toll of suffering against which any environmental gains from forestation induced by conflict pales into insignificance.

The results of this research are also consistent with the literature that emphasizes that rural–urban displacement due to violence promotes ecosystem recovery due to the reduction of human pressure on natural resources (for example, Aide and Grau 2004; and Meyerson et al. 2007). Forest degradation frequently increases in post-conflict situations. Some studies show that after the end of a conflict people resettled and expanded agricultural lands (see, for example, Stevens et al. 2011 for the case of Nicaragua's Atlantic coast). Governments also pacify former rebels and provide patronage to demobilize forces by promoting rural and agricultural development. In addition, those civilians forced displaced by the conflict return to areas abandoned during the conflict, and so new people enter into forest zones previously seen as too dangerous within which to live.

It is imperative to emphasize that there is nothing wrong with deforestation as long it is managed properly and effectively. Rain forests and their watersheds support the livelihoods of many. Therefore, their protection and conservation is of paramount importance. Enforcement of conservation of currently protected regions and areas previously administered under a 'gunpoint conservation' regime by the guerrillas will be fundamental. Hence, this study indirectly advocates for an appropriate conservation strategy when peace fully arrives in Colombia. In the past, the zones protected by the state assisted in reducing settlements and illegal drug activity. However, this might not be enough for the future (See Dávalos, 2001).

1.9 References

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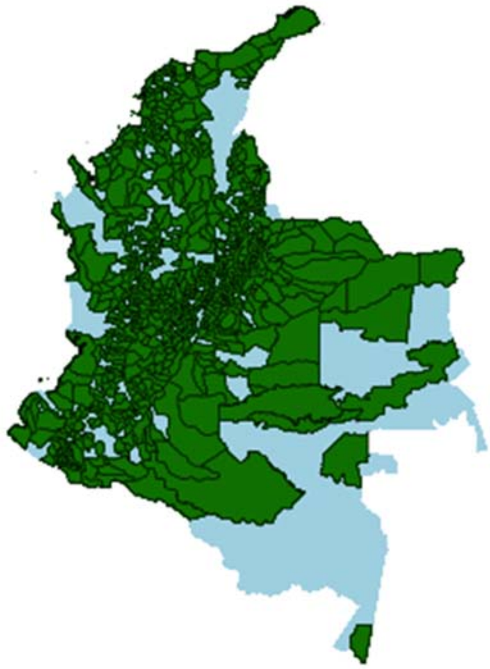
1.10 Appendix

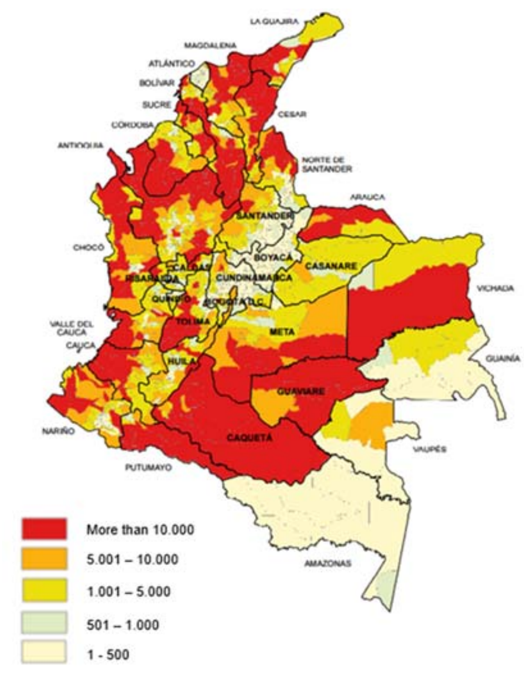
Figure 1.10.1 Final sample spatial distribution



: The municipality belongs to the sample.

Source: author

Figure 1.10.2 Forced displacement 2005-2014



Source: Centro Nacional de Memoria Histórica.

Table 1.10.1 Summary statistics of municipalities with missing values

Variable	Mean	SD	Min	Max
Share of municipality area with forest [0-100]	69.59	25.4	2.7	99.96
Forced displacement per 1000 inhabitants	13.43	31.19	0	490.33
Victims of massacres per 100,000 inhabitants (lagged one year)	0.67	6.09	0	100.64
Direct conflict kidnappings per 100.000 inhabitants (lagged one year)	0.98	7.15	0	215.32
Hectares of coca fumigated and manually eradicated (lagged one year)	98.37	533.78	0	11183.05
Percentage of the agricultural frontier with coca crops fumigates and manually eradicated (lagged one year)	0.12	0.78	0.00	24.34
Percentage of the municipal area with coca fumigated and manually eradicated (lagged one year)	0.13	0.78	0.00	23.49
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	0.17	0.37	0	1
Population	63887.63	483841.68	216	7571345
Log Population	9.39	1.16	5.38	15.84
Percentage of urban population [0-100]	41.76	23.78	3.43	99.79
Income tax revenue per inhabitants	84489.54	108837.26	0	1027696.81
Log income tax revenue per inhabitants	10.83	1.03	5.77	13.84

Variables statistics refer to a N that varies between 733 and 2334 observations for the rest of municipalities not included in the panel due to considerable presence of missing values in the period of our study 2004-2012.

Table 1.10.2 A Comparison of sample means for the included versus the excluded municipalities using t-test for difference of means

	t-test	p-value
Share of municipality area with forest [0-100]	-11.2	0.000
Forced displacement per 1000 inhabitants	-5.3	0.000
Victims of massacres per 100,000 inhabitants (lagged one year)	-1.8	0.069
Direct conflict kidnappings per 100.000 inhabitants (lagged one year)	0.4	0.689
Hectares of coca fumigated and manually eradicated (lagged one year)	3.2	0.002
Percentage of the agricultural frontier with coca crops fumigates and manually eradicated (lagged one year)	0.0005	0.99
Percentage of the municipal area with coca fumigated and manually eradicated (lagged one year)	-1.13	0.25
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-1.1	0.251
Population	-5.2	0.000
Log Population	7.1	0.000
Percentage of urban population [0-100]	2.3	0.023
Income tax revenue per inhabitants	0.8	0.452
Log income tax revenue per inhabitant	4.1	0.000

Ho: diff = mean(x) - mean(y)=0.; Ha: diff != 0.

Table 1.10.3 Effect of lagged forced displacement rate on forest cover

Dependent variable: Share of municipality area with forest [0-100]	FE
Forced displacement per 1000 inhabitants (lagged one year)	0.0022**
	(0.0011)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.088*
	(0.052)
Log Population	-3.14***
	(0.49)
Percentage of urban population [0-100]	-0.047**
	(0.023)
Log income tax revenue per inhabitants	0.049*
	(0.029)
Year 2006	-0.19***
	(0.012)
Year 2007	-0.40***
	(0.023)
Year 2008	-0.59***
	(0.031)
Year 2009	-0.86***
	(0.041)
Year 2010	-1.02***
	(0.050)
Year 2011	-1.21***
	(0.059)
Year 2012	-1.44***
	(0.068)
Constant	90.7***
	(4.99)
Observations	6826
R-Squared	0.570
F-stat	108.6
Sigma	25.72
Sigma_e	0.503

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.10.4 Effect of the presence of coca crops on forest cover (FE-IV model)

Dependent variable: Share of municipality area with forest [0-100]

	FE-IV
Presence of coca crops [Yes=1; No=0]	-0.0030
	(1.17)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.094*
	(0.051)
Log Population	-3.13***
	(0.50)
Percentage of urban population [0-100]	-0.049**
	(0.024)
Log income tax revenue per inhabitants	0.046
	(0.030)
Year 2006	-0.19***
	(0.014)
Year 2007	-0.40***
	(0.022)
Year 2008	-0.59***
	(0.033)
Year 2009	-0.85***
	(0.044)
Year 2010	-1.03***
	(0.051)
Year 2011	-1.22***
	(0.061)
Year 2012	-1.45***
	(0.068)
Observations	6826
R-Squared	0.568
F-stat	107.5

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.10.5 Determinants of forest cover fixed effects (OLS model)

Dependent variable: Estimated municipal fixed effects

	OLS
Municipality elevation (m)	0.0013*
	(0.00073)
Avg. precipitation monthly (mm)	0.13***
	(0.011)
Distance to the department capital (km)	0.030**
	(0.015)
Soils quality index [1-8]	-3.53***
	(0.70)
Constant	71.9***
	(3.56)
Observations	848
R-Squared	0.237

Robust (heteroscedasticity correction) std. err. (in parentheses)
* $p < .10$, ** $p < .05$, *** $p < .01$

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