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# Identifying Municipal Risk Factors for Leftist Guerrilla Violence in Colombia

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**Abstract:**
This study examines determinants of leftist violence at the municipal level in Colombia from 2000 through 2010. A multilevel GLMM model with a negative binomial distribution is used to take advantage of the information available at the municipal and department level. Surprisingly, inequality was not a significant covariate of violence, and agricultural GDP tended to reduce, instead of increase, guerrilla violence. The main risk factors identified include physical characteristics such as rugged topography and prior violence, but also factors that are candidates for policy action, such as unemployment, incorporation of the poor into public services, repression, and the energy and mining sector. These findings suggest interventions to decrease risks of guerrilla violence beyond merely strengthening the state. While repression tends to escalate violence, targeted policies to provide health benefits to those currently underserved, and securing mining and oil operations can effectively reduce the risk of violence.

**Keywords:** Colombia, political violence, guerrilla violence
**DOI:** 10.1515/peps-2017-0009

## 1 Introduction

Colombia has suffered from decades of internal conflict. In 2005, *Foreign Policy*'s inaugural failed-state index ranked Colombia as the second worst in the Western Hemisphere and the 14th worst in the world. By 2015, its ranking had improved to the 61st worst worldwide. Stability, however, has always varied within the country. Parts of the country were and remain safe, whereas other areas are threatened by paramilitaries, leftist guerrillas, criminal gangs, or some combination thereof.

Understanding determinants of violence at the municipal level is essential, especially given the uncertainty about the implementation of the 2016 peace agreement with the FARC (*Fuerzas Armadas Revolucionarias de Colombia*) and the beginning of formal peace talks with the ELN (*Ejército de Liberación Nacional*). The voters narrowly rejected the FARC agreement on October 2, 2016, with 50.2% percent against the agreement, although Congress approved a revised agreement later that year. Even with a peace process with the FARC, other guerrilla groups, in addition to dissident FARC forces, continue their attacks, as do new criminal groups such as BACRIM (*bandas criminales*), remobilized paramilitaries, or gangs dedicated to extortion, drug or wildlife trafficking or illegal mining.

This study focuses on the period from 2000 through 2010. Violence from leftist guerrillas peaked in 2002, but then generally declined through the end of the decade. This allows us to identify factors that encourage localized violence despite overall declines. For example, the municipality of Granada, in the department of Antioquia, had an astounding murder rate of 984 per 100,000 inhabitants in 2002, compared to a national rate of 70. This city suffered from incursions by FARC blocks 9, 34, and 47 and attacks from paramilitary groups, such as the *Bloque Metro de las Autodefensas* (Casas, 2015). To understand the dynamics of the conflict and prospects for future peace it is essential to identify areas that continue to suffer high levels of conflict in a period of general decline of violence.

## 2 A sub-national view

Ideally, studies of violence should leverage the power of a subnational analysis when appropriate (Ross, 2015, 241). With over a thousand municipalities nested into 32 mainland departments, Colombia is an ideal country

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to analyze at this level, especially given the availability of high quality data (Vargas, 2012, 222).[1] Given the significant differences in development, security and geography in Colombia, a sub-national study offers the opportunity to clarify relationships and illuminate hypothesized linkages between specific factors and violence. Although state-building during the administration of President Álvaro Uribe (2002–2010) expanded police or military presence to many municipalities that formerly were lacking, regions strongly vary in development (Bonet & Meisel, 2008; Lira, 2005), geography (Armenteras et al., 2013), and the timing and incidence of violence.

Figure 1 shows the varying intensity of leftist guerrilla human rights violations by municipality and department during the years 2000 and 2009. In 2000, Barancabermeja (35) in Santander, San Luis (24) in Antioquia, and Tibú (19) in Norte de Santander were the municipalities with the highest concentration of human rights violations. By 2009, the number of leftist human rights violations significantly decreased but dispersed into other municipalities with the highest concentration such as Bojayá (15) in Chocó, Vistahermosa (7) in Meta, and Sardinata (6) in Norte de Santander with the exception of Tibú (8) that appeared again in the sector of municipalities with high human right violations. Aggregated leftist violence at department level changes significantly. For instance, in 2000 Antioquia (270), Cauca (112), and Bolívar (81) were the departments with the highest concentrations of violence.

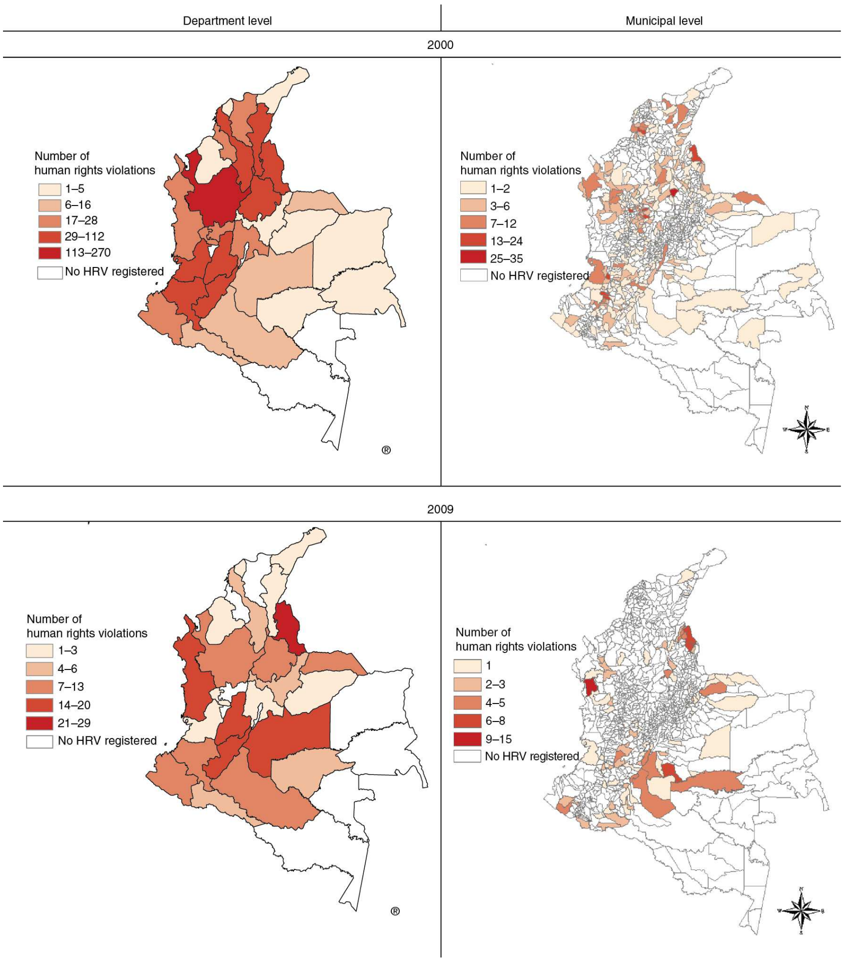



**Figure 1:** Leftist guerrilla human rights violations, 2000 and 2009.
Source: Centro de Investigación y Educación Popular (CINEP).

The maps in Figure 1 illustrate the importance of moving to a subnational analysis. Although broad regions or departments capture some of the variation, there are different patterns at the municipal level. There are also different degrees of clustering at the department or the municipal level. This means some spatial correlation, or violence spillovers, is present among departments and municipalities.

We used the Local Moran's I statistic to evaluate municipal spatial patterns, testing the hypothesis of nonzero spatial autocorrelation in leftist guerrilla violence. As the Local Moran's I results reject the hypothesis of no spatial autocorrelation (Figure 2), shows the prevalence of leftist human rights violations is clustered. Leftist human right violations tend to cluster in Antioquia, Arauca, Choco, Magdalena, and Valle del Cauca. The econometric approach used and presented in the model specification and analysis section takes into account the spatial autocorrelation present in this spatial pattern.

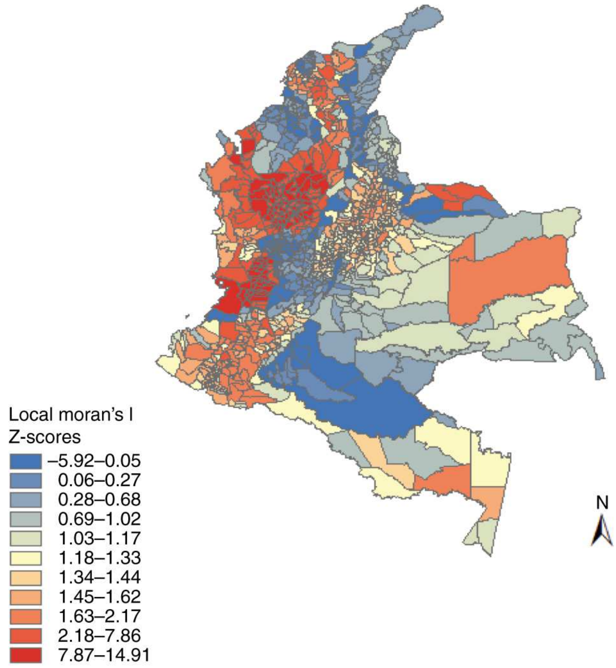



**Figure 2:** Leftist guerrilla human rights violations. Local Moran's I | Z - Scores |.

## 3 Causes of civil war and insurgency

Here, we apply several approaches and analytical frameworks to explain the patterns of leftist guerrilla violence in Colombia. Our analyses are informed by the literature on civil war, terrorism, insurgency, and the extensive literature on the Colombian conflict. The selected causes are categorized by state presence, resources vs. greed, economic grievances, repression-retaliation, theoretically important time invariant geographic and historical variables, and additional controls.

### 3.1 State presence

Understanding the political and socioeconomic context is indispensable to explaining violence. State presence is most important to understand levels of leftist violence because it can motivate violence or confer the ability to deter and effectively respond to it. The state, however, must be sufficiently strong and have a functioning judicial system, to be capable of deterring violence, defend the citizens, and maintain citizen support (O'Neill, 2001, 154). Hence adequate government function is the key to explaining conflict and resulting violence, and not grievance, social or ethnic division (Mueller, 2003, 513).

Cross-national research on civil war and insurgency supports this general idea. While analyses by Fearon and Laitin (2003, 80) and Humphreys (2005) find evidence of the importance of state capacity, measured by GDP per capita, to discourage insurgency and civil war, Burgoon (2006) focused on the impact of social spending, as a measure of state capacity to decrease terrorism. Another targeted analysis, by Kollias et al. (2009) focused on the relationship between terrorism and current and investment expenditure on domestic security and public order. Within Colombia, Vargas (2012, 214) found greater state presence, quantified through police presence and fiscal and financial institutions, was correlated with shorter violence.

While simply measuring GDP per capita is only a rough measure of state presence, there are multiple manifestations of strong state institutional capacity, from government investment in education and health, to programs targeting poverty. The period of our study coincides with decentralization that shifted both resources and responsibility to provide services to local municipalities and regional governments (Faguet & Sánchez, 2008, 1298), expanding education and health investment from a baseline of only half of the Latin American average (López, 2003, 272). Hence we first examine the state presence hypothesis by per-capita spending on housing, water, and sanitation and education.

Second, we measure how well the poor are integrated into the safety net of government services because the guerrillas justify their activity based on poverty. These claims, however, are not the only grounds for such a link, as many studies have confirmed it, including: 1) the emergence of *sicarios*, or young assassins in poor informal settlements surrounding major cities (Von der Walde, 2001, 2) FARC expansion in areas of rural poverty (Bottía Noguera, 2003, 3) a strong association between poverty and both emergence and intensity of leftist guerrilla violence (Holmes, Gutierrez de Piñeres & Curtin, 2008). Thus, we include measures of investment to alleviate poverty, despite the absence of relationship between poverty and violence from subnational studies, for example, India (Piazza, 2009).

Poverty[2] in Colombia decreased nationally during the period of interest. According to DANE, the percent of Colombians in poverty went from 49.7% in 2002 to 40.3% in 2010, with extreme poverty decreasing from 17.7% to 12.3% during the same period. But progress is not uniform, and far too many Colombians remain in poverty. Here, we use the percent of poor (*estrato* 1 & 2) that are enrolled in *Seguridad Social en Salud* (SGSSS), which may be a more precise way of indicating the type of government services that can reduce the risk of violence. The data are available annually and by municipality, in contrast to the official poverty rate, which is only available by municipality during census years.

Hypothesis 1: Areas with high state presence will have less violence.

## 3.2 Repression – retaliation

State presence alone does not guarantee the quality of the government. Many studies have shown the inflammatory impact of repression on violence (Goodwin, 2001; Holmes, Gutierrez de Piñeres & Curtin, 2008; Schock, 1996; Seligson, 1996). We include government human rights violations as our measure of repression.[3]

Hypothesis 2: Areas with government human rights violations will have more violence.

## 3.3 Economic factors

Economic factors can be examined either as a grievance that can motivate rebellion or as a resource that may motivate conflict. We focus on three economic factors: inequality, unemployment and coca eradication. Despite positive trends of declining poverty inequality in Colombia was the second highest in the Americas, and the GINI coefficient only changed from 0.573 to 0.560 during the study period (DANE, 2012, 63). Historically, socioeconomic relationships in Colombia have created an unequal social and economic structure (Vásquez, 2011), and scholars of consider inequality is factor strongly influencing violence. Land conflict and resulting inequality thought to be the main reasons behind wave after wave of Colombian conflict (Cotte Poveda, 2011; Guerrero Baron & Mond, 2001; Medina Gallego, 1990; Ortiz Sarmiento, 1991; Richani, 1997).

Coca eradication also can provoke grievances against the government. Despite demonstrating state presence, and unlike targeting smuggling operations, eradication destroys a rural resource base. Examining the effects of US drug policy in Colombia, Peceny and Durnan (2006), 97 argue US counternarcotic policies strengthened the FARC in the 1990s by pushing coca cultivation into FARC strongholds. Eradication also reduced support for the government (Holmes, Gutierrez de Piñeres & Curtin, 2008), and guerrillas and rebels can offer protection to the coca growers from government eradication efforts. Hence we also evaluate the influence of eradication on violence using reports of aerial eradication (in hectares) provided by SIMCI/UNODC.

Hypothesis 3: Areas with economic grievances will have more violence.

## 3.4 The angry agriculture sector: sectoral GDP and coffee

The agricultural sector is a proxy for poverty in the developing world because urban centers grew more rapidly and received more policy attention than agricultural regions until the recent export boom (Lipton, 1977). This is not only the case across countries [e.g. higher conflict risk in countries for countries dependent on agricultural products (Humphreys, 2005)], but within countries, for example *Sendero Luminoso* violence in Peru centered in agricultural areas both in the 1980s (Berg, 1987), or the 2000s (Holmes, 2015). Based on these findings and similar arguments for Colombia (González, 2002), we include the sectoral GDP of agriculture as a proxy for unrest in rural areas.

Hypothesis 4: Areas more dependent on agriculture will have more violence.

Despite being potentially informative, agriculture-sector GDP may include sectors linked with different types of violence, and fueled by different motivations. In Colombia, for example, capital-intensive African palm is associated with paramilitary violence (Guerrero Baron & Mond, 2001; Richani, 2007), as is extensive cattle ranching

(Álvarez, 2003; Chernick, 1998; Holmes, Gutierrez de Piñeres & Curtin, 2008). In quantifying links to leftist violence, Holmes, Gutierrez de Piñeres, and Curtin (2008) found a significant relationship with coffee cultivation. Recurrent crises in the international coffee market have made coffee-growing a hotbed of guerrilla recruitment both in the 2000s (Dube & Vargas, 2013, 1413; Rettberg, 2010, 112), and earlier time periods (Richani, 1997; Trujillo & Badel, 1997, 273–275). Therefore, as an alternative specification, we distill down the legal agricultural sector to focus on coffee production. During this period of study, coffee prices were near historic lows during 2001–2003, but then recovered and increased annually through 2011.

### 3.5 "Lootable" resources: coca and the energy and mining sector

According to Collier and Hoeffler (2004), economic resources, particularly lootable primary exports, can explain increases in conflict risk, with the highest risk of conflict when primary exports make up a quarter of GDP (Collier 2009). But this threshold has been explored in subsequent studies, with conflicting conclusions (Fearon & Laitin, 2003; Ross, 2004). Hence, Snyder (2006, 963) urged scholars to consider resources less deterministically, and develop more precise measures of resources. Since then, Snyder and Bhavnani (2005) found that lootable resources like drugs, diamonds, and the like, influence the risk of conflict; while Robinson, Torvik, and Verdier (2006, 451) looked beyond resources to contextualize resources as part of clientelistic relationships.

Numerous studies of Colombia focus on the development of new resources in the context of a weak state. Arbelaez, Echavarria, and Gaviria (2002, 42–43) documented new violence in areas with rapid resource development and weak government control. Others have found new conflict as land is put into commercial use (Escobar, 2003; Goebertus, 2008). Our study, while controlling state presence, will test the effects of disaggregated economic measures commonly theorized to be "lootable" or otherwise associated with increased leftist guerrilla violence: coca cultivation, sectoral GDP of mining and energy, and oil production.

Hypothesis 5: Areas with lootable resources will have increased violence.

### 3.6 Coca

Coca cultivation is well recognized as having the potential to fund terrorism and other forms of violence (Byman et al., 2001; Le Billon, 2001; Rochlin, 2003). Not surprisingly, this relationship has been observed in Colombia (Vargas, 2012), but not in a direct and consistent manner (Gaviria & Mejía, 2011). González (2002) argues legal smallholders start to grow coca because they are displaced by large-scale agriculture for export, magnifying preexisting conflict through a process he called the "criminalization of the peasant." In contrast, Vásquez (2011) suggests the continuous struggle for land tenure to control coca cultivation is one of the main roots of the Colombian conflict. The quantitative data, however, do not always bear this out: Holmes, Gutierrez de Piñeres, and Curtin (2008) found a relationship between leftist violence and coca cultivation from 1993 to 1998, but not from 1999 to 2002.

### 3.7 Mining and oil

There are competing expectations for relationships between mining and violence. While the ELN have resorted to extorting mining operations as income from kidnapping has dropped,[4] and FARC leaders have repeatedly focused on the gold and oil industry in their demands to end the conflict (Rettberg, 2015, 2), significant financial benefits from mining can strengthen the state through an income tax of 33% and a 1–12% royalty tax on extractions (Garay, 2013, 142), and even protect from leftist violence as in a study from Peru (Holmes, 2015, 42). Further, while guerrillas may directly loot gold and government royalties (Rettberg & Ortiz-Riomalo, 2016), narcotraffickers, paramilitaries, and corrupt politicians who use their onsite presence to facilitate claims for land titles may dominate new mining (Garay, 2013, 194, 204). Thus, paramilitaries and leftist guerrilla may both cause violence in mining areas, complicating interpretation of any results. Further, weak state presence matters: Idrobo, Mejía, and Tribin (2014) found a relationship between illegal mining and violence, but no relationship with legal mining.[5] Alternatively, government security might be prioritized in mining areas. In this study, we include production figures as an alternative specification to sectoral GDP.

The oil and the energy sector is expected to have similar dynamics, with oil increasing the risk of civil conflict in analyses by Fearon and Laitin (2003) and Ross (2004). As with mining in general, Di John (2007, 980) argued for a less deterministic and simplistic treatment of oil and state capacity, and Fearon (2005) argued oil-producing countries were more prone to civil war because of weak state presence and secession movements.

The data support this view: Lei and Michaels (2014, 154) found new oil discoveries increase the risk conflict, especially in countries with a history of prior conflict, and Colombia is not an exception, as Dube and Vargas (2013, 1413) found resource booms attracted extortion from armed groups.

Oil, like mining, generates royalties and taxes that can benefit communities. Historically, the communities affected by oil drilling were to receive some benefit. Cuéllar (2016), 4 noted a flood of revenue into departments such as Arauca and Casanare because of a royalty rate of up to 20%.[6] Oil production, however, can be diverted to violent groups through corruption or extortion. This was common in the late 1990s and early 2000s (Dunning & Wirpsa, 2004; El, 2001). Pearce (2007, 277) detailed the extensive ELN recruitment among disaffected oil workers in Arauca and diversion of funds. Similarly, Sánchez, Vargas, and Vásquez (2011) demonstrated the institutional vulnerability of specific regions to FARC rent-seeking activities. For instance, the department of Huila was considered a strategic region for FARC's activities in the 1990s because of the presence of oil companies. However, during the study period, oil-producing regions were prioritized for government protection and US aid (GAO, 2005; WOLA, 2003), which could result in fewer attacks. Moreover, oil companies spend significant funds on security and community outreach.

### 3.8 Geographic situation and prior conflict

Geography has been theorized to be important in understanding insurgency and civil war although cross-national findings have been inconsistent. Countries with more mountains have been found to have more risk of civil war according to Fearon and Laitin (2003) and Collier and Hoeffler (2004), but not in Collier (2009). Subnational studies also have conflicting conclusions. Do and Iyer (2010) found that altitude was related to the incidence of conflict in Nepal, but not its onset. Vargas (2012, 213) found that warm and rainy areas have longer violence episodes, but finds no relationship with altitude. Studies of Peru have found rough terrain to be associated with *Sendero* violence (Berg, 1987; Holmes, 2015).

Hypothesis 6: Rugged areas will have more violence.

Geography can impact development, state control, nationalism, and levels of violence. According to Clausewitz (1976), difficult terrain can make a country susceptible to insurgency. Colombia, with its extensive mountains and forests, a classic example of a country deeply influenced by geography (Bushnell, 1993, 36). Mountains can reduce the effectiveness of large government forces against small bands of well-positioned guerrillas (O'Sullivan & Miller, 1983, 65). Forest cover is also advantageous for guerrilla forces (Harkavy & Neuman, 2001, 79). Thus, it is critical to control for geography. We examine forest cover and average slope of the municipality.

Hypothesis 7: Areas with prior violence will have more violence.

There are competing interpretations of the role of previous conflicts as precursors of current violence. Fearon and Laitin (2003) concluded that the presence of a prior war (or separate civil war) is negatively associated with the onset of a new conflict. Other studies, in contrast, have urged more attention to the "war before" syndrome (Collier, 2009; Di John, 2007, 979; Holmes, 2015). Daly (2012) found a strong association of conflict emergence in areas that had organizational legacies of war. Finally, we controlled for population and gross domestic product per capita.

## 4 Data description and sources

The leftist guerrilla violence data used here comes from a Colombian Jesuit NGO, the Centro de Investigación y Educación Popular (CINEP) and their *base de datos de actores y dinámica del conflicto*, specifically their category *Infracciones al DIH.* We focus on human rights violations (HRV) to highlight the side effects of the conflict on civilians. This measure includes attacks on civilians and other human rights violations ranging from threats to politically motivated killings, but excludes attacks against military or police. This category also contains attributions of responsibility, so that actions committed by leftist guerrillas can be separated out from actions committed by paramilitary or government forces.[7] Additionally, for robustness checks, we use CINEP's category of *Acciones Bélicas* or warlike actions that tallies force on force attacks, such as a FARC attack against a military or police target. Prior violence is the mean municipal value of leftist human rights violations from 1990 to 1999, which varies from 0 to 21.6, calculated from the CINEP data. Finally, in another robustness check, we use the Colombian Ministry of Defense's terrorism statistics as an alternative source of violence data.[8] The explanatory variables are taken from varied sources. The *Departamento Administrativo Nacional de Estadistica*

(DANE) compiles unemployment, GINI, population, and sectoral GDPs (in constant 2005 billions of Colombian pesos). The sectoral GDP of Agriculture ranges from 0 to 3783. The sectoral GDP of Mining-Energy ranges from 0 to 10,091, in constant 2005 billions of Colombian pesos. Population values are annual estimations from the 2005 census. Public spending comes from *Departamento Nacional de Planeacion* (DNP) and are reported in constant 2008 thousands of Colombian pesos (COP). These figures include spending at the municipal level but only from central and departmental sources. Spending accounts are funded by 5 budget types: three of them are municipal-related (*"libre destinación"*, *"regalías"*, and *"recursos propios"*). The other two categories of municipal spending from higher administrative levels, *"forzosa inversion"*, and *"aportes departamentales,"* are used in this study to avoid endogeneity issues where violence may be explaining the local spending behavior. Public health affiliation data is the enrollment status in *Seguridad Social en Salud* (SGSSS) provided by the *Ministerio de la Proteccion Social.* Coffee cultivation is reported by Fedecafe at the department level in thousands of hectares, varying from 0 to 131. Estimates of coca cultivation, reported in hectares, were obtained from SIMCI/UNODC. Oil production, in barrels, is reported by the Ministerio de Minas y Energía and varies from 0 to over 340,000, according to the. The geographic variables are derived from the Consortium for Spatial Information's digital elevation model available here (http://srtm.csi.cgiar.org). The alternative source on Human Rights Violations is the Ministry of Defense.

Table 1 presents summary statistics at the municipal and department level.[9]

**Table 1:** Descriptive statistics (2000–2010).

| | Level | Mean | Median | SD | Min | Max | Total |
|---|---|---|---|---|---|---|---|
| Leftist Guerrilla HR Violations (CINEP)* | Mun. | 0.3 | 0 | 1.18 | 0 | 19 | 11,180 |
| Terrorist attacks (Min. Defense) | Mun | 0.43 | 0 | 2.1 | 0 | 67 | 11,180 |
| Leftist guerrilla warlike actions (CINEP) | Mun. | 0.62 | 0 | 1.75 | 0 | 31 | 11,180 |
| State presence | | | | | | | |
| Social service spending: water, sanitation, education and housing per capita (Thousands COP) | Mun | 3844.45 | 735.45 | 50,546.40 | 0 | 2,080,000 | 11,180 |
| Percentage of poor affiliated w/public health services | Mun | 0.6 | 0.61 | 0.24 | 0 | 1 | 11,180 |
| Resources/greed | | | | | | | |
| Coca cultivation (Hectares) | Mun | 96.64 | 0 | 637.3 | 0 | 16523.88 | 11,180 |
| Sectoral GDP of mining, energy and quarries (Billions COP) | Dept | 660.53 | 321 | 1001.55 | 0 | 10,091 | 11,180 |
| Oil production (barrels per day) | Dept | 16,902.26 | 4447 | 37,040.84 | 0 | 339,734 | 11,180 |
| Grievances | | | | | | | |
| Coca aerial eradication (Hectares) | Mun | 116.1 | 0 | 872.94 | 0 | 33,813.97 | 11,180 |
| Unemployment rate** | Dept | 12.22 | 12 | 2.92 | 5.9 | 22.3 | 10,434 |
| GINI coefficient** | Dept | 0.53 | 0.52 | 0.04 | 0.44 | 0.62 | 10,450 |
| Coffee cultivation (Hectares) | Dept | 44.59 | 33.54 | 42.87 | 0 | 131.12 | 11,180 |
| Sectoral GDP of agriculture, fishing and ranching (Billions COP) | Dept | 1476.18 | 1293.00 | 1039.90 | 0 | 3783 | 11,180 |
| Repression | | | | | | | |
| Government fitted | Mun | 0 | 0 | 0.4 | −9.35 | 12.39 | 11,180 |
| Geography | | | | | | | |
| Percentage of forest land | Mun | 0.22 | 0.13 | 0.23 | 0 | 0.97 | 11,180 |
| Land slope (degrees) | Mun | 13.94 | 14.48 | 7.5 | 0 | 30.46 | 11,180 |
| Prior violence (mean value 1990–1999) | Mun | 0.43 | 0.1 | 1.14 | 0 | 21.6 | 11,180 |
| Controls | | | | | | | |
| Gross domestic product per capita (Millions COP) | Dept | 7.57 | 6.71 | 4.17 | 1.7 | 29.14 | 11,180 |
| Population (Thousands) | Mun | 38.53 | 12.55 | 235.07 | 0 | 7363.78 | 11,180 |

*The number of observations for each variable is 11,180, representing observations from 1118 municipalities in 32 departments from 2000 to 2010.
**Unemployment and GINI coefficients are only available for 24 out of 32 departments.

One potential source of endogeneity is that some of the explanatory variables may be subject to simultaneous causality with violence. We analyzed variable dynamics and applied bivariate Granger causality tests to evaluate whether past values of our selected variables are useful for predicting leftist guerrilla violence.[10] Appendix B provides our Granger tests estimations. Results showed that variables related to greed or resources have suitable explanatory characteristics for leftist violence. Lagged values of coca cultivation (T-2), coffee cultivation (T-1) and oil production (T-1) can explain at 5% of confidence past and present values of guerrilla HRV. Sectoral GDPs of agriculture and mining (T-1) are significant explanatory variables (10%) for guerrilla HRV. The opposite Granger causality were not significant for all mentioned variables. We not only establish a theoretical background and causal direction for each category but also for individual effects on leftist violence activity.[11]

## 5 Model specification and analysis

Our dependent variable is highly non-normal and violates linear regression assumptions for two main reasons. First, our violence measure is a count variable that is relatively rare (the median is zero), but overdispersed. Second, subversive violence counts through time are not independent. In other words, municipalities with violence may have a higher chance of further violence compared to municipalities without violence.[12] Instead of including department or municipal dummy variables or using a fixed effect model,[13] we include three theoretically important time invariant variables: forest cover, slope, and prior conflict. The inclusion of these variables precludes a fixed effects model. Their inclusion also helps to account for the heterogeneity among units. The three time-invariant independent variables are much more than just control variables. They are linked to significant theories that predict increased levels of leftist violence.

Given the nature of the data, a multilevel hierarchical model is used to take advantage of the information available at the municipal and department level. In this case, municipalities are nested in departments, and their intrinsic characteristics vary individually (municipality) and aggregately (department). In other words, the multi-level model captures the variation among municipalities and departments, and also the variation between levels (Gelman, 2006). The mixed models can explain the fixed effects on the leftist guerrilla violence of the factors present on each municipality of the 32 mainland departments. Therefore, a way of modeling the conditional distribution of leftist guerrilla violence count using Negative Binomial is:

$$Y_{ij}|\lambda_{ij} = NB(\lambda_{ij})$$

And the link function for the Negative Binomial distribution is:

$$\eta_{ij} = \log(\lambda_{ij})$$

Which is similar to Poisson distribution but with the difference that Negative Binomial adds an error term to account for the overdispersion:

$$\lambda_{ij} = \exp(\eta_{ij} + \varepsilon_{ij})$$

The two-level GLMM model used is

$$\eta_{ij} = \beta_j X_{ij} + \nu_j Z_{ij}$$

where $X_{ij}$ are the covariates at the municipal and department level, $\beta$ are the regression coefficients, $Z_{ij}$ are the random effect variables for the two levels of the hierarchical structure, and $\nu_j$ are the random effects. The multilevel model can specify the correlation among responses from same clusters (municipalities or departments). Leftist guerrilla violence is conditional on unobserved latent variables within a municipality or department.

Leftist guerrilla violence is spatial autocorrelated as shown in Figure 2. Multilevel models are particularly well suited for situations in which there is a concern about spatial autocorrelation (Arcaya et al., 2012; Langford et al., 1999). We tested the residuals of the model specifications for spatial autocorrelation using Moran's I and found that the multilevel structure with random intercepts for each unit at the different levels served as a spatial structure that accounted for the signature of spatial dependence. Moran's I tests for spatial autocorrelation are presented in Appendix E.

Considering such conditions, a Generalized Linear Mixed Model (GLMM) is suitable to calculate the predictors' estimation.[14] The overdispersed nature of the counts of violence require an analysis of what kind of response distribution the GLMM specification requires.[15] We model the conditional distribution of leftist guerrilla violence count using the negative binomial distribution without zero-inflation component. Although we have panel data with several observations through time, the current specifications do not include time as an additional nesting level. In a nested design like this, the difference of violence in municipalities only makes sense within departments. Time is an important variable in explaining violence variation across years, but, it cannot be considered as nested since time is a continuous variable affecting both municipal and departmental level.[16] We could include the variable "years" as an additional fixed effect, however, the time fixed effect estimation would be biased due to static variables.[17] Therefore, to keep the model parsimonious, instead of considering time as another fixed effect that reduces degrees of freedom, the model prioritizes the effects of the hierarchical structure. The study focuses on the position of predictors within the hierarchical structure and their interactions acknowledging the correlation within clusters.

## 6 Results

Table 2 presents the main models using the CINEP data on leftist guerrilla violence as the dependent variable in Models 1–4 and CINEP's warlike actions in Model 5.[18] Model 1 includes sectoral GDP of agriculture and sectoral GPD of mining, whereas model 2 substitutes coffee instead of general agriculture. Model 3 includes coffee and oil instead of the respective sectorial GDPs. Model 4 replicates Model 1 including variables that are not reported by *nuevos departamentos* (GINI and unemployment) reduces the number of departments from 32 to 24.[19] As a robustness check Model 5 replicates Model 1 using warlike actions instead of human rights violations as the dependent variable. All variables in currency, land area, and production units were mean-scaled due to high variation in variable ranges.

**Table 2:** GLMM negative binomial–leftist guerrilla HRV/warlike actions (CINEP).

| | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** |
|---|---|---|---|---|---|
| | With sectoral GDPs (agriculture and mining) | With coffee production and Mining GDP | No sectoral GDPs. Coffee, mining and energy commodities | Model 1 + GINI and unemployment (24 depts) | Model 1 with warlike actions as dependent variable |
| Intercept | −0.19754 (0.47490) | −1.21699 (0.36798)*** | −1.20767 (0.33393)*** | 0.16739 (1.0139)* | −1.35148 (0.27712)*** |
| State presence | | | | | |
| – Social service spending | 0.00189 (0.00177) | 0.00145 (0.00179) | 0.00125 (0.00180) | 0.00173 (0.00184) | 0.00074 (0.001118) |
| – % poor affiliated w/public services | −1.64921 (0.23864)*** | −1.65331 (0.24025)*** | −1.24513 (0.24203)*** | −1.47341 (0.25765)*** | −0.623874 (0.14802)*** |
| Resources/greed | | | | | |
| – Coca cultivation | 0.00577 (0.00508) | 0.00561 (0.00519) | 0.00480 (0.00510) | 0.01631 (0.00949) | −0.00179 (0.002718) |
| – Mining, energy and quarries GDP | 0.19334 (0.06545)** | 0.25104 (0.07148)*** | | 0.38576 (0.10553)*** | 0.147841 (0.036966)*** |
| – Oil production | | | 0.32259 (0.03877)*** | | |
| Grievances | | | | | |
| – Coca aerial eradication | 0.00526 (0.00420) | 0.00461 (0.00428) | 0.00551 (0.00427) | −0.00059 (0.00558) | 0.00610 (0.002453)* |
| – Unemployment rate | | | | 0.03657 (0.01656)* | |
| – GINI coefficient | | | | −1.17207 (1.65660) | |
| – Coffee cultivation | | −0.21034 (0.26463) | −0.06054 (0.24266) | | |
| – Agriculture, fishing and ranching GDP | −3.33316 (0.44612)*** | | | −2.38072 (0.51017)*** | −1.00649 (0.21779)*** |
| Repression | | | | | |
| – Government HR violations (instrumented by paramilitary HR violations) | 0.13330 (0.04888)** | 0.13732 (0.05071)** | 0.13698 (0.04936)** | 0.14362 (0.05043)** | |
| Geography/prior violence | | | | | |
| – % of forest land | 1.84927 (0.35276)*** | 1.82864 (0.34258)*** | 1.71349 (0.34123)*** | 2.14637 (0.36274)*** | 1.93224 (0.27704)*** |
| – Land slope | 0.05048 (0.01096)*** | 0.05003 (0.01066)*** | 0.04847 (0.01056)*** | 0.04862 (0.01120)*** | 0.06805 (0.00845)*** |
| – Prior violence | 0.22542 (0.02021)*** | 0.22269 (0.01994)*** | 0.22551 (0.01987)*** | 0.22099 (0.0202)*** | 0.35499 (0.022744) *** |

| | | | | | |
|---|---|---|---|---|---|
| Controls | | | | | |
| – GDP per capita | −1.34706 | −2.16227 | −2.61546 | −1.98486 | −1.47184 |
| | (0.19357)*** | (0.17549)*** | (0.18295) *** | (0.26204)*** | (0.11062)*** |
| – Population | −0.01093 | 0.22174 | 0.35208 | 0.08803 | 0.13331 |
| | (0.30165) | (0.25924) | (0.24828) | (0.25376) | (0.21337) |
| # Obs, # municipalities, # departments | 11,180, 1118, 32 | 11,180, 1118, 32 | 11,180, 1118, 32 | 10,450, 1045, 24 | 11,180, 1118, 32 |
| Negative binomal dispersion parameter | 0.51748 | 0.48775 | 0.50322 | 0.53107 | 1.5315 |
| | (0.033809) | (0.031403) | (0.032625) | (0.036365) | (0.091992) |
| Random effects municipality level (intercepts) | Variance: 1.56 | Variance: 1.523 | Variance: 1.508 | Variance: 1.595 | Variance: 1.265 |
| | SD:1.249 | SD: 1.234 | SD: 1.228 | SD: 1.263 | SD: 1.125 |
| Random effects department level (intercepts) | Variance: 5.169 | Variance: 2.308 | Variance: 1.796 | Variance: 1.659 | Variance: 1.578 |
| | SD: 2.274 | SD: 1.519 | SD: 1.34 | SD: 1.288 | SD: 1.256 |
| AIC | 10358.9 | 10428 | 10375.6 | 9564.4 | 16767.1 |

$p \leq 0.001$*** $p \leq 0.01$** $p \leq 0.05$*.

In terms of state presence, surprisingly, social spending is not significant in any model. The lack of significance of social spending (education, housing and sanitation) is notable. However, we also include the percent of the poor enrolled in the public health services as an indicator of state presence. Despite well-known concerns about corruption in health provision (Hussman, 2011), the percent of the poor enrolled in the public health services is strongly negatively significant in all models. This supports the work of Faguet and Sánchez (2014) who found that decentralization has improved access to and accountability of health and educational services. Given that the FARC and other guerrillas' claim that the Colombian state is exclusionary, it is very important for the government to make a concerted effort to assist Colombians in need. This measure of incorporation into the public health system of the poorest Colombians may be a better indicator than either poverty alone or other aspects of state spending. Being in the program also may be a direct way to increase the government's legitimacy among the poorest citizens. This is strong evidence that serving the most vulnerable in society results in less guerrilla violence.

Evidence of greed or guerrilla predation of resources vary significantly by sector and specification. Surprisingly, coca is not significant in any models. However, although our time period began with higher production, from 2002 through the end of the decade, national coca cultivation was generally trending down. One possible explanation for this could be that the FARC, with its strong organization and national reach, may be distributing drug resources throughout the country to different fronts, thus masking the impact at the municipal level.[20] The results in the sectoral GDP of agriculture are surprising. Contrary to expectations, the relationship is negative and significant. Coffee production is non-significant. Closer examination may support what Dube and Vargas (2013) and Rettberg (2010) suggest; that the coffee sector is not always angry and a ripe recruiting ground for guerrillas, but is instead conditional on prices and other factors. In this period, coffee prices rebounded, and the agricultural sector was enjoying a period of strong demand for primary products in general (Ferrantino & de Piñeres, 2015), thus potentially improving the conditions of the agricultural workers and making them less likely to be recruited by guerrillas or otherwise provide them support directly, or indirectly. Contrarily, the mining and energy sector is strongly associated with increased violence in all models. There is much evidence of guerrillas extorting many industries in this sector (Dunning & Wirpsa, 2004; Pearce, 2007; Sánchez, Vargas & Vásquez, 2011), despite government efforts to increase security and prevent extortion. Although the Colombian government does try to reward local governments and citizens with royalties, illegal groups can divert these funds, either through corruption or predation. Findings are consistent when we disaggregate to oil.

In terms of grievances, surprisingly, inequality is not significant. Its inclusion in Model 4 also results in the loss of the eight *nuevos departamentos* that do not report inequality.[21] Coca eradication is not significant in Models 1–4, but is associated with increased violence in Model 5 which uses warlike actions as the dependent variable, as opposed to human rights violations. Although coca eradication can result in loss of support among coca growers, it also reflects increased military and government presence, which is necessary to conduct eradication efforts. Unemployment, however, is highly significant in Model 4, with the adjusted sample. This reinforces the need for more targeted programs to assist Colombians out of work.

The counterproductive and inflammatory impact of repression, whether government human rights violations or paramilitary human rights violations as an instrument is very clear in the first four models. In the case of Model 5, paramilitary and government human rights violations are omitted because there are some events that CINEP will code across categories. In other word, a clash may involve a warlike attack of guerrillas against police, but may also include some human rights violations against civilians in the same attack. CINEP would count this as an event in both categories, which precludes including both categories in the same analysis. Even in the context of overall decreasing violence in this decade, the revenge cycle of repression remains powerful. Although the Colombian government has made great strides in improving the professionalism of its military and police, (Holmes & de Piñeres, 2014), given the ability of government repression to incite leftist violence, it is imperative that these efforts continue to be prioritized.

Despite contrary findings in the cross-national analyses, in our subnational study of Colombia, there is extremely strong evidence of a link between geography and leftist violence. We use two measures. In the first, we examine the percent of land covered by forest on the risk of guerrilla conflict is significantly related to increased violence. Even in Model 5 when we analyze the impact on warlike actions, we have a consistent, positive relationship. We also examine measures of steep terrain, specifically average slope of each municipality. Land slope is also significant in all models. Steep terrain is advantageous for rebels in attack-retreat strategies. These findings reinforce expectations from the counterinsurgency literature that it is difficult for governments to control terrain that allows opportunities for guerrillas to hide (Clausewitz, 1976; Harkavy & Neuman, 2001; O'Sullivan, 1983; O'Sullivan & Miller, 1983). They may also reflect the obstacles to territorial control in the forest frontier of Colombia and neighboring countries (Dávalos, Sanchez & Armenteras, 2016). In effect, isolation through distance from large urban markets and low road coverage is one of the main characteristics of heavily forested municipalities in Colombia (Dávalos et al., 2011). Hence forests and rugged areas are not only potential refuges for insurgency, but also unstable because territorial control by state, or any other actors, is incomplete. Finally, the measure of prior conflict is consistently and positively associated with more leftist violence. This supports the work of Fearon and Laitin (2003), Di John (2007), Collier (2009), and Holmes (2015) who all include this in their models to take into account areas that have a protracted history of conflict. Our findings are consistent regardless if we model leftist guerrilla human rights violations or warlike actions.

## 7 Conclusions

This multi-level analysis has taken advantage of the department level economic data while including municipal variation in government spending, violence, cultivation, and geography. There are two main contributions. First, this municipal view nested in the departmental structure of Colombia can identify municipalities at higher risk of leftist violence and also highlights policy areas that may be appropriate for priority action. Second, the multilevel analysis with department and municipal units of analysis facilitates the selection of measures that more closely approximate variables of interest.

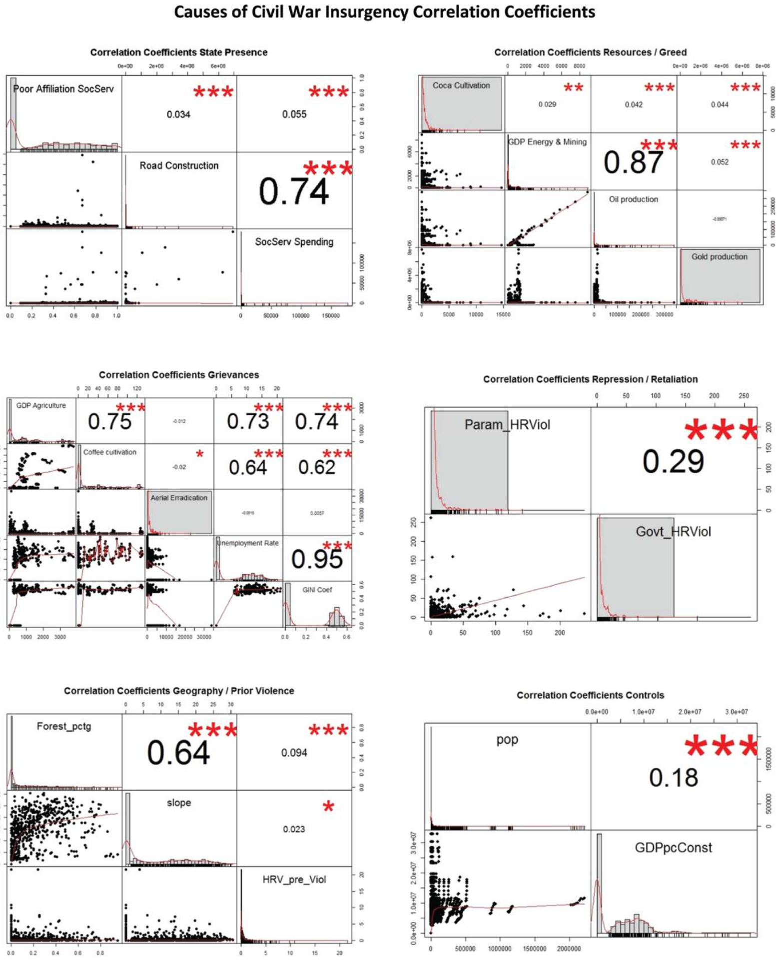
Our analyses identify priority policy actions to promote peace, including the need to both reform the royalty system, and prevent resources from being diverted by corruption or predation. Although the system was reformed in 2011 and 2013 to prevent corruption and predation (Cepeda Ulloa, 2015, 58), corruption charges continue, for example, against former Córdoba governor, Alejandro Lyons Muskus for embezzlement of royalties in 2017. We also highlight the importance of incorporating the poor into the public health system to reduce violence, and inoculate populations against guerrilla recruitment or support. Although the effectiveness of the Colombian public health has increased significantly in the past 30 years, more progress is needed to cover the internally displaced, the very poor, and some of the ethnic minorities in Colombia (Glassman et al., 2010). Similarly, the strong association of unemployment with guerrilla activity suggests the need for targeted, effective programs to improve employment opportunities. The consistent evidence of predation on the mining and energy sector highlights the importance of prioritizing areas with these resources for increased protection. The surprising results of coffee and the agricultural sector support other studies that examine price and demand. In times of strong demand and high prices, agricultural areas are less vulnerable to guerrilla activity. However, previous research of earlier time periods of crisis reminds us of the necessity of targeted programs to alleviate problems when the agricultural sector is not booming. In other words, in times of low primary product demand, extra attention to rural labor issues is critical. This study also provides a cautionary tale to the ongoing demobilization of FARC guerrillas. One of the most consistent results in this and other studies is the inflammatory effect of government repression. Avoiding mistakes of government repression is especially important as the Colombian government tries to control areas long held by guerrillas or other illegal groups. Recent attacks and assassinations of demobilized FARC members (Telesur, 2017) raise concern about another way of paramilitary or neo-paramilitary attacks against demobilized guerrillas, such as occurred against the UP in the 1980s (Daniels, 2017). Special attention should also be given to rugged areas and parts of the country that have historically plagued by earlier periods of conflict, failed land reform, and land conflicts. A likely future flashpoint would be eruptions of another round of land conflict over reform or reparations related to the peace process (Flores, 2014). Since the beginning of the land restitution process in 2011 through March 2015, at least 49 participants had been murdered and an additional 347 people related to the restitution process had received threats (Moreno et al., 2016, 15). A restitution process without sufficient security will cultivate future, additional conflict.

Second, this subnational study offers much closer measures to concepts of interest, especially resources, state presence, and geography. The power of precise measures of rough terrain (percent forest and slope) is clear across all models. Our measure of prior conflict is also important to include. These time invariant, theoretically important variables are better tests of theory than the general variables used in the crossnational research, such as the existence of previous conflict or mountainous terrain. This analysis also can highlight specifics, such as the proportion of the poor served by social programs, as opposed to a raw poverty rate. A subnational analysis also allows the disaggregation of primary exports into sectoral GDP or even production figures, as necessary to identify specific crops or products that are vulnerable to predation or sources of grievance. Future research is needed to incorporate the impact of prices, consistent with Rettberg (2010) and Dube and Vargas (2013), and the impact of boom times in general, as argued by Dube and Vargas (2013), Garay (2013), and Lei and Michaels (2014).

## Funding

Division of Civil, Mechanical and Manufacturing Innovation, Funder Id: 10.13039/100000147, Grant Number: 1541199.

# Appendix A




# Appendix B

Granger causality tests.

| | Lag | Log–deter | Chi-square | p-Value | AIC | BIC | HQ | | | | F-statistic | p-Value |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | **Granger causality resources/greed** | | | | | **Granger causality test** |
| Guerrilla and coca cultivation | 1 | 22.06 | 0.00 | 0.00 | 23.78 | 23.73 | 23.21 | Coca | → | Guerrilla | 7.10 | 0.04 |
| | 2 | 20.72 | 2.69 | 0.61 | 23.58 | 23.50 | 22.62 | Guerrilla | → | Coca | 0.01 | 0.91 |
| | 3 | −93.43 | 0.00 | 1.00 | −89.43 | −89.54 | −90.76 | | | | | |
| Guerrilla and GDP agriculture | 1 | 21.20 | 0.00 | 0.00 | 22.70 | 22.76 | 22.30 | GDP agric. | → | Guerrilla | 3.53 | 0.11 |
| | 2 | 20.45 | 2.24 | 0.69 | 22.95 | 23.05 | 22.28 | Guerrilla | → | GDP agric. | 0.89 | 0.38 |
| Guerrilla and mining | 1 | 15.94 | 6.63 | 0.16 | 18.80 | 18.72 | 17.85 | GDP min. | → | Guerrilla | 5.12 | 0.11 |
| | 2 | 19.26 | 0.00 | 0.00 | 20.98 | 20.93 | 20.40 | Guerrilla | → | GDP min. | 0.61 | 0.60 |
| | 3 | −107.50 | 0.00 | 1.00 | −103.50 | −103.61 | −104.84 | | | | | |
| Guerrilla and coffee | 1 | 9.92 | 0.00 | 0.00 | 11.64 | 11.59 | 11.06 | Coffee | → | Guerrilla | 23.20 | 0.00 |
| | 2 | 9.14 | 1.57 | 0.81 | 12.00 | 11.92 | 11.04 | Guerrilla | → | Coffee | 0.19 | 0.68 |
| | 3 | −93.56 | 0.00 | 1.00 | −89.56 | −89.67 | −90.90 | | | | | |
| Guerrilla and oil | 1 | 21.86 | 6.37 | 0.17 | 24.71 | 24.64 | 23.76 | Oil | → | Guerrilla | 53.40 | 0.00 |
| | 2 | 25.04 | 0.00 | 0.00 | 26.76 | 26.71 | 26.18 | Guerrilla | → | Oil | 2.33 | 0.24 |
| | 3 | −87.63 | 0.00 | 1.00 | −83.63 | −83.74 | −84.96 | | | | | |
| Guerrilla and gold | 1 | 38.30 | 0.00 | 0.00 | 40.01 | 39.97 | 39.44 | Gold | → | Guerrilla | 0.29 | 0.77 |
| | 2 | 35.96 | 4.68 | 0.32 | 38.82 | 38.74 | 37.86 | Guerrilla | → | Gold | 1.09 | 0.44 |
| | 3 | −90.45 | 0.00 | 1.00 | −86.45 | −86.56 | −87.79 | | | | | |

## Appendix C

Granger causality human rights violations (guerrilla, paramilitary and government).

| | | | | Variable lags specification | | |
|---|---|---|---|---|---|---|
| **Lags (months)** | **Log–determinant** | **Chi-square** | **p-Value** | **AIC** | **BIC** | **HQ** |
| 1 | 19.5 | 0 | 0 | 19.7 | 20.1 | 19.9 |
| 2 | 19.4 | 9.9 | 0.4 | 19.8 | 20.4 | 20 |
| 3 | 19.2 | 13.4 | 0.1 | 19.9 | 20.7 | 20.2 |
| 4 | 19.2 | 5.5 | 0.8 | 20 | 21 | 20.4 |
| 5 | 19 | 15.1 | 0.1 | 20 | 21.3 | 20.5 |
| 6 | 18.8 | 11.7 | 0.2 | 20 | 21.5 | 20.6 |
| 7 | 18.5 | 26.4 | 0 | 19.8 | 21.6 | 20.6 |
| 8 | 18.3 | 8.9 | 0.5 | 19.9 | 21.9 | 20.7 |
| 9 | 18.2 | 12.6 | 0.2 | 19.9 | 22.2 | 20.8 |
| 10 | 18.1 | 5 | 0.8 | 20 | 22.5 | 21 |
| 11 | 17.9 | 10.4 | 0.3 | 20 | 22.8 | 21.1 |
| 12 | 17.7 | 13.3 | 0.2 | 20 | 23 | 21.2 |
| 13 | 17.5 | 10 | 0.4 | 20 | 23.2 | 21.3 |
| 14 | 17.3 | 9.6 | 0.4 | 20 | 23.5 | 21.4 |
| 15 | 17.2 | 4.3 | 0.9 | 20.1 | 23.8 | 21.6 |
| 16 | 17.1 | 5.3 | 0.8 | 20.2 | 24.1 | 21.8 |
| 17 | 16.7 | 20.6 | 0 | 19.9 | 24.1 | 21.6 |
| 18 | 16.4 | 12.6 | 0.2 | 19.8 | 24.2 | 21.6 |
| 19 | 16.1 | 10.5 | 0.3 | 19.7 | 24.3 | 21.6 |
| 20 | 15.7 | 13.4 | 0.1 | 19.5 | 24.4 | 21.5 |
| 21 | 15.5 | 6.8 | 0.7 | 19.5 | 24.6 | 21.6 |
| 22 | 15.3 | 6.1 | 0.7 | 19.5 | 24.8 | 21.6 |
| 23 | 15.1 | 4.1 | 0.9 | 19.5 | 25.1 | 21.8 |
| 24 | 14.1 | 23.3 | 0 | 18.7 | 24.5 | 21 |

| | Granger causality test (lag selected=1) | |
|---|---|---|
| **Causal directions** | **F-statistic** | **p-Value** |
| Paramilitary→guerrilla | 0.082 | 0.776 |
| Goverment→guerrilla | 5.288 | 0.023 |
| Guerrilla→paramilitary | 3.627 | 0.059 |
| Goverment→paramilitary | 6.347 | 0.013 |
| Guerrilla→goverment | 9.165 | 0.003 |
| Paramilitary→goverment | 4.914 | 0.029 |

## Appendix D

OLS fixed effects balanced panel.

| **Oneway (individual) effect within model Municipalities** | **Years** | **Number of observations** | | |
|---|---|---|---|---|
| 1118 | 10 | 11,180 | | |
| Residuals | | | | |
| Min. | 1st Qu. | Median | 3rd Qu. | Max. |
| −6.064391 | −0.264771 | −0.034855 | 0.138515 | 15.15151 |
| Coefficients | | | | |
| Social service spending | −0.00015576 (0.00077991) | | | |

| | | |
|---|---|---|
| % Poor affiliated with public services | −1.0412<br>(0.08531) | *** |
| Coca cultivation | 0.0047722<br>(0.0024169) | * |
| Agriculture, fishing and ranching GDP | −0.89082<br>(0.11873) | *** |
| Mining, energy and quarries GDP | −0.019055<br>(0.016666) | |
| Aerial erradication | 0.0076375<br>(0.0020391) | *** |
| Government HR violations | 0.15969<br>(0.022072) | *** |
| GDP (per capita) | −0.030119<br>(0.045779) | |
| Population | −13.494<br>(0.94526) | *** |

$p \le 0.001$*** $p \le 0.01$** $p \le 0.05$*.

| | |
|---|---|
| Total sum of squares: | 10,784 |
| Residual sum of squares: | 9931.8 |
| R-Squared: | 0.079005 |
| Adj. R-Squared: | −0.024152 |
| F-statistic: | 95.8194 on 9 and 10053 df, p-value: < 2.22e-16 |

Residual tests
Breusch-Pagan LM test for cross-sectional dependence in panels
p-Value: 2.2E-16
Alternative hypothesis: cross-sectional dependence
Pesaran CD test for cross-sectional dependence in panels
p-Value: 2.2E-16
Alternative hypothesis: cross-sectional dependence
Breusch-Godfrey/Wooldridge test for serial correlation in panel models
P-Value: 2.2E-16
Alternative hypothesis: serial correlation in idiosyncratic errors

# Appendix E

Moran's I test for Models' residuals spatial autocorrelation.

| | **Model 1 With sectoral GDPs (agriculture and mining)** | **Model 2 With coffee production and mining GDP** | **Model 3 No sectoral GDPs. Coffee, mining and energy commodities** | **Model 4 Model 1+GINI and unemployment (24 depts)** | **Model 5 Model 1 with warlike actions as dependent variable** |
|---|---|---|---|---|---|
| Observed | −0.00034 | 0.00012 | −0.00004 | −0.00021 | −0.00009 |
| Expected | −0.00009 | −0.00009 | −0.00009 | −0.00010 | −0.00009 |
| SD | 0.00029 | 0.00029 | 0.00028 | 0.00029 | 0.00028 |
| p-Value | 0.38 | 0.48 | 0.87 | 0.70 | 0.99 |

Research hypothesis: spatial autocorrelation.

## Appendix F

The GLMM-ADBM with a negative binomial distribution and variance specification = ϕμ is the model with the lowest AIC.

Model comparison.

| Model | Akaike information criterion (AIC) | dAIC | Degrees of freedom |
|---|---|---|---|
| Negative binomial two levels (variance = ϕμ) CINEP violence/agriculture GDP | 11082 | 0 | 20 |
| Negative binomial two levels (variance = ϕμ) CINEP violence/coffee cultivation | 11093.1 | 11.1 | 20 |
| Negative binomial two levels (variance = μ (1 + μ/k)) coffee cultivation | 11892.9 | 810.9 | 21 |
| Negative binomial two levels (variance = μ (1 + μ/k)) agriculture GDP | 12064.1 | 982.1 | 21 |
| Negative binomail zero-inflated two levels GDP agriculture | 12287.1 | 1205.1 | 19 |
| Negative binomial zero-inflated one level coffee cultivation | 12354.5 | 1272.5 | 18 |
| Negative binomial zero-inflated one level agriculture GDP | 12436.3 | 1354.3 | 18 |

The model pre-selection also showed that the variance of the municipal random intercepts is greater than the variance of the departmental random intercepts ($\sigma^2_{municipal} > \sigma^2_{departmental}$) with a considerable range of variation ($\sigma_{municipal} = 0.9$, $\sigma_{departmental} = 0.75$). Such level of variation at the two hierarchical levels indicates that multilevel modelling with a non-normal response function is suitable for municipal and departmental factor estimation to explain leftist guerrilla violence as the dispersion parameter for the negative binomial distribution is significant.

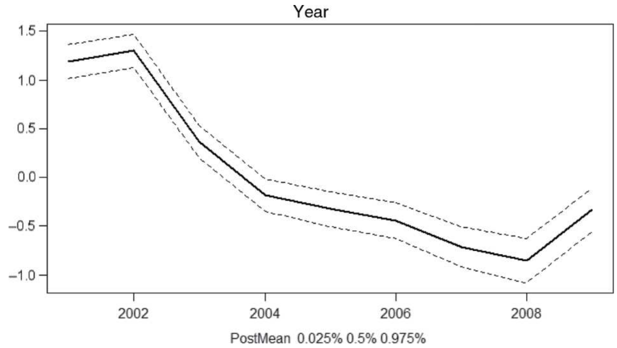
## Appendix G

Bayesian INLA model considering time, municipality, department variables as random effects.

| | Mean | SD | 0.025 quant | 0.5 quant | 0.975 quant | Mode |
|---|---|---|---|---|---|---|
| Fixed effects | | | | | | |
| (Intercept) | −3.435 | 0.301 | −4.031 | −3.434 | −2.848 | −3.431 |
| SocServicespc_b08 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| pctj_hthcov | −0.416 | 0.256 | −0.918 | −0.416 | 0.086 | −0.416 |
| CC_Hect_T2 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| GDP_Agr_T1 | −0.001 | 0.000 | −0.001 | −0.001 | 0.000 | −0.001 |
| GDP_Min_T1 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| AE_Hect | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Govt_fitted | 0.114 | 0.042 | 0.034 | 0.114 | 0.199 | 0.112 |
| Forest_pctg | 1.737 | 0.366 | 1.021 | 1.736 | 2.456 | 1.735 |
| Slope | 0.034 | 0.012 | 0.009 | 0.034 | 0.058 | 0.034 |
| GDPpcConst | 0.039 | 0.026 | −0.012 | 0.039 | 0.089 | 0.040 |
| HRV_pre_Viol | 0.409 | 0.040 | 0.332 | 0.409 | 0.487 | 0.408 |
| Pop | 0.115 | 0.143 | −0.165 | 0.114 | 0.399 | 0.113 |
| Random effects | | | | | | |
| Size for the nbinomial observations (1/overdispersion) | 0.615 | 0.044 | 0.538 | 0.611 | 0.709 | 0.603 |
| Precision for ID_Mun_c | 0.152 | 0.015 | 0.125 | 0.151 | 0.185 | 0.148 |
| Precision for Year | 2.367 | 1.338 | 0.690 | 2.075 | 5.751 | 1.560 |
| Precision for ID_Dept_c | 17,310 | 17,880 | 950 | 11,880 | 64,650 | 2424 |

Expected number of effective parameters (SD): 509.34 (15.13)
Number of equivalent replicates: 21.95
Marginal log-Likelihood: −6024.31

Mean variation of Violence from 2000 to 2009




## Appendix H

GLMM-ADMB negative binomial on HRV reported by CINEP including time as a fixed effect.

| | **Model 1**<br>**With sectoral GDPs (agriculture and mining)** | **Model 2**<br>**With coffee production and mining GDP** | **Model 3**<br>**No sectoral GDPs. Coffee, mining and energy commodities** | **Model 4**<br>**Model 1+GINI and unemployment (24 depts)** | **Model 5**<br>**Model 1 with warlike actions as dependent variable** |
|---|---|---|---|---|---|
| Intercept | 678.38374<br>(69.352)*** | 761.37776<br>(66.902)*** | 687.97122<br>(71.53)*** | 672.00<br>(76.3)*** | 356.000<br>(33.800)*** |
| State presence | | | | | |
| – Social Service Spending | 0.00242<br>(0.00238) | 0.00243<br>(0.00243) | 0.00233<br>(0.002) | 0.00249<br>(0.002410) | 0.000335<br>(0.001230) |
| – % poor affiliated w/public services | −0.46294<br>(0.3437) | −0.3343<br>(0.33996) | −0.3211<br>(0.341) | −0.434<br>(0.368000) | 0.27400<br>(0.184000) |
| Resources/greed | | | | | |
| – Coca cultivation | 0.01211<br>(0.00994) | 0.01243<br>(0.01034) | 0.01246<br>(0.01) | 0.0383<br>(0.017900)* | −0.00471<br>(0.003470) |
| – Mining, Energy and Quarries GDP | 0.02299<br>(0.0748) | | 0.04552<br>(0.07669) | −0.0253<br>(0.144000) | 0.0436<br>(0.037800) |
| – Oil production | | | 0.13429<br>(0.054)* | | |
| Grievances | | | | | |
| – Coca aerial eradication | 0.00809<br>(0.00768) | 0.00793<br>(0.00783) | 0.00803<br>(0.008) | −0.000911<br>(0.008460) | 0.010200<br>(0.003320)** |
| – Unemployment rate | | | | 0.092200<br>(0.023400)*** | |
| – GINI Coefficient | | | | −3.540000<br>(2.310000) | |
| – Coffee cultivation | | 0.37765<br>(0.29525) | 0.38677<br>(0.288) | | |
| – Agriculture, fishing and ranching GDP | −2.9694<br>(0.59359)*** | | | −2.9000<br>(0.559000)*** | −0.609<br>(0.221000)** |
| Repression | | | | | |
| – Government HR violations | 0.19051<br>(0.0917)* | 0.19283<br>(0.09306)* | 0.1967<br>(0.093)* | 0.19800<br>(0.095600)* | 0.0478<br>(0.037200) |
| Geography/prior violence | | | | | |
| – % of forest land | 2.38821<br>(0.48132)*** | 2.63415<br>(0.45588)*** | 2.57198<br>(0.457)*** | 2.840000<br>(0.50000)*** | 2.13000<br>(0.298000)*** |
| – Land slope | 0.05524<br>(0.01452)*** | 0.04597<br>(0.01392)*** | 0.04722<br>(0.014)*** | 0.051500<br>(0.014900)*** | 0.067400<br>(0.009040)*** |
| – Prior HR/WL violence | 0.33935<br>(0.03646)*** | 0.33015<br>(0.03587)*** | 0.3311<br>(0.036)*** | 0.327000<br>(0.036700)*** | 0.39000<br>(0.025400)*** |

| | | | | | |
|---|---|---|---|---|---|
| – Year | −0.33941 | −0.38161 | −0.34484 | −0.336000 | −0.179 |
| | (0.03475)*** | (0.03351)*** | (0.036)*** | (0.038300)*** | (0.0169000)*** |
| Controls | | | | | |
| – GDP per capita | 0.53886 | 0.13714 | −0.34675 | 0.706000 | −0.473 |
| | (0.30538) | (0.29591) | (0.343) | (0.45000) | (0.14900)** |
| – Population | −0.04304 | 0.21971 | 0.28197 | −0.165000 | 0.1730 |
| | (0.38452) | (0.34931) | (0.345) | (0.358000) | (0.22000) |
| # Obs, # municipalities, # departments | 11,180, 1118, 32 | 11,180, 1118, 32 | 11,180, 1118, 32 | 10,450, 1045, 24 | 11,180, 1118, 32 |
| Negative binomal dispersion parameter | 0.13434 | 0.13034 | 0.13064 | 0.13661 | 0.72522 |
| | (0.0063041) | (0.0061173) | (0.0061261) | (0.006645) | (0.032076) |
| Random effects municipality level (intercepts) | Variance: 2.894 | Variance: 2.799 | Variance: 2.814 | Variance: 2.99 | Variance: 1.598 |
| | SD: 1.701 | SD: 1.673 | SD: 1.677 | SD:1.729 | SD: 1.264 |
| Random effects department level (intercepts) | Variance: 3.986 | Variance: 2.307 | Variance: 2.129 | Variance: 2.135 | Variance: 1.063 |
| | SD: 1.997 | SD: 1.519 | SD: 1.459 | SD: 1.461 | SD: 1.031 |
| AIC | 15283.6 | 15319.9 | 15313.7 | 14153.5 | 20593.8 |

$p \leq 0.001$*** $p \leq 0.01$** $p \leq 0.05$*.

## Appendix I

GLMM-ADMB Negative Binomial on terrorist violence reported by the Ministry of Interior.

| | **Model 1** **With sectoral GDPs (agriculture and mining)** | **Model 2** **With coffee production and mining GDP** | **Model 3** **No sectoral GDPs. Coffee, mining and energy commodities** | **Model 4** **Model 1+GINI and unemployment (24 depts)** |
|---|---|---|---|---|
| Intercept | −3.5934 (0.33514)*** | −4.11724 (0.38536)*** | −4.07768 (0.3835)*** | −2.26277 (0.82471)** |
| State presence | | | | |
| – Social service spending | 0.00283 (0.00172) | 0.00283 (0.00172) | 0.0028 (0.000172) | 0.00328 (0.00183) |
| – % poor affiliated w/public services | −0.08543 (0.21195) | −0.13004 (0.21298) | −0.07668 (0.21919) | −0.14831 (0.23256) |
| Resources/greed | | | | |
| – Coca cultivation | 0.00228 (0.00457) | 0.00196 (0.00454) | 0.002 (0.00454) | 0.01136 (0.00907) |
| – Mining, energy and quarries GDP | 0.04489 (0.04564) | 0.05949 (0.04595) | | 0.09448 (0.07863) |
| – Oil production | | | 0.04032 (0.02673) | |
| Grievances | | | | |
| – Coca aerial eradication | 0.00456 (0.00422) | 0.00422 (0.000419) | 0.00433 (0.00419) | 0.00474 (0.00589) |
| – Unemployment rate | | | | −0.02254 (0.01548) |
| – GINI coefficient | | | | −1.67956 (1.4572) |
| – Coffee cultivation | | 0.93003 (0.29549)** | 0.91846 (0.29404)** | |
| – Agriculture, fishing and ranching GDP | 0.11976 (0.3157) | | | −0.10339 (0.29438) |
| Repression | | | | |
| – Government HR violations | 0.05703 (0.04165) | 0.05638 (0.04152) | 0.05609 (0.04142) | 0.025 (0.04274) |
| Geography/prior violence | | | | |
| – % of forest land | 1.57061 (0.36412)*** | 1.74947 (0.36516)*** | 1.73751 (0.36544)*** | 1.83475 (0.38459)*** |
| – Land slope | 0.02946 (0.01122)** | 0.02332 (0.01132)* | 0.02316 (0.01132)* | 0.0319 (0.01165)** |
| – Prior HR/WL violence | 0.19201 (0.02186)*** | 0.18701 (0.02181)*** | 0.18736 (0.02183)*** | 0.17893 (0.02174)*** |

| | | | | |
|---|---|---|---|---|
| Controls | | | | |
| – GDP per capita | 0.06606 | 0.03885 | −0.00394 | 0.00327 |
| | (0.1355) | (0.12295) | (0.13365) | (0.19368) |
| – Population | 0.91917 | 1.03491 | 1.04417 | 0.85504 |
| | (0.26957)*** | (0.28257)*** | (0.28246)*** | (0.24548)*** |
| # Obs, # Municipalities, # departments | 11,180, 1118, 32 | 11,180, 1118, 32 | 11,180, 1118, 32 | 10,450, 1045, 24 |
| Negative binomal dispersion parameter | 0.5486 | 0.55458 | 0.5548 | 0.52862 |
| | (0.032483) | (0.032913) | (0.03293) | (0.03382) |
| Random effects municipality level (intercepts) | Variance: 2.099 | Variance: 2.094 | Variance: 2.097 | Variance: 2.081 |
| | SD:1.449 | SD: 1.447 | SD: 1.448 | SD:1.443 |
| Random effects department level (intercepts) | Variance: 1.567 | Variance: 2.092 | Variance: 2.061 | Variance: 0.6954 |
| | SD: 1.252 | SD: 1.446 | SD: 1.436 | SD: 0.8339 |
| AIC | 12026.6 | 12013.8 | 12013.2 | 10718.5 |

$p \leq 0.001$*** $p \leq 0.01$** $p \leq 0.05$*.

# Notes

1 A 33rd department is the island of San Andres. Certain data are only reported at the municipal level for census years (1993, 2005).
2 Unfortunately, in Colombia, consistent and comparable estimates of poverty are scarce. DANE changed how it calculated poverty beginning with 2002 and has not recalculated estimates before that date. Moreover, the only municipal estimates are available for census years. Department estimates are available from 2002 to present, except 2006 and 2007, which were not reported due to problems with the survey, however, the *nuevos departamentos* do not report these statistics.
3 However, repression also can include retaliation strategies that could produce simultaneity in human rights violations (HRV). In that vein, we used a vector autoregression (VAR) model to investigate interdependency and time-series-based or Granger causality among HRV time series of the three great actors. The 2000–2010 VAR series showed that guerrilla violence Granger causes paramilitary HRV but not in the opposite direction. Guerrilla HRV Granger causes government violations and also in the contrary direction. Based on such analysis and to account for the endogenous guerrilla-government relationship we implemented an instrumental variable approach, estimating government violence instrumented by paramilitary HRV which is exogenous to guerrilla HRV in a preliminary regression (1st stage), to use government HRV estimations in the main multilevel model. Granger causality tests and instrumental variable procedure are shown in Appendix C and Appendix D respectively.
4 "La extorsión en el sur de Bolívar, 'mina' para el Eln" *El Tiempo* January 28, 2013. http://www.eltiempo.com/archivo/documento/CMS-12555107 (Accessed May 13, 2016)
5 The proxy for illegal mining used by Idrobo, Mejía, and Tribin (2014), 93 includes average slope for each municipality.
6 The spending of royalties was perceived to be rampant and corrupt.
7 Since these three great actors of HRV are moved by different motivations, it is necessary to understand interactions and causal directions among them. Such interactions and directions were modeled with Vector Autorregressive Models and Granger causality tests that provided the baseline for endogeneity treatment. This analysis is presented in Appendix C. The instrumental variable (IV) technique is used in the analysis to account for repression/retaliation actions among leftist guerrilla, paramilitaries and government forces.
8 However, this is only available by municipality since 2003. Unfortunately, none of these sources are disaggregated by type of action or by perpetrator.
9 We considered if our variables are related measures of overall, theoretically important categories as potential causes of conflict. For instance, variables like road construction, coffee production and oil production are significantly correlated with social service spending (water, sanitation, education and housing), sectoral GDP of agriculture and GDP of mining, energy and quarries respectively. We omitted the effect of road construction and created different model specifications that separate sectoral GDPs from coffee and oil production. Preliminary diagnostics of variables on each category allowed us to select the variables that showed singular dynamics and low levels of correlation. Correlation tests of significance are provided in Appendix A.
10 Granger causality is based on temporal precedence and non-zero correlation assumptions. It is not testing the non-spuriousness of a causal relationship. To account for spurious causality, we ran vector autoregression models and impulse response functions to demonstrate and confirm causal relationship and directions found in Granger tests.
11 In the case of gold production, the relationship with violence is not significant in either direction. Therefore, we omitted gold production from the analysis. When included, it was not significant.
12 We can observe a significant variation of violence among municipalities in CINEP Data, ranging from 0 to 19 leftist human rights violations and from 0 to 31 warlike actions per year. A similar trend is evident in the Ministry of Interior's terrorism statistics, with attacks varying from 0 to 67 annually.
13 Notwithstanding, an OLS panel fixed effects model was specified to check if model assumptions are being violated. Panel estimates and residual tests to check serial correlation and cross-sectional dependence in panels (Appendix D) confirmed suspected OLS violations.
14 The GLMM specification uses the Auto Differencing Model Builder (ADBM) methodology implemented in the R package (Skaug et al., 2016) to calculate via optimization process the fixed effects and random effects of the parameters. The ADBM programming framework focuses on non-linear models with large number of parameters (Fournier et al., 2012), which allows the use of non-normal distributions to account for the over-dispersion of the leftist guerrilla violence.
15 The most common response distributions for over-dispersed data are Poisson, binomial, and negative binomial that can consider or not the excess of zeros presence (zero-inflated models). The final model was selected from several specifications. The tested models showed that the specification with a negative binomial response distribution and without the zero-inflated component has the best goodness of fit according to the Akaike Information Criteria (AIC). AIC is a measure of relative quality of statistical models. The tested models and their AICs are shown in Appendix F.
16 To verify the time trend of insurgent violence, we estimated an alternative Bayesian model based on integrated nested Laplace approximations (INLA). INLA specification was used to capture dynamic aspects of the data, and to verify whether potential effects of static variables could affect our "time-pooled" model. We have to consider that longitudinal property of some variables such as the geographic and prior violence are considered as "static" given that land slope and forestland have no variation through time, and prior violence is only a reference from the past. We also know from preliminary descriptive analysis that violence has a downward trend in the period of study. INLA models confirm that there exist dynamic implications for the level of violence. Yet, controlling for the time effect, posterior distributions for the static variables show credible intervals with similar patterns in terms of positive/negative effects as the obtained by GLMM models considering all methodological differences. INLA model results are presented in Appendix G.
17 In fact, we ran models including "years" as the time variable. In all models the time variable contributed to the violence decrease and was statistically significant with very low p-values, that raised the concern of potential bias. Results are presented in appendix H.
18 Appendix I contains models using acts of terrorism, provided by the Ministry of Interior, instead of the CINEP data as the dependent variable. The results are less robust: the percent of poor affiliated with public services drops significance in all models; coffee switched significance with GDP agriculture; mining and oil lose significance. Paramilitary and government human rights violations lose significance in all models.
19 Often the *nuevos departamentos* (new departments created by the 1991 constitution) do not report statistics. These include Amazonas, Arauca, Casanare, Guainía, Guaviare, Putumayo, Vaupés and Vichada. These departments are sparsely populated and contain only about 5% of the Colombian population, despite accounting for almost half of Colombia's terrain (Direccin de Metodologa y Produccin Estadstica–DIMPE, 2013, 2). Additionally, the GINI estimates for 2006 and 2007 were not reported by DANE because of problems with the survey. We have imputed values for those missing years by basic linear interpolation.
20 A possibility suggested by an anonymous reviewer.
21 Only 3 percent of the municipalities of the eight *Nuevos Departamentos* had leftist guerrilla violence, and Model 4 shows identical results compared with Models 1–3 that contain all 32 departments.

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