The Effects of Drug Enforcement on Violence in Colombia 1999-2010: A Spatial Econometric Approach

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Abstract

In this paper paper, I use Mejía and Restrepo's (2011) strategy to disentangle the causal relationship between drug enforcement and violence. To test this relationship, I use information on Colombian municipalities during the period 1999 – 2010. Due to technological reasons related to the quality of terrain, climate, and locational characteristics of the Colombian territory, cocaine production is more productive at low altitudes. Using the altitude of each municipality and distance from capital cities as sources of exogenous variation, I estimate the effect of drug enforcement on violence in Colombia. To control for a possible omitted-variable bias in the estimations, I run a Panel Data Spatial Durbin Model (SDM). Additionally, I construct a set of indices with comparable units of measure which allows me to determine which percentage of the Colombian violence data is explained by drug enforcement. The results indicate that the Colombian government's enforcement activities increased in 0.98% the homicide rate and in 1.24% the displacement rate and the war among drug dealers increased in 4.00% the homicide rate and 0.16% the displacement rate in the period 1999 – 2010.

JEL Classification: H56, K14, K42, L65
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1 Introduction

Illegal markets for narcotics are usually correlated positively with violence[1]. This correlation has elicited an intense debate because it is still unclear whether violence creates the incentives for the illegal markets for narcotics to exist or viceversa, and who are the main perpetrators of such violence. In this debate, the effects of the government's enforcement activities on the violence generated in these markets have generally been underestimated. I argue that drug enforcement has first– and second–order effects on the violence generated in these markets, especially in source countries[2].

In those countries, the government engages in prosecuting activities that sometimes involve military expenditure to enforce prohibition. As prohibition applies to commodities supplied by *decentralized markets*, drug dealers are able and willing to use their profits to fight back the government's prosecuting activities. This military power also allows them to solve their potential commercial disputes violently, if needed. This is called the *drug war in source countries*. Thus, the first-order effect refers to the direct violence that results from the government and drug dealers' military expenditures on the *drug war*. The second–order effect refers to the violence that emerges from the drug dealers' military expenditure on their drug war. This war occurs due to the absence of a legal system where drug dealers can solve their commercial disputes pacifically and drug markets exhibiting contracting environments with high transaction costs induced by enforcement.

To test the latter hypotheses, I use information on violence, drug and drug enforcement variables from Colombia during the period 1999 – 2010. Since 1999, Colombia has formally embarked in a program called "Plan Colombia", aimed at reducing the amount of cocaine produced and distributed in the country and overseas. This program involves, among others, the use of military tactics to incentivize Colombians not to participate in the cocaine market. As a result, the Colombian central government has declared all citizens who decide to produce narcotics and use force to fight back its drug enforcement activities as military targets.

To test the effects of the government's drug enforcement military activities, it would be ideal to use a set of measures that permits to compare the levels of military expenditures of all participants in the drug war per municipality. However, the Colombian vice–president's office only collects information on drug enforcement and drug war outcomes for every municipality of the country. With that multiplicity of measurement units and, in certain cases, same–purpose variables, three problems arise.

First, some drug enforcement and drug war variables are *almost perfectly spatially correlated*. This correlation generates a multicollinearity problem that results in estimations with erratic and statistically insignificant estimates associated with those variables. Second, even if we are able to orthogonalize those variables, their estimated coefficients might be affected by their measurement units, which makes the estimates' magnitude meaningless and unreliable. If we decide to use single measures that proxy for the drug war military expenditures, it is a priori unclear which variables are more appropriate to proxy for those expenditures. When we find *a way* to categorize and organize them, it is again unclear how to interpret the measurement units of the resulting proxies due to the measurement units diversity of the variables that compose them. Finally, some of the proxies for drug war military expenditure are endogenous to the proxies for violence.

The simplest way to circumvent the first two problems is to construct a set of indices that proxy for the government's and drug dealers' military expenditures. The methodology proposed in this paper to compute these indices permits to categorize municipalities according to the government's military expenditure against drug dealers (Eradication Index), drug dealers' military expenditure against the government (Anti-Eradication Index) and drug dealers' military expenditure against other drug deal-

[1]Violence is generally measured as the rate of homicides or displacement per $100,000$ inhabitants.

[2]A source country is defined as a country that has historically produced narcotics. For a list of illicit drugs and source countries, see CIA (2013).

ers (Drug Dealers' War Index). The methodology employed allows me to compute these indices having similar measurement units, which make their estimated coefficients objectively comparable. Additionally, as these indices are computed such that they are all in the unit interval and the regressands are expressed in logarithms, the indices' estimated coefficients indicate the *average percentage* in which the violence rate increases in the municipalities with the *largest military expenditure* relative to those with *zero military expenditure* on drug war.

To overcome the last problem, I employ a joint strategy: On the one hand, I use Mejía and Restrepo's (2011) strategy to disentangle the real effects of drug production on enforcement variables. Due to technological reasons associated with the quality of terrain, climate and locational characteristics of the Colombian territory, cocaine production is more productive at low altitudes. Mejía and Restrepo's (2011) strategy consists of running a 2SLS model using the altitude per municipality as an exogenous source of variation in the first stage to determine how much violence is explained by the Colombian drug war. I argue that given the Colombian government's centralized structure in drug enforcement decision making and policy application, two other sources of variation can be used: the distance of a municipality to Bogotá, the country's capital, and to the capital of *departamento*[3] in which it is located. A priori, there is no reason why drug enforcement variables are correlated with municipalities' altitude and distances to capitals other than by a technological issue associated with cocaine production. To control for potential omitted variables that also help explain violence in the Colombian municipalities, I run a panel data Spatial Durbin Model, which helps control for fixed, temporal and geographical factors.

On the other hand, using the latter sources of variation and the idea that drug war military expenditures are determined by the municipalities' spatial and geographical characteristics for cocaine production, I am able to reclassify municipalities according to their spatially-determined drug war military expenditures. As this reclassification does not use violence variables to estimate the proxies to recompute the indices, any correlation between the recomputed indices and violence variables can be understood as a causal correlation.

My results suggest that the Colombian violence is explained by both the central government's drug enforcement activities and the actions taken by drug dealers to fight back that enforcement. Furthermore, that violence is also explained by the efforts exerted by those groups to control the territory, where they not only produce narcotics but also extract the rents from other natural resources (such as gold and petroleum). Additionally, I find that the war among drug dealers has also an important effect on the levels of violence in Colombia. Drug dealers use violent methods to resolve their conflicts, affecting both the homicide rate and the displacement rate in the country.

This paper is organized as follows: section (1) is this introduction. Section (2) presents a short overview of the theoretical relation among drugs, drug enforcement, and violence. Section (3) presents the data used to test my hypotheses, with an emphasis on the spatial characteristics of the data used. Section (4) explains the empirical strategy pursued to test my hypotheses. Section (5) presents the results. Section (6) concludes the paper and section (6) contains the appendix.

[3]A *departmento* is similar to a U.S. state, but differs from an administrative viewpoint. A state has a constitution apart from the national constitution, whereas a *departmento* follows the single set of rules determined by the national constitution and legislature. After the constitution of 1991, Colombia initiated a decentralization process that involved the appropriation by *departmentos* and municipalities of their property taxes. However, both the police and the army are financed with national taxes and their prosecuting activities are decided entirely at the national level.

2 Theoretical Background

2.1 A General Perspective

Illegal markets for narcotics are usually associated with violence. This correlation has triggered an intense debate on who generates such violence and whether violence really leads to the production of narcotics or viceversa. The empirical evidence on this correlation is mixed, and three competing hypotheses have emerged as possible explanations for this regularity. A first hypothesis states that it is violence that generates the production of narcotics. Using a unique data set on Western Casualties in Afghan territory during the war against the Taliban regime after the 9/11, Lind et al. (2012) argue that the rise in Afghan opium production since 2002 can be explained by the deterioration of the social and economic infrastructure that emerged after the war. They argue that the conflict made "illegal opportunities more profitable as they increase the perceived lawlessness and destroy infrastructure crucial to alternative crops"(p. 1).

These authors use as an exogenous measure of conflict the number of western soldiers killed in Afghan territory, who, they argue, had nothing to do with drug eradication activities. They claim that the conflict against the Taliban generated a negative externality that led many Afghan farmers to produce heroin. Díaz and Sanchez (2004), using information from Colombian municipalities for the period $1994 - 2000$ and spatial econometric methods, show that the geographical intensification of conflict in Colombia, measured as the number of attacks perpetrated by irregular groups such as FARC, ELN and AUC [4], is the principal cause of the expansion of illegal crops of coca and poppy plants in the country. The authors demonstrate the close geographical correlation between the illegal groups' presence and the production of cocaine in the municipalities in which they operate.

In both studies similar doubts linger. On the one hand, why are these "rebel" groups also located in geographical areas with coca or poppy crops and the largest homicide rates? Aren't these groups directly involved in the production of narcotics to budget their war, for which they also fight back the government's eradication activities? On the other hand, why do individuals recur to the production of drugs? And why is this production profitable when anything else is not?

In regards to the first doubt, Lind et al. (2012) cannot disregard the possibility that heroin production might have been generated by the need of the Taliban for a quick revenue, which they called drugs-for-arms hypothesis. The same applies to the Colombian guerrillas and paramilitary groups and their involvement in the cocaine traffic[5]. If the drugs-for-arms hypothesis is true, this would imply that the relationship between violence and the production of narcotics is biunivocal: when a group in conflict needs a quick and secured source of revenue, they may recur to the production of narcotics to obtain it, even if unintended in the first place, which in turn generates more violence. Such violence might be associated with the military expenditure of those groups to accomplish their political goals or defend their territory from the government's eradication activities. Thus, the politically-motivated violence is the only one that can be ascribed to the first hypothesis, as the other is triggered by the existence of narcotics in that territory and the intention of the government to eradicate it militarily.

As the first hypothesis does not give a satisfactory answer to the latter questions, a second hypothesis arises in the literature: the production, transportation, distribution, and retailing of drugs generate violence. This hypothesis relies on the fact that illegalization leaves drug dealers without a legal system to resolve their commercial and legal disputes. Caulkins et al. (2006) argue that drug dealers use violence to resolve disputes and secure geographical positions in the retail market for narcotics.

[4]FARC (Fuerzas Revolucionarias de Colombia) and ELN (Ejército de Liberación Nacional) are both leftist guerilla groups, and AUC (Autodefensas Unidas de Colombia) is a right-wing paramilitary group.

[5]see LeoGrande and Sharpe (2000) and Thoumi (2002) for a detailed analysis of the evolution of the illegal markets for narcotics in Colombia and its effects on violence.

They argue that those individuals who have a larger propensity to use violence secure themselves the safest places on the retail market, which is where drug enforcement has the smallest probability to affect them negatively. As for a source country, Angrist and Kugler (2008), using a similar data set as Díaz and Sanchez (2004), state that the productivity of soil and the geographical location of Colombia create huge incentives for illegal groups to exploit these resources to produce illegal goods such as cocaine. Hence, municipalities with a significant production of cocaine are more violent. This relation is explained by the competition among rival groups, who compete for a share in the market, and with the government, who plays a predatory game with these groups. In this literature, the production of drugs is an endogenous variable that depends on the amount of enforcement and military capabilities of irregular groups to fight back the prosecuting agencies and their rival competitors (See Mejía and Posada (2008) and Mejía (2008) for papers that develop this idea).

In a recent paper, Mejía and Restrepo (2011) propose an identification strategy to disentangle the causal relationship between the existence of illegal markets and violence. Based on several insights about the technological features of the production of cocaine in Colombia provided by Mejía and Rico (2010)[6], these authors use the altitude of a municipality to proxy for the productivity of the cultivation of the coca plant. The underlying idea is that the plant produces more cocaine when harvested between 0 and 1700 meters above the sea level. As a result, if the existence of illegal markets has a real causal effect on violence, a 2SLS strategy that uses the altitude of each municipality might help uncover such a relationship. They show, using a panel of Colombian municipalities, that the existence of illegal markets for cocaine has a positive effect on the level of violence in Colombia.

Two drawbacks can be pointed out from Mejía and Restrepo's (2011) paper. On the one hand, altitude might also be correlated with drug enforcement activities of the Colombian government, and not only with what drug dealers do to gain a market share in the Colombian cocaine market. Hence, we must also control for enforcement activities of the Colombian government to be able to use the production of cocaine as a proxy for the violence generated by drug dealers in the illegal markets for cocaine. On the other hand, it is unclear why drug dealers have to resolve disputes violently when they can agree not to. In other words, illegality is not a sufficient condition to secure a violent outcome. Mirron (2001) argues that not all illegal activities generate violence or even an illegal market for them. He argues that there must be something else that induces both the illegal markets and violence to coexist. Using a panel of countries in which gun control data exist, he suggests that "differences in the enforcement of drug prohibition are an important factor in explaining differences in violence rates across countries"(p. 615).

Mirron (2001) relies on two factors that must be satisfied in order for illegal markets to exist and generate violence. First, a banned activity must generate huge amounts of resources to its suppliers. And second, enforcement activities are high, making transaction costs in the illegal markets sufficiently high as to impede drug dealers use of coasean-type mechanisms to resolve their possible commercial disputes. The Colombian case satisfies both conditions: some Colombian regions have a huge comparative advantage in producing goods that the rest of the world is highly interested in demanding at relatively high prices even when illegal. This powerful financial incentive generates that illegal groups try to create a public good —i.e., security for the production of drugs— in the most suitable regions. Additionally, enforcement efforts by the Colombian government have been relatively high, especially since "Plan Colombia" was enacted and put into action in 1999.

The last two hypotheses insinuate that the bulk of violence is explained by what drug dealers do against each other. However, the drug war also implies that the enforcement agencies engage in prosecuting activities and military actions against drug dealers, especially in source countries. For instance, "Plan Colombia" is the archetypal case of enforcement activities by the government

[6]See Gootenberg (2008) for a thorough analysis of cocaine production in the Andean Countries.

that involve the use of military tactics and methods to eradicate the production and manufacture of narcotics (see Acevedo et al. (2008) and GAO (2008)). This program has received good evaluations by its overall effects on the reduction of violence in Colombia, especially in the reduction of homicides of people younger than 29 years old (see Barón (2009)). Nonetheless, is it possible to assure that the government's drug enforcement actions do not have an effect on violence?

I argue that they do. There are two type of effects that enforcement activities have on violence: first–and second–order effects. A first–order effect is, for instance, the number of soldiers and police officers as well as the number of drug dealers who die in the drug war. This is an effect of enforcement because this violence occurs usually in the course of the eradication activities performed by the government, in which they use military tactics to reach the areas where production is taking place. As rebel groups obtain sufficient funds from the traffic of a highly demanded illegal commodity, when the government performs eradication activities, its enforcement agencies are threatened by military machinery that eventually reach them mortally too[7]. The second–order effect is the number of drug dealers who get killed in their drug war. This is an effect of enforcement because illegality and high enforcement efforts place wealthy drug dealers in an anarchic contractual environment where the death and displacement of people seem to be the common results.

2.2 A Simple Model

To clarify ideas, let us suppose that we have the economy laid out in section (A.0.1). In that economy, we could split municipality j's rate of violence[8] in the following way:

$$v_j = \beta_1 M_j^g + \beta_2 M_j^r + \beta_3 M_j^{ir} + \text{rest} \tag{1}$$

where $\beta_1 M_j^g$ represents the proportion of violence that is attributed to the government's drug enforcement military expenditure in municipality j, M_j^g. $\beta_2 M_j^r$ represents the proportion of violence that is explained by the drug dealers' anti-enforcement military expenditure in municipality j, M_j^r. $\beta_1 M_j^g + \beta_2 M_j^r$ is called in section (2.1) the first–order effect of enforcement. Finally, $\beta_3 M_j^{ir}$ represents the proportion of violence explained by drug dealers' military expenditure to control the territory to produce drugs, M_j^{ir}. This is called the second–order effect of enforcement.

If we had perfect and reliable information on M_j^g, M_j^r and M_j^{ir} and each category in which v_j can be divided, including the categories of our interest, we could easily determine the values of β_1, β_2 and β_3 by solving simple linear equations for each municipality. However, such information is unavailable, at least for Colombia. v_j is only available at aggregated levels, and there is only information on drug enforcement and drug war outcomes. In the next section, I explain the information available. In this one, two consequences of such a lack of *perfect* information on drug war military expenditures and violence variables are emphasized: on the one hand, β_1, β_2 and β_3 will have to be estimated using regression analysis. The latter implies that these betas will represent average values for the time period considered.

On the other hand, we need to control for three factors to obtain reliable estimates of the betas: first, we must control for v_j's over-counting. Second, proxies for M_j^g, M_j^r and M_j^{ir} must be constructed allowing for objectively comparable and reliable estimates. They also must represent the fact that

[7] If violence is measured as the rate of forcefully displaced people, the first–order effect is the number of civilians that are displaced by both the eradication and anti-eradication activities performed by both groups involved in the drug war.

[8] The rate of homicides and displacement per $100,000$ inhabitants will be used below as proxies for the rate of violence. In the next section, the composition of both rates are explained. Here, I will use violence as a generic term to refer to those empirical estimates of violence.

Colombian drug military expenditures have a geographical component that must be accounted for. Finally, some of the available proxies for M_j^g, M_j^r and M_j^{ir} are endogenous to the proxies for violence. Consequently, we must find an exogenous source of variation that determines those military expenditures, which is at the same time uncorrelated with the used proxies for violence.

In the next section, I describe my strategy to circumvent the problems associated with the military expenditures measurement. In section (4), I explain the empirical strategy to tackle the endogeneity and over-counting problems. There, I also explain the strategy used to obtain the exogenous proxies for military expenditures that take into account their spatial components.

3 The Data

3.1 Sources and Variables

To test the model laid out in equation (A.12), I use the homicide rate per $100,000$ inhabitants as a proxy for violence. These rates are collected by the Colombian vice president's office, and are a compilation of violent homicides that occurred in each of the 1122 municipalities of the country during the period 1999-2010 [9]. Each of these rates contains the number of individuals who were assassinated violently. It includes police officers, soldiers and prosecutors as well as any other individual who *dies violently* in each municipality. In this regards, the Colombian vice president's office does not keep separate records of each of the categories that compose the total homicide rate of every municipality. Consequently, as a measure of violence, it includes more homicides than can actually be ascribed to the drug war. In the empirical strategy section, I explain how I handle this problem.

As a robustness check of my results, I also use the number of forcefully displaced people per municipality that the same source collects to compute the rate of displacement per $100,000$ inhabitants for each municipality. The source defines an individual as forcefully displaced when the person is *forced* to migrate within the national territory because her life, security, and/or freedom are at stake due to the military actions of any of the groups involved in the conflict (i.e., guerrillas, AUC, drug dealers or the government's forces themselves). Because of the latter definition, I can also test whether the geographically-located drug enforcement activities of the central government are generating displacements or these are only the result of the existence of drugs as Mejía and Restrepo (2011) claim.

I use information on drug enforcement outcomes collected by the vice–president's office to proxy for the Colombian government's drug enforcement military expenditure on every municipality. This data set contains information on the amount of coca crops hectares that Colombia's prosecuting agencies eradicated either manually or by aspersion in the period $1999-2010$. It also includes the number of performed operations in each intervened municipality to eradicate the number of declared hectares. This data set also contains information on the number of destroyed labs dedicated to the production of narcotics in the same period. Since 1999, the Colombian vice-president's office also started to collect information on the amount of attacks initiated by the government's enforcement agencies, such as the army or the police, against illegal groups. These groups include drug gangs and politically-motivated groups, such as FARC, ELN or AUC, also known to be involved in the production of narcotics.

To my knowledge, the number of attacks initiated by the government has never been used to proxy for drug enforcement activities of the central government in Colombia. Figure (1) shows that this omission is not a minor one. The graph depicts the Colombian homicide rate and the logarithm of the coca crops of the municipalities with high[10] and low levels of government attacks. From the graph,

[9]For an analysis of the sources, its quality, and possible explanations about their discrepancies, see: Restrepo and Aguirre (2007). For the official definition of the variables used in this paper, see: Vice-Presidencia de Colombia (2012) (Spanish Version).

[10]To compute figure (1), a municipality was defined as a high-government-attacked municipality when it was included

it is clear that municipalities with more military attacks by the government have substantially larger homicide rates and coca production than municipalities with fewer of them.

Apart from the endogeneity problem associated with using the previous variable as a proxy for the Colombian government's drug enforcement military expenditure, running all these variables together also results in a multicollinearity problem because some of them are almost perfectly correlated. There are several ways to avoid this issue. One way is to perform a principal component analysis to orthogonalize these variables. Another way is to perform a common factor analysis, which determines the least number of factors that can account for the common variance of the set of enforcement variables (See Comrey (1973) and Hair et al. (1992) for analysis on these methods). As both methods depend on the variables' measurement units, it is unclear the measurement units of the resulting proxy, which affects the way I interpret the estimated results of drug enforcement variables on violence.

Another methodology to circumvent the multicollinearity problem is the one used by the Index of Economic Freedom, which summarizes in a single measure 10 variables exhibiting a potential multicollinearity problem if used together[11]. Caudill et al. (2000) argue that when the variables to compute an index are trying to proxy for a single dimensional variable, indexing and common factor analysis give equivalent results when their estimated proxies are used in regression analysis. However, indexing is simpler and indices can be computed such that they allow for objectively comparable estimates in regression analysis, avoiding the issue of the measurement units presented in the other two methodologies. Besides, Index Theory [12] allows us to assure that an index has the following two properties: first, it is able to capture the distribution of any compact set used to create the index, converting the moments' units of the domain set into the index units. Second, the correspondence that maps the domain set into the index numbers affects the accuracy of the index to capture the domain set distribution.

Bearing that in mind, I construct the following Eradication Index:

$$I_E = \frac{\sum_i^6 I_{E,i}}{18} \tag{2}$$

where[13],

$$I_{E,i} = \begin{cases} 3 & \text{if} \quad Var_i > percentile(a_i, 70) \\ 2 & \text{if} \quad percentile(a_i, 30) < Var_i < percentile(a_i, 70) \\ 1 & \text{if} \quad min(a_i) < Var_i < percentile(a_i, 30) \\ 0 & \text{if} \quad Var_i = 0 \end{cases} \tag{3}$$

where a_i is a non-zero vector composed of the elements of Var_i, and Var_i is any of the 6 aforementioned variables used to compute this index.

in the upper tail of the distribution of the number of attacks initiated by the government against irregular groups (defined by the 70th percentile of the distribution or above).

[11] Beach and Kane (2008) presents an analysis of the Index of Economic Freedom

[12] See Hájek (2009) for a mathematical analysis of the properties of indices.

[13] The choice of the percentile values to construct these indices are based on the distributions of its composing variables. However, my results are not sensitive to small changes in the threshold values for each category.

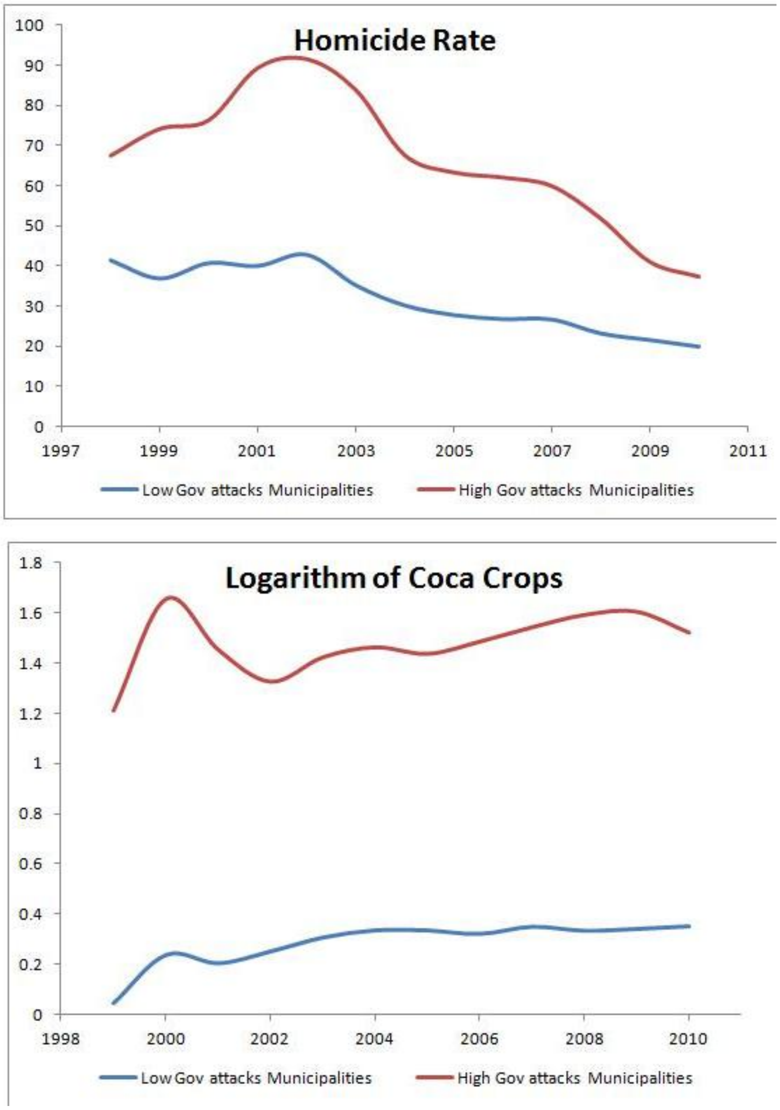


Figure 1: Homicide Rate and Coca Crops divided by Intensity of Government's Attacks

Several features are worth noting about the latter index. First, the index-composing variables are split between those municipalities with zero and strictly positive drug enforcement outcomes. This implies that my initial comparison will be between these two categories. Second, the highest possible score for a municipality is 18[14]. Thus, $I_E \,\epsilon\, [0,1]$. Third, if I run the model laid out in equation (A.12), using I_E to proxy for the government's drug enforcement military expenditure and the regressands in logarithms, $\beta_1 I_E$ would measure the percentage in which a municipality's violence rate changes with an enforcement level of I_E relative to a municipality with zero enforcement. To clarify the latter idea, let us assume that we have a municipality' violence rate v expressed in logarithms. This v assumes different values depending on which level of drug war intensity a municipality has. If the latter possibility is true, let $v_{I_E=1}$ and $v_{I_E=0}$ represent a municipality's violence rate with a drug enforcement index of 1 and 0, respectively. *Ceteris paribus*, β_1 can be expressed as follows:

[14]There are six variables. If a municipality scores 3 in all 6 enforcement variables (i.e., it is located in the 70th percentile or above in the distributions of all the index composing variables), it will score 18=6x3.

$$\beta_1 = v_{I_E=1} - v_{I_E=0} = \beta_1(I_E = 1 - I_E = 0) \tag{4}$$

As the v's are expressed in logarithms, β_1 represents the percentage in which the violence rate changes by going from $I_E = 0$ to $I_E = 1$. As a result, if β_1 is positive, it means that drug enforcement increases in β_1% the Colombian municipalities' violence rate. If β_1 is negative, it means that drug enforcement decreases that rate in the same percentage. Fourth, I_E possesses 18 possible values, permitting to measure exhaustively the different eradication levels produced by the government across the country. If we wanted to determine the change in the violence rate's growth rate explained by moving I_E from one eradication level I_E^i to a higher one I_E^j, we would simply perform the algebraic operation $\beta_1(I_E^j - I_E^i)$.

The vice–president's office also collects information on the number of attacks perpetrated by irregular groups against official buildings, such as police stations or military bases, and official forces, such as the police or army. This variable has traditionally been used to proxy for the geographically-located military activities of irregular groups in Colombia. In fact, this is the main variable that Díaz and Sanchez (2004) use to test whether violence increases cocaine production. According to paper written by Díaz and Sanchez (2004), this variable might be endogenous to the existing proxies for violence. Apart from this endogeneity problem, I could also construct an index for this variable to obtain comparable estimates with those of the previous index. As a result, I construct the following Anti–Eradication Index:

$$I_{AE} = \begin{cases} \frac{3}{3} = 1 & \text{if} \quad irreattacks > percentile(a, 70) \\ \frac{2}{3} & \text{if} \quad percentile(a, 30) < irreattacks < percentile(a, 70) \\ \frac{1}{3} & \text{if} \quad min(a) < irreattacks < percentile(a, 30) \\ \frac{0}{3} = 0 & \text{if} \quad irreattacks = 0 \end{cases} \tag{5}$$

where a is again a non-zero vector composed of the elements of *irreattacks*, and *irreattacks* is the number of attacks perpetrated by irregular groups against the government's security forces. This index satisfies similar features to the ones mentioned for the previous index. In this case, β_2 represents the highest possible percentage change in the violence rate that is explained by the irregular groups' highest level of military expenditure against drug enforcement (I_{AE}=1). As in the previous case, if I wanted to determine the change in the violence rate' growth rate explained by moving I_{AE} from one eradication level I_{AE}^i to a higher one I_{AE}^j, I would again simply perform the algebraic operation $\beta_2(I_{AE}^j - I_{AE}^i)$.

In turn, Mejía and Restrepo (2011) use the coca cultivation figures from SIMCI[15] to proxy for the drug dealers' war. The vice–president's office also collects information on two other variables that I argue also capture that war: the number of massacres committed by irregular groups in their regions or areas of influence, and the number of incidents and accidents with mine fields. These two variables are also available from 1999 to 2010, and they are computed taking into account how closely they are related to the conflict among irregular groups in Colombia. In that sense, massacres are defined to be perpetrated by irregular groups in their conflict on their areas of influence[16], and mine fields appear to be used by irregular groups to protect their coca, marihuana and poppy fields[17].

Running these variables together also results in a multicollinearity problem as in the eradication

[15] Sistema Integrado de Monitoreo de Cultivos Ilícitos– A United States Office for Drugs and Crime in Colombia. See its web-site: UNITED NATIONS OFFICE ON DRUGS AND CRIME (2012).

[16] See Human Right Watch (2010) for a thorough analysis of the possible causes, main perpetrators, and main modus operandi in which massacres are committed in Colombia.

[17] see Human Right Watch (2007) for a thorough analysis of guerrilla use of landmines in Colombia, and its consequences on the civil population.

index case. Following the same logic laid out for that index, I construct the following Drug Dealers War Index:

$$I_{DW} = \frac{\sum_i^3 I_{DW,i}}{9} \tag{6}$$

where,

$$I_{DW,i} = \begin{cases} 3 & \text{if} \quad Var_i > percentile(a_i, 70) \\ 2 & \text{if} \quad percentile(a_i, 30) < Var_i < percentile(a_i, 70) \\ 1 & \text{if} \quad min(a_i) < Var_i < percentile(a_i, 30) \\ 0 & \text{if} \quad Var_i = 0 \end{cases} \tag{7}$$

where a_i is again a non-zero vector composed of the elements of Var_i, and Var_i is any of the 3 variables mentioned above used to compute this index. In this case, β_3 would represent the highest percentage change in the violence rate that is explained by the drug dealers' highest level of military expenditure on drug war (I_{DW}=1). As in the previous cases, if I wanted to determine the change in the violence rate's growth rate explained by moving I_{DW} from one eradication level I_{DW}^i to a higher one I_{DW}^j, I would again simply perform the algebraic operation $\beta_3(I_{DW}^j - I_{DW}^i)$.

Finally, it should be pointed out that all those variables might be correlated because they occur in municipalities where there is an insufficient central government presence, its rule of law is very scarce and there are huge economic opportunities to produce narcotics without the pressure of enforcement. I include as controls for the central government's presence the square kilometers per capita of a municipality[18] [19], the logarithm of its population, its distance[20] to Bogotá and to its capital of *departmento*. These two last variables do not vary across years, which makes them not the best control variables for a panel. Additionally, it is untrue that distance captures correctly the institutional strength of a region. Given the centralized structure of Colombian military expenditure[21], there are regions with larger economic power that attract more resources on security from the central government. Thus, I computed the following two variables:

$$dbogota_i = 1 - (\frac{1}{1 + dbogotamun_i}) * \frac{DepGDP}{BogotaGDP} \tag{8}$$

$$dcapitals_i = 1 - (\frac{1}{1 + dcapitalsmun_i}) * \frac{DepGDP}{BogotaGDP} \tag{9}$$

where $dbogotamun_i$ and $dcapitalsmun_i$ are the distances of municipality i to Bogotá and the

[18]The idea behind this instrument is that a larger area per capita indicates a smaller police presence, which reduces the efficiency of the government's enforcement activities. As a result, a larger area per capita signifies a worse institutional presence, which implies a better location for producing illegal narcotics with a smaller probability of capture.

[19]An alternative measure would be the local government's public expenditure. However, that information is not available at the municipality level, avoiding me to use it as an instrument.

[20]The distances expressed in miles or kilometers are not available for every municipality. Moreover, for some municipalities their distances changed because roads were built or improved during our period of analysis as a policy response to cocaine production. As a result, I use the coordinate system of every municipality expressed in degrees to construct a measure of distance for each of them. As such, this system does not take into account the possible natural barriers that make a municipality inaccessible. However, it still can capture the relative distance of a municipality to the main capitals, where most of the military bases are, and from which military attacks are planed and executed, which is precisely what I want to control for.

[21]See Avella (2009) for an analysis on the historical Colombian public expenditure levels and institutional organization.

capital of *departmento* in which municipality i is located, respectively. $BogotaGDP$ is the Bogotá's 2010 real GDP and $DepGDP$ is the 2010 real GDP of the *departmento* in which municipality i is located both measured by DANE[22].

The values of $dbogota_i$ and $dcapitals_i$ are between 0 and 1. The *closer* a municipality is to Bogotá and its capital city of departamento, the closer $dbogota_i$ and $dcapitals_i$ are to 0. To define *proximity*, these measures take into account the economic importance of the *departamento* in which municipality i is located relative to that of Bogotá. For instance, when I look at figures (A.1) and (A.2)[23] in the appendix, I realize that a municipality in the southern *departamento* of Amazonas is as far away from Bogotá than a municipality located in the northern *departamento* of La Guajira. However, La Guajira is economically richer than Amazonas. My measures are able to differentiate the relative importance of those two municipalities through the relative weight that La Guajira's and Amazonas' GDPs have on that of Bogotá[24].

It is clear that the distance measures computed in equations (8) and (9) are not the best proxies to capture the institutional strength of a municipality relative to Bogotá or its capital of *departmento*, which is assumed to determine its assignment of security forces to eradicate coca leaves by the Colombian central government . The reason is that accessibility might also be an important factor to determine whether a municipality is good for the production of coca leaves, and to determine whether the Colombian central government dedicates resources to eradicate coca crops in that municipality. Unfortunately, there is not a good measure of accessability for every municipality of the country, and a radial distance seems not to be a bad instrument to capture institutional presence within a *departamento* and the country. At least, that seems to be true for coca crops production in Colombia and the prosecuting activities that the government has followed to eradicate this production.

Coca production in Colombia has historically taken place in municipalities with large rural opportunities for the crop. These municipalities are usually located far away from the capital cities where the rural property size is larger and income lower relative to those of the main capital cities. The latter can be seen when we compare the average of the rural property size in figure (A.2a) and the GDP by *departamento* in figure (A.2b) with the drug dealers war index[25] in figure (A.4c) in the appendix, where we realize that coca production is mainly taking place far away from the main capital cities of the country where the average of the rural property size is larger and in *departamentos* with a smaller GDP relative to that of Bogotá's. Additionally, the *pattern* of the average of the rural property size indicates that the average of the rural property size in a municipality increases in a sort of radial way the farther the municipality is from the main capital city of the *departamento* in which the municipality is located as well as the farther it is from Bogotá. As a result, if a municipality's

[22]DANE(Departamento Administrativo Nacional de Estadísticas) is the official center that collects colombian socioeconomic information.

[23]The maps presented in figure (A.2) were taking from SIGOT (Sistema de Información Geográfica para la Planeación y el Ordenamiento Territorial) website, which is the official site where the Colombian central government publishes the country's spatial and geographical information. The GDP information at the municipality level is not available for all the municipalities of the country for the period of analysis, and the average of the rural property size per municipality is only available for 1101 municipalities (out of 1122) for 2007 and 2009. Due to this lack of information, I was not able to include these two variables as instruments to control for the potential of a municipality to produce coca crops.

[24]In the regression results presented below, the distance variables were used as indicated in this section. However, several alternatives were pursued. One alternative is to compute them only using the GDP ratios. As there is only GDP information by *departamento*, one solution is to assume that all the municipalities of a single *departamento* had the same GDP. This alternative provided statistically insignificant estimates for the unique distance variable computed because all the variability gained using the distance variables proposed in the text is lost within a single *departamento*. As a result, it losses explanatory power because it is useless to explain the huge differences that exist within a single departamento in terms of cocaine production and violence.

[25]This index is mainly determined by the production of coca leaves and the number of accidents and incidents with mine fields.

rural property size average and income are good predictors for its potential to have coca production, the distance variables computed in equations (8) and (9) also seem a good alternative to capture that potential because they capture the radial development that take place in most of the *departamentos* of the country, which also increase the potential for the production of coca crops. In fact, when I run a simple OLS regression of the logarithm of coca crops size against the distance variables computed in equations (8) and (9), the following results are obtained[26]:

$$log(crops) = -5.15^{***} + 2.49^{**}dbogota + 5.64^{***}dcapitals \qquad (10)$$

If equation (10) adequately captures the relationship between the logarithm of coca crops and the distance variables[27], it indicates the percentage in which the coca crops production increases in municipalities that are far way from Bogotá and their capital of *departamento*. Thus, the most distant municipalities from Bogotá have a 2.49% more coca crops production and the most distant municipalities from their capital of *departamento* have a 5.64% more coca crops production. In this sense, coca production seems to be taken place in distant municipalities from the main capital cities. Consequently, if the government also follows a similar logic with respect to the eradication of narcotics as the one followed by coca producers, I argue that the distance variables might also help determine the assignment of security forces by the Colombian central government to eradicate and control the production of narcotics on a municipality because the military machinery and tactics used by the government can be applied to most of the country, without having accessability a determining influence on the decision whether to eradicate or not on a municipality difficult to access.

Table (A.1) in the appendix presents a summary table for the variables used in this study. Two points are worth noting about table (A.1). On the one hand, the values presented on the table are averages of the variables for the period $1999-2010$. When I observe the 5 *summary numbers* for the three indices, which summarizes their distributions, two characteristics are observed: first, the distributions of the eradication (I_E) and drug-dealers-war (I_{DW}) indices are both positively skewed. This implies that most of the Colombian municipalities are categorized as being of low-enforcement and low-drug-dealers-war levels. I also can observe that the maximum values in the average distributions of I_E and I_{DW} are 0.81 and 0.71, which implies that there was *not* a single municipality that received central government's drug–enforcement and drug-dealers-war activities in every year of the data set. Consequently, there were municipalities in which those drug outcomes were more common, while for most of the municipalities, those drug activities took place rather intermittently during the period of my data set. Second, the distribution of I_{AE} is, in contrast, negatively skewed, with a median value of zero. Besides, the maximum value in the I_{AE} average distribution is 1. Consequently, anti-eradication activities were concentrated in a reduced amount of municipalities, while for most of the municipalities, those drug activities never took place.

On the other hand, I do not include variables that control for income or labor market variables because the information on these variables is deficient or nonexistent. Sometimes, the proxies used in some studies are endogenous to the homicide rate or of poorer quality than normal. To overcome such a deficiency in information, I will run a panel data Spatial Durbin Model (SDM) with fixed and temporal effects. This model helps control for omitted variables not included in the regressions, which can be useful to explain the violence in Colombian municipalities. In the next subsection, I argue that

[26](***) indicates that the estimated parameter is statistically significant at 1% and (**) indicates that the estimated parameter is statistically significant at 5%.

[27]It is obvious that the estimated parameters of equation (10) are not perfectly estimated because there is an omitted variable bias in their estimation. A similar regression analysis is performed in table (A.5) controlling for this omitted variable bias. The result obtained in that table (not shown in the table) is similar to the one obtained in equation (10). Thus, the results of equation (10) are indicative of the positive correlation between coca production and distance from capital cities in Colombia.

spatial methods are necessary to run these regressions and in section (4), I present my identification strategy to test my hypotheses.

3.2 A spatial correlation

An extensive literature documents the spatial correlation of the homicide rate and the existence of drugs in Colombia (Mejía and Rico (2010); Díaz and Sanchez (2004); Holmes et al. (2006); & Gootenberg (2008)). Figures (A.3) and (A.4) in the appendix show averages for the main variables used in this paper. On the top of each graph, I present the average of the logarithm of the homicide and displacement rates per municipality for the period $1999 - 2010$. A first characteristic I can observe on these maps is that not all municipalities present homicides or forcefully displaced people during this period. On all maps, the blue color represents a value of zero for the variable under examination. The small cluster of southern municipalities close to the Amazon region[28] and another on the west coast are the only ones with zero homicides during the period. The same happens with the rate of displaced people, which exhibits a smaller cluster of southern municipalities with zero values. These regularities might occur because those municipalities are mostly uninhabited. Most of the terrain of those municipalities comprises natural reserves and, in some cases, is difficult to access.

Second, in general I observe that the country presents both high homicide and displaced people rates in almost its entire territory. However, there are municipalities in which the situation is worse. In figures (A.3a) and (A.3b), the red color indicates a spatial concentration of the violence variables in specific regions of the country. The most problematic ones are close to Venezuela, Panamá, and Buenaventura Port, located on the Pacific coast, which are all exit points used by irregular groups to smuggle cocaine overseas[29].

Third, figures (A.3c), (A.3d), (A.4c), and (A.4d) present the drug war indices as defined in the previous sub-section. On the maps, I observe that the indices are also spatially concentrated with a larger proportion of Colombian municipalities exhibiting a value of zero in all three indices. In this case, a key point can be noted: both the Eradication Index (figure (A.3c)) and the Drug Dealers War Index (figure (A.4c)) are more spatially concentrated around the areas in which most of the homicides and displacements take place; whereas the Anti-Eradication Index is less scarcely concentrated around the same areas. However, all three indices are spatially correlated with both endogenous variables to a certain degree[30]. This fact is confirmed when I analyze table (A.2) in the appendix, where I rank the main variables of this study by *departamento*. In this table, I observe that there are *departamentos* with high values in both endogenous variables and all three indices; for example, Guaviare, Caqueta, Arauca and Putumayo, among others.

It is worth noticing that the indices' maps confirm the intuition about the indices average distributions laid out in section (3.1). On the one hand, it is clear on the maps that anti-eradication activities are taking place on clusters of municipalities. Those clusters are located in the South –Meta, Guaviare, Caquetá and Putumayo *departmentos*–, Northeast –Arauca, Norte de Santander and Cesar *departmentos*–, Northwest –Bolivar, Sucre, Córdoba and Antioquia *departmentos*–, and Southwest –South of Choco, Valle del Cauca, Cauca and Nariño *departmentos*. Additionally, when I compare

[28]See figure (A.1) for a detailed map of Colombia and its main international frontiers.

[29]See the Moran I's tests below.

[30] If we compute Moran I's tests to tests whether these variables are spatially correlated, the following results are obtained: 0.14, 0.12 and 0.13 for the correlation between the logarithm of homicide rate and the eradication, anti-eradication and drug dealers war indices respectively, and 0.26, 0.17 and 0.28 for the correlation between the logarithm of the displacement rate and the eradication, anti-eradication and drug dealers war indices, respectively, being all these tests statistically significant at 1%. In order to compute these indices, I use the 5-nearest neighbors contingent matrix. The numbers obtained for the Moran I's tests indicate that there is a spatial correlation between the dependent variables and the drug war indices.

those clusters with the altitude per municipality shown in figure (A.4d), it seems as if Colombian anti-eradication activities were geographically located at the bottom of the main mountain chains that crosses Colombia[31]. On the other hand, Eradication and Drug Dealers War Indices are scattered around over almost the entire country, both exhibiting many small municipalities on the top of the mountain chains with zero values. It is also clear on the maps that these last two indices are also geographically distributed relative to the Colombian mountain chains. It seems that the altitude and distance to Bogotá are good exogenous sources of variation to explain all three indices' variability. In the next section, I explain how to exploit them to obtain exogenous proxies for the drug war indices.

Finally, I observe that all those variables exhibit a high spatial autocorrelation. In table (A.1) in the appendix, I compute Moran I's test[32] for each of the variables used in this study. This test indicates that when determining the causal correlation among those variables, I must also include controls for the spatial autocorrelation that they exhibit. In the following section, I also explain how I perform that task.

4 The Empirical Strategy

My main interest is to test whether drug enforcement has an effect on violence in Colombia. To attain that, my empirical strategy consists of three stages: first, I run the following model under the same idea proposed in equation (A.12):

$$v = \beta_0 + \rho W v + X\beta + WX\theta + \epsilon \tag{11}$$

where v represents a (N*T)x1 vector containing any of the two endogenous variables used in this study: the logarithm of the homicide or the (forcefully) displaced people rates, both per $100,000$ inhabitants. $N = 1122$ is the number of Colombian municipalities and $T = 12$ is the number of years used for estimation. X is a (N*T)x7 matrix containing the following variables: I_E, the Eradication Index proposed in equation (2); I_{AE}, the Anti-Eradication Index proposed in equation (5); and I_{DW}, the Drug Dealers War Index proposed in equation (6). X also contains some institutional controls such as the logarithm of the population, municipality area per capita, and the *"distance"* of each municipality to Bogotá and its capital of *departamento* as defined by equations (8) and (9) respectively. Following Anselin (1988) and LeSage and Pace (2009), I include in the estimations Wy and WX to proxy for omitted variables that might help explain the variability of the endogenous variables but for which there is not information available. W is a spatial weight matrix constructed using the 5 nearest neighbors of each municipality[33].

As all the variables in X vary across time, equation (11) can be estimated including fixed or time effects, where the parameters associated to the indices [34] are the main parameters of interest. However,

[31] One chain goes from Nariño (South) to Santander and Norte de Santander (Northeast), and the other from Nariño to Antioquia (Northwest).

[32] I also use the 5-nearest neighbor contingent matrix to compute these tests.

[33] A common problem in spatial econometrics is the choice of the aggregation level used to construct the weight matrices. I tried three different combinations of weight matrices: 5, 10, and 15 nearest neighbors. My results show that when I increase the number of neighbors considered, the estimated first- and second-order effects of section 2.2 above become slightly stronger for all three indices. These results might be explained by the fact that the municipalities with the worse drug war and violence outcomes tend to be in *departamentos* with large extensions of territory and few municipalities, such as Guaviare (4), Putumayo (13), Vichada (4), Arauca (7), and Guainía (9). All these municipalities are more likely to be close neighbors in econometric terms, when the number of neighbors considered to construct the weight matrix increases. Consequently, throughout the presentation of the econometric model and the results, I always refer to or use the 5-neighbor contingent matrix. This matrix allows me to capture the neighbors' influence on a municipality, without taking into account neighbors from distant *departamentos* for those special cases.

[34] The parameters β_1, β_2 and β_3 of 1.

in this specification some of the variables used to compute all three indices are endogenous. Specifically, the number of military attacks initiated by the central government against irregular groups, which is one of the main variables used to compute I_E, is endogenous to the violence rates. These attacks are performed by the army and police, who consider the level of violence as well as the required level of coca eradication in each municipality, to perform their enforcement activities in a municipality. This is in contrast to the other 5 variables used to compute I_E, which are performed by Policía Antinarcóticos[35]. Mejía and Restrepo (2011) argue that coca crops, which is one of the variables used to compute I_{DW}, are also endogenous to the level of violence. I argue that massacres and incidents and accidents with mine fields, the other two variables used to compute I_{DW}, are also endogenous to the levels of violence in Colombia. Following Mejía and Restrepo (2011), I must find an exogenous source of variation that helps explain those variables but at the same time is uncorrelated with either the homicide or displacement rates.

These authors use the altitude per municipality to proxy for the existence of illegal markets for cocaine in Colombia. They point out that, for technological reasons related to soil and climate conditions, coca plants provide larger concentrations of cocaine at lower altitudes. As a result, municipalities located at lower altitudes have more coca crops and more violence associated to the illegal markets for cocaine that results from these crops. Mejía and Restrepo (2011) argue that there is no reason why the altitude might be correlated with violence other than through its effect on cocaine production. According to the model laid out in section (A.0.1), this conclusion is imprecise because cocaine production is also endogenous to the eradication and anti-eradication military expenditures performed by the central government and drug dealers in each municipality.

I argue that a municipality's distance to its capital of *departamento* and Bogotá, the measures computed in equations (8) and (9), also help explain the productivity of coca production in Colombia for two reasons. First, it is more difficult and expensive to produce coca crops in capital cities or near them due to a stronger police presence. In these municipalities, the most important economic and public administrative activities of each *departamento* take place. This leads the central government to allocate relatively more resources on police to these capital cities. Second, the Colombian central government organizes and executes its military operations using strategically–positioned military bases. These military bases are located near or within the capital cities of the most important *departamentos*[36]. These two features suggest that the distance of a municipality to its capital of *departamento* is a good source of exogenous variation to capture the opportunity costs of cocaine production in Colombia. The spatial analysis laid out in section (3.2) indicates that the distance to Bogotá is also a good source of variation.

Those exogenous sources of variation are used to determine the *potential* intensity of attacks targeted to a municipality by drug dealers and the government to perform anti-eradication and eradication activities as follows:

$$y = \beta_0 + \rho W y + X\beta + W X\theta + \epsilon \tag{12}$$

where y is a (N*T)x1 vector that contains either of the following two endogenous variables: the number of attacks initiated by the government against irregular groups or the number of attacks

[35] Antinarcotics police. This is a police unit that follows a source of information different to the amount of homicides or displaced people to plan and perform their tasks. They use the number of crops captured by SIMCI, which are values that are available when coca crops are almost ready for harvesting, which occurs at least six months after the coca trees are planted (See SIMCI web-site for technical issues regarding possible delays in coca crops satellite data collection). In that sense, Antinarcotics police plan their enforcement activities based on a database that might be *lagged at least six months*.

[36] See Dube and Naidu (2012) for an analysis of the Colombian military operations, the location of its military bases, and the possible consequences of these military operations on violence.

initiated by irregular groups against the central government's security forces. X is a (N*T)x3 matrix containing my exogenous sources of variation. As the altitude per municipality does not vary over time, I cannot include fixed or time effects to estimate equation (12), because they are perfectly correlated with my instrument. To control for omitted variables that might help explain any of these two variables, I also include Wy and WX.

I use $\hat{y} = \hat{\beta}_0 + X\hat{\beta}$ as a proxy for drug enforcement and anti-enforcement activities of the government and irregular groups. These variables measure the *potential* intensity of attacks a municipality might have due to its *potential* for coca production, given by its own geographical and spatial position. Notice that I do not include any of the spatial effects to compute the proxies. Thus, every $\hat{y}_i$ is computed only using the information contained in X for municipality i and the β's are computed net of possible omitted variables that also help explain why a municipality receive military attacks by any of the groups considered.

In turn, I use the proxies obtained in the previous step to estimate the following model:

$$y = \beta_0 + \rho W y + X\beta + W X\theta + \epsilon \tag{13}$$

where in this case y is a (N*T)x1 vector containing either the logarithm of hectares of coca crops captured by SIMCI, the number of massacres committed by irregular groups in their areas of influence or the number of incidents and accidents with mine fields, which are known to be used to protect the coca crops from being eradicated. X in this case contains the exogenous sources of variation used in equation (12), along with the proxies for drug enforcement and anti-enforcement activities computed from the same equation. Again, I include Wy and WX to proxy for omitted variables that might help explain any of the last three variables used to compute I_{DW}.

Using equation (13), I use $\hat{y} = \hat{\beta}_0 + \hat{X}\hat{\beta}$ as instruments to proxy for the variables used to compute I_{DW}. $\hat{X}$ does not contain any of the proxies for drug enforcement and anti-enforcement activities computed from equation (12). As a result, the computation of I_{DW} is net of those enforcement activities. Also, $\hat{X}\hat{\beta}$ is a measure that resembles the drug dealers war' instrumentalized proxy computed by Mejía and Restrepo (2011). Thus, my results are directly comparable with those found by them.

Then, the final stage involves recomputing all indices as explained in equations (2), (5), and (6), using the proxies found in equations (12) and (13), with a slight difference that the vector a in those equations is now composed of the entire array of values of the computed proxies without a priori division of every array between zero and positive values. With these recomputed indices, I run again the model laid out in equation (11), concluding my empirical strategy. Before analyzing the results, two points are worth noting: first, the measurement units of the recomputed indices are entirely comparable with those of the original indices; as a result, the interpretation of the estimated coefficients associated to these new indices is the same. Second, my methodology to recompute the indices do not bias the estimated results in any systematic way. The recomputed indices reorganize municipalities according to their estimated potential to have drug war military expenditures, resulting from their geographical and spatial location, which is a priori unrelated to violence. As a consequence, any correlation between these indices and the proxies for violence can be understood as a causal correlation.

5 Results

5.1 Initial Results

The lack of information associated to income or labor market variables for the Colombian municipalities forces me to rely on indirect methods to control for a potential omitted-variable bias in our estimations. This section is based on Elhorst (2003) and Elhorst (2012), who formally present the rationale behind running a Panel Data Spatial Durbin Model to control for this econometric problem. They also present the empirical application where they indicate the different existing alternatives to test whether the spatial and panel data effects controlled for with this model are really of statistical significance.

A good feature of spatial econometrics methods is that they also allow to use a municipality's neighbors information to estimate the effects of the municipality's drug war indices on its *own* violence outcomes. This interrelation also allows to determine the effect of a municipality's drug war indices on its *neighbors*' violence outcomes. These effects are called the direct and indirect effects of the drug war indices on violence, respectively. It is worth noticing that these two effects are conceptually and quantitatively different from the drug enforcement's first– and second-order effects defined in the introduction. The first–order effect of drug enforcement includes the direct and indirect effects of I_E and I_{AE} on violence. The second–order effect includes the direct and indirect effects of I_{DW}.

The estimation results of equation (11) are presented in tables (A.3) and (A.4) in the appendix. Table (A.3) presents the estimation results for the logarithm of the homicide rate; table (A.4) does it for the logarithm of the displacement rate. In the first column of each table, I present the estimated coefficients provided by MATLAB without including fixed or time effects. LeSage and Pace (2009) argue that these estimated coefficients are not the main interest of the spatial econometric analysis, but the direct, indirect and total effects computed from them. Even though I analyze the estimated spatial effects, which were computed as explained by Elhorst (2003), I follow Elhorst (2012) in presenting these estimated regression coefficients for the sake of results completeness.

On columns 2 to 4 of each table, I present the estimated direct, indirect, and total effects of equation (11). In turn, from column 5 to 12 of each table, I present the same types of results as in the first four columns including fixed, time, and fixed and time effects, respectively. I also present in each table the tests to ascertain whether a Panel Data Spatial Durbin Model is the correct specification to estimate equation (11), as explained by Elhorst (2012). According to Elhorst (2012), there are two alternatives to test whether the correct model to run is a panel data Spatial Durbin Model(SDM), Spatial Autoregressive Model (SAR) or a Spatial Error Model (SEM). There is a common argument underlying both alternatives: the SDM model can be reduced to either the SAR model or the SEM model. The main difference between the two alternatives is that one compares the performance of the particular model (SAR or SEM) with the general model (SDM), and the other compares the performance of the general model (SDM) with the particular model (SAR or SEM).

The alternative that goes from the particular model to the general model uses simple LM tests to determine which model better explains the variability of the data. There are two types of tests to use with this alternative: One type compares the SAR (or SEM) model with the SDM model without controlling for the possibility that the data also follows a SEM (or SAR) model jointly with the SAR (or SEM) model. These tests are labeled *LM_spatial_lag* in tables (A.3) and (A.4) in the appendix for the comparison between the SAR model with the SDM model and *LM_spatial_error* for the comparison between the SEM model and the SDM model. The other type of tests to use with this alternative compares the SAR (or SEM) model with the SDM model controlling for the possibility that the data also follows a SEM (or SAR) model jointly with the SAR (or SEM) model. These tests are labeled *Rob._LM_spatial_lag* in tables (A.3) and (A.4) in the appendix for the comparison between the SAR model with the SDM model and *Rob._LM_spatial_error* for the comparison between the SEM model and the SDM model.

In turn, the alternative that goes the general model to the particular model uses either Wald or LR tests to determine which model better explains the variability of the data. In this case, these tests are labeled *Wald_spatial_lag* or *LR_spatial_lag* in tables (A.3) and (A.4) in the appendix for the comparison between the SDM model with the SAR model and *Wald_spatial_error* or *LR_spatial_error* for the comparison between the SDM model with the SEM model. In both testing alternatives, the null hypothesis is that the data does not follow the SDM model (either the SAR or SEM models) against the alternative hypothesis that it does follow the SDM model. As a result, a large value in any of the latter tests indicate that the SDM model better explains the variability of the data.

Several results can be derived from table (A.3). First, following Elhorst (2012), all tests indicate that the best specification to run equation (11) is a Panel Data Spatial Durbin Model. In other words, there are omitted variables that help explain violence in Colombia, which are properly captured by Wy and WX in equation (11). All the estimated values of ρ in table (A.3) indicate that there is a positive correlation between municipality i's homicide rate and the homicide rate of municipality i's surrounding municipalities. As a result, there are geographical factors not controlled for with the fixed or time effects that also help explain the homicide rate in Colombia in the period $1999-2010$. Second, regardless of whether I include fixed, time, or both effects together, there is a positive correlation between the Eradication Index (I_E) and both the logarithm of the homicide and displaced people rates in Colombia. The estimated impact of the Colombian government's military eradication activities is very stable across specifications. In section (3.1), the interpretation of the estimated results associated to these indices is explained. There, it is said that β_1 [37] represents the percentage change of the violence rate resulting from drug enforcement. As I consider spatial effects, β_1 is estimated by the total spatial effects, composed of the sum of the direct and indirect effects of I_E on v.

Second, tables (A.3) and (A.4) indicate that the government's drug enforcement activities generated a total increase in the homicide rate between 1.14% and 2.47% and a total increase in the displacement rate between 1.02% and 2.84%. According to these results, the total effects appear to be mainly driven by the direct effects of enforcement. In other words, it appears that coca eradication activities generate violence in the municipalities in which they are performed. However, I cannot give these results a causal interpretation because I_E is endogenous to both the levels of violence and the production of narcotics.

Third, the attacks of irregular groups against the government's security forces do generate homicides and displaced people in Colombia. According to table (A.3), the estimated impact of the irregular groups' activities on violence is also very stable across specifications. These activities generate an estimated total increase in the homicide rate between 0.53% and 1.33% and an estimated total increase in the displaced people rate between 0.76% and 1.84%. According to these results, when irregular groups attack a municipality, their actions also affect contiguous municipalities. These attacks are most likely targeted to gain control of the territory. However, I_{AE} is endogenous to several factors apart from the simple production of cocaine. As a result, I cannot yet ascertain if these attacks only respond to the interests that irregular groups have on the territory for cocaine production or other factors, such as the availability of petroleum or gold.

Finally, the drug war among dealers, captured by I_{DW}, is also positively correlated with the violence in Colombia, as Mejía and Restrepo (2011) argue. According to my preliminary results, the drug dealers' war generates a total increase in the homicide rate between 0.61% and 2.77% and a total increase in the displaced people rate between 2.69% and 7.53%. It is interesting to note that the indirect effects of the drug dealers' war is not as stable for the homicide rate than as for the displacement rate. My preliminary results indicate that the drug dealers' war affect more heavily the homicide rate of the municipality where it takes place than the homicide rate of its surrounding municipalities. In contrast, the drug dealers' war not only affects directly the displacement rate of the municipality in which it takes place, but also the displacement rate of those municipalities around it. Consequently, according to my preliminary results, people seem to abandon their homes when drug dealers attack each other in their municipalities of residence, or when they do it in the surrounding municipalities. However, I cannot give these results a causal interpretation because I_{DW} is endogenous to the levels of violence, the production of narcotics and the government's eradication activities.

To provide a causal interpretation, I perform a 2SLS analysis that is presented in the next section.

[37] The parameter associated to the drug enforcement military expenditures of equation (1).

Before entering in that discussion, an important point is noted here: *if* I_E, I_{AE} and I_{DW} really capture the Colombian drug war military expenditures of all participants in the drug war during the period $1999 - 2010$, there were substantial first– and second–order effects of enforcement in Colombia. The estimated first–order effect of enforcement derived from tables (A.3) and (A.4) is between 2.27% and 3.00% for the homicide rate and between 2.12% and 3.83% for the displaced people rate. The estimated second-order effect of enforcement is between 0.61% and 2.77% for the homicide rate and between 2.69% and 7.53% for the displacement rate.

5.2 2SLS Results

The results of the first stage of the IV estimations are presented in table (A.5) in the appendix, which is divided in two parts. The upper part of table (A.5) presents the estimation results for the number of attacks initiated by the government against irregular groups and the number of attacks initiated by irregular groups against the government's security forces. Thus, it presents the results of equation (12) in section (3.1). In turn, the lower part of table (A.5) presents the estimation results for the logarithm of coca crops, the number of accidents and incidents with mine fields, and the number of massacres perpetrated by irregular groups in their areas of influence. These are the results of equation (13) in section (3.1).

The first column of each set of regression results in table (A.5) presents the estimated coefficients provided by MATLAB. The other 3 columns present the direct, indirect, and total effects, which were also computed as explained by Elhorst (2003) and Elhorst (2012). I also present the tests to determine whether a Panel Data Spatial Durbin Model is the correct specification to estimate equations (12) and (13), as explained by Elhorst (2012). The estimation results in table (A.5) do not control for any of the panel data fixed or time effects. The latter is due to two reasons: first, fixed effects are perfectly correlated with the altitude per municipality, one of the instruments in those estimations. Second, time effects resulted statistically insignificant.

From table (A.5), several insightful results can be obtained. A first general result is that a Spatial Durbin Model is the correct specification to estimate equations (12) and (13). The latter can be concluded from the tests indicating that these estimations cannot be reduced to either a panel data SAR or SEM models. This result might indicate that the government attacks irregular groups not only because they are producing narcotics, but also because of their criminal activities, such as robberies, kidnappings, and the like. The same can be said from irregular groups' attacks. These groups have an interest in the territory that goes beyond the sole production of narcotics.

Additionally, the number of attacks perpetrated by both groups is explained by the altitude in the expected sign. If the altitude really captures the coca crops productivity, the number of attacks of both groups is explained to some extent by the *potential* that municipalities have for cocaine production. In regards to these attacks, I obtain two interesting results: on the one hand, the direct and indirect spatial effects of the distance variables are statistically insignificant, but the total effects are weakly significant for the number of attacks initiated by the government against irregular groups. It seems that distances to capital cities and Bogotá do not entirely capture the government's military attacks against irregular groups. However, the distance of municipalities to capital cities has some influence on that decision: the *farther* municipalities were to Bogotá and the *closer* they were to capital cities, the more the government attacked irregular groups in these municipalities.

On the other hand, the distance variables are statistically significant for the irregular groups' number of attacks; however, the results are mixed. The total effects of the distance variables indicate that the number of attacks of irregular groups increased when the municipalities were *farther* from Bogotá and *closer* to their capital cities of *departamento*. These latter results are explained by the estimated direct and indirect effects of the distance variables. The direct effects indicate that the number of attacks of irregular groups increased when the municipalities were both *closer* to Bogotá and their capital of *departamento*. The indirect effects indicate that the municipalities' neighbors were less likely to be attacked when the municipalities were *closer* to Bogotá and their capital cities of *departamento*. This result might indicate that municipalities that were jointly close to capital cities and Bogotá had fewer attacks by these groups. This latter result is confirmed by the spatial analysis laid out in section (3.2), where we observe that the number of irregular groups' attacks have a concentration at the bottom of the mountain chains that crosses Colombia from South to Northwest and Northeast. However, in those municipalities that are really far away from the mountain chains or at the top of them, near to Bogotá, the attacks were zero during the entire period under examination. That is illustrated, for example, in the South of Colombia, in spite of being a region entirely dedicated to the production of coca crops, as indicated in figure (A.3c).

Based on the empirical strategy explained in section (4) for equation (12), I use $\hat{y} = \hat{\beta}_0 + \hat{X}\hat{\beta}$ to obtain exogenous proxies for the government and irregular groups' drug war military expenditures on the Colombian municipalities. As explained in section (4), I use the latter $\hat{y}$'s in the estimations of equation (13) to obtain net exogenous measures of the Colombian drug dealers' war. The regressions of equation (13) are presented in the lower part of table (A.5), where *govconthat* and *irreconthat* represent the proxies for the government and irregular groups' drug war military expenditures obtained from equation (12).

In regards to the results for the variables used to compute I_{DW}, the total effects of the altitude indicate that it negatively affects all three variables. That concurs with the results obtained by Mejía and Restrepo (2011), who also found out that cocaine production is negatively related to the altitude per municipality in Colombia. This result also confirms my intuition that the number of incidents and accidents with mine fields and massacres are also associated with the altitude in the expected sign. If the altitude really captures a municipality's cocaine productivity potential, my results indicate that mine fields and massacres also seem to respond to the drug dealers' war that Mejía and Restrepo (2011) attempt to control for only using coca crops as a proxy.

The results also confirm my intuition that the military actions of the government to eradicate narcotics, captured by *govconthat*'s total effects, have also an effect on the three variables. Additionally, they show that these actions *reduced* the number of hectares of coca produced, *reduced* the number of mine fields used by irregular groups, and *increased* the number of massacres in the country. All the latter results can be interpreted as follows: first, coca crops showed a downward tendency during the period of analysis[38]. This was clearly the response of the tougher drug enforcement policy initiated with "Plan Colombia".

Second, *govconthat*'s total effects on the number of incidents and accidents with mine fields are mostly influenced by *govconthat*'s indirect effects. The *govconthat*'s direct effect indicates that the government's direct actions to eradicate coca crops in the affected municipalities *increased* the incentives of irregular groups to use mine fields to protect the coca cultivated areas from eradication. The *govconthat*'s indirect effect indicates that once an area was totally controlled by the government, this territorial control reduced the total amount of mine field cases. Finally, *govconthat*'s total effects on massacres are weakly statistically significant. This result is mainly influenced by the *govconthat*'s direct effects. Thus, it seems that coca eradication military attacks also increased the incentives for irregular groups to commit massacres on the municipalities where eradication took place.

When I analyze the total effects of the anti-eradication activities, the results are less clear-cut to understand. First, *irreconthat*'s total effects indicate that the irregular groups' anti-eradication activities *reduced* the coca crops in Colombia. That result is influenced by *irreconthat*'s indirect

[38]For a thorough analysis of coca crops in South America, see the United Nations Office for Drugs and Crime (UNODC) website on crops monitoring in the world: UNITED NATIONS OFFICE ON DRUGS AND CRIME (2013).

effects, which implies that when a municipality was more attacked, their neighbors produced fewer coca crops. This might indicate that irregular groups made more attacks in those municipalities near to coca production centers subjected to eradication. As *irreconthat*'s direct effects are statistically insignificant for coca production and coca production was reduced in the whole period, it seems that the overall effect was that the irregular groups' attacks did not attain what they intended to.

Second, *irreconthat*'s total, direct, and indirect effects on the number incidents and accidents with mine fields are all either statistically insignificant or weakly significant. This result might indicate that anti-eradication military actions and mine fields are *substitute inputs* to protect the coca fields. Finally, *irreconthat*'s total effects on massacres are statistically significant. This result is mainly influenced by *irreconthat*'s indirect effects and can be interpreted as that of coca crops. It seems that irregular groups' anti-eradication attacks increased the number of massacres in the municipalities where they attacked, which were in territories where they were losing influence.

In general, it appears that my empirical strategy gives sound proxies to be used in the second stage of the IV strategy. I compute these proxies using $\hat{y} = \hat{\beta}_0 + \hat{X}\hat{\beta}$ and the estimated coefficients from table (A.5). Table (A.1) in the appendix shows summary statistics for the re–computed indices and figure (A.5) presents their maps. A quick comment is in order: it seems that the procedure to recompute the indices do not bias in any systematic way their values. However, these new indices have a slightly different distribution, being I_E's distribution the most similar to the original one. Even though, it does not appear that the new indices are re-computed in a way that favors my hypothesis.

The second IV stage is presented in tables (A.6) and (A.7) in the appendix, which replicates equation (11) and tables (A.3) and (A.4) using the new indices obtained from equations (12) and (13) to proxy for the drug war military expenditures. From tables (A.6) and (A.7), several results are also obtained. First, the tests to ascertain the type of model to run again indicates that a Spatial Durbin Model is the best specification for our data. There are omitted factors that help explain the violence in Colombia different from the drug war variables, which are properly captured by Wv and WX terms in equation (11).

Second, my results seem to indicate that the government's drug enforcement activities *do generate* violence in Colombia. Based on $\hat{I_E}$'s total effects on the logarithm of the homicide and displacement rates, the estimated impact of these actions is positive. According to tables (A.6) and (A.7), the government's eradication activities *increased* the homicide rate between 0.75% and 1.84% and the displacement rate between 0.99% and 5.82%. All these estimates are statistically significant at common significant levels.

Third, $\hat{I_{AE}}$'s estimated total effects indicate that anti-eradication activities by irregular groups *increased* violence in Colombia. However, these estimated effects are not stable across specifications, especially for the homicide rate. My results indicate that the sign and statistical significance of the effect of the irregular groups' anti-eradication activities varies when I include fixed effects in the estimations. It seems that the activities that these groups perform on the territory they are fighting for influence the way in which their actions affect the homicide rate. Fixed effects might be capturing structural homicides that occur in the territory. There must be structural homicides that are controlled and determined by these groups. My results indicate that when these structural homicides are not controlled for, the irregular groups' attacks have a statistically insignificant positive direct effect on the municipalities in which they attack and a statistically significant negative indirect effect on the surrounding municipalities where they attack. This result can be interpreted as implying that once these groups have gained a sufficient important territorial control over a set of contingent municipalities, their military actions against the government to control the territory with the intention to produce cocaine reduce the homicide rate of the entire area, except where they are attacking. In contrast, when I control for these structural homicides, their actions to control the territory only affect positively the homicide rate on the territories where they attack. The latter is not true for the displacement rate where the effect of the irregular groups' anti-eradication activities is always positive across specifications.

Finally, $\hat{I_{DW}}$'s total effects indicate that the drug dealers' war have mixed effects on violence in Colombia, especially for the displacement rate. According to my results, this war generated a change in the homicide rate between 2.29% and 4.37%. $\hat{I_{DW}}$'s direct and indirect effects are also rather stable across specifications. They indicate that the drug dealers' war increased the homicide rate in the municipalities where this war took place and the surrounding municipalities as well. The latter is not true for the displacement rate. In this case, the inclusion of fixed effects also affects the sign and statistical significance of the drug dealers' war effects on violence. It seems that there are structural phenomena that are intertwined with the drug dealers' war in the Colombian municipalities which obscure the pure effect of the drug dealers' war actual influence on the displacement rate. Once these structural variables are controlled for with the fixed effects, the total, direct and indirect effects of the drug dealers' war on the displacement rate become statistically insignificant and with a contrary sign to one expected.

In all the results presented in tables (A.6) and (A.7), the inclusion of fixed effects affected the value of the estimated results. If I assume that the models containing these effects provide us with the most accurate estimations, as the F tests at the bottom of tables (A.6) and (A.7) indicate, our results show that drug enforcement has had important effects on violence in Colombia. Tables (A.6) and (A.7) indicate that the government's eradication military expenditure generated an increase of 1.84% in the homicide rate and 0.99% in the displacement rate. The drug dealers' war generated an increase of 4.00% in the homicide rate and 0.16% in the displacement rate. And, the irregular groups' anti-eradication activities generated an increase of 0.14% in the homicide rate and an increase of 0.25% in the displacement rate. My results indicate that there were substantial first– and second–order effects of enforcement in Colombia. The first–order effect is 0.98% for the homicide rate and 1.24% for the displacement rate. The second–order effect is 4.00% for the homicide rate and 0.16% for the displacement rate.

6 Conclusion

In this paper, I argue that drug enforcement in a source country does generate violence, where the latter is measured as rate of homicides or displacement per $100,000$ inhabitants. I use data on drugs from Colombia during the period 1999–2010 to test this hypothesis. I find that drug enforcement has two effects: first– and second–order effects. The first-order effect refers to the direct violence generated by the drug war between the government and drug dealers. When the government spends on military activities to control the production of narcotics, there are eventually victims that results from that expenditure. Drug enforcement might also have an impact on the feeling of security of the inhabitants of the areas where the drug war take place, forcing them to move to safer regions where they are not affected by these activities.

However, this is not the only effect of enforcement. As narcotics are supplied by decentralized markets, drug dealers have the monetary and the military power to fight back against the government's drug enforcement activities and against other drug gangs, with which a pacific resolution of conflicts seems to be simply impossible. Our results also indicate that Colombian violence derives from factors other than the country's drug war. Colombian drug dealers also generate violence not associated to cocaine production. This happens when drug dealers gain sufficient military power to control a territory, which generates spillover effects over other activities on which violence is also used. This is true, for instance, when irregular groups use the profits of narcotics to fight territorial control in regions with other natural resources such as gold or petroleum. This also occurs when these groups use their military power to position themselves as the ultimate regulators of their regions of influence.

A meaningful conclusion reached in this paper is that in Colombia the use of mine fields is explained by the production of cocaine and the drug enforcement activities of the central government. As a result, one of the worst consequences of the Colombian conflict is actually incentivized by the Colombian drug war. Another conclusion is that Colombian data show that there existed first– and second–order effects of drug enforcement in the period $1999-2010$: my results indicate that the first–order effect is 0.98% for the homicide rate and 1.24% for the displacement rate in the period 1999-2010 and the second–order effect is 4.00% for the homicide rate and 0.16% for the displacement rate.

As a final conclusion, I cannot claim that the military tactics are the best methods to completely control the existence of drugs in Colombia. Despite the strength gained by the Colombian army and police from "Plan Colombia", there are still Colombians interested in participating in the production of cocaine. Given the existence of an international market providing these individuals with funds to fight back the central government's security forces, the result is that *more Colombians* are dying every day for the war against drugs.

Appendix

A.0.1 The model

A.0.1.1 The problem

Let us use the following simple model which is based on Mejía (2008)'s. Let us assume that there are N municipalities in a country. This country is assumed to have a central government authority that determines the set of rules that each of the N municipalities must follow[39]. There are N_g groups who, have already decided to produce cocaine[40] and are willing to engage in an anti-predatory game (or anti-prohibition activities) against the government, if it decides to engage in a predatory game (prohibition activities) against these groups. Each of the N_g are also willing to fight their share in the drug market violently given the contractual environment in which they have to operate. The government is assumed to have decided to prosecute the production of cocaine, and it's willing to engage in a predatory game to enforce such decision[41]

In this scenario, if group i decides to produce cocaine in municipality j, it has to spend M_j^r dollars on military activities against the government and $M_{i,j}^{ir}$ dollars on military actions against the other rival groups in order to seize territory in the following way:

$$L_{i,j} = (1-\rho_j^g)\rho_{i,j}^{ir} L_j \tag{A.1}$$

where L_j is the amount of territory in municipality j,

[39]Colombia is a presidential regime with a single legislature making policy decisions for the entire country.

[40]These N_g might be purely drug dealers, who produce drugs to simply gain a revenue, or irregular groups who decide to seek a quick revenue in the production of drugs to supplement their other sources to accomplish their political objectives. What matters in the sequel is that both drug dealers and irregular groups spend military resources to produce cocaine, regardless of their objective at wanting to produce narcotics.

[41]For the sake of our argument, it does not matter whether the government reached this decision following the median voter preference or the lobby of a single group within the country. What matters is the government's willingness to use the army to prosecute the production of cocaine, and the amount of money it is likely to invest in this activity. Hence, we also assume that the economy has already solved the social problem of cocaine prohibition, and that there are people who find profitable to join cocaine "*firms*", even if it is illegal, and follow the rules they impose to solve their internal social problem for coordinating the production of cocaine.

$$\rho_j^g = \frac{M_j^g}{M_j^g + \phi_j M_j^r} \tag{A.2}$$

is the proportion of land gained by the government when it spends M_j^g dollars on military actions in municipality j against all groups who are willing to spend resources on military actions on the same municipality, and

$$\rho_{i,j}^{ir} = \frac{M_{i,j}^{ir}}{M_{i,j}^{ir} + \sum_{k \neq i=1}^{N_g} M_{k,j}^{ir}} \tag{A.3}$$

is the proportion of land gained by group i when it spends $M_{i,j}^{ir}$ dollars on military actions in municipality j against all groups that are seeking to produce on the same municipality. Equations A.2 and A.3 are called Contest Success Functions, which are functions widely used in the economic analysis of conflict (see Skaperdas (1996)).

Equation A.2 assumes that $\frac{dM_j^g}{dM_j^r} = \phi_j \frac{M_j^r}{M_j^g}$. As a result, a larger ϕ_j implies a larger military efficiency of group i's military expenditure on municipality j relative to the government's. In contrast, equation A.3 assumes that each group has the same military efficiency than the rest in all municipalities of the country. This simplification is assumed because a priori each regular group can settle down in every municipality, whereas the colombian government uses military bases to position its military forces to attack. Not all municipalities have military bases. See Dube and Naidu (2012) for an analysis on the way colombian government performs its military operations, the location of its military bases and the possible consequences of these military operations on violence.

Using equations A.1–A.3, group i's maximization problem is:

$$\max_{I_{i,j}, M_j^r M_{i,j}^{ir}} \pi_i(I_{i,j}, M_j^r, M_{i,j}^{ir}) = \sum_{j=1}^{N_p} [P_d \theta_j I_{i,j}^{\alpha} L_{i,j}^{1-\alpha} - I_{i,j} - M_j^r - M_{i,j}^{ir}] \tag{A.4}$$

where $I_{i,j}$ is the amount of resources invested by group i in inputs for the production of cocaine in municipality j, P_d is the international price of cocaine, and N_p is the number of municipalities in which all cocaine producers have decided to invest military resources to produce cocaine [42].

A.0.1.2 The solution

Equation A.4 can be solved in several ways. By its consistency characteristics, we will find the sub-perfect nash equilibrium of this problem. For an analysis of the characteristics of a sub-perfect nash equilibrium solution, see Fudenberg and Tirole (1991). To attain that, we will first determine the optimal value of $I_{i,j}$ and then determine the values of M_j^r to finally find the values of $M_{i,j}^{ir}$ for every group i and for every municipality j, in which cocaine producers decide to produce. Thus, we want to determine the optimal amount of resources in inputs that every group is willing to invest in the production of cocaine after having already (optimally) invested in war.

Taking first order conditions with respect to $I_{i,j}$ in equation A.4, we get the following condition:

$$I_{i,j} = (P_d \theta_j \alpha)^{\frac{1}{1-\alpha}} L_{i,j} = (P_d \theta_j \alpha)^{\frac{1}{1-\alpha}} (1 - \rho_j^g) \rho_{i,j}^{ir} L_j \tag{A.5}$$

[42] For simplicity, we assume that if a group i decides to invest military resources in municipality j, all (N_g-1) remaining groups will also invest military resources in the same municipality. An alternative derivation would consider the case in which a subset of the N_g invest in municipality j; however, for our purposes, it is innocuous to assume that all groups behave similarly in terms of investing in the same municipality j or not.

Inserting equation A.5 in equation A.4, we obtain the following expression:

$$\pi_i(M_{i,j}^{ir}), M_j^r, M_{i,j}^{ir}) = \sum_{j=1}^{N_p}[(P_d\theta_j)^{\frac{1}{1-\alpha}}\sigma L_{i,j} - M_j^r - M_{i,j}^{ir}] \tag{A.6}$$

where $\sigma = (\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}})$. Using equation A.6, we can determine the optimal value of $M_{i,j}^{ir}$. Taking first order conditions to equation A.6 with respect to $M_{i,j}^{ir}$, we get the following expression:

$$M_{i,j}^{ir} = \sqrt{(P_d\theta_j)^{\frac{1}{1-\alpha}}\sigma(1-\rho_j^g)L_j \sum_{k\neq i=1}^{N_g} M_{k,j}^{ir}} - \sum_{k\neq i=1}^{N_g} M_{k,j}^{ir} \tag{A.7}$$

Equation A.7 applies for every group i who decides to produce cocaine in municipality j. As a result, equation A.7 can be solved for a symmetric value of $M_{i,j}^{ir}$ for which $M_{k,j}^{ir} = M_{i,j}^{ir} = M_j^{ir}$ for all groups $k \neq i = 1, 2, \cdots, N_g$. Then, $M_{i,j}^{ir}$ becomes:

$$M_j^{ir} = \frac{(N_g-1)(P_d\theta_j)^{\frac{1}{1-\alpha}}\sigma(1-\rho_j^g)L_j}{(N_g)^2} \tag{A.8}$$

Inserting equation A.8 in equations A.1 and A.6, we obtain the following expression for the optimal revenue of group i:

$$\pi_i(M_j^r) = \sum_{j=1}^{N_p}[\frac{(P_d\theta_j)^{\frac{1}{1-\alpha}}\sigma(1-\rho_j^g)L_j}{N_g^2} - M_j^r] \tag{A.9}$$

Finally, from equation A.9 we can obtain the optimal value for M_j^r. Deriving this expression with respect to M_j^r, we get:

$$M_j^r = \frac{\sqrt{(P_d\theta_j)^{\frac{1}{1-\alpha}}\sigma L_j \phi_j M_j^g}}{\phi_j N_g} - \frac{M_j^g}{\phi_j} \tag{A.10}$$

I can use equation A.10 to obtain the following expression for M_j^{ir} in terms of M_j^g:

$$M_j^{ir} = \frac{(N_g-1)(P_d\theta_j)^{\frac{1}{1-\alpha}}\sigma L_j}{(N_g)^2} - \frac{(N_g-1)}{N_g}\sqrt{\frac{(P_d\theta_j)^{\frac{1}{1-\alpha}}\sigma L_j M_j^g}{\phi_j}} \tag{A.11}$$

A.0.1.3 Digression

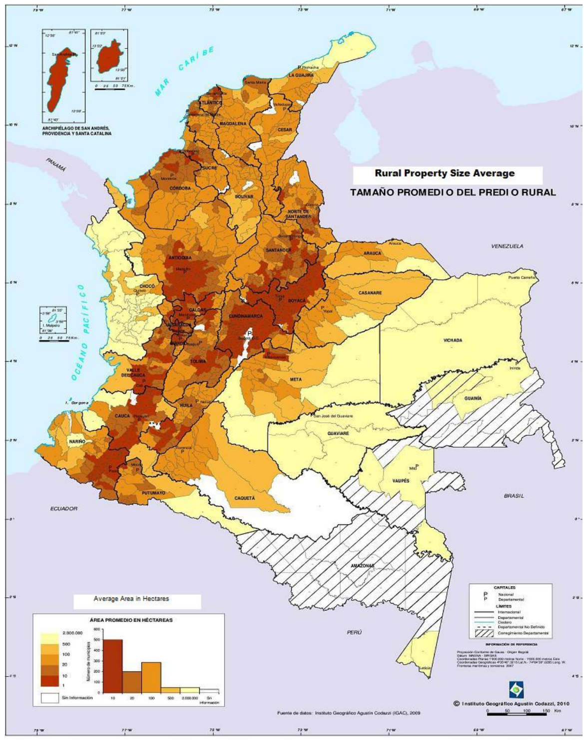
If the most worrisome consequence in the war against drugs is violence generated by the government's and drug producers' drug military expenditure, the model presented in section A.0.1 provides one insightful result. If we had perfect information about military expenditures made by all parties on municipality j to produce or avoid the production of narcotics and the violence rate in the same municipality associated to the drug war, we could split municipality j's violence rate in the following way:

$$v_j = \beta_1 M_j^g + \beta_2 M_j^r + \beta_3 M_j^{ir} + \text{rest} \tag{A.12}$$

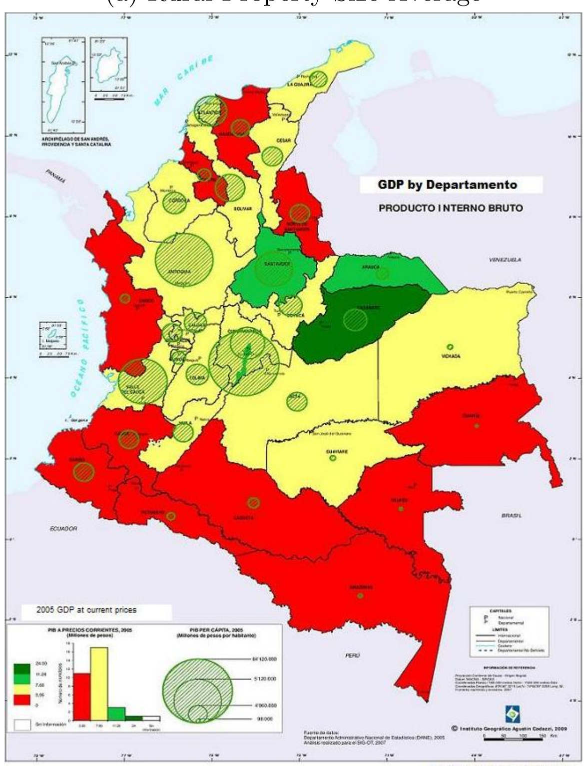
where $\beta_1 M_j^g$ represents the violence rate explained by the government's drug enforcement military expenditure. $\beta_2 M_j^r$ represents the violence rate explained by drug dealers' anti-enforcement military expenditure. $\beta_1 M_j^g + \beta_2 M_j^r$ is what we called the first-order effect of enforcement in the introduction. Finally, $\beta_3 M_j^{ir}$ represents the violence rate due to the drug dealers' war when they fight over the control of the territory to produce drugs. This is the second–order effect of enforcement.

A.0.2 Figures and Tables

Figure A.1: Map of Colombia: Administrative Division

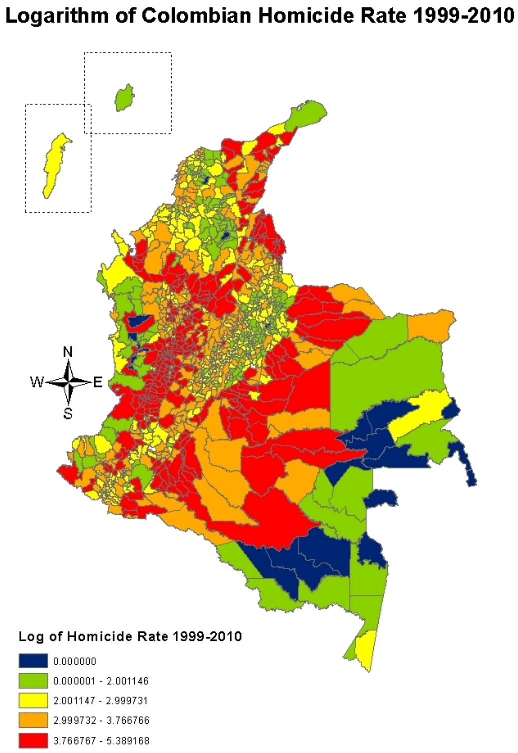


(a) Rural Property Size Average

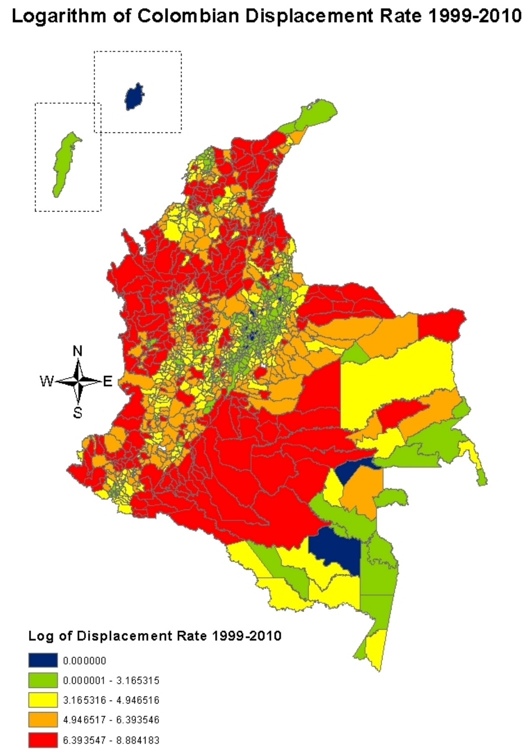


(b) 2005 GDP by *Departamento*

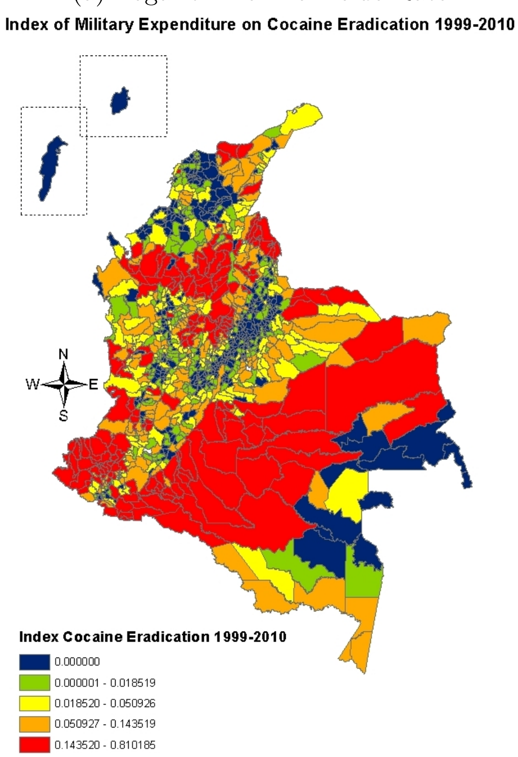
Figure A.2: Rationale behind using the distance variables



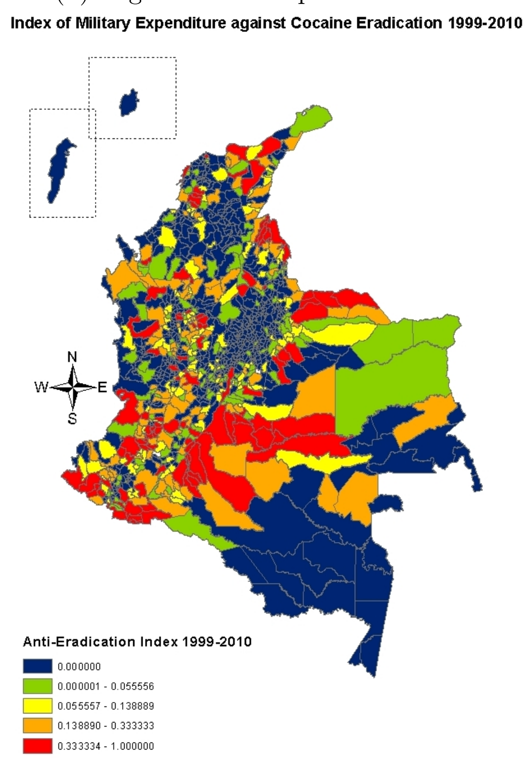
(a) Logarithm of Homicide Rate



(b) Logarithm of Displacement Rate

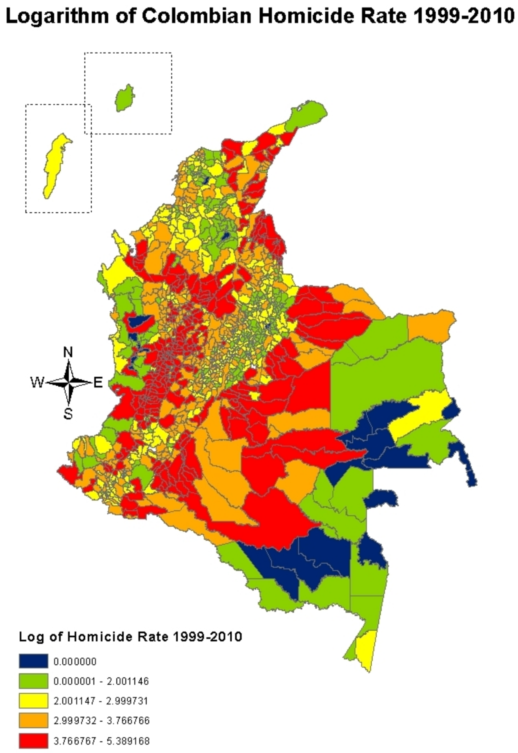


(c) Index of Cocaine Eradication

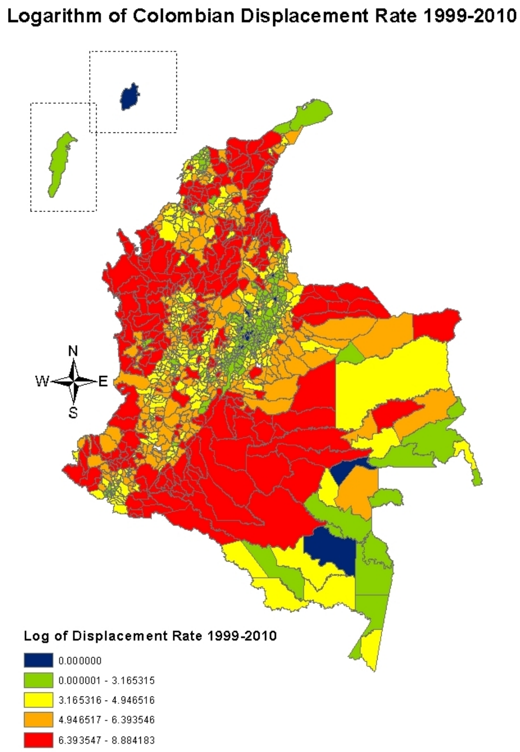


(d) Anti-Eradication Index

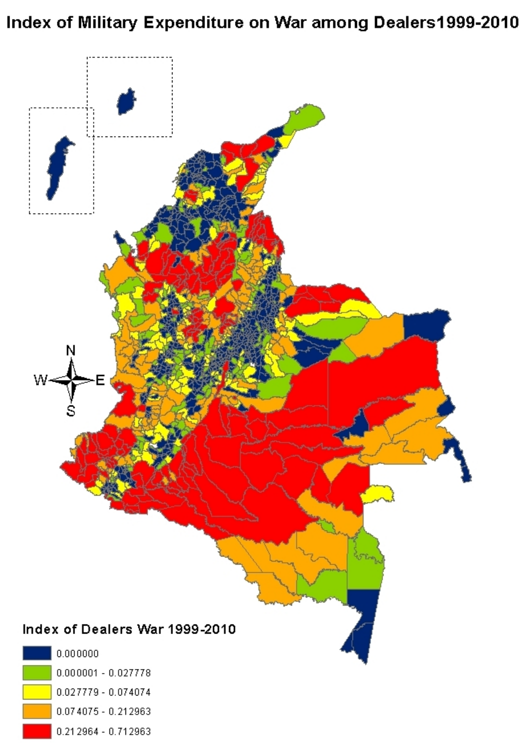
Figure A.3: Endogenous Variables VS Eradication and Anti-Eradication Indices



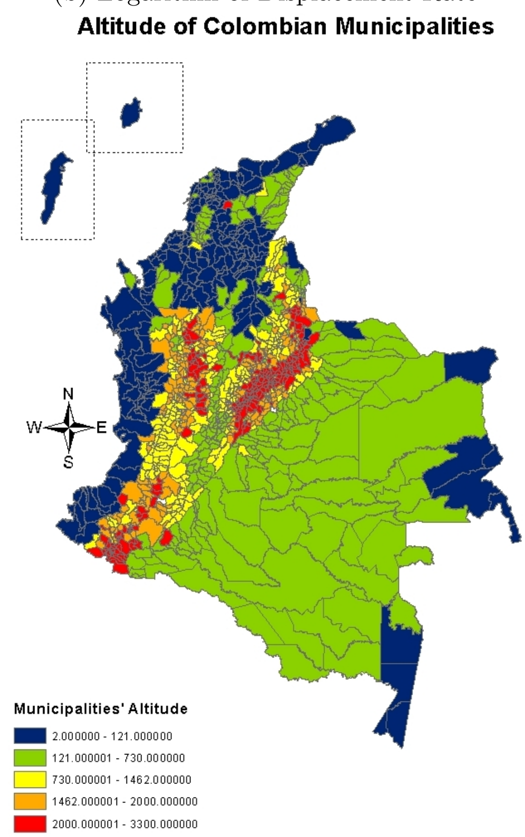
(a) Logarithm of Homicide Rate



(b) Logarithm of Displacement Rate

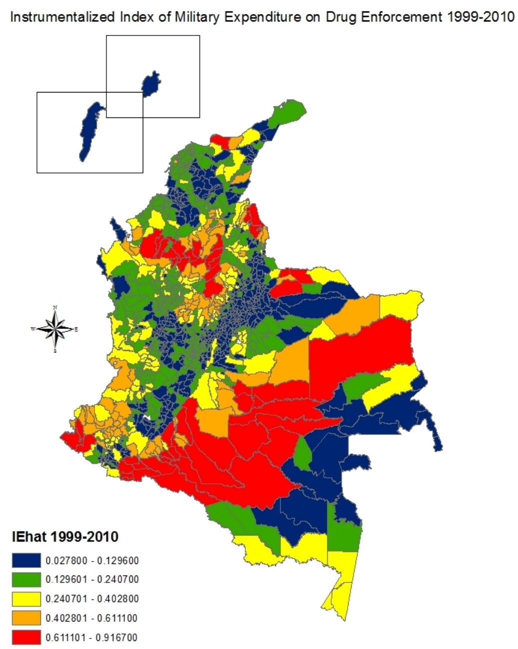


(c) Dealers War Index

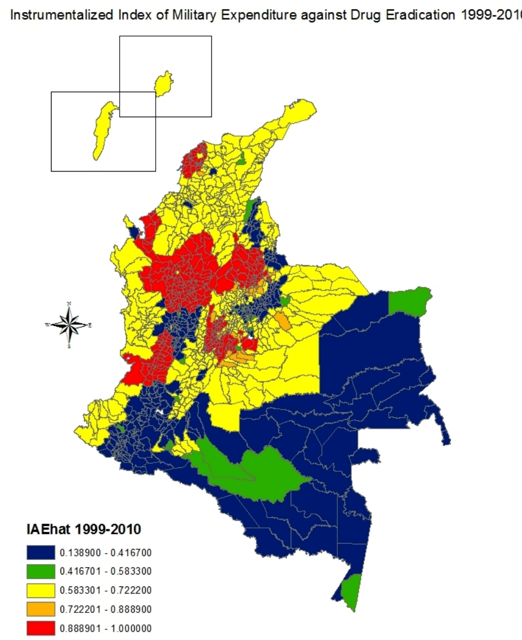


(d) Altitude

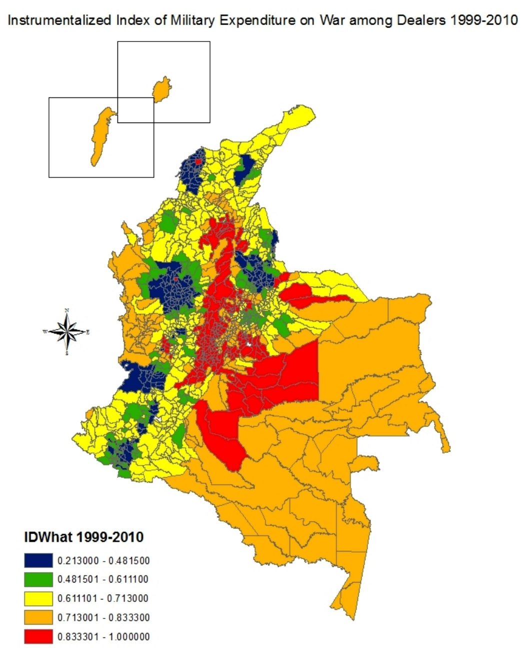
Figure A.4: Endogenous Variables VS Dealers War Index and Altitude



(a) Instrumentalized I_E



(b) Instrumentalized I_{AE}



(c) Instrumentalized I_{DW}

Figure A.5: Instrumentalized Drug War Indices

Variables	**loghrate**	**logdrate**	I_E	I_{AE}	I_{DW}	**dbogota**	**dcapitals**	**logpop**	**altitude**	$\hat{I}_E$	$\hat{I}_{AE}$	$\hat{I}_{DW}$
mean	2.83	4.68	0.069	0.09	0.072	0.94	0.89	9.56	1142.03	0.20	0.66	0.66
std	1.71	2.74	0.16	0.27	0.15	0.06	0.11	1.10	917.37	0.17	0.26	0.16
min	0	0	0	0	0	0	0	4.81	2	0.02	0.14	0.21
prctile. 25%	1.94	3.32	0.019	0	0.01	0.89	0.86	8.88	180	0.11	0.33	0.56
prctile 50%	3.27	5.30	0.069	0.083	0.074	0.96	0.94	9.48	1103.5	0.153	0.66	0.66
prctile 75%	4.11	6.63	0.81	1	0.71	0.98	0.96	10.15	1850	0.23	0.1	0.78
max	7.20	11.36	1	1	1	1	1	15.81	3300	0.92	1	1
Moran Coef.	0.37	0.55	0.43	0.20	0.43	0.73	0.87	0.33	0.82			
p-value	0	0	0	0	0	0	0	0	0			
Correlation Coefficients												
loghrate	1	0.33	0.24	0.23	0.23	0.11	0.15	0.33	-0.07	0.2033	0.11	-0.04
logdrate		1	0.37	0.23	0.40	-0.12	-0.07	0.22	-0.39	0.375	0.06	0.041
I_E			1	0.30	0.67	-0.10	-0.10	0.19	-0.19	0.851	-0.066	0.08
I_{AE}				1	0.38	-0.03	-0.002	0.31	-0.08	0.222	-0.05	-0.07
I_{DW}					1	-0.05	-0.05	0.19	-0.21	0.597	-0.035	0.061
dbogota						1	0.85	0.07	0.31	0.017	-0.64	-0.02
dcapitals							1	0.15	0.24	-0.004	-0.672	0.411
logpop								1	-0.18	0.01	-0.14	0.09
altitude									1	0.198	0.125	-0.191
$\hat{I}_E$										1	0.085	0.068
$\hat{I}_{AE}$											1	-0.059
$\hat{I}_{DW}$												1

Table A.1: Summary Statistics

Position	loghrate	logdrate	I_E	I_{AE}	I_{DW}	altitude
1	RISARALDA	CAQUETA	GUAVIARE	ARAUCA	GUAVIARE	BOYACÁ
2	VALLE DEL CAUCA	GUAVIARE	PUTUMAYO	PUTUMAYO	CAQUETA	NARIÑO
3	ARAUCA	ARAUCA	CAQUETA	CAQUETA	ARAUCA	C/MARCA*
4	CAQUETA	PUTUMAYO	ARAUCA	CAUCA	PUTUMAYO	CALDAS
5	CALDAS	META	VICHADA	META	META	QUINDÍO
6	GUAVIARE	CESAR	META	GUAVIARE	VAUPES	RISARALDA
7	QUINDÍO	CHOCÓ	NARIÑO	RISARALDA	VICHADA	CAUCA
8	META	BOLIVAR	CAUCA	NORTE DE SANTANDER	BOLIVAR	SANTANDER
9	HUILA	MAGDALENA	NORTE DE SANTANDER	CASANARE	NORTE DE SANTANDER	ANTIOQUIA
10	CASANARE	ANTIOQUIA	ANTIOQUIA	HUILA	CAUCA	NORTE DE SANTANDER
11	ANTIOQUIA	LA GUAJIRA	BOLIVAR	NARIÑO	ANTIOQUIA	VALLE DEL CAUCA
12	PUTUMAYO	CASANARE	AMAZONAS	VALLE DEL CAUCA	GUAINA	HUILA
13	TOLIMA	SUCRE	CHOCÓ	ANTIOQUIA	NARIÑO	TOLIMA
14	CESAR	CAUCA	CESAR	LA GUAJIRA	AMAZONAS	PUTUMAYO
15	LA GUAJIRA	HUILA	LA GUAJIRA	TOLIMA	CHOCÓ	CASANARE
16	NORTE DE SANTANDER	VICHADA	CORDOBA	CESAR	LA GUAJIRA	META
17	CAUCA	NORTE DE SANTANDER	CALDAS	QUINDÍO	CESAR	CAQUETA
18	NARIÑO	CORDOBA	VALLE DEL CAUCA	CALDAS	CORDOBA	CESAR
19	C/MARCA*	RISARALDA	SANTANDER	CHOCÓ	VALLE DEL CAUCA	GUAVIARE
20	CORDOBA	CALDAS	CASANARE	SUCRE	CALDAS	ARAUCA
21	SUCRE	VALLE DEL CAUCA	TOLIMA	VAUPES	SANTANDER	VAUPES
22	ATLÁNTICO	NARIÑO	MAGDALENA	MAGDALENA	CASANARE	CHOCÓ
23	SANTANDER	TOLIMA	GUAINÍA	BOLIVAR	MAGDALENA	AMAZONAS
24	MAGDALENA	QUINDÍO	RISARALDA	VICHADA	HUILA	LA GUAJIRA
25	VICHADA	C/MARCA*	BOYACÁ	ATLÁNTICO	TOLIMA	VICHADA
26	BOLIVAR	GUAINÍA	HUILA	C/MARCA*	RISARALDA	MAGDALENA
27	CHOCÓ	ATLÁNTICO	VAUPES	SANTANDER	SUCRE	GUAINÍA
28	SAN ANDRÉS	AMAZONAS	C/MARCA*	GUAINÍA	C/MARCA*	SUCRE
29	BOYACÁ	SANTANDER	QUINDÍO	BOYACÁ	QUINDÍO	CORDOBA
30	AMAZONAS	BOYACÁ	SUCRE	CORDOBA	BOYACÁ	BOLIVAR
31	VAUPES	VAUPES	ATLÁNTICO	AMAZONAS	SAN ANDRÉS	ATLÁNTICO
32	GUAINÍA	SAN ANDRÉS	SAN ANDRÉS	SAN ANDRÉS	ATLÁNTICO	SAN ANDRÉS

*** CUNDINAMARCA**

Table A.2: Ranking of *Departamentos* by Variable

Dependent Variable: **loghrate**																
Variables	**SDM_FE**				**SDM_FE**				**SDM_FE**				**SDM_FE**			
	No Fixed or Time Effects				**Fixed Effects**				**Time Effects**				**Fixed and Time Effects**			
	Estimates	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**
Intercept	-0.98***															
I_E	1.20***	1.20***	-0.06	1.14***	0.90***	0.91***	0.34	1.27***	1.25***	1.28***	0.44	1.71***	1.05***	1.09***	1.38***	2.47***
I_{AE}	0.35***	0.41***	0.93***	1.33***	0.35***	0.38***	0.62***	1.00***	0.34***	0.38***	0.68***	1.05***	0.31***	0.32***	0.21*	0.53***
I_{DW}	0.62***	0.63***	0.14	0.77**	0.90***	0.95***	1.37***	2.32***	0.62***	0.62***	-0.003	0.61**	0.98***	1.03***	1.74***	2.77***
ρWy	0.49***				0.26***				0.46***				0.19***			
Obs.	13464				13464				13464				13464			
σ^2	1.94				1.46				1.94				1.44			
R^2	0.34				0.54				0.34				0.55			
Corrected R^2	0.34				0.50				0.34				0.51			
Log L	-23870.63				-21182.04				-23828.04				-20983.06			
LM_Spatial_Lag	3482.58***				652.42***				3096.99***				324.83***			
LM_Spatial_Error	3345.32***				589.87***				2968.76***				265.66***			
Rob._LM_Spatial_Lag	193.37***				101.58***				179.66***				132.19***			
Rob._LM_Spatial_Error	56.11***				39.03***				51.42***				73.02***			
Wald_Spatial_Lag	N.A.				75.79***				59.86***				75.50***			
LR_Spatial_Lag	70.27***				83.05***				59.88***				81.64***			
Wald_Spatial_Error	286.00***				108.09***				184.59***				112.83***			
LR_Spatial_Error	186.31***				118.69***				182.98***				123.05***			
Haussman_Test					57.67***								71.62***			
F_Effects					4.96***				0.04				5.28***			
*** Statistically significant at 1%; ** Statistically significant at 5%; * Statistically significant at 10%																

Table A.3: Regressions without Controlling for Endogeneity

Dependent Variable: **logdrate**																
Variables	**SDM_FE**				**SDM_F E**				**SDM_FE**				**SDM_FE**			
	No Fixed or Time Effects				**Fixed Effects**				**Time Effects**				**Fixed and Time Effects**			
	Estimates	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**
Intercept	0.40*															
I_E	1.40***	1.45***	0.78	2.23***	0.40***	0.55***	2.30***	2.84***	1.38***	1.41***	0.32	1.72***	0.32**	0.35**	0.66**	1.02***
I_{AE}	0.21***	0.30***	1.30***	1.60***	0.23***	0.27***	0.49**	0.76***	0.24***	0.34***	1.50***	1.84***	0.30***	0.33***	0.78***	1.12***
I_{DW}	2.27***	2.60***	4.93***	7.53***	0.68***	0.98***	4.86***	5.84***	2.28***	2.57***	4.48***	7.05***	0.54***	0.64***	2.06***	2.69***
$\rho W y$	0.66***				0.55***				0.62***				0.37			
Obs.	13464				13464				13464				13464			
σ^2	3.42				2.09				3.41				2.00			
R^2	0.55				0.75				0.55				0.76			
Corrected R^2	0.54				0.72				0.55				0.73			
Log L	-28019.55				-23906.12				-27905.98				-23326.37			
LM_Spatial_Lag	9514.34***				5486.69***				7950.10***				1530.30***			
LM_Spatial_Error	9054.52***				5145.10***				7451.19***				1456.17***			
Rob._LM_Spatial_Lag	661.69***				408.77***				632.91***				122.05***			
Rob._LM_Spatial_Error	201.87***				67.18***				133.99***				47.92***			
Wald_Spatial_Lag	N.A.				79.19***				21.21***				43.86***			
LR_Spatial_Lag	20.70***				85.51***				21.71***				47.93***			
Wald_Spatial_Error	206.71***				149.28***				202.27***				68.88***			
LR_Spatial_Error	186.31***				161.51***				238.63***				74.49***			
Haussman_Test					40.74***								44.18***			
F_Effects					8.68***				0.07				9.63***			
*** Statistically significant at 1%; ** Statistically significant at 5%; * Statistically significant at 10%																

Table A.4: Regressions without Controlling for Endogeneity

Variables	Dependent Variable: **govcont**				Dependent Variable: **irrecont**			
	SDM				**SDM**			
	No Fixed or Time Effects				**No Fixed or Time Effects**			
	Estimates	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**
Intercept	0.70***				-1.50***			
Alt	-0.0002***	-0.0002***	-0.0002***	-0.0004***	-0.00042***	-0.00041***	0.00003	-0.0002***
dbogota	-0.50	-0.23	3.48	3.25*	-4.69***	-4.09**	11.48***	7.39***
dcapitals	-1.03	-1.11	-0.65	-1.77*	-7.64***	-7.39***	3.71**	-3.69***
$\rho W y$	0.53***				0.43***			
Obs.	13464				13464			
σ^2	7.21				9.01			
R^2	0.21				0.13			
Corrected R^2	0.21				0.13			
Log L	-32767.22				-34131.02			
LM_Spatial_Lag	2916.38***				1671.90***			
LM_Spatial_Error	2909.45***				1730.14***			
Rob._LM_Spatial_Lag	8.31***				95.08***			
Rob._LM_Spatial_Error	1.34				153.32***			
LR_Spatial_Lag	34.50***				54.59***			
Wald_Spatial_Error	87.04***				88.80***			
LR_Spatial_Error	89.88***				91.65***			

Variables	Dependent Variable: **logcrops**				Dependent Variable: **mines**				Dependent Variable: **massacres**			
	SDM				**SDM**				**SDM**			
	No Fixed or Time Effects				**No Fixed or Time Effects**				**No Fixed or Time Effects**			
	Estimates	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**
Intercept	-0.23				2.55***				0.29***			
govconthat	0.10	-0.06	-2.48***	-2.54***	0.66***	0.48***	-3.69***	-3.21***	0.02**	0.02**	-0.01	0.01*
Irreconthat	0.08	0.05	-0.55***	-0.50***	0.03	0.04	0.16	0.20*	0.11***	0.11***	-0.27***	-0.16***
Alt	-0.001***	-0.001***	-0.001***	-0.002***	0.0002	0.0001	-0.0012***	-0.0011***	-0.000004	-0.0000006	-0.000051***	-0.00006***
$\rho W y$	0.67***				0.36***				0.23***			
Obs.	13464				13464				13464			
σ^2	13.32				20.69				0.17			
R^2	0.50				0.22				0.11			
Corrected R^2	0.50				0.22				0.11			
Log L	-37207.15				-39652.23				-7137.44			
LM_Spatial_Lag	8019.02***				625.79***				302.83***			
LM_Spatial_Error	7799.96***				391.96***				336.71***			
Rob._LM_Spatial_Lag	275.98***				595.99***				70.59***			
Rob._LM_Spatial_Error	56.92***				362.15***				104.47***			
LR_Spatial_Lag	184.64***				625.67***				896.74***			
Wald_Spatial_Error	336.03***				863.29***				978.73***			
LR_Spatial_Error	344.02***				874.97***				937.19***			
*** Statistically significant at 1%; ** Statistically significant at 5%; * Statistically significant at 10%												

Table A.5: Regressions Controlling for Endogeneity: first-step regressions

Dependent Variable: **loghrate**																
Variables	**SDM_FE**				**SDM_FE**				**SDM_FE**				**SDM_FE**			
	No Fixed or Time Effects				**Fixed Effects**				**Time Effects**				**Fixed and Time Effects**			
	Estimates	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**
Intercept	-1.03***															
$\hat{I_E}$	0.92***	0.94***	0.42***	1.36***	0.34***	0.35***	0.40**	0.75***	0.94***	0.99 ***	0.73***	1.71***	0.47***	0.51***	1.32***	1.84***
$\hat{I_{AE}}$	0.17	0.11	-1.15***	-1.04***	0.51**	0.53**	0.07	0.60	0.17	0.11	-1.19***	-1.08***	0.46**	0.45*	-0.30	0.14
$\hat{I_{DW}}$	0.43**	0.53**	1.84***	2.38***	0.61	0.74	3.63**	4.37***	0.40*	0.50**	1.79***	2.29***	0.58	0.70	3.31**	4.00***
ρWy	0.48***				0.29***				0.46***				0.23***			
Obs.	13464				13464				13464				13464			
σ^2	1.96				1.49				1.95				1.47			
R^2	0.33				0.53				0.33				0.54			
Corrected R^2	0.33				0.49				0.33				0.50			
Log L	-23930.63				-21322.64				-23871.02				-21142.68			
LM_Spatial_Lag	3096.11***				729.49***				2699.83***				404.46***			
LM_Spatial_Error	2757.92***				2786.14***				698.66***				2346.68***			
Rob._LM_Spatial_Lag	339.15***				65.89***				353.25***				35.54***			
Rob._LM_Spatial_Error	0.96				35.06***				0.11				16.00***			
Wald_Spatial_Lag	N.A.				69.62***				115.31***				66.17***			
LR_Spatial_Lag	109.54***				75.02***				114.75***				72.51***			
Wald_Spatial_Error	188.37***				69.88***				223.22***				74.71***			
LR_Spatial_Error	199.97***				74.53***				223.97***				81.98***			
Haussman_Test					102.75***								91.96***			
F_Effects					4.80***				0.06				5.09***			
*** Statistically significant at 1%; ** Statistically significant at 5%; * Statistically significant at 10%																

Table A.6: Regressions Controlling for Endogeneity: second-step regressions

Dependent Variable: **logdrate**																
Variables	**SDM_FE**				**SDM_FE**				**SDM_FE**				**SDM_FE**			
	No Fixed or Time Effects				**Fixed Effects**				**Time Effects**				**Fixed and Time Effects**			
	Estimates	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**	**Estimates**	**Direct**	**Indirect**	**Total**
Intercept	-7.65***															
$\hat{I_E}$	1.70***	1.96***	3.85***	5.82***	0.21**	0.33***	2.04***	2.38***	1.73***	1.97***	3.70***	5.67***	0.15	0.18*	0.81***	0.99***
$\hat{I_{AE}}$	0.04	0.12	1.10***	1.22***	-0.09	0.09	3.02***	3.10***	0.04	0.10	0.89***	0.98***	-0.36	-0.33	0.58	0.25
$\hat{I_{DW}}$	0.83***	1.15***	1.10***	1.22***	0.46	0.19	-5.03*	-4.84	0.87***	1.20***	4.98	6.17***	0.87	0.79	-0.63	0.16
ρWy	0.66***				0.56***				0.61***				0.38***			
Obs.	13464				13464				13464				13464			
σ^2	3.47				2.09				3.45				2.01			
R^2	0.54				0.74				0.54				0.76			
Corrected R^2	0.54				0.72				0.54				0.73			
Log L	-28111.11				-23938.97				-27970.03				-23386.91			
LM_Spatial_Lag	9361.42***				5240.21***				7678.88***				1497.87***			
LM_Spatial_Error	8459.49***				5026.45***				6733.06***				1416.11***			
Rob._LM_Spatial_Lag	934.70***				231.58***				951.81***				141.05***			
Rob._LM_Spatial_Error	32.76***				17.81***				5.99**				59.29***			
Wald_Spatial_Lag	N.A.				46.82***				85.05***				18.05**			
LR_Spatial_Lag	78.91***				59.71***				87.81***				19.18***			
Wald_Spatial_Error	338.01***				69.94***				263.37***				18.31***			
LR_Spatial_Error	328.95***				103.13***				373.81***				19.26***			
Haussman_Test					119.38***								69.72***			
F_Effects					8.91***				0.08				9.75***			
*** Statistically significant at 1%; ** Statistically significant at 5%; * Statistically significant at 10%																

Table A.7: Regressions Controlling for Endogeneity: second-step regressions

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