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ON THE UNINTENDED CONSEQUENCES OF ANTI-DRUG ERADICATION PROGRAMS IN PRODUCER COUNTRIES**

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Abstract

This paper studies the effects of the biggest anti-drug program ever applied in a drug-producer country. I use a unique and rich data set with 1-square-kilometer satellite information on the location of coca crops between 2000 and 2010 in Colombia to identify the effects of spraying herbicides on coca production and on the welfare conditions of coca-producing areas. I exploit the exogenous variation created by governmental restrictions to spraying in protected areas (i.e., natural parks and indigenous territories) to identify the effects of the program. My results suggest that there is only a quarter reduction in coca grown per hectare sprayed, whereas there are sizable unintended negative effects on the welfare conditions of the treated areas. Specifically, if the share of area sprayed in a given municipality increases by 1%, poverty rates increase 4 percentage points, school dropout increases 0.82 percentage points, infant mortality rates increase 1.26 percentage points, and homicide rates increase 4.23 percentage points. Although some of these effects revert 3 years after the treatment implementation, the effects on poverty rates and infant mortality seem permanent.

JEL Classification: O12, O13, O54, I32 and I38.

Keywords: Public Policy, Latin America, and Welfare.

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1 Introduction

As of 2013, the total expenditures by the United States on the war against illegal drugs accounts for approximately $40 billion dollars per year [2]. Based on information in the budget summary of the National Control Strategy of the White House, on average, 12% of these resources where spent on international initiatives to reduce drug supply. However, few efforts have been directed at studying supply side anti-drug policies. According to the World Drug Report of 2012 , by the year 2011, 18 countries were implementing supply interventions mainly focused on the forced eradication of opium poppy and coca leaf crops—the main inputs of heroin and cocaine production, respectively. This paper investigates the effectiveness and welfare consequences of aerially spraying herbicides on coca crops in Colombia.

According to data from the United Nations Office of Drugs and Crime (UNODC), of all the countries that have implemented these types of initiatives in the last two decades, Colombia has applied the most aggressive strategy in terms of resources invested. In particular, data by UNODC indicates that by 2000 , 74% of the world's supply of cocaine was produced in Colombia. This facilitated the direction of a vast amount of financial resources from the Colombian and the U.S. governments towards reducing the cocaine supply. Between 2000 and 2010, the U.S. government spent around 6 billion dollars on international supply control in Colombia (Office of National Control Policy), making Colombia the third largest recipient of military foreign aid from the U.S. (after Israel and and Egypt)[2]. In addition, between 2000 and 2010 the Colombian government disbursed US$668 million/year in its war against illegal drug production. Combined, these expenses account for approximately 1.1% of the country's GDP.

Despite the huge amount of resources invested, as of today, there is very little empirical evidence at the micro level on the impact of these programs. Most of the related work consists of theoretical models calibrated with aggregate data to simulate the effect of anti-drug policies on drug trafficking or econometric analysis based on aggregate time series (see for example Rydell et al. (1996), Moreno-Sanchez at al. (2003), Diaz and Sanchez (2004), Mej´ıa (2008) , Chumacero (2008), Costa-Storti and De Grauwe (2008), Grossman and Mej´ıa (2008), Tragler et al. (2008), Dion and Russel (2008), and Mej´ıa and Restrepo (2011)). These studies conclude that the forced destruction of coca and opium crops is an ineffective strategy for drug control. The main limitations of these studies is that they use aggregate data, which possess a considerable threat of endogeneity; their results are driven by theoretical assumptions; and they ignore other unintended effects of these programs.

This paper contributes to the existing literature by using a unique and rich data set with 1-square-kilometer satellite data on the location of coca crops to assess the impact of anti-drug programs in producer countries. I investigate the effect of aerial spraying with herbicides not only on coca production, but also, on the welfare

[2] As estimated by Becker and Murphy in the Wall Street Journal article of January 4, 2013. [2]The data on top recipients of U.S. foreign assistance is available at:
http://www.fas.org/sgp/crs/row/R40213.pdf

condition of coca-producing areas, and analyze the spillover effects of the program on other non-treated areas.

The data collection is done by the Integrated Monitoring System of Illicit Crops of the United Nations of Drugs and Crime to guarantee that there is no data manipulation. The data includes information on all the areas that had coca crops between 2000 and 2010. I use this data set to study the effect of spraying on coca production in the short (12 months) and long term (24 to 36 months), and to check if spraying spreads coca production into neighbouring areas that were not treated (i.e., creates spillovers). Moreover, I aggregate these data on municipality units and combine them with other governmental sources to identify the effects of the program on violence outcomes (homicide rates and forced displacement), education outcomes (enrollment rates and school dropout), infant mortality, and poverty rates.

The identification of the causal effects of aerial spraying is challenging given that treatment is not randomly assigned, but is targeted through satellite images. The targeting mechanism creates two types of endogeneity issues. *Crosssection endogeneity* in coca production arises since the targeted areas have more hectares of coca. It also arises for the socioeconomic indicators because coca growing is illegal in the country and so coca-producing areas are the ones with the lowest governmental presence (hence the ones with the worst socioeconomic outcomes). *Panel endogeneity* or feedback effects may arise for the socioeconomic outcomes because areas with worsening conditions could have increasing coca cultivation that in turn leads to increased spraying.

To identify the effects of spraying on coca production and social outcomes, I instrument spraying with the exogenous variation created by governmental restrictions to spraying in protected areas (i.e., natural parks and indigenous territories) and the time variation in financial resources available for aerial spraying induced by U.S. anti-drug international expenditures. In particular, my instrument is constructed as the interaction of these two variables. Since aerial spraying is forbidden in protected areas, and I show that this rule in enforced in Colombia, coca crops outside these areas face a higher likelihood of being treated. Moreover, the likelihood of spraying should increase for non-protected areas when U.S. anti-drug expenditures are higher, but not for protected areas.

My results suggest that when aerial spraying increases in one hectare, coca production in that hectare decreases by 25%. I obtain similar results when I use a random sample collected at the producer level. These results are persistent 12 and 36 months after the treatment implementation. I also check for evidence of spillovers from the program and find no evidence that coca production increases in the non-treated areas neighboring the treated ones. This may suggest that if producers are changing locations, they may be going to areas farther away from the treated ones, or even to other countries with similar coca-growing conditions and less enforcement (i.e., Peru and Bolivia). The aggregate figures support this hypothesis.

I also find that spraying drastically worsens the welfare conditions in treated areas. Specifically, when the share of area sprayed increases by 1% in each municipality, poverty rates increase by 4 percentage points. These effects persist 2 years after the fumigations. Moreover, spraying is reflected in worse education and health conditions of coca producers. A 1% increase in the share of area sprayed reduced secondary school enrollment by -2.13 percentage points and increases dropout rates by 0.82 percentage points. This suggests that as a result of the program, older children may be pulled out of school to work and help compensate for the income shock caused by the fumigations. The negative effect of the program on education outcomes reverts 1 year after the treatment implementation. This is in line with the results of Beegle et al.(2006), who document the impact of a loss in the crop's value on child labor.

Related to health outcomes, I find that when the share of area sprayed increases by 1%, infant mortality increases by 1.26 percentage points. This effect may be explained by a combination of a direct effect of the herbicide on health outcomes as documented by Mej´ıa and Camacho (2012) and an indirect effect of the program caused by the income shock. This effect persists 2 years after the fumigations.

I also find evidence of an increase in violence outcomes 1 year after treatment implementation. My results indicate that when the share of area sprayed increases by 1% in each municipality, homicide rates increase by 4.23 percentage points and the number of individuals displaced increases by 39.51. Local authorities suggested the negative effect of aerial spraying on violence may be explained by the military check-ups that take place on the ground before the aircraft begin their flights. These inspections may be increasing the likelihood of a confrontation between the authorities and the drug traffickers, which increases violence in the treated areas in the short run. Moreover, this effect may be explained by drug traffickers retaliating in response to the crop eradication. These explanations are consistent with the fact that these effects seem to disappear in the long term.

In the next section, I describe the existing involuntary eradication programs; section 3 describes the data; section 4 presents the identification strategy; section 5 presents the results; and section 6 presents some robustness checks. Finally, section 7 offers concluding remarks.

2 Forced Eradication Anti-Drug Programs

Currently, the only types of forced eradication programs implemented in the world are manual eradication and aerial spraying. Manual eradication is performed by a group of men who destroy coca or opium poppy crops by hand (UNODC (2012)). Aerial spraying is executed with an herbicide called glyphosate, which small aircraft spray as close as possible to the ground. For 2010, Colombia, Mexico, Peru, Morocco, Myanmar, Bolivia and Afghanistan were the countries most actively involved in these initiatives.

In terms of scale, of the 18 countries that implement these programs, Colombia applies the most aggressive eradication strategy. Data from the Colombian Antinarcotics Police (DIRAN) suggest that between 2000 and 2010, 787,096 ha (or 3,039 mi^2) were sprayed in Colombia. This is more than double the size of Mexico's eradication program, which takes second place in terms of the number of hectares eradicated (UNODC (2012)). Aerial spraying began to be implemented in Colombia in 1978 (Gaviria and Mejia (2011)), and it is the biggest forced eradication program in the world (UNODC (2012)). Yet, data on the size of the program began to be collected only in 1986. Since that year, the program has grow extensively. The total area sprayed increased from 870 to 103,302 hectares between 1986 and 2010.

Figure I presents the evolution of the hectares eradicated by type of program and hectares grown during the last decade. The time series show that the rise in hectares sprayed has been coupled with a reduction in coca production in the last decade. However, the causality of the program on the total hectares of coca cultivated cannot be inferred from these aggregate figures alone.

Aerial spraying is mainly targeted through satellite images produced and processed by UNODC. These satellite pictures are taken in the last months of the year and are processed with great detail to identify the exact location of the crops. This information is then passed to the Antinarcotics National Police (DIRAN), in charge of executing the fumigations. Before the fumigations are performed, DIRAN confirms the location of the crops through flight inspections. Due to the magnitude of the area cultivated in Colombia and the governmental financial restrictions, not all the coca crops are sprayed in Colombia. Thus, the program concentrates on areas where there is a higher crop density.

The manual eradication program began in 2007 and maintains a modest size given its high costs in terms of human lives[3]. Reports from DIRAN estimate that since its implementation, 135 men have been killed through explosions of mines hidden in the ground to prevent the eradication. In 2010, 32,140 hectares were eradicated through this program. Hence, the aerial spraying program was 5 times as large as the manual eradication program for that year.

Unlike the manual eradication program, aerial spraying has been implemented for more than 30 years and has a known targeting mechanism. Thus, this study will focus on identifying the effectiveness and welfare consequences of the aerial spraying program[4].

3 The Data

Over the years, the scarcity of good quality data has been the main limitation in studying the effectiveness of anti-drug programs in producer countries. Around 1999, UNODC launched the Illicit Crop Monitoring Programme. It aimed at collecting satellite images of the countries the most coca, opium and cannabis, including Colombia, Peru, Bolivia, Afghanistan, Lao People's Democratic Republic, Myanmar and Morocco. These images allow identifying the exact location and size of the coca, opium, or cannabis crops, and are collected annually. UNODC not only processes the satellite images to determine the size of crops but verifies this information by flying in areas that are chosen randomly throughout each country. Thus, this is the highest quality available data on the location of illicit crops.

[3] This program was being implemented in 18 countries in 2010.

[4] This paper excludes all the observations that were treated by both programs (this accounts for 0.52% of the grid sample.)

Despite the great efforts by UNODC, evaluating the effectiveness of antidrug programs in producer countries remains constrained by the lack of data on treatment recipients and by the unclear targeting mechanisms different governments use. The aerial spraying program in Colombia is a unique exception since the Antinarcotics Police (DIRAN) records the exact location where the small aircraft open their valves to start spraying glyphosate and close them to stop.

I combine these unique sources of information and construct two data sets to identify the impact of aerial spraying on coca-producing areas. The first one is balanced panel data at the grid level, which corresponds to an area of 1 km^2, or 100 hectares. It includes all grids that had at least 1 hectare of coca between 2000 and 2010. For each unit of observation I observe the hectares of coca grown, the hectares aerially sprayed, the hectares manually eradicated, and the exact location of each of the 1,115,840 grids in the sample. I use this sample to identify the effect of aerial spraying on coca production. Table A.1 of Appendix A presents descriptive statistics for this data set. The table shows that on average each grid had 0.11 hectares manually eradicated, 0.54 hectares aerially sprayed, and 0.84 hectares of coca.

The second data set aggregates the grid data by municipality and combines it with other governmental information on welfare outcomes. This results in a balanced panel that contains the 288 municipalities with at least 1 hectare of coca between 2001 and 2010[5]. This data set includes information on violence-related outcomes (i.e., homicide rates per 100,000 inhabitants and forced displacement), education outcomes (i.e., enrollment rates and school dropout); infant mortality rates, and poverty rates.

Table A.4 in Appendix A presents the descriptive statistics for this sample. The table shows that the municipalities in the sample have low levels of socioeconomic development and high levels of violence. This is because coca crops are illegal in the country and thus are cultivated only in remote areas with very low governmental presence. I use this data set to assess the welfare consequences of aerial spraying on coca producer municipalities in Colombia. Appendix A also presents the data sources and the definition of each variable in this data set.

Finally, Table I presents a summary of the information available in both data sets.

4 Estimation Framework

To address the endogeneity issues of spraying with coca production and with the socioeconomic conditions, I estimate the effect of the program using instrumental variables. In particular, I use the following specification:

$$Y_{it} = \alpha_0 + \alpha_1 Spr_{it} + g_t + k_i + e_{it} \tag{1}$$

$$Spr_{it} = \beta_0 + \beta_1 OutsidePA_i * U.S.Exp_t + g_t + k_i + u_{it} \tag{2}$$

[5] Colombia is divided into 1,123 municipalities.

where Y_{it} represents coca production or welfare indicators by grid or municipality i in year t; Spr_{it} is the treatment intensity measured as hectares sprayed; g_t are time fixed effects; k_i are grid or municipality fixed effects; $OutsidePA_i$ is an indicator variable that takes the value of 1 if the grid is located outside protected areas, and it corresponds to the number of hectares outside protected areas for the municipality sample; and $U.S.Exp_t$ are the U.S. international antidrug expenditures in real billions of 2010 dollars. For the municipality data, I scale hectares grown, sprayed, and lying outside the protected areas by the total area. This is necessary due to the diverse size of municipalities in Colombia. In this specification the coefficient of interest is α_1, which identifies the local average treatment effect of the program for the group of compliers.

In equations 1 and 2, I instrument the treatment assignment with an interaction of the exogenous variation created by governmental restrictions to spraying in protected areas and U.S. international supply anti-drug expenditures. By governmental mandate, protected areas—i.e., natural parks and indigenous territories— cannot be sprayed in Colombia [6] . According to the National Geographical Institution in Colombia (i.e., Instituto Geogr´afico Agustin Codazzi), natural parks and indigenous territories comprise 12% and 27.6% of Colombia, respectively. Moreover, around 5% of the total population lives in these areas. Figure II presents the exact location of these areas throughout the country. It is worth noting that there are coca crops inside these areas. For instance, in 2010 18% of the total hectares of coca were located in protected areas.

The time variation in the instrument is induced by the variation in the U.S. supply anti-drug expenditures. Since according to the Office of National Drug Control Policy approximately 25% of the U.S. international expenditures on anti-drug supply efforts was directed to Colombia during the period of analysis, it should be expected that higher expenditures would imply a higher treatment intensity in non-protected areas.

Because non-protected areas have a higher likelihood of being treated and treatment intensity should increase when there are higher U.S. international anti-drug expenditures, the correlation between the instrument and the treatment intensity should be positive.

4.1 Assessing the instrument's quality

I begin by presenting some evidence on the correlation between the instrument and the treatment intensity. Figure III presents the hectares sprayed by deciles of the share of area outside protected areas at the municipality level— $OutsidePA_i$. Panel A of Figure III presents fitted values of hectares sprayed on deciles of $OutsidePA_i$ for years with different levels of U.S. supply expenditures. The figure suggests that: (i) municipalities with a higher share of non-protected areas had a higher number of hectares sprayed, and (ii) in years when the U.S. anti-drug

[6] According to Decree 143 of 1991, aerial spraying is prohibited in indigenous territories and natural parks. The decree also establishes a 100 meter band around these areas for which aerial spraying is also forbidden. Resolution 0015, approved the 5th of August of 2005, allows aerial spraying in natural parks if several requirements are fulfilled. However, to date, these conditions have not been met and aerial spraying has never been done in protected areas.

expenditures were higher (as shown in Panel B), the intensity of treatment increased more for non-protected areas; in other words, the slope of the fitted lines increases when U.S. anti-drug expenditures are higher.

A formal test on the correlation between the instrument and spraying intensity, the so-called relevance assumption, as defined by Imbens and Angrist (1994), Abadie (2003) and Angrist et al. (1996), is presented in Tables II and III. The tables present the results of the first stage of the instrumental variables regression as specified in equation (2) for the samples with units by grid and municipality. Both tables show the estimates of three regressions: column (1) presents the first stage regression using the interaction of the area outside protected areas and the U.S. anti-drug expenditures, and columns (2) and (3) present the results of the regression using each of these variables individually.

The results for column (1) confirm that the relevance assumption is satisfied. The coefficient on the instrument has a positive sign and is statistically significant. The R^2 is 18% and 17% for the grid and municipality sample, respectively. In addition, the partial R^2 is higher than 5% for both samples, and the F-test for excluded instruments takes a value of 48.87 for the grid and 21.71 for the municipality data. For the case of a single endogenous regressor, Staiger and Stock (1997) suggest rejecting the hypothesis of weak instrument if this F-statistic is higher than 10. Hence, these estimates rule out concerns of having the finite sample bias of IV (as defined by Bound, Jaeger and Baker (1995)). Moreover, the estimates in columns (2) and (3) confirm that each of the variables has predictive power on the treatment intensity and affect it in the expected direction.

The second assumption that must be satisfied for the validity of my identification strategy is the exclusion restriction. There will be a violation in the exclusion restriction only if $corr(Instrument_{it}, u_{it} | k_i, g_t) \neq 0$. In other words, exclusion restriction requires that the instrument only affects the outcomes through aerial spraying. Since the estimates of equations (1) and (2) include year and grid or municipality fixed effects, my identification strategy is not threatened by the static potential differences between protected and non-protected areas, nor by changes in aggregate trends across years.

The instrument is effectively comparing non-protected areas with a high change in enforcement expenditures with protected areas with a low change in enforcement expenditures. In other words, the identifying assumption will be violated if the instrument intensity is directly correlated with coca production or the socieconomic conditions.

I address this concern through two exercises that show no systematic differences in the growth of public expenditures or public investment by instrument intensity. This is a strong test, since public expenditures and investment are directly determined by transfers from the central government, and these transfers are a direct function of the socieconomic conditions in each municipality. Hence, no differences in the growth of these variables can be considered evidence that the instrument has no direct effect on the outcomes I evaluate in this paper.

The first exercise is presented in Figures IV and V with data by municipality. I cannot use the sample with observations at the grid level since I only observe hectares of coca, hectares sprayed, and hectares manually eradicated for that sample. In the figures, I divided the municipality panel into two groups according to instrument intensity. The high instrument intensity group includes all the observations with an instrument decile higher than 5, whereas the low intensity group includes all municipalities with deciles equal to or lower than five. The figures suggest that there are no differences in the growth rates of public expenditures, public investment, public education expenditures, or public health expenditures between groups in the period under analysis.

The second exercise is presented in Figures VI and VII and is also constructed with municipality data. The figures present fitted regressions of public expenditures and public investment on deciles of the share of unprotected areas. These figures confirm that: (i) there is no difference in public expenditures and public investment between municipalities with different shares of unprotected areas in each year, and (ii) in years with higher public expenditures or investment there are no systematic changes in the distribution of resources by municipalities with different shares of unprotected areas.

Finally, in order to interpret α_1 in equation (1) as the local average treatment effect of aerial spraying on the outcomes, I need to rule out the existence of defiers; this is reasonable since protected areas should be less exposed to aerial spraying throughout the period of analysis. Figure VIII shows evidence that supports the validity of this assumption. As can be seen, those municipalities with a higher share of protected areas have very low levels of aerial spraying.

4.2 Other threats to internal validity

An important threat to my identification strategy is potential possible manipulation of the treatment by producers. If producers are aware of the governmental restrictions on aerial spraying in protected areas and they do not face restrictions in changing locations, it could be expected that they would move their coca crops to protected areas to prevent fumigation. If that were the case, the instrument could no longer be used as a plausibly exogenous variation for treatment assignment. Figure IX presents deciles of the percentage of area that is non-protected against the percentage of area that is covered by coca crops in each municipality. The figure suggests that there is not a concentration of coca crops in protected areas throughout the period of analysis.

Another concern with the validity of the results is that the government may have been substituting the aerial spraying program with manual eradication in the protected areas. Figure X presents the deciles of the area that is unprotected areas against the mean hectares that are manually eradicated (both as a percentage of total area). The figure suggests that the government is not increasing the number of hectares manually eradicated in protected areas. In fact, Decree 143 of 1991 in Colombia imposes restrictions on any involuntary eradication program implemented in protected areas.

5 Empirical Results

Tables IV and V present the estimates of equations (1) and (2). I only use the grid sample to identify the impact of the program on drug production since it is the only outcome available at this level; the municipality data is used to assess the effects of the program on the welfare outcomes. To identify the long-term effect of the program, I lag the treatment in equation 2 one and two years[7].

5.1 Impact on Drug Production

Table IV presents the estimates for the effect of spraying on hectares of coca. The results suggest that in the treated grids the hectares of coca cultivated were reduced by -0.21 per additional hectares sprayed. Given that the mean hectares of coca by grid was 0.84, this amounts to a reduction of 25% on the treated grids.

The long-term estimates present a similar pattern, showing a negative impact of the program. In particular, the effect of the program one year after the treatment is -0.36 ha and two years after the program is -0.18 ha. Hence, there is evidence of a sustained negative effect of the program in the long term (i.e., 1 or 2 years after the fumigations)[8].

There are several reasons why aerial spraying may not have a higher impact on coca leaf production. For instance, D´avalos et al. (2009), Caulkins and Hao (2008), and Mej´ıa and Restrepo (2011), suggest that some of the ways producers may reduce the effect of the herbicides on coca are: (1) applying manual defoliation, (2) selecting highly productive coca varieties with more resistance to the herbicides, or (3) switching to agroforestry coca, which mixes tall plants such as plantains or fruits with coca to prevent the effect of fumigations.

5.2 Are there spillover effects on coca production?

In this subsection, I check whether the program is creating spillover effects. These effects will occur if, for example, when the hectares of coca cultivated drops in the treated areas, if increases in nearby untreated areas. I use the following specification to test for spillovers:

$$Coca_{-it} = \alpha_0 + \alpha_1 Spr_{it-1} + g_t + k_i + e_{it} \quad (3)$$

where Spr_{it-1} represents the total ha sprayed in municipality i in $t-1$; $Coca_{-it}$ represents the total hectares of coca grown in the municipalities that belong to the same department as municipality i but which were not treated in $t-1$ or in t[9]; and g_t and k_i stand for year and municipality fixed effects. Standard errors were

[7] It was not possible to assess the impact of the program after more than 2 years given the sample size restrictions in the municipality panel data.

[8] I do not identify heterogeneous effects of the program on coca production by region.

[9] Colombia is divided into 1123 municipalities, which can be grouped into 32 departments.

clustered at the municipality level in the estimates. Appendix B presents the estimates of equation 3, which suggest no evidence of a spillover effect of the program on coca production. In particular, the effects show the opposite sign, suggesting that coca production decreased in the municipalities not treated by the program, too. I also estimate this specification with the grid sample, analyzing the effect around the adjacent grids that were not treated in the previous period. The results are not statistically significant for any specification[10].

This may indicate that if coca producers are changing locations as a result of the program, they may be moving to areas farther away from the treated areas or to other countries with similar coca-growing conditions (e.g., Peru or Bolivia). In fact, the aggregate series of coca production by country gathered and processed by UNODC support this argument. While coca production fell in Colombia by 60.81% (from 163,300 to 64,000 hectares) between 2000 and 2010 , it increased by 136% in Peru (from 43,400 to 62,500 hectares) and by 44% in Bolivia (from 14,600 to 34,500 hectares) during this period. However, despite the increase of hectares grown in Peru and Bolivia, the world's coca production decreased from 221,300 to 151,200 hectares between 2000 and 2010.

5.3 Impact on Welfare Outcomes

Table V assess the effect of the program on the welfare indicators of cocaproducing areas. Specifically, the table presents the effects of the program on: poverty rates, education outcomes, infant mortality, and violence.

Poverty rates are constructed based on the percentage of the rural population under the poverty line [11] . Since poverty rates were constructed with the information available in the population census of 2005, they are available only for that year. Hence, the estimates will not include fixed effects by municipality. The estimates suggest that the areas that had a 1% higher share of area aerially sprayed had rural poverty rates 4 percentage points higher in the short term. More strikingly, these effects seem to be maintained in the long term. Specifically, areas that had a 1% higher share of area aerially sprayed face rural poverty rates 3 percentage points higher 1 and 2 years after the treatment implementation. These effects are large since, according to the Food and Agriculture Organization of the United Nations, rural poverty rates in Latin America only fell only 7% between 1980 and 2010, from 60 to 53 %.

For the education outcomes, I find a significant effect of the program on secondary enrollment and school dropout only in the short term. The results suggest that when the share of area sprayed increases by 1%, secondary enrollment rates decrease by 2.13 percentage points and school dropout rates increase by 0.82 percentage points. Given the mean values of these variables for the periods of interest in the rural areas, this represents a decrease of 2.9% in secondary enrollment rates and 7.5% in school dropout. When compared to the changes in these variables across time, the effects of the program on secondary

[10] I also checked for the spillover effects of the program in all of the other socioeconomic indicators at the municipality level and find no statistical evidence of spillovers for any of them.

[11] The poverty line is 60% of the median household income, from data published by the Colombian Statistical Department in the population census of 2005.

enrollment rates are small, and the effect on school dropout rates is large. In particular, during the period of analysis secondary enrollment rates increased by 43.8% (from 58.49 to 84.16) and school dropout rates fell by 3.8% (from 11.80 to 11.34)[12]. I do not find any effect on primary enrollment rates.

Together these results indicate that since a relevant part of the household's income is reduced by aerial spraying the older children are being pulled out of school to work and compensate for the income shock (as suggested in a theoretical model by Basu and Van (1998)). Similar responses to negative income shocks on the probability that children enter employment, leave school, and fail to advance have been documented by Jacoby and Skoufias (1997) in rural India, Duryea et al. (2007) in Brazil, and Beegle et al. (2006) in Tanzania. For example, Beegle et al.(2006) find that when hit by a transitory negative shock in the value of crops, rural households tend to increase their use of child labor by 30%. This is in line with the permanent income hypothesis that suggests households that lack buffer stocks and are credit constrained tend to use other mechanisms to smooth consumption. Indeed, this is the case in coca-producing areas that have rural poverty rates of nearly 60% of the total population.

The estimates also point to a negative and significant effect of the program on infant mortality in both the short and long term. The coefficients indicate that when the share of area treated increases by 1% or approximately 688 hectares[13], infant mortality increases by 1.26, 0.97 and 0.94 percentage points, the same, one, and two years after the fumigations. This is a big effect considering that the mean number of hectares sprayed in each municipality is 450, and that Colombian infant mortality rates (including all the country's municipalities) changed only 0.50 percentage points between 2006 and 2007, the two years for which there is available information of this outcome.

The increase in infant mortality in the treated areas may be explained by the direct effect of the herbicide on human health and the indirect effect of spraying through the increase in rural poverty rates. Unfortunately, there is not enough data at the individual level to identify precisely the size of the direct and indirect effects. Yet, other studies that have analysed the direct effect of glyphosate on human health suggest that it generates a negative effect on health outcomes. For example, Mej´ıa and Camacho (2012) use daily panel data on the individuallevel registers of medical consultations, emergency room visits, hospitalizations, and procedures that took place in any health service institution in Colombia between 2003 and 2007, and daily data on spraying intensity to identify the effects of the program. In particular, they check for different patterns in the reported pathologies 15 days after a fumigation in the treated municipalities. They find that, on average, a 1 km^2 increase in the area sprayed increases by 0.2 percentage points the probability of having a skin pathology 15 days after the treatment, and that an increase in one standard deviation in the area sprayed in the municipality of residence increases the probability of an abortion by 0.025 of a standard deviation. Given that the standard deviation of aerial spraying takes a value of

[12] For secondary enrollment rates this corresponds to the change between 2005 and 2010 , and for school dropout this corresponds to the change between 2007 and 2009. These are the only years for which these variables are available in coca-producing areas.

[13] The number is obtained based on the mean values of the share of area sprayed (0.26 percent of total area) and the total area in each municipality (2,649 km^2).

1651 in my sample[14], and that the standard deviation of abortion in their sample takes a value of 0.2, these represent a very small effect.

The results by Mej´ıa and Camacho (2012) suggest that a significant portion

of the negative effect that I identify on infant mortality may be driven by the indirect effects of spraying on rural poverty. However, more data is needed to provide a more precise decomposition of the direct and indirect effects of the program on health outcomes. Other evidence of the effect of negative income shocks on health outcomes has been found by Adda et al. (2009) and Ferreira and Schady (2009).

Finally, table V also reports the effects of aerial spraying on homicide rates per 100,000 inhabitants and number of individuals displaced by force in each municipality. The estimates in column (1) suggest that when the share of area sprayed increases by 1%, the homicide rates increase by 4.23 percentage points and the number of displaced individuals increases to around 39.52. Although it may seem these are huge effects, they are small relative to the change in these variables between 2000 and 2010. Specifically, homicide rates and forced displacement fell by 20.95 percentage points and 509 individuals, respectively, during this period.

In the past, several studies have shown the relation between drug trafficking and violence (see for instance Angrist and Kugler (2008), Dube and Vargas, (2008) and Dell (2011)), but the role that anti-drug involuntary eradication programs have on violence has never been studied before from the micro perspective. Local authorities suggested the negative effect of aerial spraying on violence may be explained by the military check-ups that take place on the ground before the aircraft begin their flights. To guarantee the security of the pilots, aerial spraying only begins once a group of men from the military or the police check the aircraft trajectory to prevent any retaliation of drug traffickers against the aircraft. These check-ups may be increasing the violence level in the treated areas in the short run by increasing the likelihood that authorities have more confrontations with drug traffickers.

An alternative explanation for this effect may be a retaliation response from drug traffickers as a consequence of the eradication. Both of these explanations are consistent with the fact that these effects seem to disappear in the long-term estimates.

6 Robustness Check

6.1 Estimates by Producer

In this section, I use a sample collected by SIMCI-UNODC at the producer level to check the effects of the program on drug production outcomes. The sample consists of two rounds of cross sections: the first collected between 2005 and

[14] This information is not available in their paper.

2006, and the second between 2007 and 2010. The producers to be surveyed were chosen by dividing the country into seven regions according to geographical characteristics. Each of the regions was divided into areas of 1 km^2, and all those grids with coca production were identified through the satellite images. The producers that were surveyed were selected randomly from the areas with coca.

The surveys contain information on the socioeconomic characteristics of producers, productivity related variables (i.e., number of harvests and kgs/ha), and the geographic location of rural producers. In the survey, I observe which producers were aerially sprayed within the last 12 months. The sample has 2535 observations. Appendix C presents the descriptive statistics of this sample. For the productivity variables, the information was collected directly on the coca crops by field workers of UNODC and not only self-reported by coca producers.

I use this sample to run equations (1) and (2) for three outcomes related to drug production: (i) hectares cultivated, (ii) kilograms of coca per hectare, and (iii) number of harvests per year. Given that there are few observations where producers are located inside protected areas, I use the distance from the location of coca producers to the border of the nearest protected area as an instrument for aerial spraying. It is expected that those producers near or within protected areas face a lower probability of being aerially sprayed. Figure XI presents some graphical evidence on the relation between the distance to the nearest protected area and aerial spraying.

As I did for the grid and municipality sample, here I multiplied the instrument by total U.S. international anti-drug expenditures. Table VI presents the estimates of the first stage equation. The estimates include the producer's age, education, and gender as well as dummies for year, region, department, and municipality. They confirm a positive effect of the instrument on the treatment assignment and reject the possibility of weak instruments.

Table VII presents the results of the OLS and 2SLS estimates of equation (1). For both, the effect of aerial spraying is negative. Yet, the impact of the program increases in absolute value for the 2SLS coefficients. This is in line with the idea that OLS estimates were biased in absolute value towards zero in the cross section.

The 2SLS results suggest that at the time of the survey the producers that were sprayed in the previous 12 months had 0.31 less hectares of coca grown relative to the other producers. This is a reduction of approximately 26%, given that the mean number of ha of coca cultivated is 1.15. The table also shows that at the time of the survey the kilograms per hectare were 81.98 lower for treated producers. This is a reduction of around 8% given a mean value of kgs/ha of 1020.97 in the data set. In addition, the results suggest that the number of harvests collected by producers that were sprayed was 0.98 lower relative to the other producers. This is a reduction of around 22% given a mean value of 4.35 for the number of harvest per year. In particular, the total hectares cultivated is around 26% lower for the treated producers relative to the control group.

These results are reassuring since they point to results similar to the ones obtained with the sample with grid units. Although I cannot address the panel endogeneity for this case, and the coefficients may be underestimating the effect of the program, at least they point to the same signs and similar magnitudes.

6.2 Placebo Test

As another robustness check, I run a placebo test using the same specification as equations (1) and (2) but replacing the dependent variable with latitude and longitude in the grid sample and with rain and altitude in the municipality sample. There is no reason why aerial spraying should be affecting those variables; hence, this is a good test for the quality of the data and estimates. Appendix D presents the results. They confirm the expected behavior, showing no relation of any of the dependent variables with aerial spraying.

7 Conclusions

This paper identifies the impact of aerial spraying on coca-producing areas in Colombia. In general, previous studies that assess the effects of anti-drug policies in producer countries have focused on theoretical models and aggregate time series. Moreover, these studies have traditionally focused on the effects that these programs have on drug production; yet, to the best of my knowledge, none of them has ever assessed how these programs affect the socioeconomic conditions of coca-producing areas (with the exception of health outcomes). This paper contributes in this direction by presenting a clean identification strategy that uses micro data to offer a complete overview of the effects that these programs generate on drug production, poverty, education, health, and violence.

Since aerial spaying is targeted through satellite images, there are various concerns when trying to identify its effect. Most of these are related with the endogeneity between aerial spraying and the outcomes. Specifically, that: (i) since coca crops are illegal in Colombia they are located in the poorest and most remote areas with the lowest governmental presence (what I called *cross-section* endogeneity), and (ii) changes in socioeconomic indicators across time make some areas more susceptible to beginning to cultivate coca (what I called *panel* endogeneity). To correct for these issues, I identify the effect of the program using instrumental variables.

The instrument exploits the plausible exogenous variation created by governmental restrictions in protected areas and the time variation in U.S. international supply anti-drug expenditures. I show that since protected areas cannot be sprayed, the likelihood of being sprayed increases outside of these areas. Moreover, in years when U.S. international supply anti-drug expenditures are higher, aerial spraying increases in non-protected areas while it remains the same in protected areas.

I study the effects of the program in the short term (12 months after treatment implementation) and in the long term (24 and 36 months after treatment reception). The results are striking: although aerial spraying reduces coca cultivation by 25% in the short term and these effects are permanent, there is a strong deterioration of the socioeconomic indicators in the treated areas. In particular, I find negative effects of the program on all rural welfare indicators. This is of great concern taking into account that the coca-producing regions are already the poorest areas of Colombia.

I also find evidence of a permanent increase in infant mortality. Specifically, infant mortality rates increase by 1.3 percentage points in areas that are aerially sprayed. Similar results were identified on skin pathologies and abortion rates by Mej´ıa and Camacho (2012).

My results also point to other negative effects of the program that somehow tend to disappear over time. For example, I find that 12 months after the treatment implementation there is an increase in school dropout of 7.5%, a decrease in secondary enrollment of 2.9%, higher homicide rates (they increase by 4.23 percentage points), and a higher number of individuals displaced by force (an increase of 39.52).

In sum, these results suggest that although involuntary eradication programs are inducing a small reduction in coca production, they create severe negative unintended effects over the treated population. These individuals may perceive that these effects are caused by the government, which in turn, may generate political unrest in coca-producing areas, further fueling the Colombian civil conflict. This points to the urgency of exploring new alternatives for controlling illicit crop production in producer countries or of combining aerial spraying with other support programs that may counteract the negative effects for cocaproducing areas.

Although this paper is able to cleanly identify the effectiveness of aerial spraying in Colombia, its main limitation is that the mechanisms that explain these effects cannot be distinguished. This may be overcome in the future if better information becomes available in coca-producing areas.

8 References

Abadie, A. J. and Imbens, G. 2002. "Instrumental Variables Estimates of the Effect of Subsidized Training on the Quantiles of Trainee Earnings." *Econometrica* 70: 91-117.

Abadie, A. J. 2003. "Semiparametric Instrumental Variable Estimation of Treatment Response Model." *Journal of Econometrics* 113: 231-263.

Adda, J., Gaudecker, H., and Banks, J. 2009. "The Impact of Income Shocks on Health: Evidence from Cohort Data." *Journal of the European Economic Association* 7 (6): 1361-1399.

Angrist, J., Imbens,G., and Rubin., D. 1996. "Identification of causal effects using instrumental variables." *Journal of the American Statistical Association* 91: 444-72.

Angrist, J. and Krueger A. 2008. "Rural Windfall or a new resource curse? Coca, Income and Civil Conflict in Colombia." *The Review of Economics and Statistics*. Vol. XC (2).

Basu, K. and Van, P.H. 1998. "The Economics of Child Labor." *The American Economic Review* 88 (3): 412-427.

Beegle, K., Dehejia, R., and Gatti, R. 2006. "Child Labor and Agricultural Shocks." *Journal of Development Economics* 81 (1): 80-96.

Bound, J., Jaeger, A., and Baker, R. 1996. "Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variable is Weak." *Journal of the American Statistical Association* 90: 443-450.

Caulkins, J. and Hao, H. 2008. "Modeling drug market supply disruptions: Where do all the drugs not go?" *Journal of Policy Modeling* 30: 251-270.

Chumacero, R. 2008. "Evo, Pablo, Tony, Diego, and Sonny General Equilibrium Analysis of the Illegal Drugs Market." Policy Research Working Paper 4565. The World Bank.

Costa Storti, C. and De Grauwe, P. 2008. "Modeling the Cocaine and Heroin Markets in the Era of Globalization and Drug Reduction Policies." Paper presented at the CESifo Venice summer institute.

D´avalos, L.M. and Bejarano, A.C. 2008. "State of the Wild 20082009: A global portrait of wildlife, wildlands, and oceans." Washington, D.C.: Island Press.

Dell, M. 2010. "Trafficking Networks and the Mexican Drug War." Job Market Paper.

Diaz, A. and Sanchez, F. 2004. "A Geography of Illicit Crops (Coca Leaf) and Armed Conflict in Colombia." Crisis States Programme. Working Paper Series N. 1 (47).

Dion, M. and Russler, C. 2008. "Eradication Efforts, the State, Displacement and Poverty: Explaining Coca Cultivation in Colombia During Plan Colombia." *Journal of Latin American Studies* 40(3): 399-421

Dube, O. and Vargas, J. 2008. "Commodity price shocks and civil conflict: Evidence from Colombia." Working Paper.

Ferreiro, F. and Schady, N. (2009). "Aggregate Economic Shocks, Child Schooling and Child Health." *The World Bank Research Observer* 24 (2).

Gaviria, A. y Mejia D. 2011. "Polticas antidroga en Colombia: xitos, fracasos y extravos." Universidad de los Andes. Editorial Kimpres. Bogota.

Grossman, H. and Mejia, D. 2008. "The War Against Drug Producers." *Economics of Governance* 9(1): 5-23.

Imbens, G. and Wooldridge, J. 2007. "What's New in Econometrics." Lecture Notes Summer 2007 NBER.

Imbens, G. W. and Angrist, J. D. 1994. "Identification and estimation of local average treatment effects." *Econometrica* 62(2): 467-475.

Jacoby, H. and Skoufias, E. 1997. "Risk, financial markets, and human capital in a developing country." *Review of Economic Studies* 64 (3): 311335.

Mejia, D. 2008. "The War on Illegal Drugs: The interaction of anti-drug policies in producer and consumer countries." Mimeo, Universidad de los Andes.

Mejia C. and Camacho, A. 2012. "The Health Consequences of Aerial Spraying of Illicit Crops: The Case of Colombia." Mimeo.

Mejia, D. and Posada, J. 2008. “Cocaine Production and Trafficking: What do we know?” Policy Research Working Paper 4618. The World Bank.

Mejia, D. and Restrepo, P. (2011). “The War on Illegal Drugs in Producer and Consumer Countries: A simple analytical framework.” Documento CEDE No. 2, 2011. Universidad de los Andes. Forthcoming as Chapter 10 in the book
Illicit Trade and the Global Economy (P. De Grawe and C Costa-Sorti, eds.), MIT Press.32

Moreno-Sanchez, R., Kraybill. D., and Thomson, S. 2003. “An Econometric Analysis of Coca Eradication Policy in Colombia.” *World Development* 31 (2): 375-383.

Office of National Control Policy (2012). Budget Summary of the U.S. Washington D. C.

Rydell, P., Caulkins, J., and Everingham, S. 1996. “Enforcement or Treatment: Modeling the Relative Efficacy of Alternatives for Controlling Cocaine.” *Operations Research* 44(5): 687-95

Staiger, D. and J. Stock. 1997. “Instrumental Variables Regression with Weak Instruments.” *Econometrica* 68: 1055-1096.

Tragler, G., Caulkins, J., and Feichtinger, G. 2001. “Optimal Dynamic Allocation of Treatment and Enforcement In Illicit Drug Control.” *Operations Research* 49(3): 352-62.

UNODC (2010). World Drug Report -2010. New York.

UNODC (2011). World Drug Report -2011. New York.

UNODC (2012). World Drug Report -2012. New York.

Wright, S. 1992. “Adjusted P-Values for Simultaneous Inference.” *Biometrics* 48: 1005-1013.

9 Tables and Figures

Table I: Summary of Data Sets

	Data Set 1	Data Set 2
Units	Grid (1 squared km=100 ha)	Municipality
Years	2000-2010	2001-2010
Frequency	Yearly	Yearly
Type of Data	Panel	Panel
Observations	1,115,840	2880
Coca (ha)	Yes	Yes
Aerial Spraying (Ha)	Yes	Yes
Manual Eradication(Ha)	Yes	Yes
Other Variables	–	Violence, Education, Health, Poverty, Geographic Characteristics, Area, Rural Population, Government Expenditures, and Authorities Presence.

Note: The data on hectares of coca was processed by the United Nations Office of Drugs and Crime (UNODC) through satellite images collected every December. Data on hectares aerially sprayed comes from the Colombian Antinarcotics National Police (DIRAN). All other variables come from diverse agencies of the Colombian government. See Appendix A for the specific sources.

Table II: First Stage Results (Grid-point sample)

Dependent Variable: Ha Sprayed			
Independent Variables	(1)	(2)	(3)
$Instrument_{it}$	0.48***		
	(0.06)		
$I(OutsideProtectedAreas)_i$		0.64***	
		(0.03)	
$U.S.\ International\ Supply\ Anti\text{-}drug\ Expenditures_t$			0.4
			(0
Year FE	X	X	
Grid FE	X		X
R-squared	0.18	0.2	0.08
F-Test (excluded instruments)	48.87	269.52	62.91
Partial R-squared	0.08	0.09	0.03
N. of Clusters		101440	
Observations		1115840	
Mean Values			
$Instrument_{it}$		1.27	
$I(OutsideProtectedAreas)_i$		0.84	
$U.S. International Supply\ Anti\text{-}drug\ Expenditures_t$		1.51	

Note: The table presents the first stage estimates of the specification presented on equations (1) and (2) for the data with grid units. Each grid corresponds to an area of 1 square kilometer. The sample includes all the grids in Colombia that had a positive number of hectares of coca cultivated between 2000 and 2010. U.S. international anti-drug expenditures are expressed in real billions of 2010 dollars. $I(OutsideProtectedAreas)_i$ is an indicator variable that takes the value of one if the grid is outside indigenous territories and natural parks. Clustered standard errors at the grid level are presented in parentheses. *** Significant at 1% level.

Table III: First Stage Results (Municipality Sample)

Dependent Variable: Area Sprayed (% of Total Area)			
Independent Variables	(1)	(2)	(3)
$Instrument_{it}$	0.18***		
	(0.03)		
$Share\ Outside\ Protected\ Areas_i$		0.32***	
		(0.07)	
$U.S.\ International\ Supply\ Anti\text{-}drug\ Expenditures_t$			2.04*
			(0.0
Year FE	X	X	
Municipality FE	X		X
R-squared	0.17	0.2	0.11
F-Test (excluded instruments)	21.71	19.91	17.96
Partial R-squared	0.05	0.06	0.04
N. of Clusters		288	
Observations		2880	

Mean Values	
$Instrument_{it}$	1.29
$ShareOutsideProtectedAreas_i$	0.86
U.S.InternationalSupply Anti-drug $Expenditures_t$	1.50
Aerial Spraying (ha)	0.26

Note: The table presents the first stage estimates of the specification presented on equations (1) and (2). The sample includes all the Colombian municipalities that had a positive number of hectares of coca cultivated between 2001 and 2010. Since municipalities vary in size, all variables expressed in hectares were scaled by total area. U.S. international anti-drug expenditures are expressed in real billions of 2010 dollars. $ShareOutsideProtectedAreas_i$ corresponds to the percentage of total area outside indigenous territories and natural parks in each municipality. Clustered standard errors at the municipality level are presented in parentheses. *** Significant at 1% level.

TableIV:ImpactofSprayingonCocaProduction(Grid-pointSample)

	DependentVariable:Coca(ha)		
	Short-term	2yearsaftertreatment	3yearsaftertreatment
IndependentVariables	(1)	(2)	(3)
HaSprayedatt	-0.21***		
	(0.04)		
HaSprayedatt-1		-0.36***	
		(0.07)	
HaSprayedatt-2			-0.18***
			(0.06)
YearFE	X	X	X
GridFE	X	X	X
R-squared	-5.89	-25.19	-9.73
N.ofClusters	101440	101440	101440
Observations	1115840	1014400	912960
MeanValues			
HaSprayed	0.54		
Coca(ha)	0.84		

Note:Thetablepresentstheestimatesofthestructuralequationofthespecificationpresentedinequations(1)and(2)by2SLSusing $I(Outside\ Protected\ Areas)_i * U.S.\ Anti\text{-}drug\ Expenditures_t$ as an instrument. The estimates correspond to the data set by grid units. Each grid corresponds to an area of 1 square kilometer. The sample includes all the grids in Colombia that had a positive number of hectares of coca cultivated between 2000 and 2010. Column (1) presents the effect of the program 1 to 12 months after the treatment reception, column (2) presents the effect 13 to 24 months after the treatment reception, and column (3) presents the effect of the program 25 to 36 months after the treatment implementation. *Coca* represents the total hectares of coca cultivated observed through satellite images. Clustered standard errors at the grid level arepresentedinparentheses.***Significantat1%leveland**Significantat5%level.

Table VI: First Stage Results (Producer Sample)

Dependent Variable: $I(Sprayed > 0)$

TableV:ImpactonWelfareIndicators(MunicipalitySample)

	1 yearafter	2yearsafter	3yearsafter
	(1)	(2)	(3)
PovertyRates	0.04***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)
PrimaryEnrollment	-0.71	-1.18	-1.93
	(3.23)	(5.75)	(4.28)
SecondaryEnrollment	-2.13***	-1.75	-1.09
	(0.43)	(4.3)	(4.2)
SchoolDropout	0.82***	0.36	0.34
	(0.26)	(0.67)	(3.45)
InfantMortality	1.26***	0.97*	0.94***
	(0.29)	(0.31)	(0.26)
HomicideRate	4.23**	-5.1	-3.56
	(1.60)	(5.62)	(3.45)
ForcedDisplacement	39.52***	37.26	41.99
	(15.79)	(39.95)	(90.95)
MeanValues			
PovertyRates(Percentageofruralpopunderpovertyline)	0.56		
PrimaryEnrollment(Registeredstudents/Popinage)	128.93		
SecondaryEnrollment(Registeredstudents/Popinage)	71.21		
SchoolDropout(Registeredstudents/studentsfinishingyear)	10.8		
InfantMortality(Deathsofind.youngerthan1year/Ind.bornalive)	44.1		
HomicideRate(Homicides/100,000inh)	55.85		
ForcedDisplacement(N.ofindividuals)	592.7		
AreaSprayed(%ofTotalArea)	0.26		
NofClusters	288		
Observations	2880	2592	2304

Note:Thetablepresentstheestimatesofthestructuralequationofthespecificationpresentedinequations(1)and(2)by2SLSusing $ShareOutsideProtectedAreas_i * U.S.Anti-drugExpenditures_t$ asaninstrument.Eachrowinthetablereportstheresultsofaseparateregression thatstudiestheimpactofsprayingoneachoftheindependentvariableslistedabove.Theestimatescorrespondtothedatasetbymunicipalityunits. ThesampleincludesallColombianmunicipalitiesthathadapositivenumberofhectaresofcocacultivatedbetween2001and2010.Eachregression includedfixedeffectsbymunicipalityandyear.Column(1)presentstheeffectoftheprogram1to12monthsafterthetreatmentreception,column presentstheeffect13to24monthsafterthetreatmentreception,andcolumn(3)presentstheeffectoftheprogram25to36monthsafterthe treatmentimplementation.Clusteredstandarderrorsatthemunicipalitylevelarepresentedinparentheses.*Significantat10%,**Significantat %,and***Significantat1%.

Independent Variables	(1)	(2)	(3)
$Instrument_{it}$	0.03***		
	(0.00)		
$Min\ Distance\ to\ Protected\ Areas_i$		0.02***	
		(0.00)	
$U.S.\ International\ Supply\ Anti\text{-}drug\ Expenditures_t$			
			(0.05)
Covariates	X	X	X
R-squared	0.46	0.45	0.43
Partial R-squared	0.1	0.08	0.13
F (excluded instrument)	29.3	13.77	160.9
Observations	2102	2102	2102
Mean Values			
Instrument$_{it}$		89.44	
MinDistancetoProtectedAreas$_i$		51.67	
U.S.InternationalSupply Anti-drug Expenditures$_t$		1.69	
I(*Sprayed* > 0)		0.23	

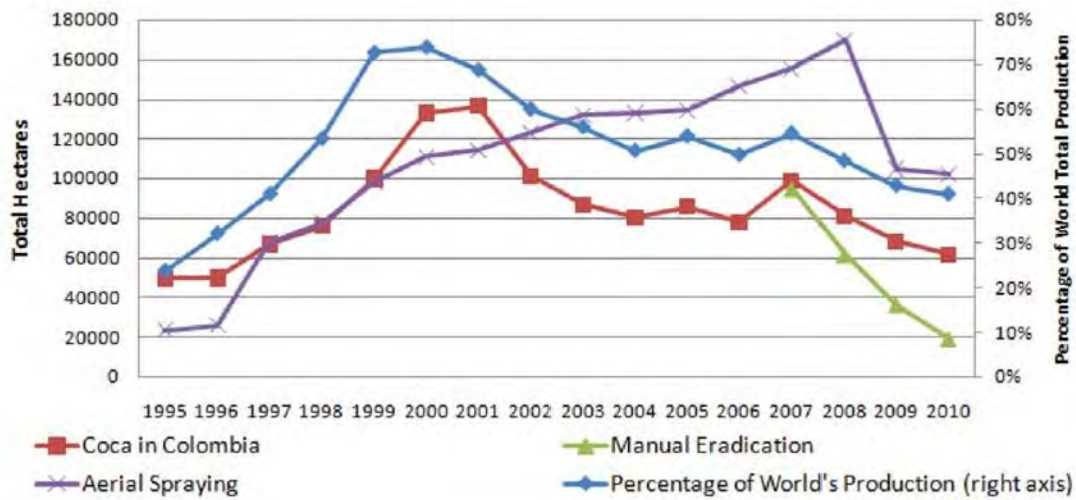
Note: The table presents the first stage regression of the equations (1) and (2). The estimates correspond to the data collected at the producer level by the United Nations Office of Drugs and Crime (UNODC). The sample consists of two rounds of cross sections, one collected between 2005 and 2006, and the second between 2007 and 2010. The producers that were surveyed were selected randomly from the areas with coca. *I*(*Sprayed* > 0) corresponds to an indicator variable that takes the value of one if the producer was sprayed 12 months before the survey. *MinDistancetoProtectedAreas* represents the minimum distance between each producer and the nearest border to a protected area. U.S. international anti-drug expenditures are expressed in real billions of dollars of 2010, and $Instrument_{it} = MinDistancetoProtectedAreas_i * U.S.Anti - drug\ Expenditures_t$. The covariates included in the regressions were age, education, and gender. The estimates also included dummies for year, region, department, and municipality. Only the estimations with the U.S. Expenditures do not included dummies for year. Robust standard errors are presented in parentheses. * Significant at 10%, ** Significant at 5%, and *** Significant at 1 %.

Table VII: Impact of Spraying on Drug Production (Producer Sample)

	Dependent Variables					
	Coca (ha)		Kgs/Ha		N. Harvest	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Indp. Variable	(1)	(2)	(3)	(4)	(5)	(6)
$I(Sprayed > 0)$	-0.04**	-0.31***	-76.60**	-81.63**		
	(0.01)	(0.02)	(34.22)	(37.70)		

Covariates	X	X	X	X	X	X
R-squared	0.35	0.18	0.48	0.40	0.60	0.60
Observations	2099	2099	2099	2099	2099	2099
		Mean Values				
Coca (ha)		1.15				
Kgs/Ha		1022.41				
N of Harvests		4.48				
I(*Sprayed* > 0)		0.23				

Note: The table reports the estimates of equation (1) and (2) by OLS and 2SLS. The estimates correspond to the micro data collected at the producer level by the United Nations Office of Drugs and Crime (UNODC).The sample consists of two rounds of cross sections, one collected between 2005 and 2006, and the second between 2007 and 2010. The producers that were surveyed were selected randomly from the areas with coca. $I(Sprayed > 0)$ corresponds to an indicator variable that takes the value of one if the producer was sprayed 12 months before the survey. Columns (2), (4) and (6) report the results of an instrumental variables regression using $MinDistancetoProtectedAreas_i * U.S.Anti-drug\ Expenditures_t$ as an instrument. *Coca* represents the number of hectares of coca cultivated by each producer, *Kgs/Ha* is a proxy for productivity that measures the total kilograms of coca produced per hectare cultivated, and *N.Harvest* measures the number of times producers collect the coca crops per year. The covariates included at the producer level were age, education and gender. The estimates included dummies for year, region, department, and municipality. Robust standard errors are presented in parentheses. * Significant at 10%, ** Significant at 5%, and *** Significant at 1 %.



FigureI:CocaProduction,AerialSprayingandManualEradicationinHectares

Note:HectaresofcocacultivatedandhectaresmanuallyeradicatedwhereobtainedfromfromUNODC.Thedataontotalhectaresaeriallysprayed comesfromtheColombianAntinarcoticsPolice.ThebluelinecorrespondstotheColombiancocaproductionasapercentageoftheworld's production,whichamountstotheaggregatecocaproductionofBolivia,Peru,andColombia.ThesedataisgatheredandprocessedthroughsatelliteimagesbyUNODC.

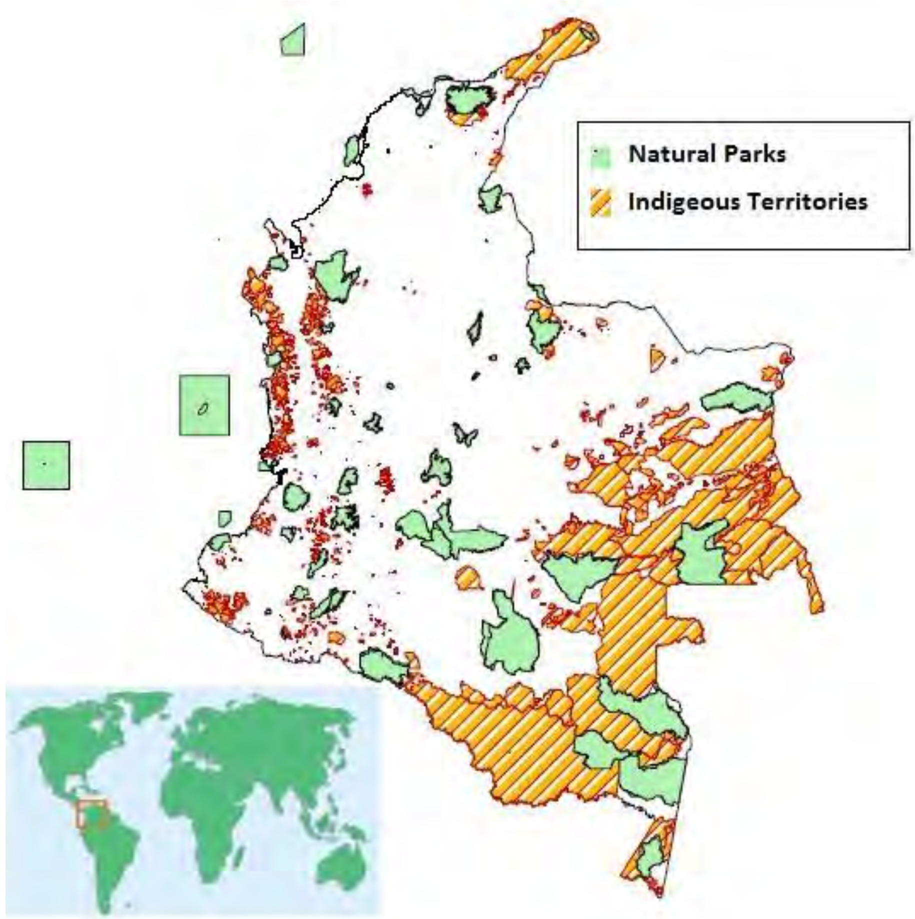
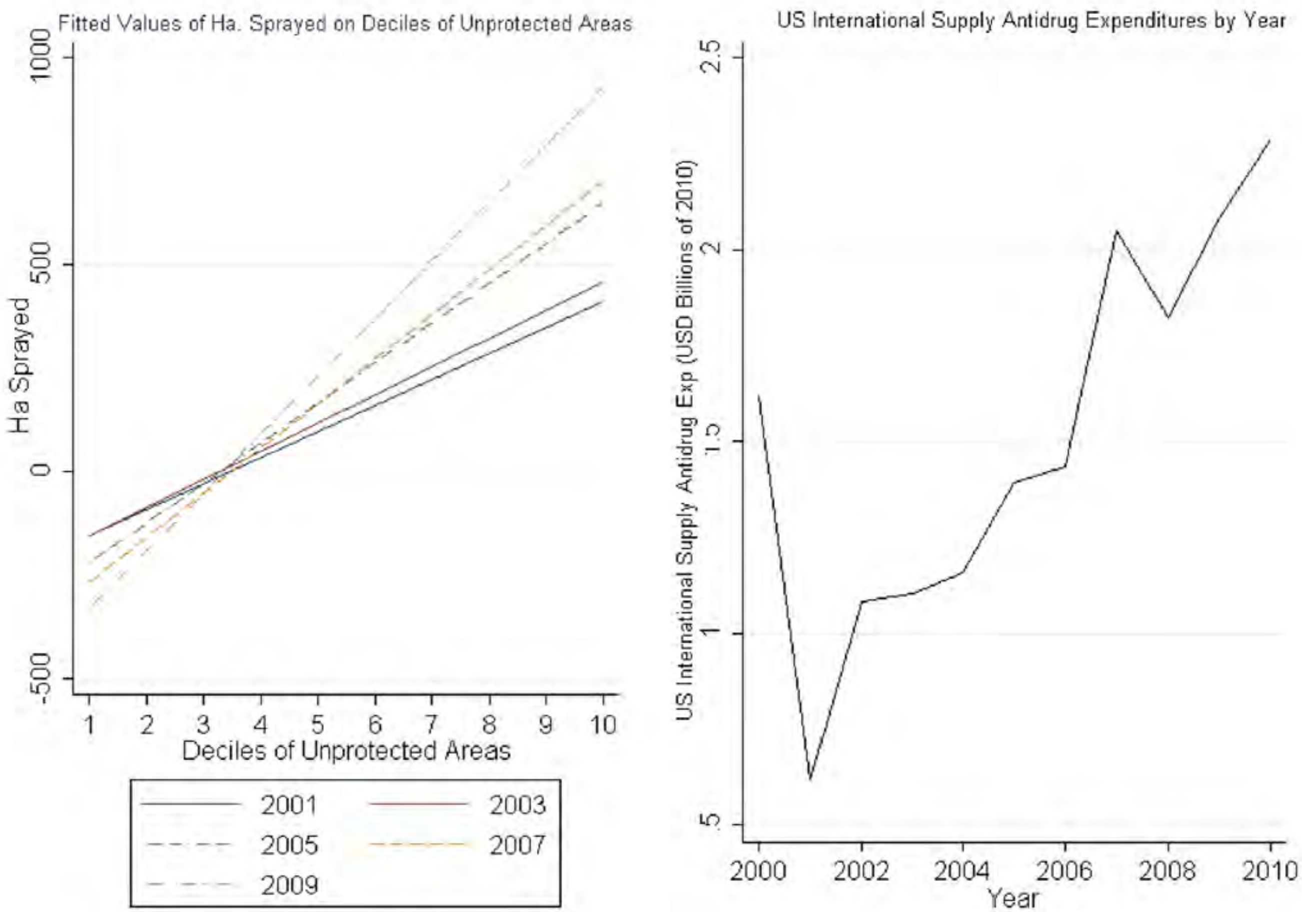


Figure II: Location of Protected Areas in Colombia

Note: This figure presents the geographic location of natural parks and indigenous territories in Colombia. By governmental mandate, natural parks and indigenous territories cannot be sprayed in Colombia. Natural parks and indigenous territories comprise 12% and 27.6% of the Colombian territory, respectively. The source of the geographical location of protected areas is the National Geographical Institution in Colombia (i.e., Instituto Geografico Agustin Codazzi).

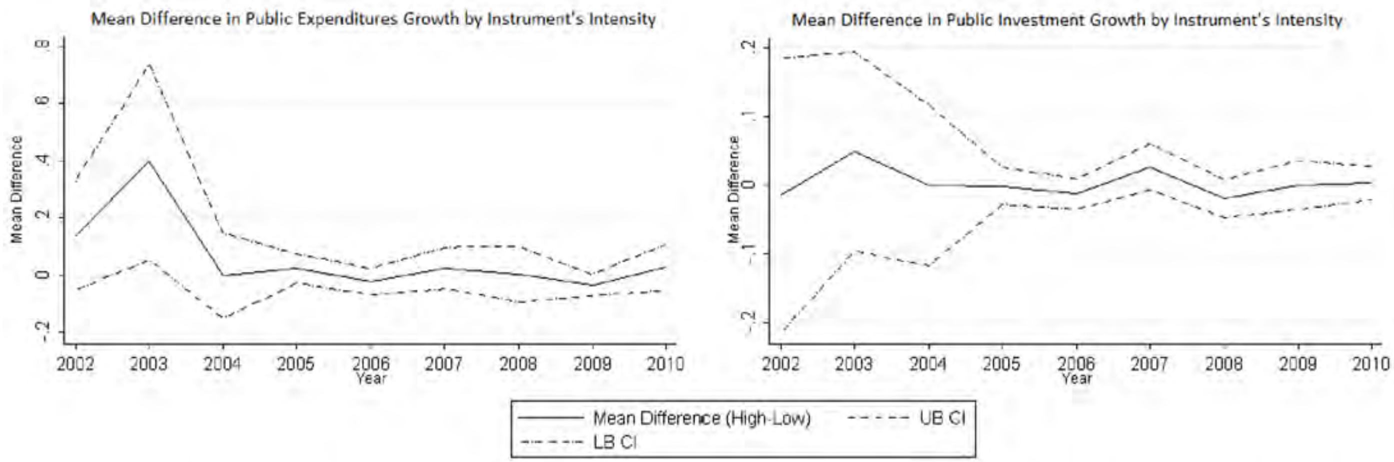


PANEL A

PANEL B

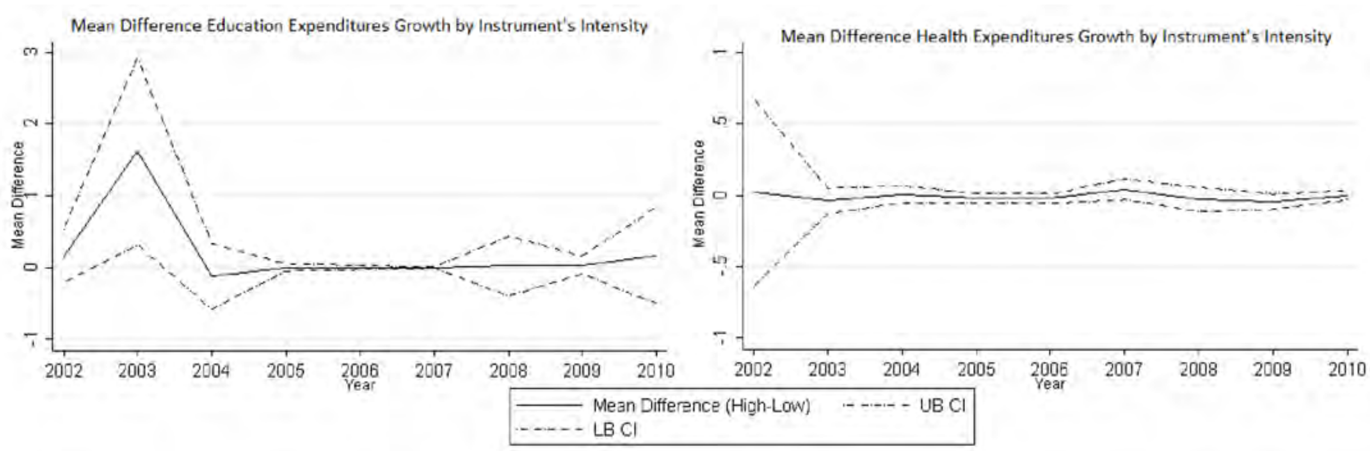
FigureIII:TreatmentIntensityandInstrumentVariation

Note:PanelAwasconstructedwiththemicrodatabymunicipality.Itpresentsafittedlineofthetotalnumberofhectaressprayedbydecilesofthe shareofunprotectedareasineachmunicipality.Higherdecilesof *UnprotectedAreas* correspondtomunicipalitieswithalowershareofprotected areasinitsterritory.Thepanelpresentsadifferentfittedlinefortheoddyearsbetween2000and2010.IntheseyearsU.S.internationalanti-drug expendituresexpressedinrealbillionsof2010wereincreasing(seePanelB).Thefiguresuggeststhat:(i)municipalitieswithahighershareof non-protectedareashadahighernumberofhectaressprayed,and(ii)inyearswhentheU.S.anti-drugexpenditureswerehigher(asshowninPanel B),theintensityoftreatmentincreasedmorefornon-protectedareas.



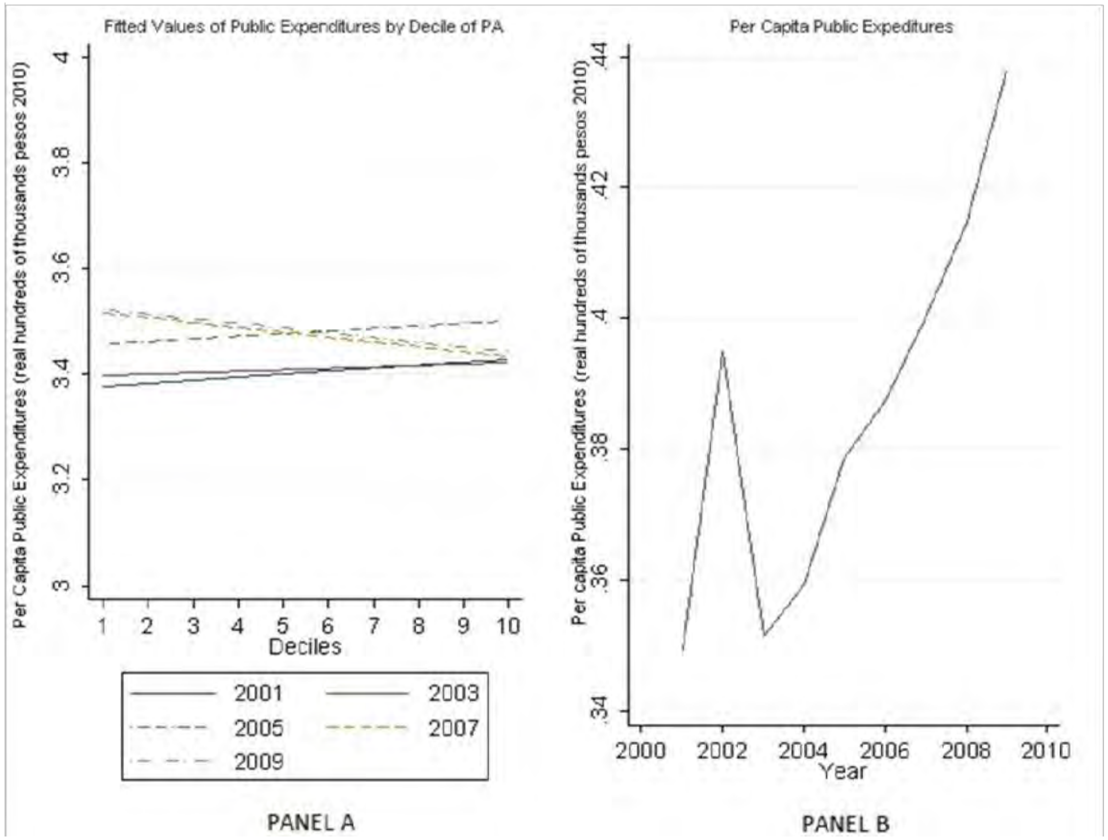
FigureIV:MeanDifferenceinPublicExpendituresandInvestmentGrowthbyInstrument'sIntensity

Note:Thisfigurewasconstructedwithmicrodatabymunicipality.Foreachyearthe $instrument_{it} = ShareOutsideProtectedAreas_i * U.S.Anti\text{-}drugExpenditures_t$ wasdividedintotwogroupsaccordingtoitsintensity.Thehighinstrumentintensitygroupincludesalltheob-servationswithaninstrumentdecilehigherthanfive,whereasthelowintensitygroupincludesallmunicipalitieswithdecilesequaltoorlowerthan five.Thefiguresshowthatthereisnostatisticaldifferenceinthepublicexpendituresandpublicinvestmentgrowthbetweengroups.Thedataon publicexpendituresandpublicinvestmentcomefromtheColombianNationalPlanningDepartment.



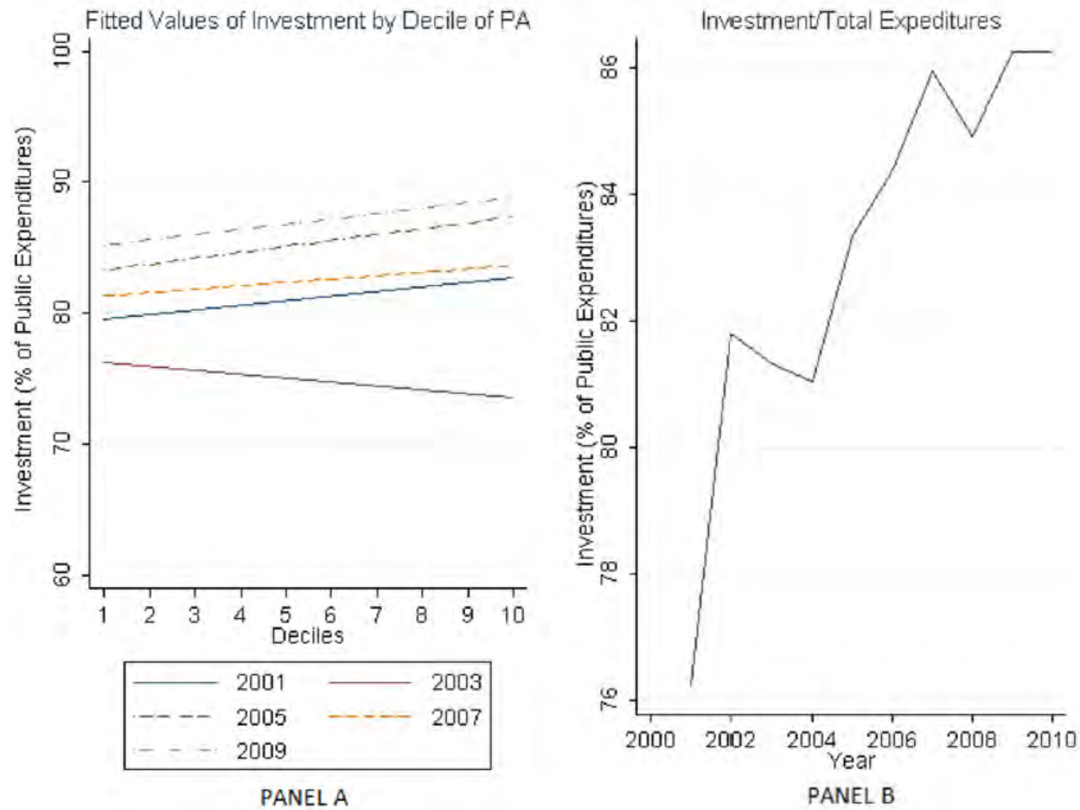
FigureV:MeanDifferenceinPublicExpendituresGrowthbyInstrument'sIntensity

Note:Thisfigurewasconstructedwithmicrodatabymunicipality.Foreachyearthe $instrument_{it} = ShareOutsideProtectedAreas_i * U.S.Anti\text{-}drugExpenditures_t$ wasdividedintotwogroupsaccordingtoitsintensity.Thehighinstrumentintensitygroupincludesalltheobservationswithaninstrumentdecilehigherthan5,whereasthelowintensitygroupincludesallmunicipalitieswithdecilesequaltoorlowerthan five.Thefiguresshowthatthereisnostatisticaldifferenceinthepublicexpendituresandpublicinvestmentgrowthbetweengroups.Thedataon publicexpendituresandpublicinvestmentcomefromtheColombianNationalPlanningDepartment.



FigureVI:PerCapitaPublicExpendituresandInstrument’sIntensity

Note:PanelAwasconstructedwiththemicrodatabymunicipality.Itpresentsafittedlineofthepercapitapublicexpendituresbydecilesofthe shareofunprotectedareasineachmunicipality.HigherdecilesofUnprotectedAreascorrespondtomunicipalitieswithalowershareofprotected areasinitsterritory.Thepanelpresentsadifferentfittedlinefortheoddyearsbetween2000and2010.Intheseyearspercapitapublicexpenditures expressedinhundredsofthousandsofrealpesosof2010wereincreasing(seePanelB).



FigureVII:PublicInvestmentandInstrument'sIntensity

Note:PanelAwasconstructedwithdatabymunicipality.Itpresentsafittedlineofthepublicinvestment(asa%ofpublicexpenditures)by decilesoftheshareofunprotectedareasineachmunicipality.HigherdecilesofUnprotectedAreascorrespondtomunicipalitieswithalowershare ofprotectedareasintheirterritory.Thepanelpresentsadifferentfittedlinefortheoddyearsbetween2000and2010.

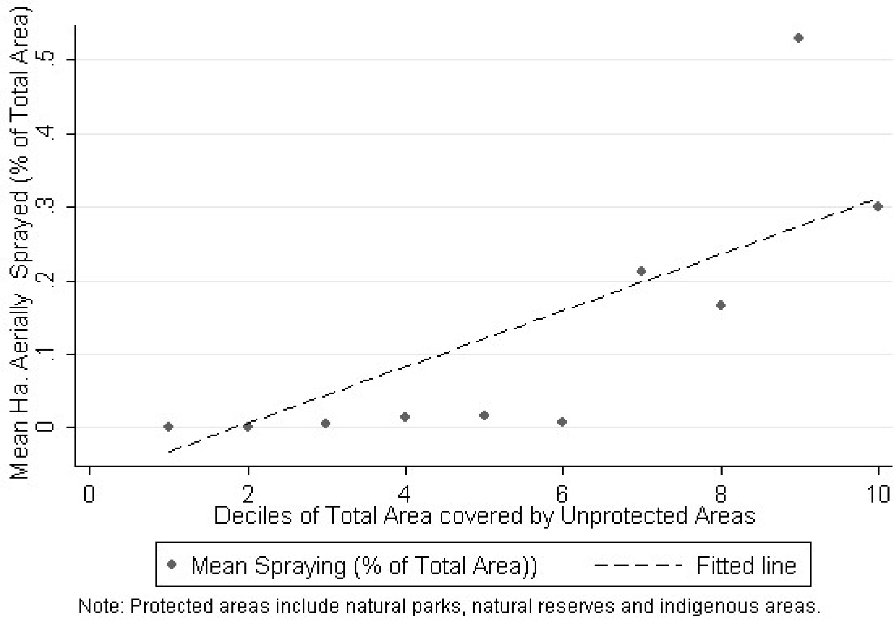


Figure VIII: Aerial Spraying in Unprotected Areas

Note: This figure was constructed with data at the municipality level. It shows the mean hectares of area sprayed as a percentage of total area in each municipality against deciles of the share of area covered by unprotected areas. It confirms that municipalities with a lower share of protected areas have a higher number of hectares aerially sprayed.

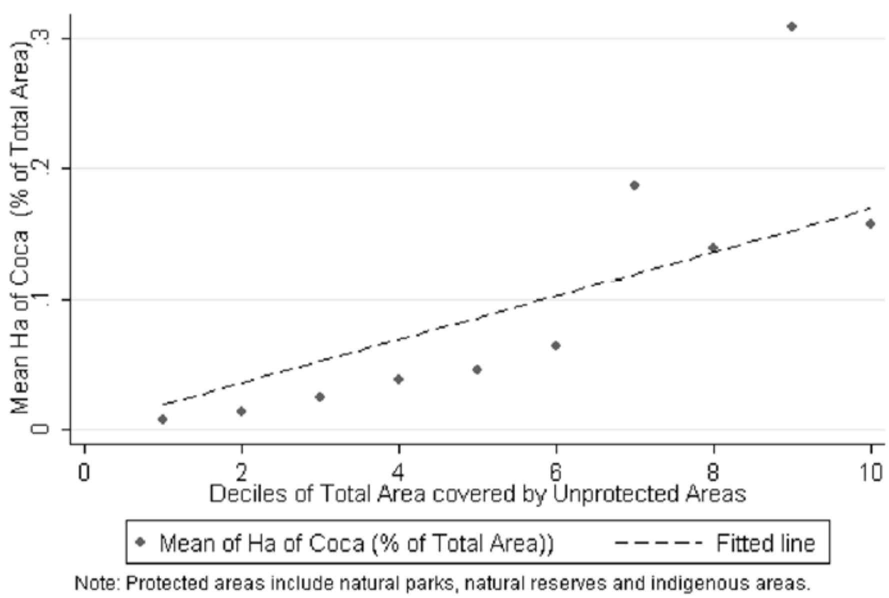


Figure IX: Coca Cultivation in Unprotected Areas

Note: This figure was constructed with data at the municipality level. It shows the mean hectares of coca cultivated as a percentage of total area in each municipality against deciles of the share of area covered by unprotected areas. It confirms that municipalities with a higher share of protected areas do not have a higher number of hectares of coca cultivated.

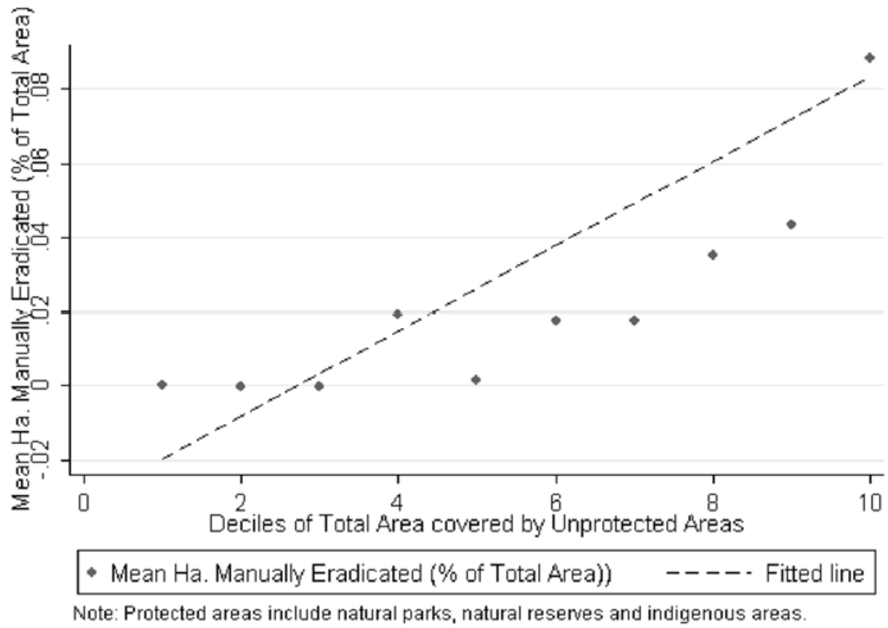


Figure X: Manual Eradication in Unprotected Areas

Note: This figure was constructed with data at the municipality level. It shows the mean hectares manually eradicated as a percentage of total area in each municipality against deciles of the share of area covered by unprotected areas. It confirms that municipalities with a higher share of protected areas do not have a higher number of hectares manually eradicated.

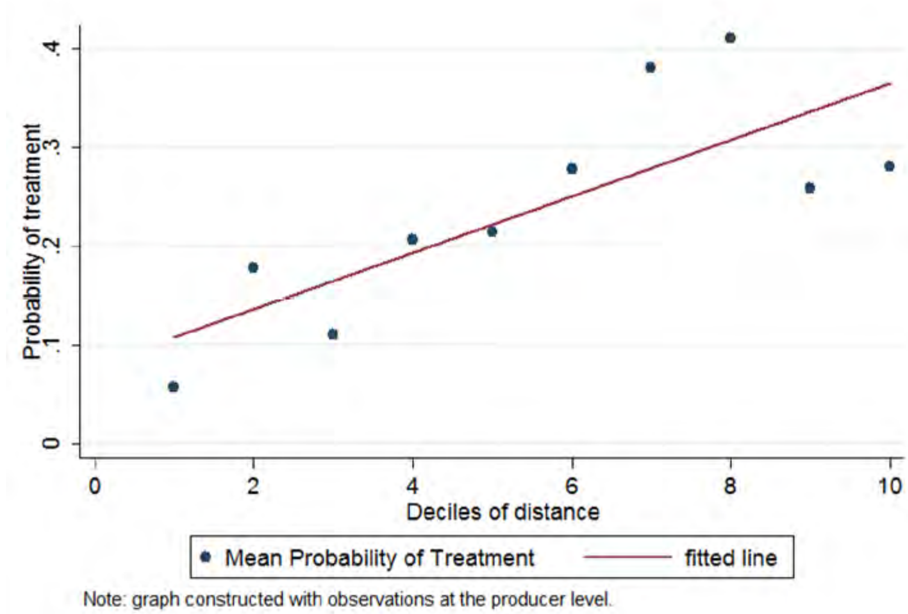


Figure XI: Distance to Nearest Protected Area and Probability of Treatment

Note: This figure was constructed with data collected at the producer level. It shows the probability that a producer was aerially sprayed against deciles of the minimum distance of each producer to the nearest protected area. It confirms that producers located farther away from protected areas have a higher probability of being sprayed.

Appendices

A Descriptive Statistics and Sources

Table A.1: Descriptive Statistics - Grid Sample

	Mean	St Deviation
Manually Eradicated (Ha)	0.11	1.51
Aerial Spraying (Ha)	0.54	26.89
Coca	0.84	2.46
N of Observations	1115840	
N of Groups	101440	
Years	11	
Period	2000 to 2010	

Note: this table presents the descriptive statistics of a panel data set with grid units. Each grid corresponds to an area of 1 km^2. The sample includes all the grids in Colombia that had a positive number of hectares of coca cropped between 2000 and 2010.

Table A.2: Data Sources - Municipality Sample

Outcome	Variable	Source
Drugs	Aerial Spraying	Antinarcotics National Police (DIRAN)
	Manual Eradication	UNODC
	Hectares of Coca	UNODC
Violence	Homicide Rates	Vicepresidency
	Armed Confrontations	Vicepresidency
	Displaced Individuals	Administrative Dep. For Social Prosperity
Education	Primary Enrollment Rate	Ministry of Education
	Secondary Enrollment Rate	Ministry of Education
	School Drop-Out Rate	Ministry of Education
Health	Infant Mortality	National Statistical Department (DANE)
Poverty	Unsatisfied Basic Needs	National Statistical Department (DANE)
	Quality of Life Index	National Planning Department
	Poverty Rate	Constructed with data from the 2005 (CEDE)

Note: this table describes the sources of the variables available in the sample by municipality. The sample includes all the Colombian municipalities that had a positive number of hectares of coca cropped between 2001 and 2010. They account for 288 muncipalities.

Table A.3: Variable Definitions- Municipality Sample

Variable	Definition	Years
Homicide Rates	Homicides /100,000 pop	2001-2010
Armed Confrontations	Number of actions	2001-2010
Displaced Individuals	Number of individuals	2001-2010
Primary Enrollment Rate	(Registered students/Pop in age)*100	2005-2010
Secondary Enrollment Rate	(Registered students/Pop in age)*100	2005-2010
School Dropout Rate	(Registered students/students that finish academic year)*100	2007-2009
Infant Mortality	(Deaths of ind. younger than 1 year / Ind. born alive)*100	2006, 2007
Unsatisfied Basic Needs	(Indv with unsatisfied need/Total pop)*100	2005 and 2010
Quality of Life Index	Maximum Value (excellent conditions)=100, Min Value=0	2005
Poverty Rate	Percentage of rural pop under poverty line*	2005

Note: this table describes the definitions and years of availability of the variables included in the sample by municipality. The sample includes all the Colombian municipalities that had a positive number of hectares of coca cropped between 2001 and 2010. They account for 288 muncipalities.

Table A.4: Descriptive Statistics - Municipality Sample

	Observations	Mean	St_Dev
Sprayed	2680	429.6385	1615.627
Manual Eradication	1072	70.24467	1058.197
Coca	2680	290.6657	868.6115
Homicide Rates	2680	54.90541	66.80186
Displaced Individuals	2680	582.6216	1242.691
Primary Enrollment Rate	1340	129.3728	37.45113
Secondary Enrollment Rate	1340	71.43532	29.17269
School Drop-Out Rate	804	10.69174	5.798444
Infant Mortality	536	44.03243	18.23138
Poverty Rate	268	0.5698644	0.093297

Note: this table presents the descriptive statistics of a panel data set by municipality. The sample includes all the municipalities in Colombia that had a positive number of hectares of coca cropped between 2000 and 2010.

B Spillover Effects

Table B.1: Results of Equation (3)- (Municipality Sample)

Dependent Variable: Ha of Coca in Area not Sprayed in t-1			
Independent Variable	(1)	(2)	(3)
Ha Sprayed in t-1	0.1***	0.1***	-0.11***
	(0.01)	(0.01)	(0.03)
R-squared	0.02	0.04	0.005
Observations	2880	2880	2880
N of Clusters	288	288	288
Year FE		X	X
Mun FE			X

Note: this table presents the results of the regression of equation (3) by OLS. The estimates correspond to the micro data set by municipality units. The sample includes all Colombian municipalities that had a positive number of hectares of coca cropped between 2001 and 2010. *HaSprayedint*−1 represents the total ha sprayed in municipality i in $t-1$, and the dependent variable is the total hectares of coca cropped in the municipalities that belong to the same department as municipality i but which were not treated in $t-1$ or in t. Clustered standard errors at the municipality level are presented in parentheses. Regressions include dummies for region. *** Significant at 1% level.

C Descriptive Statistics for Producer's Sample

Table C.1: Descriptive Statistics

	2005-2006 - Total		2007-2010 - Total	
Variable	Mean	St Dev	Mean	St Dev
Gender	0.9087222	0.2881076	0.936095	0.2446904
Age	38.34148	11.35844	40.6126	11.69249
Education (Years)	3.582412	1.497889	4.064167	1.996461
Experience	6.644788	4.298623	6.771643	3.579531
N. Household Members	5.102483	2.250969	5.016029	3.34812
Coca 1st Eco. Activity	0.9698634	0.1710246	0.8681664	0.3384575
Sell Coca Leaf	0.3406667	0.4741041	0.5041651	0.5002009
Area of Farm (Ha)	19.88769	38.68512	16.6291	32.21931
N. of Workers /Ha of coca	4.880347	4.663753	3.95868	4.822073
N. Workers / Ha of coca	6.053402	7.929141	9.868221	8.04295
Harvested Area	1.071285	0.864355	1.081115	0.953343
N. Harvest/Year	4.360391	2.039785	4.33752	1.383656
Kgs of Coca/Ha coca	1097.494	398.098	928.2207	410.5222
Number of obs	1389		1146	

Note: this table presents the descriptive statistics of the micro data set collected at the producer level by the United Nations Office of Drugs and Crime (UNODC). The sample consists of two rounds of cross sections, one collected between 2005 and 2006, and the second between 2007 and 2010. The coca-producers that were surveyed were selected randomly from the areas with coca.

D Placebo Test

Table D.1: Place Test (Grid Sample)

Dependent Variable:	Latit ude		Longi tude	
	OLS	2SLS	OLS	2 SLS
	(1)	(2)	(1)	(2)
Ha Sprayed	0.20	-0.46	-0.76	1.33
	(1.54)	(6.19)	(0.82)	(12.62)
Year FE	X	X	X	X
Grid FE	–	–	–	–
R-squared	0.98			
N. of Clusters	1014 40		1014 40	
Observations	1115840		1115840	

Note: this table presents the results of the same specification as equations (1) and (2) but replacing the dependent variable with latitude and longitude using data from the grid sample. Each grid corresponds to an area of 1 km^2. The sample includes all the grids in Colombia that had a positive number of hectares of coca cropped between 2000 and 2010. Clustered standard errors at the grid level are presented in parentheses. Regressions include dummies for region, department, and municipality. *** Significant at 1% level.

Table D.2: Place Test (Municipality Sample)

Dependent Variable	Rain				
	OLS	OLS -Panel	2SLS-Panel	OLS	2 SLS
	(1)	(2)	(3)	(1)	(2)
Area Sprayed (% of Total Area)	0.75	0.32	-661.47	-45.14	314.58
	(5.44)	(1.37)	(1127.21)	(33.9)	(681.94)
Year FE	X	X	X	X	X
Grid FE		X	X	–	–
R-squared	0.41	0.01	-0.1	0.38	0.07
N. of Clusters	288				
Observations	2880				

Note: this table presents the results of the same specification as equations (1) and (2) but replacing the dependent variable with rain and altitude. The estimates correspond to the micro data set by municipality units. The sample includes all Colombian municipalities that had a positive number of hectares of coca cropped between 2001 and

2010. Clustered standard errors at the municipality level are presented in parentheses. Regressions include dummies for region and department. *** Significant at 1% level.