# On the Unintended Consequences of Anti-drug Eradication Programs in Producing Countries**

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**Abstract**

While the war against drugs has consumed approximately 40 billion dollars per year in the last four decades, there is very limited evidence on its effectiveness. This paper studies the effects of the biggest anti-drug program ever applied in a drug-producing 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 with 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 in 1%, poverty rates increase in 4 percentage points, school drop-out increases in 0.82 percentage points, infant mortality rates increase 1.26 percentage points, and homicide rates increase in 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.

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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[1]. Although there is some evidence on the effectiveness of demand side interventions, 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. This paper investigates the effectiveness and welfare consequences of aerial spraying with herbicides of 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 US governments towards reducing cocaine's supply. Between 2000 and 2010 the US government spent around 6 billion dollars in international supply control in Colombia (Office of National Control Policy), making Colombia the third recipient of military foreign aid from the US (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), Mejía (2008), Chumacero (2008), Costa-Storti and De Grauwe (2008), Grossman and Mejía (2008), Tragler et al. (2008), Dion and Russel (2008), and Mejía 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 posses considerable threats of endogeniety, 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 asses the impact of anti-drug programs in producing countries. I investigate effect of aerial spraying with herbicides not only on coca production, but more

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

importantly, on the welfare conditions of coca-producing areas, and analyze the spillover effects of the program to 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)[3], and to check if spraying spreads coca production in the neighbouring areas that were not treated (i.e., creates spillovers). Moreover, I aggregate these data on municipality units and combine it 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. *Cross section endogeneity* in coca production arises since the targeted areas have more hectares of coca. It also arises for the socioeconomic indicators since coca growing is illegal in the country and hence coca-producing areas and 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 the time variation in US 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 US anti-drug expenditures are higher, but it should not be affected for the 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 suggesting that treated producers do not go back to coca production. I also check for evidence of spillovers of the program and find no evidence that coca production increases in the non-treated areas close to the treated ones. This may suggest that if

[3]given that some outcomes and not observed throughout the period of analysis the long term affects can only be assessed 3 years after the program implementation

producers are changing locations they may be going to areas further away from the treated ones, or even 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 on 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 in -2.13 percentage points and increases dropout rates by 0.82 percentage points. These suggest that as a result of the program older children may be pulled out of school to work and compensate 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 by 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 Mejía 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 on 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, increasing violence on the treated areas in the short run. Moreover, this effect may be explained by retaliation from drug traffickers as a 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, sprayed from small aircrafts as closely as possible to the ground. Figure 1 shows the intensity of these programs. The figure shows that in 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 been growing extensively. The total area sprayed increased from 870 to 103,302 hectares between 1986 and 2010.

Figure 2 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[4]. 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 the manual eradication program for that year.

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

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[5].

# 3 The Data

In the last years, the low availability 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 main-growing countries of 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 data available on the location of illicit crops in the world.

Despite the great efforts by UNODC, the evaluation of the effectiveness of anti-drug programs in producing countries remains constrained by the lack of data on treatment recipients and by the unclear targeting mechanisms used by the different governments. The aerial spraying program in Colombia is a unique exception since the Antinarcotics Police (DIRAN) records the exact location where the small aircrafts open the valves to start spraying glyphosate, as well as the location where they are closed.

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 a 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 the period 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 1,1115,840 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 had 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 of Colombia that had at least 1 hectare of coca between 2001 and 2010[6]. This data set includes informa-

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

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

tion 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 A2-2 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 violence. This is explained since coca crops are illegal in the country, and hence, they are only cultivated in remote areas with very low governmental presence. I use this data set to asses 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 1 presents a summary of the information available in both data sets.

# 4 Estimation Framework

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

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

$$Spr_{it} = \beta_0 + \beta_1 Outside\,PA_i * US\,Exp_t + g_t + k_i + u_{it} \tag{2}$$

where $Y_{it}$ represents coca production or welfare indicators by grid or municipality $i$ in year $t$; $Spri_{it}$ is the treatment intensity measured as hectares sprayed; $g_t$ are time fixed effects; $k_i$ are grid or municipality fixed effects; $Outside\,PA_i$ is an indicator variable that takes the value of 1 if the grid is located outside protected areas, and corresponds to the number of hectares outside protected areas for the municipality sample; and $US\,Exp_t$ are the US international anti-drug expenditures in real billions of dollars of 2010. For the municipality data I scale hectares grown, sprayed and 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 $\alpha_1$ 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 the US international supply anti-drug expenditures. By governmental mandate, protected areas—i.e., natural parks and indigenous territories— cannot be sprayed in Colombia[7]. According to the Na-

[7] According to Decree 143 of 1991 aerial spraying is prohibited in indigenous territories and

tional Geographical Institution in Colombia (i.e., Instituto Geográfico Agustin Codazzi) natural parks and indigenous territories occupy 12% and 27.6% of the Colombian territory, respectively. Figure 3 presents the exact location of these areas throughput the country. It is worth pointing out that there are coca crops inside and outside of these areas in Colombia. 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 US supply anti-drug expenditures. Since according to the Office of National Drug Control Policy around 25% of the US international expenditures on anti-drug supply efforts was directed to Colombia during the period of analysis, it should be expected that higher expenditures will 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 expenditures in the US 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 4 presents the hectares sprayed by deciles of the share of area outside protected areas at the municipality level—$Outside\,PA_i$. Panel A of Figure 4 presents fitted values of hectares sprayed on deciles of $Outside\,PA_i$ for years with different levels of US supply expenditures. The figure suggests that: i) municipalities with a higher share of non-protected areas had a higher number of hectares sprayed, and that ii) in years when the US anti-drug 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 US anti-drug expenditures are higher.

A formal test on the correlation between the instrument and spraying intensity, the so called the relevance assumption as defined by Imbens and Angrist (1994), Abadie (2003) and Angrist et al. (1996), is presented in Tables 2 and 3. 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 US anti-drug expenditures, and columns (2) and (3) present the results of the regression using each of these variables individually.

natural parks. The decree also establishes a 100 meter band around these areas for which aerial spraying is also forbidden. The resolution 0015 approved the 5th of August of 2005 allows aerial spraying in natural parks if several requirements are fulfilled. Yet, as of today these conditions have never been met and aerial spraying has never been done in protected areas.

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. Also 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 only be a violation in the exclusion restriction 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 on 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 of no direct effect of the instrument on the outcomes that I evaluate in this paper.

The first exercise is presented in Figures 5 and 6 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 7 and 8 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.

Also, there may be a concern that since Colombia is one of the top coca producer's, the US international anti-drug expenditures may be affected by the results of the aerial spraying program in this country. If that were the case then the exclusion restriction will be violated. To address this concern I run all the estimates replacing US international anti-drug expenditures with a time trend. Since in practice US international anti-drug expenditures have been increasing in time (see Figure 4) a time trend should introduce a similar variation in the estimates excluding any endogeneity concerns. The results of the first stage of this exercise are presented in Appendix B. They point to similar results. Moreover, I also estimate equations (1) and (2) using the interaction of protected areas and the time trend for all the outcomes evaluated in this paper and find very similar results in terms of magnitudes, signs and statistical significance. This alleviates the concerns that US anti-drug expenditures may be endogenous.

Finally, in order to be able to interpret $\alpha_1$ 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 9 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 given by a possible manipulation of the treatment by producers. If producers are aware of the governmental restrictions to aerial spraying on protected areas and they do not face restrictions to change locations, it could be expected that they will move their coca crops to protected areas to prevent the fumigations. If that were the case the instrument could no longer be used as a plausibly exogenous variation for treatment assignment. Figure 10 presents deciles of the percentage of area covered by non-protected against the percentage of area 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 11 presents the deciles of the area covered by unprotected areas against the mean hectares 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 4 and 5 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 asses 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[8]. It is important to clarify that each grid in my sample is rarely treated more than once across time. Hence, when lagging the treatment reception I am identifying the long-term rather than the cumulative effect of the program.

## 5.1 Impact on Drug Production

Table 4 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)[9].

There are several reasons why aerial spraying may not be having a higher impact on coca leaf production. For instance, Dávalos et al. (2009), Caulkins and Hao (2008), and Mejía and Restrepo (2011), suggest some of the ways that 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.

[8] 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

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

## 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 drop in the treated areas, they increase in other close areas that were not treated by the program. I use the following specification to test for spillovers:

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

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 $t$[10]; $g_t$ and $k_i$ stand for year and municipality fixed effects. Standard errors were clustered at the municipality level in the estimates. Appendix C 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 coca production decreased in the municipalities not treated by the program as well. 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 [11].

This may indicate that if coca producers are changing locations as a result of the program, they may be moving to areas further 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 in 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 has been decreasing from 221,300 to 151,200 hectares between 2000 and 2010.

## 5.3 Impact on Welfare Outcomes

Table 5 asses the effect of the program on the welfare indicators of coca-producing 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[12]. Since poverty rates were constructed with the

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

[11] 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.

[12] The poverty line is the 60% of the median household income from the data published by

information available in the population census of 2005 they are only available 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 areas that had a 1% higher share of area aerially sprayed face rural pverty 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 7% between 1980 and 2010 from (60 to 53%).

For the education outcomes I only find a significant effect of the program on secondary enrollment and school dropout 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 on these variables across time the effects of the program on secondary enrollment rates are small, and the effect over school dropout rates are large. In particular, during the period of analysis secondary enrollment rates increased in 43.8% (from 58.49 to 84.16) and school dropout rates fell by 3.8% (from 11.80 to 11.34)[13]. I do not find any effect on primary enrollment rates.

Together these results may be indicating 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 in the probability that children enter employment, leave school and fail to advance in school 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 in 30%. This is in line with the permanent income hypothesis that suggests that households that lack buffer stocks and are credit constraint tend to use other mechanisms to smooth consumption. Indeed, this is the case of coca-producing areas that have rural poverty rates of nearly 60% of total population.

The estimates also point to a negative and significant effect of the program on infant mortality in the short and the long term. The coefficients indicate that when the share of area treated increases in 1% or approximately 688 hectares[14],

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the Colombian Statistical Department in the population census of 2005.

[13]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 in which these variables are available on coca-producing areas.

[14]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 $km^2$)

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 taking into account that the mean number of hectares sprayed in each municipality is of 450, and since the Colombian infant mortality rates (including all the municipalities of the country) changed only in 0.50 percentage points between 2006 and 2007, the two years for which there is available information of this outcome.

The deterioration of infant mortality in the treated areas may be explained by the direct effect of the herbicide on human health and the indirect effect of aspersion 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 significant but small effect on health outcomes. For example, Mejía and Camacho (2012) use daily panel data on the individual-level 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 aspersion 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 in 0.025 of a standard deviation. Given the standard deviation of aerial spraying takes a value of 1651 in my sample[15], and that the standard deviation of abortion in their sample takes a value of 0.2, these represent very small effect.

The results by Mejía and Camacho (2012) suggest that an important size of the negative effect that I identify on infant mortality may be driven by the indirect effects of aspersion on rural poverty. However, to give a more precise decomposition of the direct and indirect effects of the program on health outcomes more data is needed. Other evidence of the effect of negative income shocks on health outcomes has been also found by Adda et al. (2009) and Ferreira and Schady (2009).

Finally, table 5 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 in 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 in 20.95 percentage points, and 509 individuals during these period.

[15] This information is not available in their paper

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 of 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, one collected between 2005 and 2006, and the second between 2007 and 2010. The producers to be surveyed were chosen by dividing the country in seven regions according to geographical characteristics. Each of the regions was divided in 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 D 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 12 presents some graphical evidence on the relation between the distance to the nearest protected area and aerial spraying.

As for the case of the grid and municipality sample, I multiplied the instrument by total US international anti-drug expenditures. Table 6 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 7 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 last 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/year. In particular, the total hectares cultivated in 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, and hence this a good test for the quality of the data and of the estimates. Appendix E 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 over drug production, yet to the best of my knowledge, none of them has ever assess how these programs affect the socioeconomic conditions on 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 the satellite images there are various concerns when trying to identify its effect. Most of these are related with the two endogeneity types between the treatment assignment and the outcomes, mainly 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 that ii) changes in socioeconomic indicators across time make some areas more susceptible to begin cultivating 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 US 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 US 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 in time, there is a strong deterioration of the socioeconomic indicators in the treated areas. In particular, I find negative effects of the program on rural 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 an increase in infant mortality that is permanent in time. Specifically, infant mortality rates increase in 1.3 percentage points in areas that are aerially sprayed. Similar results were identified on skin pathologies and abortion rates by Mejía and Camacho (2012).

My results also point to other negative effects of the program that somehow tend to disappear in 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 in 4.23 percentage points) and a higher number of individuals displaced by force (they increase in 39.52).

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

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# 9 Tables and Figures

Table 1: 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 | 2680 |
| 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, and 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 2: 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) | |
| $US\,International\,Supply\,Anti-drug\,Expenditures_t$ | | | 0.45*** |
| | | | (0.05) |
| 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 | |
| $US\,International\,Supply\,Anti-drug\,Expenditures_t$ | | 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. US international anti-drug expenditures are expressed in real billions of dollars of 2010. $I(Outside\,Protected\,Areas)_i$ 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 3: 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) | |
| $US\,International\,Supply\,Anti-drug\,Expenditures_t$ | | | 2.04*** |
| | | | (0.05) |
| 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 | |
| $Share\,Outside\,Protected\,Areas_i$ | | 0.86 | |
| $US\,International\,Supply\,Anti-drug\,Expenditures_t$ | | 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. US international anti-drug expenditures are expressed in real billions of dollars of 2010. $Share\,Outside\,Protected\,Areas_i$ 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.

Table 4: Impact of Spraying on Coca Production (Grid-point Sample)

| | Dependent Variable: Coca (ha) | | |
|---|---|---|---|
| | Short-term | 2 years after treatment | 3 years after treatment |
| Independent Variables | (1) | (2) | (3) |
| Ha Sprayed at t | -0.21*** | | |
| | (0.04) | | |
| Ha Sprayed at t-1 | | -0.36*** | |
| | | (0.07) | |
| Ha Sprayed at t-2 | | | -0.18*** |
| | | | (0.06) |
| Year FE | X | X | X |
| Grid FE | X | X | X |
| R-squared | -5.89 | -25.19 | -9.73 |
| N. of Clusters | 101440 | 101440 | 101440 |
| Observations | 1115840 | 1014400 | 912960 |
| | Mean Values | | |
| Ha Sprayed | | 0.54 | |
| Coca (ha) | | 0.84 | |

Note: The table presents the estimates of the structural equation of the specification presented in equations (1) and (2) by 2SLS using $I(Outside\, Protected\, Areas)_i * US\, Anti-drug\, Expenditures_t$ 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 are presented in parentheses. ***: Significant at 1% level; **: Significant at 5% level.

Table 5: Impact on Welfare Indicators (Municipality Sample)

| Independent Variable | Short-term (1) | 2 years after treatment (2) | 3 years after treatment (3) |
|---|---|---|---|
| Poverty Rates | 0.04*** | 0.03*** | 0.03*** |
| | (0.01) | (0.01) | (0.01) |
| Primary Enrollment | -0.71 | -1.18 | -1.93 |
| | (3.23) | (5.75) | (4.28) |
| Secondary Enrollment | -2.13*** | -1.75 | -1.09 |
| | (0.43) | (4.3) | (4.2) |
| School Drop-out | 0.82*** | 0.36 | 0.34 |
| | (0.26) | (0.67) | (3.45) |
| Infant Mortality | 1.26*** | 0.97* | 0.94*** |
| | (0.29) | (0.31) | (0.26) |
| Homicide Rate | 4.23** | -5.1 | -3.56 |
| | (1.60) | (5.62) | (3.45) |
| Forced Displacement | 39.52*** | 37.26 | 41.99 |
| | (15.79) | (39.95) | (90.95) |
| N of Clusters | 288 | 288 | 288 |
| Observations | 2880 | 2592 | 2304 |

| Mean Values | |
|---|---|
| Poverty Rates | 0.56 |
| Primary Enrollment | 128.93 |
| Secondary Enrollment | 71.21 |
| School Drop-out | 10.8 |
| Infant Mortality | 44.1 |
| Homicide Rate | 55.85 |
| Forced Displacement | 592.7 |
| Area Sprayed (% of Total Area) | 0.26 |

Note: The table presents the estimates of the structural equation of the specification presented in equations (1) and (2) by 2SLS using $Share\,Outside\,Protected\,Areas_i * US\,Anti-drug\,Expenditures_t$ as an instrument. Each row in the table reports the results of a separate regression that studies the impact of spraying on each of the independent variables listed above. The estimates correspond to the data set by municipality units. The sample includes all Colombian municipalities that had a positive number of hectares of coca cultivated between 2001 and 2010. Each regression included fixed effects by municipality and year. 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. Clustered standard errors at the municipality level are presented in parentheses. *: Significant at 10%, **: Significant at 5%, ***: Significant at 1%.

Table 6: First Stage Results (Producer Sample)

| Independent Variables | Dependent Variable: $I(Sprayed > 0)$ (1) | (2) | (3) |
|---|---|---|---|
| $Instrument_{it}$ | 0.03*** | | |
| | (0.00) | | |
| $Min\, Distance\, to\, Protected\, Areas_i$ | | 0.02*** | |
| | | (0.00) | |
| $US\, International\, Supply\, Anti-drug\, Expenditures_t$ | | | 0.73*** |
| | | | (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 | |
| $Min\, Distance\, to\, Protected\, Areas_i$ | | 51.67 | |
| $US\, International\, Supply\, Anti-drug\, Expenditures_t$ | | 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. $Min\, Distance\, to\, Protected\, Areas$ represents the minimum distance between each producer and the nearest border to a protected area. US international anti-drug expenditures are expressed in real billions of dollars of 2010, and $Instrument_{it} = Min\, Distance\, to\, Protected\, Areas_i * US\, Anti-drug\, Expenditures_t$. 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 US Expenditures do not included dummies for year. Robust standard errors are presented in parentheses. *: Significant at 10%, **: Significant at 5%, ***: Significant at 1%.

Table 7: 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** | -0.93*** | -1.17*** |
| | (0.01) | (0.02) | (34.22) | (37.70) | (0.22) | (0.36) |
| 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 $Min\,Distance\,to\,Protected\,Areas_i * US\,Anti-drug\,Expenditures_t$ 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%, ***: Significant at 1%.

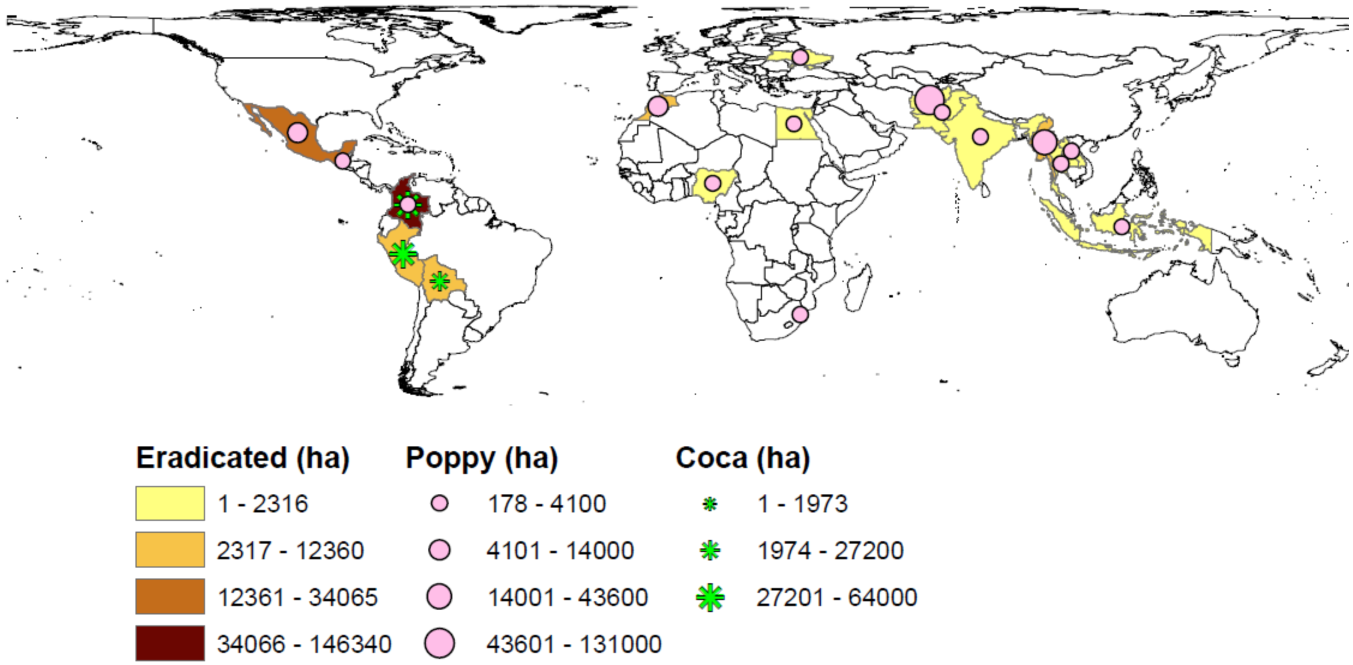



Figure 1: Intensity of Forced Eradication Programs in the World

Note: The figure was constructed with information available in the World Drug Reports of the United Nations Office of Drugs and Crime (UNODC) from 2008 through 2012. The yellow through brown areas identify the 18 countries that as of 2010 were implementing involuntary eradication programs (i.e., manual eradication or aerial spraying). The pink circles and green stars represent the intensity of total hectares of opium poppy and coca cultivated, respectively. These information was gathered by UNODC based on satellite pictures.

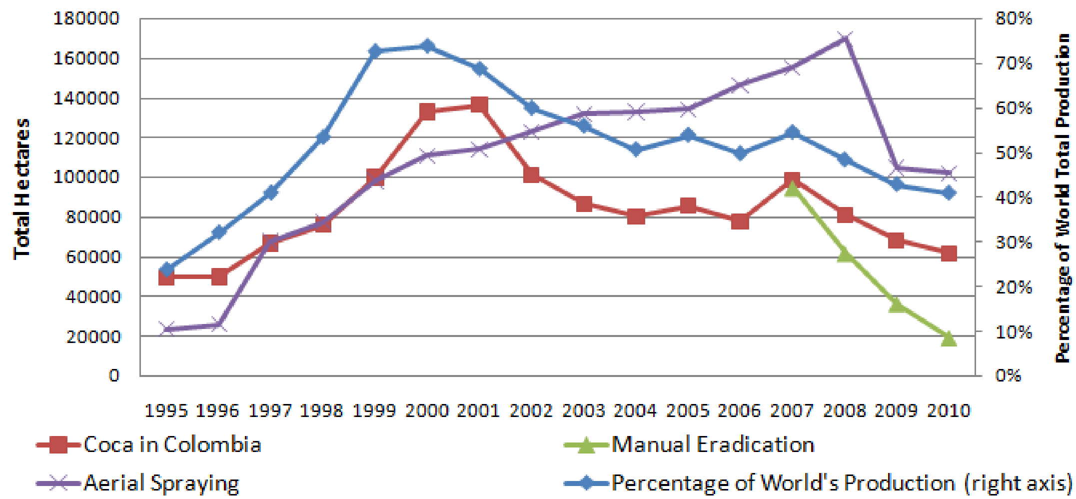



Figure 2: Coca Production, Aerial Spraying and Manual Eradication in Hectares

Note: The red, purple and green lines are expressed in total hectares. Hectares of coca cultivated and hectares manually eradicated where obtained from from UNODC. The data on total hectares aerially sprayed comes from the Colombian Antinarcotics Police. The blue line corresponds to the Colombian coca production as a percentage of the world's production, which amounts to the aggregate coca production of Bolivia, Peru and Colombia. These data is gathered and processed through satellite images by UNODC.

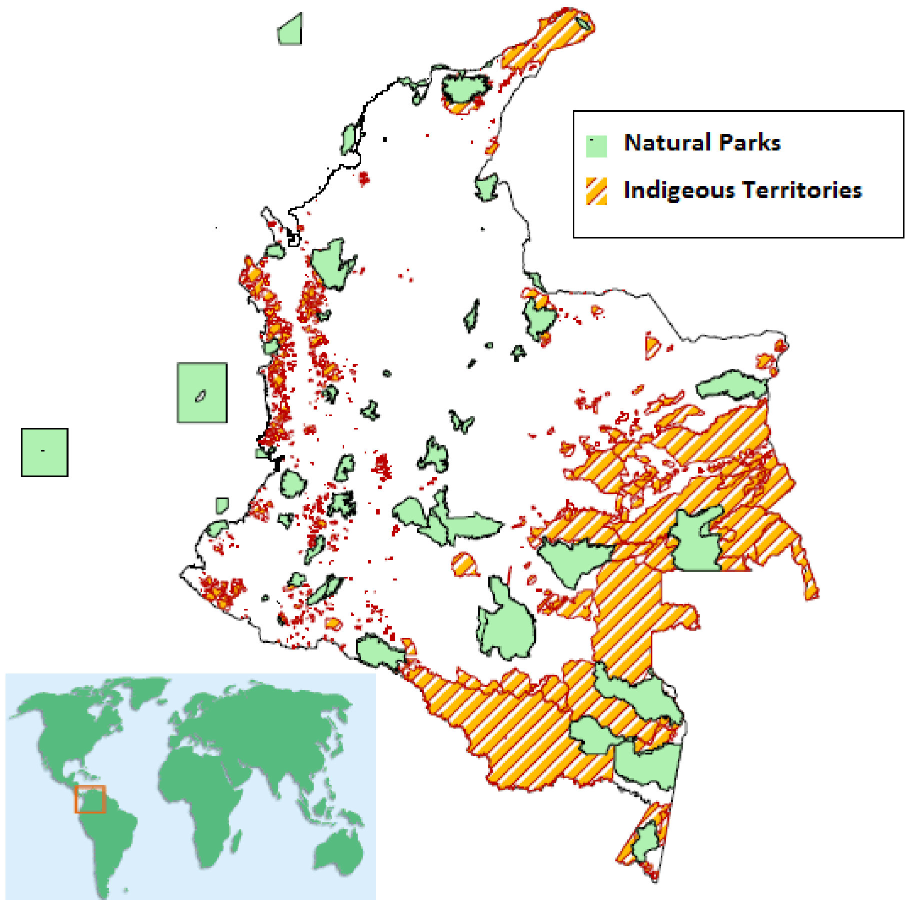
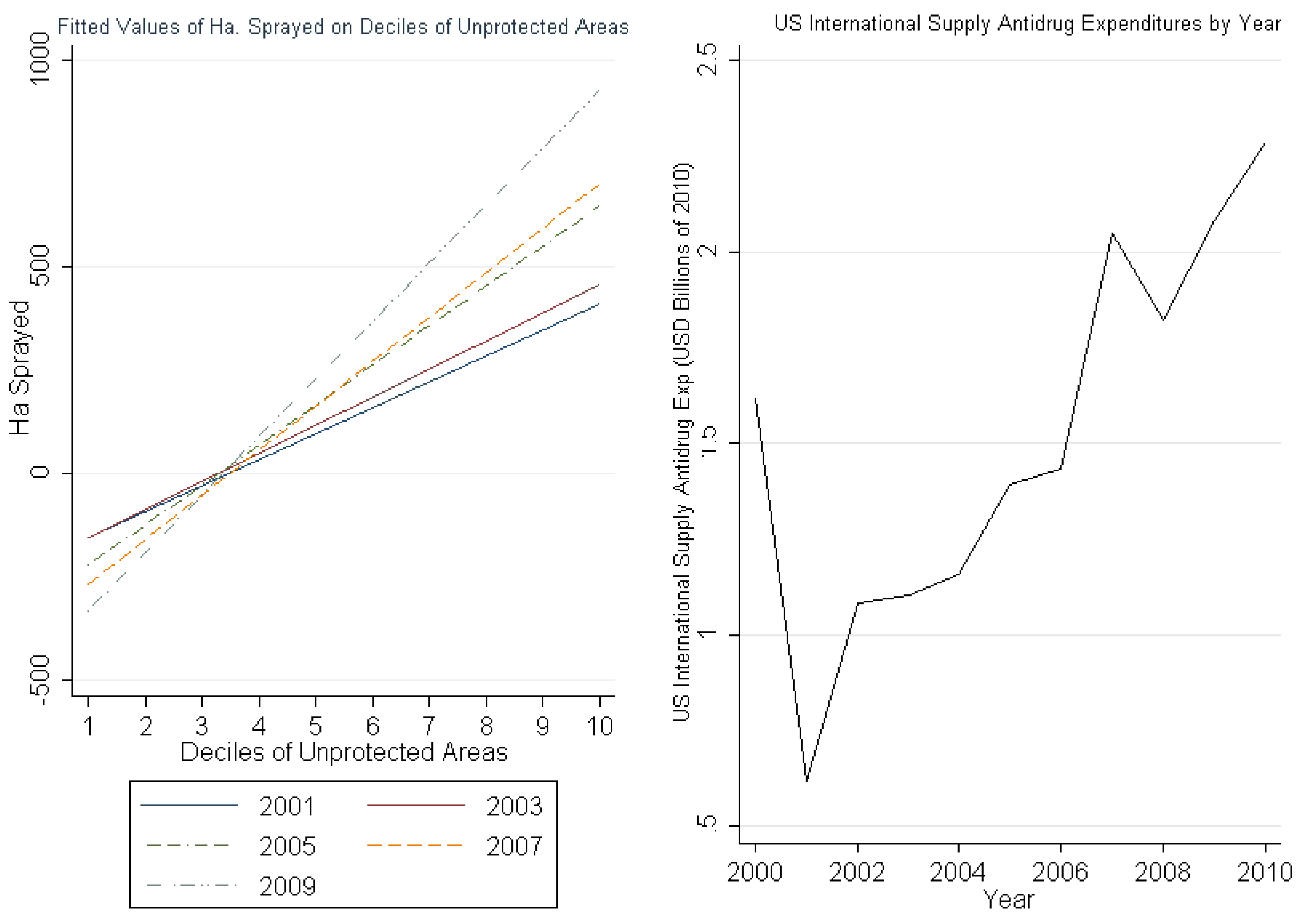



Figure 3: Location of Protected Areas in Colombia

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 occupy 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

Figure 4: Treatment Intensity and Instrument Variation

Note: Panel A was constructed with the micro data by municipality. It presents a fitted line of the total number of hectares sprayed by deciles of the share of unprotected areas in each municipality. Higher deciles of *Unprotected Areas* correspond to municipalities with a lower share of protected areas in its territory. The panel presents a different fitted line for the odd years between 2000 and 2010. In these years US international anti-drug expenditures expressed in real billions of 2010 were increasing (see Panel B). The figure suggests that: i) municipalities with a higher share of non-protected areas had a higher number of hectares sprayed, and that ii) in years when the US anti-drug expenditures were higher (as shown in Panel B), the intensity of treatment increased more for non-protected areas.

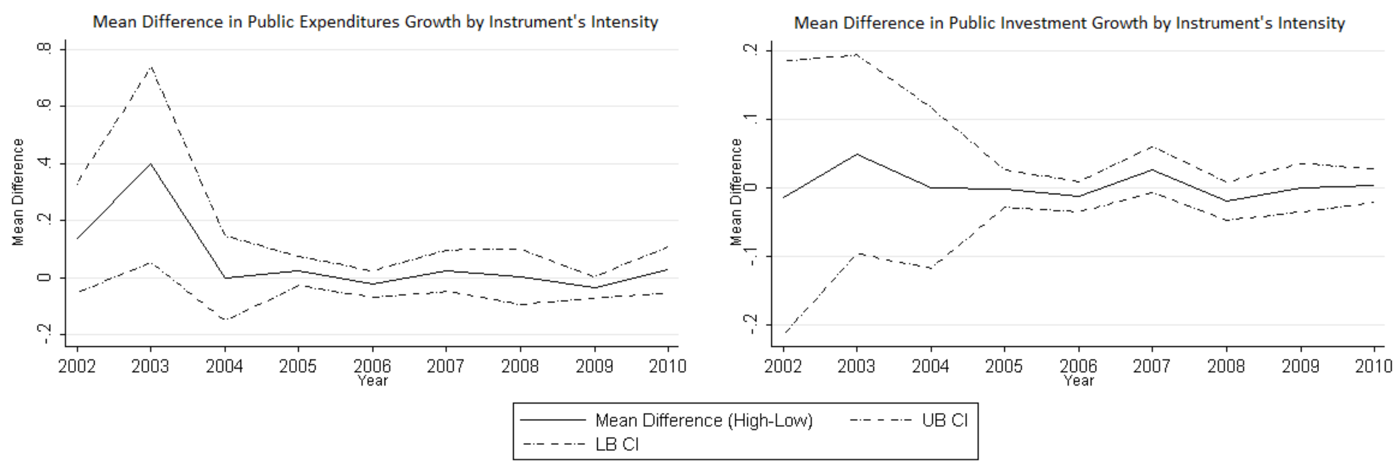



Figure 5: Mean Difference in Public Expenditures and Investment Growth by Instrument's Intensity

Note: This figure was constructed with micro data by municipality. For each year the $instrument_{it} = Share\,Outside\,Protected\,Areas_i * US\,Anti-drug\,Expenditures_t$ was divided into two groups according to its 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 show that there is no statistical difference in the public expenditures and public investment growth between groups. The data on public expenditures and public investment comes from the Colombian National Planning Department.

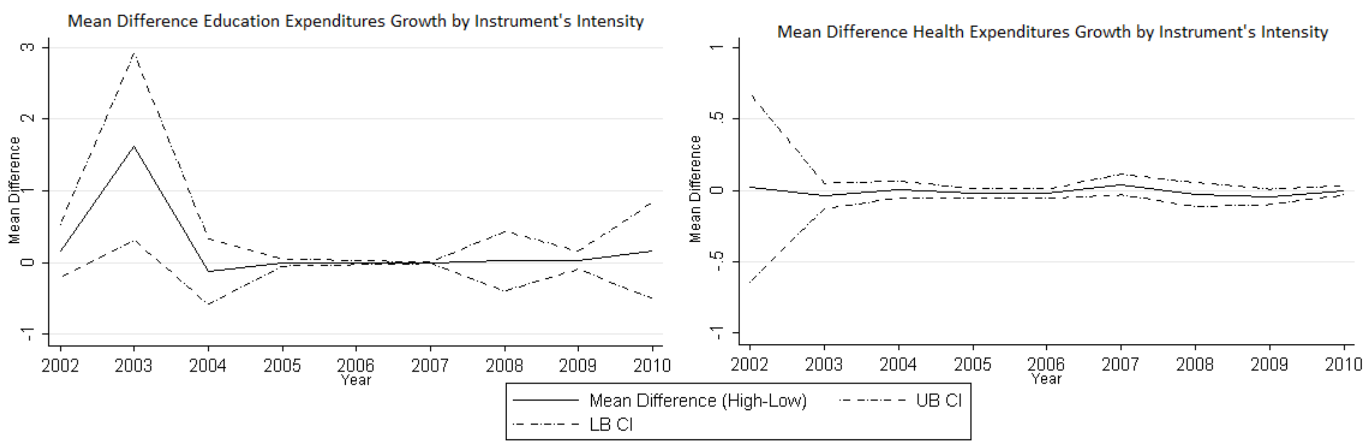



Figure 6: Mean Difference in Public Expenditures Growth by Instrument's Intensity

Note: This figure was constructed with micro data by municipality. For each year the $instrument_{it} = Share\,Outside\,Protected\,Areas_i * US\,Anti-drug\,Expenditures_t$ was divided into two groups according to its 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 show that there is no statistical difference in the public expenditures and public investment growth between groups. The data on public expenditures and public investment comes from the Colombian National Planning Department.

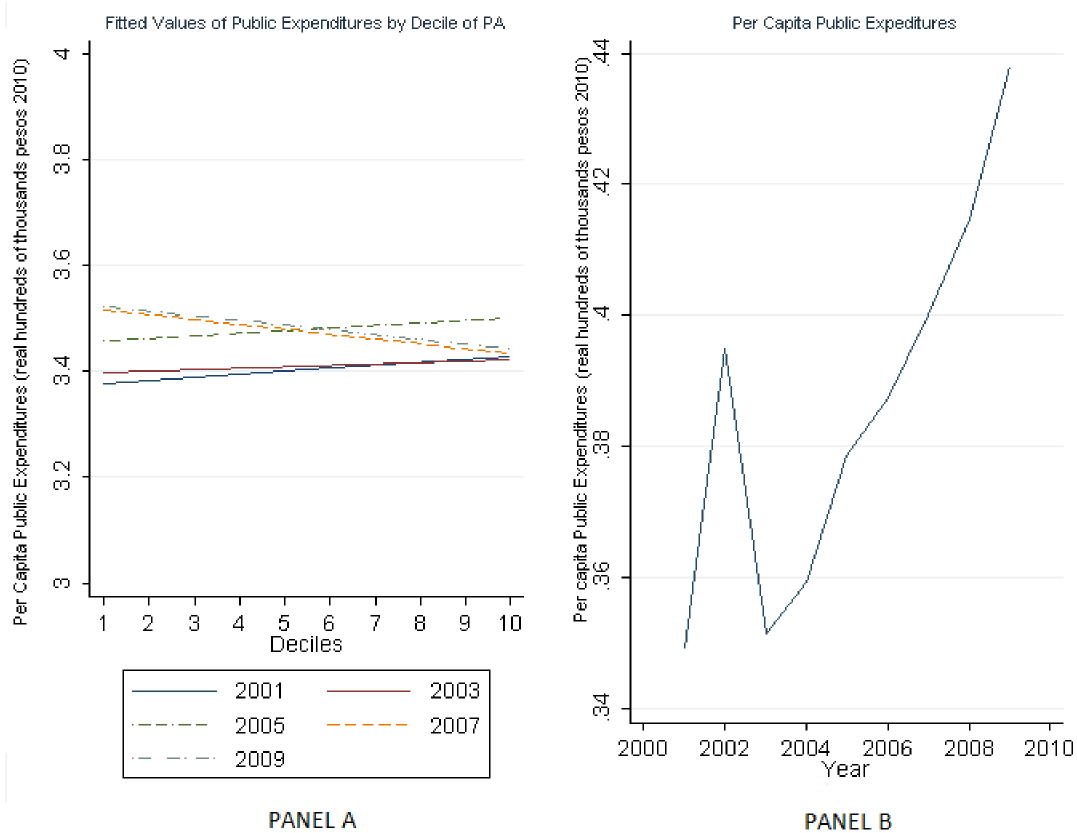



Figure 7: Per Capita Public Expenditures and Instrument's Intensity

Note: Panel A was constructed with the micro data by municipality. It presents a fitted line of the per capita public expenditures by deciles of the share of unprotected areas in each municipality. Higher deciles of Unprotected Areas correspond to municipalities with a lower share of protected areas in its territory. The panel presents a different fitted line for the odd years between 2000 and 2010. In these years per capita public expenditures expressed in hundreds of thousands of real pesos of 2010 increasing (see Panel B).

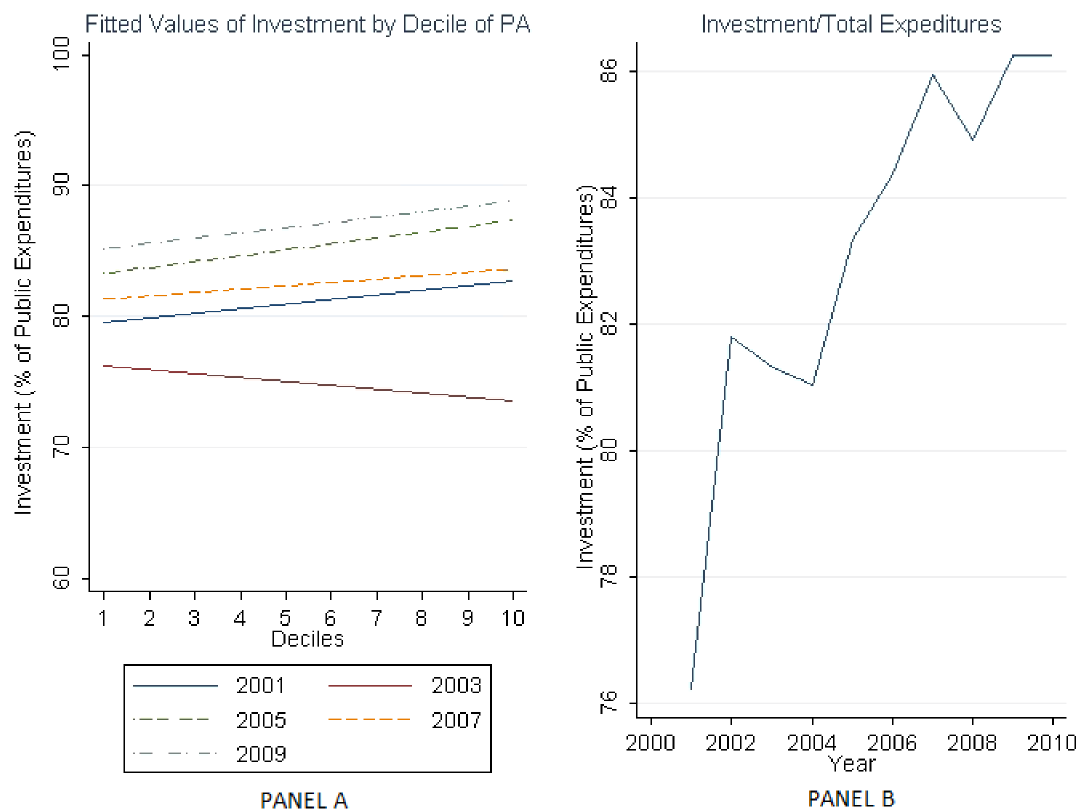



Figure 8: Public Investment and Instrument's Intensity

Note: Panel A was constructed with data by municipality. It presents a fitted line of the public investment (as a % of public expenditures)by deciles of the share of unprotected areas in each municipality. Higher deciles of Unprotected Areas correspond to municipalities with a lower share of protected areas in its territory. The panel presents a different fitted line for the odd years between 2000 and 2010.

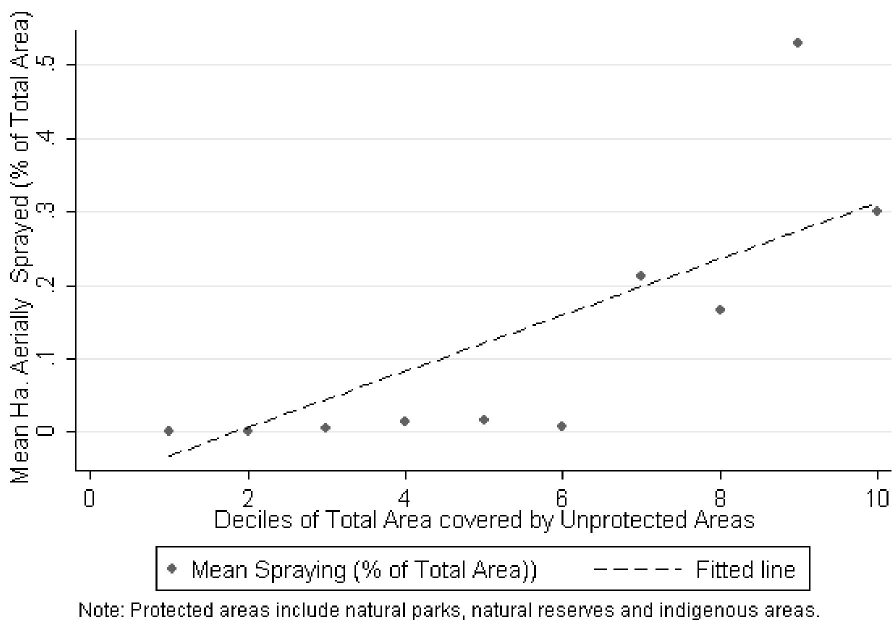



Figure 9: Aerial Spraying in Unprotected Areas

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.

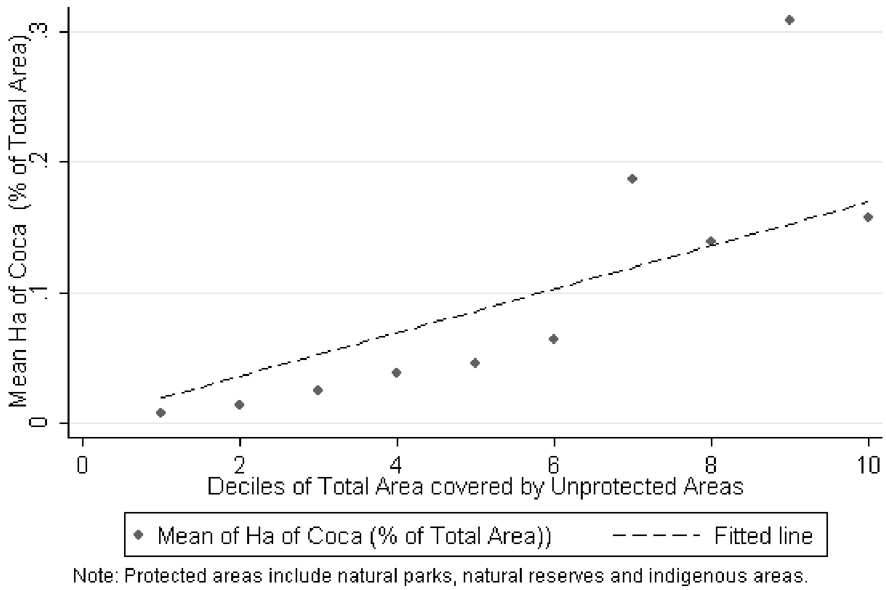
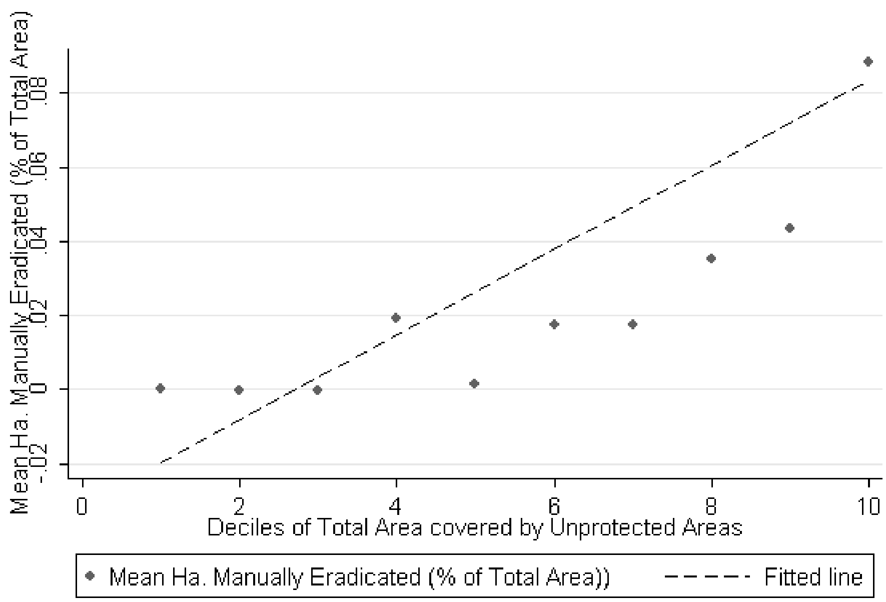



Figure 10: Coca Cultivation in Unprotected Areas

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.




Note: Protected areas include natural parks, natural reserves and indigenous areas.

Figure 11: 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.

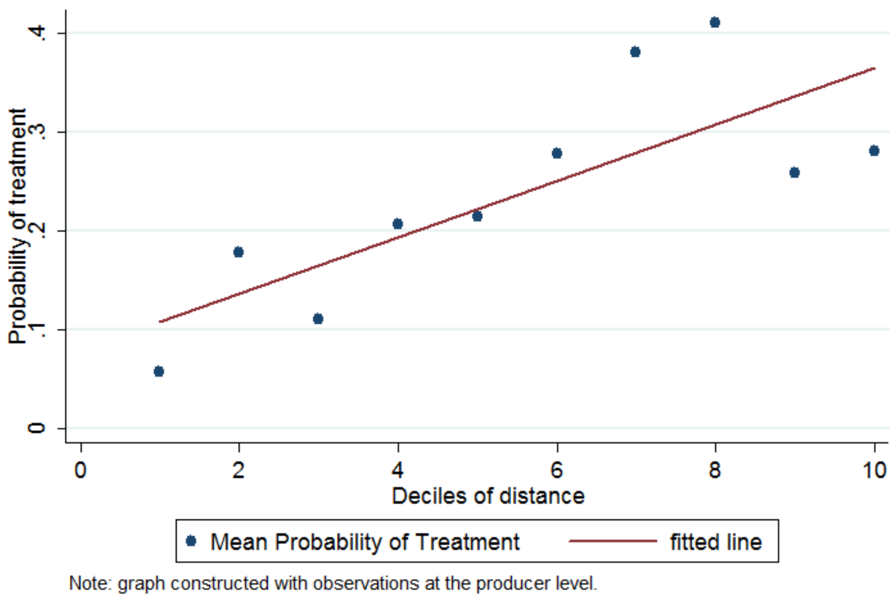



Figure 12: Distance to Nearest Protected Area and Probability of Treatment

Note: This figure was constructed with data collected at the produce 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 further away from protected areas have a higher probability of being sprayed.

# Appendixes

# A Descriptive Statistics and Sources

Table 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 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 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 Drop-Out Rate | (Registered students/students that finish academic year)*100 | 2007-2009 |
| Infant Mortality | (Deaths of ind. younger than 1 year / Ind. borned alife)*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 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 Time Trend replacing US Anti-drug Expenditures

Table B-1: First Stage Regression (Grid Sample)

| Independent Variables | (1) | (2) | (3) |
|---|---|---|---|
| $Instrument_{it}$ | 0.10*** | | |
| | (0.00) | | |
| $I(Outside\,Protected\,Areas)_i$ | | 0.64*** | |
| | | (0.03) | |
| $Time\,Trend_t$ | | | 0.09*** |
| | | | (0.00) |
| Year FE | X | X | |
| Grid FE | X | | X |
| $R^2$ | 0.09 | 0.2 | 0.11 |
| F-Test (excluded instruments) | 576.92 | 269.52 | 144.89 |
| Partial $R^2$ | 0.07 | 0.09 | 0.04 |
| N. of Clusters | | 101440 | |
| Observations | | 1115840 | |

Note: this table presents the first stage results of the specification of equation (2) replacing the US antidrug expenditures with a time trend. Since US antidrug expenditures are always increasing a similar variation may be obtained from a time trend. I also run the instrumental variables regressions for all the outcomes studied in the paper using this instrument. The results are similar in magnitude and sign to the ones presented in the paper. Clustered standard errors at the grid level are presented in parentheses. Regressions include dummies for region, department and municipality. ***: Significant at 1% level.

Table B-2: First Stage Regression (Municipality Sample)

| Independent Variables | (1) | (2) | (3) |
|---|---|---|---|
| $Instrument_{it}$ | 0.08*** | | |
| | (0.00) | | |
| $ShareOutsideProtectedAreas_i$ | | 0.32*** | |
| | | (0.07) | |
| $TimeTrend_t$ | | | 0.05*** |
| | | | (0.00) |
| Year FE | X | X | |
| Municipality FE | X | | X |
| R-squared | 0.17 | 0.2 | 0.2 |
| F-Test (excluded instruments) | 11.71 | 19.91 | 14.6 |
| Partial R-squared | 0.04 | 0.06 | 0.02 |
| N. of Clusters | | 288 | |
| Observations | | 2880 | |

Note: this table presents the first stage results of the specification of equation (2) replacing the US antidrug expenditures with a time trend. Since US antidrug expenditures are always increasing a similar variation may be obtained from a time trend. I also run the instrumental variables regressions for all the outcomes studied in the paper using this instrument. The results are similar in magnitude and sign to the ones presented in the paper. Clustered standard errors at the municipality level are presented in parentheses. Regressions include dummies for region, and department. ***: Significant at 1% level.

# C Spillover Effects

Table C-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. $Ha\,Sprayed\,in\,t-1$ 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.

# D Descriptive Statistics for Producer's Sample

| | 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 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.

# E Placebo Test

Table E-1: Place Test (Grid Sample)

| Dependent Variable: | Latitude | | Longitude | |
|---|---|---|---|---|
| | OLS | 2SLS | OLS | 2SLS |
| | (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 | 101440 | | 101440 | |
| 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 E-2: Place Test (Municipality Sample)

| Dependent Variable | Rain | | | | |
|---|---|---|---|---|---|
| | OLS | OLS -Panel | 2SLS-Panel | OLS | 2SLS |
| | (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.