On the Unintended Consequences of Enforcement on Illegal Drug Producing Countries**

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Abstract

This paper studies the effects of the biggest antidrug program ever applied in a drug producing country. I use satellite information on the exact location of coca crops between 2000 and 2010 in Colombia to identify the effects of spraying herbicides on coca production. I exploit the variation created by restrictions to spraying in protected areas (i.e., indigenous territories and natural parks) and the time variation of U.S. international antidrug expenditures to identify the effects of the program. My results suggest that coca cultivation is reduced by 0.07 hectares per additional hectare sprayed. However, spraying induces unintended negative effects on the welfare conditions of the treated areas and spillover effects in neighboring countries. Despite the reduction under coca cultivation, cocaine production remains steady due to a sharp increase on cocaine yields. In sum, the program's costs are by far higher than its potential benefits.

JEL Classification: O12, O13, O54, I32 and I38.
Keywords: Crime, Illegal Markets, and Welfare.

**: I would like to thank the United Nations Office on Drugs and Crime for providing the data for this study. I am extremely grateful to Adriana Lleras-Muney for her guidance in this project. I also thank Daniel Mejia, Aprajit Mahajan, Walker Hanlon, Paola Giuliano, Leah Boustan, Peter Reuter, Mark Kleiman, Christian Dippel, Ilyana Kuziemko, and seminar participants of LACEA in Lima, the IEN at Harvard University, the Workshop on Illegal Drug Markets, Crime and Violence at UCLA, APPAM 2013 Fall Conference, and the ISSDP at Universidad de los Andes, for helpful comments and suggestions. All remaining errors are my own.

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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]. According to information of the Office of National Drug Control Policy of the White House, on average, 12% of these resources where spent on international initiatives to reduce illegal drug supply. However, few efforts have been directed at studying supply side antidrug policies[2]. 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 the 18 countries that have implemented supply antidrug interventions 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 Drug Control Policy), making Colombia the third largest recipient of military foreign aid from the U.S. (after Israel and and Egypt)[3]. 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 (Mejía and Restrepo (2011)).

Despite the huge amount of resources invested, as of today, there is 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 antidrug 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 possess a considerable threat of endogeneity; their results are driven by theoretical assumptions; and they ignore other unintended effects of these programs.

Two recent studies that attempt to address the endogeneity concerns between spraying and coca cultivation are Reyes (2014) and Mejía et al. (2014). The former instruments spraying with the distance between sprayed areas and the closest military base finding a positive correlation between coca cultivation and the treatment. The main limitation of

[1]As estimated by Becker and Murphy in the Wall Street Journal article of January 4, 2013.

[2]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.

[3]The data on top recipients of U.S. foreign assistance is available at: http://www.fas.org/sgp/crs/row/R40213.pdf

this analysis is that the location of military bases is likely endogenous to the one of coca crops. Mejía et al. (2014) exploit the variation induced by a diplomatic friction between the governments of Colombia and Ecuador that resulted in a free-spraying zone within a 10 km band along the border with Ecuador and inside Colombia beginning in 2006. The authors employ regression discontinuity and conditional differences in differences to identify the effects of the program on coca cultivation. Their results suggest that spraying one additional hectare reduces coca cultivation by about 0.02 to 0.065 hectares.

This paper contributes to the existing literature by employing a unique and rich data set with 1-square-km cells collected through satellite data to study the effects of an antidrug supply policy, by studying the effects of the an antidrug program over the whole territory where the program was implemented (on contrast to the Mejia et al.(2014) where the analysis is focused in a region of the country), and by investigating not only the effect of spraying on coca production, but also, on the welfare conditions of coca-producing areas and its spillover effects on other non-treated areas (including neighboring countries).

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 medium term (24 to 36 months), and to check if spraying spreads coca production into neighbouring areas that were not treated (i.e., spillover effects). 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. *Cross-section 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 time feedback effects arise because areas with increasing coca cultivation have more spraying, which may lead to worsening socio-economic conditions and more coca cultivation.

To identify the effects of spraying on coca cultivation 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. antidrug 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 increases more proportionally for unprotected areas when U.S. international antidrug expenditures are higher, relative to protected areas. This last is my source of variation.

My results suggest that when the likelihood of being sprayed increases by 1%, coca production decreases by 0.07 hectares per square kilometer. This suggests that eradicate 1 hectare of coca per square km (1 square km=100 hectares) spraying will have to increase by 14.3 hectares per square km (to increase the likelihood of being sprayed by 14.3%). 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 worsens the welfare conditions in treated areas. Specifically, when the share of area sprayed increases by 1% in each municipality, poverty rates increase by 0.22 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 0.11 percentage points and increases dropout rates by 0.04 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 0.07 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 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 0.67 percentage points and the number of individuals displaced increases by 4.97. 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.

Despite the reduction on the total area under coca cultivation in Colombia (it stood at three quarters of its level in 1990), the quantity of cocaine manufactured was at least as high as the one manufactured in 2001 (UNODC, 2013). This was due to a sharp increase of cocaine yields in Colombia[4]. In fact, based on data on cocaine seizures from the Antinarcotics Colombian Police and data collected at coca farms from UNODC in 2001 it was possible

[4]Cocaine yields are measured as total kilograms of cocaine per hectare of coca leaf.

to produce 4.2 kg of cocaine per hectare of coca in 2001, whereas this yields increased to an average range of 5.1 to 6.8 kg per hectare in 2010. In other words, coca-producers and cocaine traffickers are also actively modifying their behavior in response to higher levels of enforcement which has resulted maintained cocaine's supply stable.

In sum, considering its sizable financial cost, the small effects on coca cultivation and cocaine supply, the negative unintended consequences on the population living in coca-producing areas (who are the poorest and most vulnerable in Colombia), and the negative spillover effects on neighboring countries, it can be concluded that the program's costs are by far higher that its potential benefits. This calls to the urgency of applying other policy alternatives such as supporting the development and implementation of alternative legal crops and strengthening governmental presence in coca-producing areas.

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; section 6 presents some robustness checks; and section 8 presents a brief cost-effectiveness analysis of the program. Finally, section 7 offers concluding remarks.

2 Forced Eradication antidrug 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[5]. 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[6].

3 The Data

Over the years, the scarcity of good quality data has been the main limitation in studying the effectiveness of antidrug 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.

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 square km or 100 hectares. It includes all grids that had at least 1 hectare of coca between 2000 and 2010. For each unit of observation

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

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

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[7]. 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:

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

$$Spr_{it} = \beta_0 + \beta_1 Outside\,PA_i * U.S.\,Exp_t + g_t + k_i + u_{it} \quad (2)$$

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 an indicator dummy for being sprayed (for the grid sample) or the share of area sprayed (for the municipality sample); 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 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 dollars of 2010. For the municipality data, I scale hectares grown, sprayed, and lying outside the protected areas by

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

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 antidrug expenditures. By governmental mandate, protected areas—i.e., natural parks and indigenous territories— cannot be sprayed in Colombia[8]. According to the National Geographical Institution in Colombia (i.e., Instituto Geográfico 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.

To create time variation on the instrument, I interact protection areas with the U.S. international antidrug expenditures in real billions of dollars of 2010. According to the annual budget of the Office of National Drug Control Policy of the White House (ONDCP) between 2000 and 2010 the U.S. disbursed 17.6 real billion of dollars of 2010, to reduce the international supply of illegal drugs. The time evolution of these expenditures is presented in Figure III, Panel B. Because between 1990 and 2000 Colombia produced more than 50% of the world's cocaine[9], the country received 30% of those resources throughout 2000 and 2010. In particular, according to the data published in the annual budget summary of ONDCP between 2000 and 2010 Colombia received 5.3 real billions of dollars of 2010 to improve security conditions and reduce drug supply. Hence, it should be expected that higher U.S. expenditures would induce 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 antidrug 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—$Outside\,PA_i$. Panel A of Figure III presents fitted values of hectares sprayed on deciles of $Outside\,PA_i$ for years with different levels of U.S. international antidrug expenditures. The figure suggests that: (i) municipalities

[8] 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.

[9] See the annual World Drug Reports by the United Nations Office of Drugs and Crime.

with a higher share of non-protected areas had a higher number of hectares sprayed, and (ii) in years when the U.S. international antidrug 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. antidrug 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. international antidrug 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 14% 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 60.00 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 the $corr(Instrument_{it}, u_{it}|k_i, g_t) \neq 0$. In other words, the 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 time trends across years[10].

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. The identifying assumption will be violated if there are variables changing in time correlated with U.S. international antidrug expenditures that affect protected and non-protected areas in different ways. For example, a violation to the exclusion restriction might take place if when U.S. international antidrug expenditures change the local (i.e., municipality) or central governments modify their behavior in different ways in municipalities with a different share of unprotected areas.

I address this concern through two exercises that rule out any differential changes in behavior for the local or the central governments in areas with different shares of unprotected areas. Table IV presents a regression of each municipality's public income and expenditures

[10]This rules out any business cycle variation at the aggregate level for Colombia or the U.S., as well as any variation on international commodity prices.

(as total and by type) on the instrument. These variables represent the local government's behavior and they are presented in real billions of Colombian pesos of 2010. The regressions include fixed effects by year and municipality and all standard error are clustered at the municipality level. The table suggests that there is no correlation between the instrument and any of the variables. Hence, the local governments show no differential response to changes in U.S. international antidrug expenditures between areas with a different share of protected areas.

Table V presents a similar exercise, but now the independent variables correspond to the transfers made by the central government to each municipality. The table presents the regressions of total transfers and transfers by type (i.e., health, education, and other purposes) on the instrument. The results rule out any different response of the central government to changes in U.S. antidrug expenditures between municipalities with different share of protected 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 IV 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 V 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 VI 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 VI and VII 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[11]. To identify the medium-term effect of the program, I lag the treatment in equation 2 one and two years[12]

5.1 Impact on Drug Production

Table VI presents the estimates for the effect of spraying on hectares of coca. They point to small effects of the program. As expected the OLS estimates overestimate the effects of the program since the sprayed areas tend to have more coca. My most preferred estimates presented in column (3) take a value of -1.19 ha per square km (1 square km =100 hectares). Given the estimates on column (1) from table II, when U.S international antidrug expenditures increase in $1 billion the grids that are inside an unprotected area the likelihood of being sprayed by 18%. Hence, on average, increasing the likelihood of being aerially sprayed by 1% reduces the hectares of coca cropped by 0.07 ha per square km (i.e., 1.19 over 18). Thus, to reduce 1 hectare of coca per grid (1 grid=100 hectares) the likelihood of being sprayed will have to increase in 14.3%, that is, 14.3 additional hectares will need to be sprayed.

The medium-term estimates present a similar pattern, showing a sustained negative effect of the program in the medium term (i.e., 1 or 2 years after the fumigations)[13].

There are several reasons why aerial spraying may not have a higher impact on coca leaf production. For instance, Dávalos et al. (2009), Caulkins and Hao (2008), and Mejía 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.

[11] For all the estimates I calculated clustered standard errors at the grid or municipality level. Moreover, for the grid level estimates I also verified the robustness of the the results to spatial correlation between grids. For this purpose, I verified the sensitivity of the results to the estimation of Conley (1999) spatial standard errors assuming that: i) the correlation between grid-level cells is zero for areas bigger than 300x300 hectares (which groups 6 one square km cells) and ii) the correlation between grid-level cells is zero for areas bigger than 500x500 hectares (which groups 25 one square km cells). Since the standard errors are almost exactly the same as the ones obtained by clustering at the grid level, I only report the latter to save space.

[12] 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.

[13] 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 drops in the treated areas, if increases in nearby untreated areas. I use the following specification to test for spillovers:

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

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[14]; and g_t and k_i stand for year and municipality fixed effects. Standard errors were 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[15].

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 VII assess 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. Given the estimates of column (1) of table III, when U.S. antidrug expenditures increase in $1 billion and the share of area in an unprotected area increases by 1% the share of sprayed area increases at least by 18%. This implies that, to be interpreted correctly, all the coefficients in table VII need to be divided by 18.

Poverty rates are constructed based on the percentage of the rural population under the

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

[15]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.

poverty line[16]. 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 0.22 percentage points higher in the short term. More strikingly, these effects seem to be maintained 1 and 2 years after the treatment implementation. These effects are moderate since, according to the Food and Agriculture Organization of the United Nations, rural poverty rates in Latin America only fell by 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 0.11 percentage points and school dropout rates increase by 0.04 percentage points. When compared to the changes in these variables across time, the effects of the program on secondary enrollment rates are small, and the effect on school dropout rates is large. In particular, during the period of analysis secondary enrollment rates increased from 58.49 to 84.16 and school dropout rates fell by from 11.80 to 11.34[17]. 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 medium term. The coefficients indicate that when the share of area treated increases by 1% infant mortality increases by 0.07, 0.05, and 0.05 percentage points, the same, one, and two years after the fumigations. This is a relevant effect considering infant mortality rates 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

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

[17] 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.

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, 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 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 square km 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 1651 in my sample[18], 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 Mejía 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 VII 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 0.67 percentage points and the number of displaced individuals increases to around 4.97. These 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 antidrug 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.

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

6 Robustness Check

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 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 square km, 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 VII 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 antidrug expenditures. Table VIII 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. The results in column (1) suggest that when U.S. international antidrug expenditures increase in $1 billion and the minimum distance from a protected area decreases in 1 km the likelihood of being sprayed increases by at least 3% for coca-producers.

Table IX 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.

Considering the estimates of column (3) in table VIII, the results suggest that when the likelihood of being sprayed increases in 1% each producer crops 0.10 less hectares of coca (i.e., -0.31 over 3), the kilograms per hectare are reduced in 27.32 kg/ha (i.e., 81.98 over 3), and the number of harvests collected by producers are reduced in 0.39 (i.e., 1.17 over 3).

These results are reassuring since they point to negative effects of the program on coca bush cultivation. Although I cannot address the panel endogeneity for this case, and the coefficients may be underestimating the effect of the program, they point to the same signs.

7 On the Program's Cost-Effectiveness

My results suggest that coca cultivation is reduced in 0.07 ha when the likelihood of being sprayed increases by 1%. Hence, to reduce a hectare of coca per square km (1 square km=100 ha) the likelihood of being sprayed will have to increase 14.3%, that is, hence spraying will have to increase by 14.3 hectares per square km. According to Walsh et al. (2008) the average cost per additional hectare sprayed for the U.S. is $750 and for every dollar spend by the U.S. Colombia spends about 2.2 dollars (see Mejia, Restrepo, and Rozo, (2014)). Hence, these numbers suggest that the approximate direct cost or eradicating one hectare of coca is $120,000. As a result of the higher enforcement, Colombia has decreased coca cultivation in 74,532 hectares between 2001 and 2010, which amounts to an approximate financial cost of $2.55 billions of dollars.

Despite the fact that higher enforcement in Colombia has displaced coca cultivation to Bolivia and Peru, coca cultivation in the Andean region (which accounts for the world's supply of coca leaf) as a whole fell by 59,700 hectares between 2001 and 2010. However, as area under coca cultivation stood at three quarters of the level in 1990, the quantity of cocaine manufactured was at least as high as the one manufactured in 2001 (UNODC, 2013). This was due to a sharp increase of cocaine yields in Colombia. In fact, based on data on cocaine seizures from the Antinarcotics Colombian Police and data collected at coca farms from UNODC, in 2001 it was possible to produce 4.2 kg of cocaine per hectare of coca, whereas this yields increased to an average range of 5.1 to 6.8 kg per hectare in 2010. In other words, coca-producers and cocaine traffickers are also actively modifying their behavior in response to higher levels of enforcement which resulted in a stable cocaine supply throughout the period of analysis.

Considering, its financial cost, the small effects on coca cultivation and cocaine supply, the negative unintended consequences of aerial spraying on the population living in coca-producing areas (who are the poorest and most vulnerable in Colombia), and the negative spillover effects on neighboring countries, it can be concluded that the program's costs are by far higher that its potential benefits. In fact, there are other policy alternatives that are less harmful for the population living in coca-producing areas such as supporting the development and implementation of alternative legal crops and strengthening governmental presence in those areas.

8 Conclusions

This paper identifies the impact of aerial spraying on coca-producing areas in Colombia. In general, previous studies that assess the effects of antidrug 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) or its spillover effects on non-treated areas (including neighboring countries).

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 antidrug expenditures. I show that since protected areas cannot be sprayed, the likelihood of being sprayed increases outside of these areas. Hence, in years when U.S. international supply antidrug 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 medium term (24 and 36 months after treatment reception). The results are striking: coca cultivation is reduced only by 0.07 ha per square km when the likelihood of being sprayed increases by 1% (hence, to eradicate 1 hectare of coca per square km spraying needs to increase by 14.3 hectares per square km) and there is a 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. 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.

Moreover, although I find no evidence of spillovers in the non-treated areas near 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.

In addition, although aerial spraying is inducing a reduction in coca production, it has also increased cocaine yields, and hence, cocaine's supply is at least as high as it was in 2000. In sum, the costs of the program are too high to be justified by its potential benefits. This points to the urgency of exploring new alternatives for controlling illicit crop production in producer countries.

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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10 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: $I(Sprayed > 0)$			
Independent Variables	(1)	(2)	(3)
$Instrument_{it}$	0.18***		
	(0.01)		
$I(Outside\,Protected\,Areas)_i$		0.07***	
		(0.00)	
$U.S.\,Exp_t$			0.2***
			(0.00)
Year FE	X	X	
Grid FE	X		X
R-squared	0.14	0.1	0.11
F-Test (excluded instruments)	60	269.52	95.66
Partial R-squared	0.08	0.09	0.11
N. of Clusters		101440	
Observations		1115840	

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 antidrug expenditures are expressed in real billions of 2010 dollars. $I(Outside\,Protected\,Areas)_i$ 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 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)	
$U.S.\,Exp_t$			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	

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 antidrug expenditures are expressed in real billions of 2010 dollars. $Share\,Outside\,Protected\,Areas_i$ 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 IV: Ruling out the Correlation between the Instrument and the Local Government's Behavior

	Dependent Variable expressed in real billions of pesos (2010=100)							
	Public Income	Tax-Income	Non-tax Income	Public Exp.	Admin. Exp.	Debt Exp.	'*Regalias*' Income	Fiscal Balance
$Outside\, PA_i * U.S.\, Exp_t$	-22.20	-12.80	-9.46	-3.91	-2.47	-1.43	-1.52	5.18
	(20.23)	(10.66)	(9.48)	(3.83)	(2.48)	(1.36)	(1.89)	(6.14)
Mun FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.96	0.97	0.73	0.97	0.96	0.47	0.5	0.45
N. of Clusters				269				
Years available				2001-2010				
Obs.				2690				

Note: The table presents a regression of fiscal variables on the instrument. The instrument corresponds to an interaction of U.S. international antidrug expenditures ($US\, Exp_t$) expressed in real billions of dollars of 2010 and the share of unprotected areas ($Outside\, PA_i$) which corresponds to the percentage of total area outside indigenous territories and natural parks in each municipality. All fiscal variables are expressed in billions of Colombian pesos of 2010. *Regalías* denotes the share of income received by a municipality due to exploitation of natural resources such as oil and other minerals. The sample includes all the Colombian municipalities that had a positive number of hectares of coca cultivated between 2001 and 2010. Clustered standard errors at the municipality level are presented in parentheses. *** Significant at 1% level.

Table V: Ruling out the Correlation between the Instrument and the Central Government's Behavior

	Dependent Variable expressed in real billions of pesos (2010=100)			
	Education Transfers	Health Transfers	Other Purposes Transfers	Total Transfers
$Outside\, PA_i * U.S.\, Exp_t$	-15.19	1.60	3.22	18.62
	(12.59)	(1.76)	(2.75)	(18.70)
Mun FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
R-squared	0.83	0.32	0.94	0.69
N. of Clusters	261			
Years available	2002-2010			
Obs.	2349			

Note: The table presents a regression of the public transfers from the Central Colombian government to each of the municipalities on the instrument. The instrument corresponds to an interaction of U.S. international antidrug expenditures ($US\, Exp_t$) expressed in real billions of dollars of 2010 and the share of unprotected areas ($Ouside\, PA_i$) which corresponds to the percentage of total area outside indigenous territories and natural parks in each municipality. All fiscal variables are expressed in billions of Colombian pesos of 2010. The sample includes all the Colombian municipalities that had a positive number of hectares of coca cultivated between 2002 and 2010. Clustered standard errors at the municipality level are presented in parentheses. *** Significant at 1% level.

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

	Dependent Variable: Coca (ha per square km)				
	OLS	OLS	2SLS	2SLS	2SLS
	Short-term	Short-term	Short-term	1 year after treatment	2 years after treatment
	(1)	(2)	(3)	(4)	(5)
Ha Sprayed at t	0.66**	0.21**	-1.19***		
	(0.01)	(0.01)	(0.09)		
Ha Sprayed at t-1				-1.51***	
				(0.11)	
Ha Sprayed at t-2					-1.92***
					(0.14)
Year FE	X	X	X	X	X
Grid FE	X	X	X	X	X
N. of Clusters				101440	
Observations	1115840	1115840	1115840	1014400	912960

Note: The table presents the estimates of the structural equation of the specification presented in equations (1) and (2) by 2SLS using $I(Outside\,Protected\,Areas)_i * U.S.\,Exp_t$ 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. Columns (1) through (3) presents the effect of the program 1 to 12 months after the treatment reception, column (4) presents the effect 13 to 24 months after the treatment reception, and column (5) 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 and ** Significant at 5% level.

Table VII: Impact on Welfare Indicators (Municipality Sample)

	1 year after	2 years after	3 years after
	(1)	(2)	(3)
Poverty Rates (d)	0.04***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)
Primary Enrollment (b)	-0.71	-1.18	-1.93
	(3.23)	(5.75)	(4.28)
Secondary Enrollment (b)	-2.13***	-1.75	-1.09
	(0.43)	(4.3)	(4.2)
School Dropout (c)	0.82***	0.36	0.34
	(0.26)	(0.67)	(3.45)
Infant Mortality (c)	1.26***	0.97*	0.94***
	(0.29)	(0.31)	(0.26)
Homicide Rates (a)	12.23***	-5.1	-3.56
	(1.60)	(5.62)	(3.45)
Forced Displacement (a)	89.52***	37.26	41.99
	(15.79)	(39.95)	(90.95)
Mean Values			
Poverty Rates (Percentage of rural pop under poverty line)			0.56
Primary Enrollment (Registered students/Pop in age)			128.93
Secondary Enrollment (Registered students/Pop in age)			71.21
School Dropout (Registered students/students finishing year)			10.8
Infant Mortality (Deaths of ind. younger than 1 year / Ind. born alive)			44.1
Homicide Rate (Homicides /100,000 inh)			55.85
Forced Displacement (N. of individuals)			592.7
Area Sprayed (% of Total Area)			0.26
N of Clusters		288	
Observations (a)	2880	2592	2304
Observations (b)	1440	1440	1440
Observations (c)	576	576	576
Observations (d)	288	288	288

Note: The table presents the estimates of the structural equation of the specification presented in equations (1) and (2) by 2SLS using $Share\,Outside\,Protected\,Areas_i * U.S.\,antidrug\,Expenditures_t$ 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 except the regression in which poverty rates are used as a independent variable. 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 errors at the municipality level are presented in parentheses.* Significant at 10%, ** Significant at 5%, and *** Significant at 1%.

Table VIII: First Stage Results (Producer Sample)

	Dependent Variable: $I(Sprayed > 0)$		
Independent Variables	(1)	(2)	(3)
$Instrument_{it}$	0.03***		
	(0.00)		
$Min\, Distance\, to\, Protected\, Areas_i$		0.02***	
		(0.00)	
$U.S.\, International\, Supply\, Anti\text{-}drug\, Expenditures_t$			0.73***
			(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

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. U.S. international antidrug expenditures are expressed in real billions of dollars of 2010, and $Instrument_{it} = Min\, Distance\, to\, Protected\, Areas_i * U.S.\, antidrug\, Expenditures_t$. 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 IX: 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 $Min\,Distance\,to\,Protected\,Areas_i * U.S.\,antidrug\,Expenditures_t$ 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%.

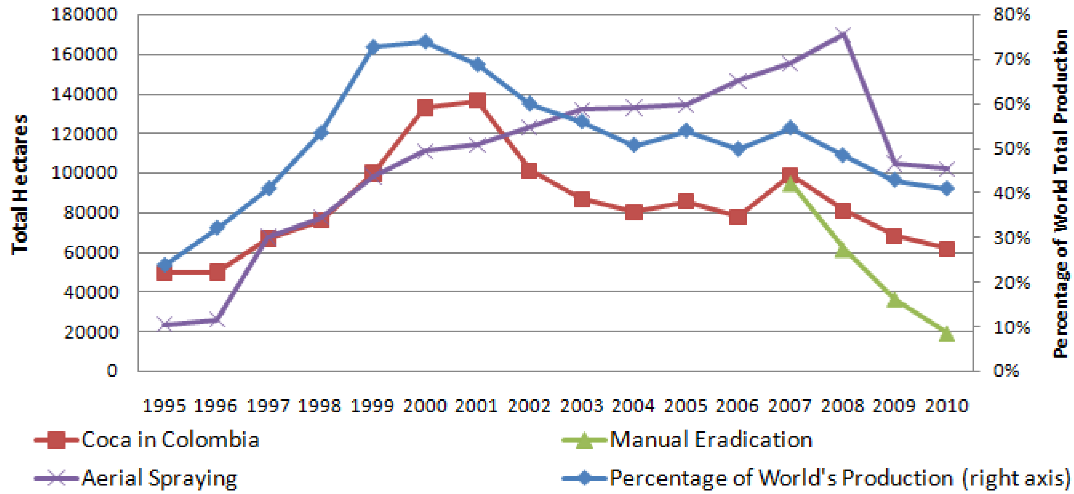

Figure I: Coca Production, Aerial Spraying and Manual Eradication in Hectares

Note: Hectares of coca cultivated and hectares manually eradicated come from UNODC. The data on total hectares aerially sprayed comes from the Colombian Antinarcotics Police. The 'percentage of world's production' 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.

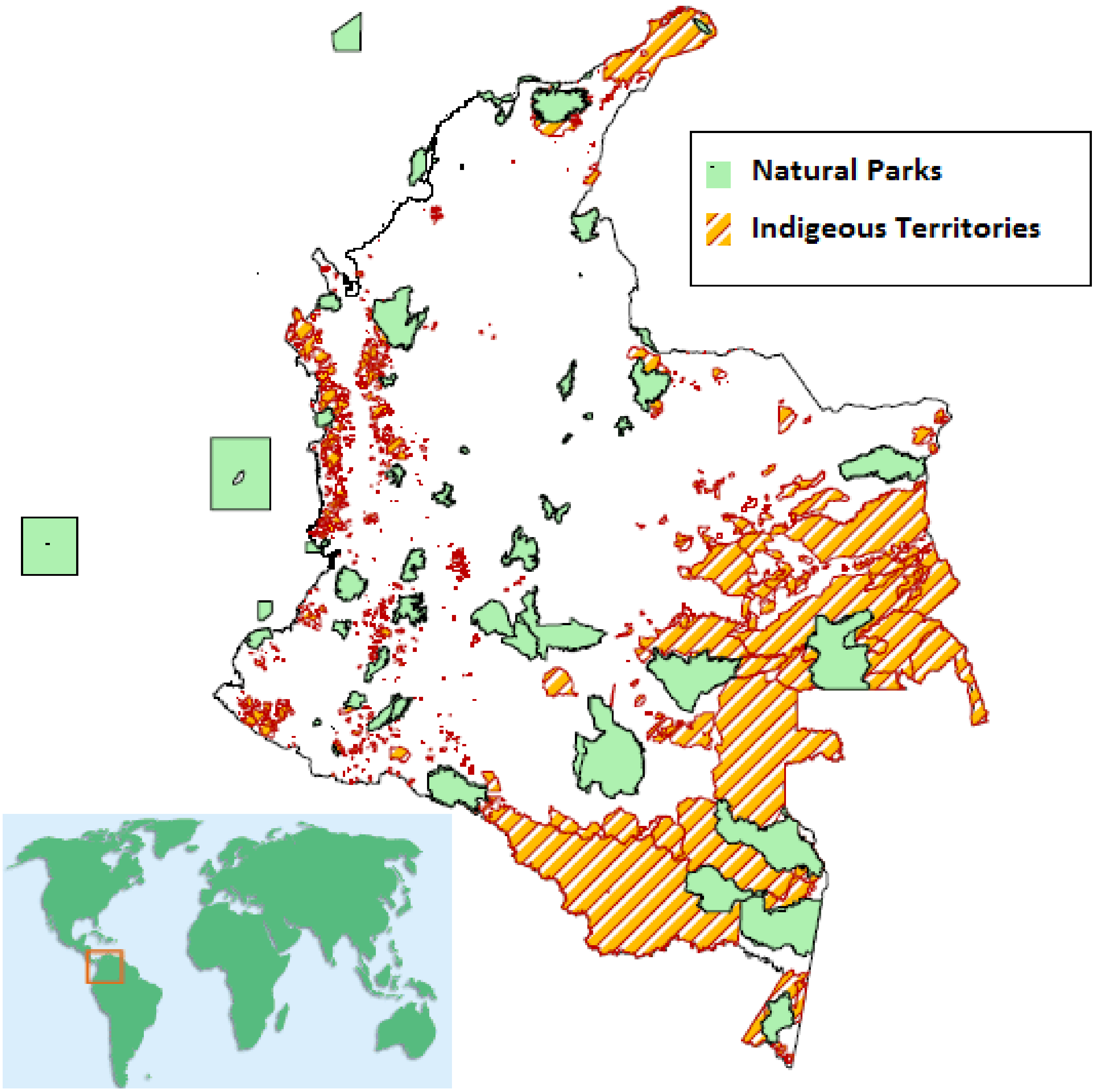

Figure II: Location of Protected Areas in Colombia

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).

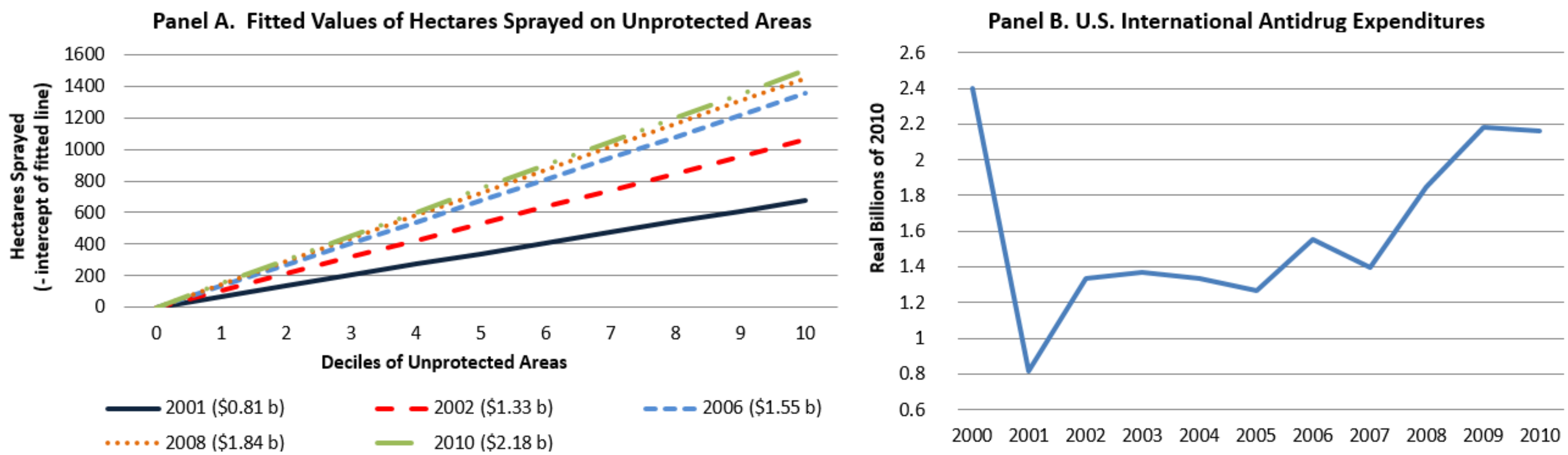

Figure III: Instrument Strength and Time Evolution of U.S. Antidrug Expenditures

Note: Panel A was constructed by aggregating the grid data by municipality. It presents a fitted line of the total number of hectares sprayed by deciles of the share of unprotected area 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 fitted line for years with different U.S. international antidrug expenditures (values are presented in the legend on parentheses in Panel A). During these years U.S. international antidrug expenditures expressed in real billions of dollars 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 (ii) in years when the U.S. antidrug expenditures were higher (as shown in Panel B), the intensity of treatment increased more for non-protected areas.

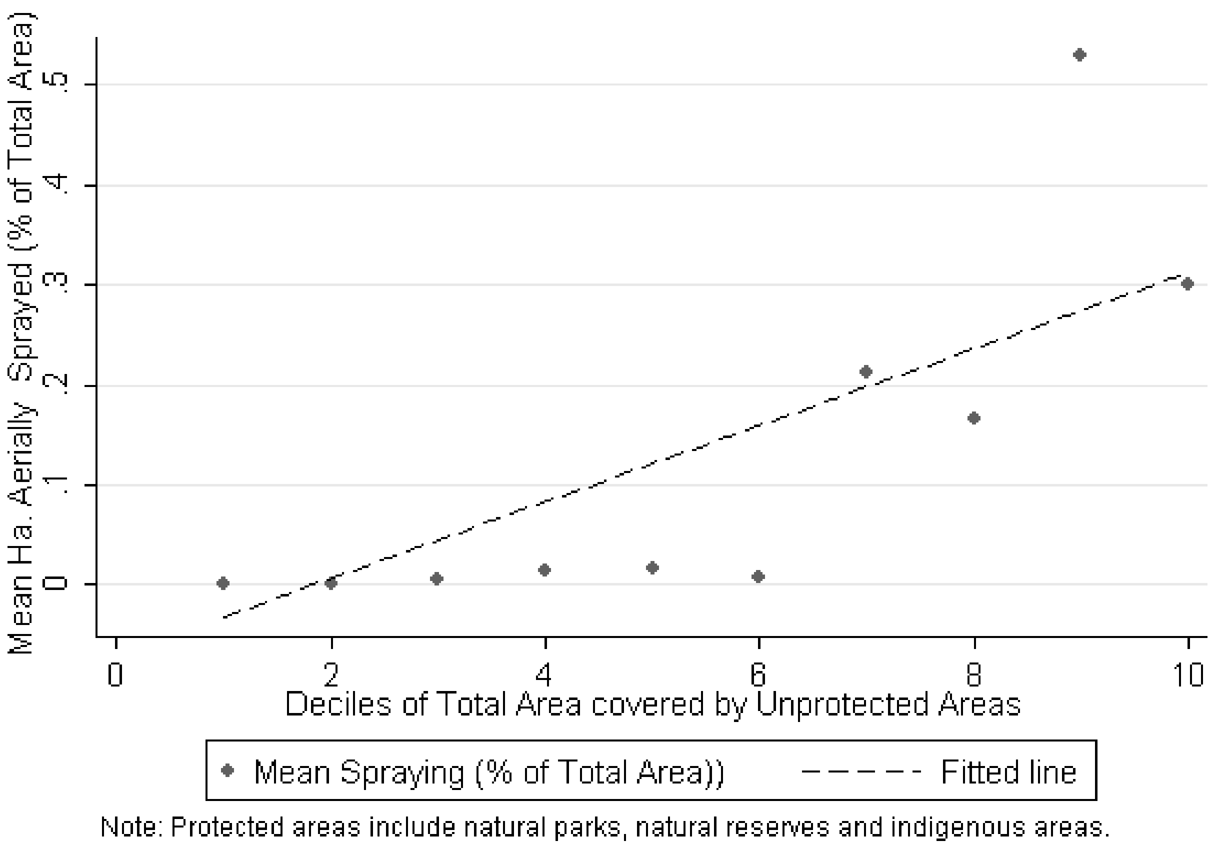

Figure IV: Aerial Spraying in Unprotected Areas

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.

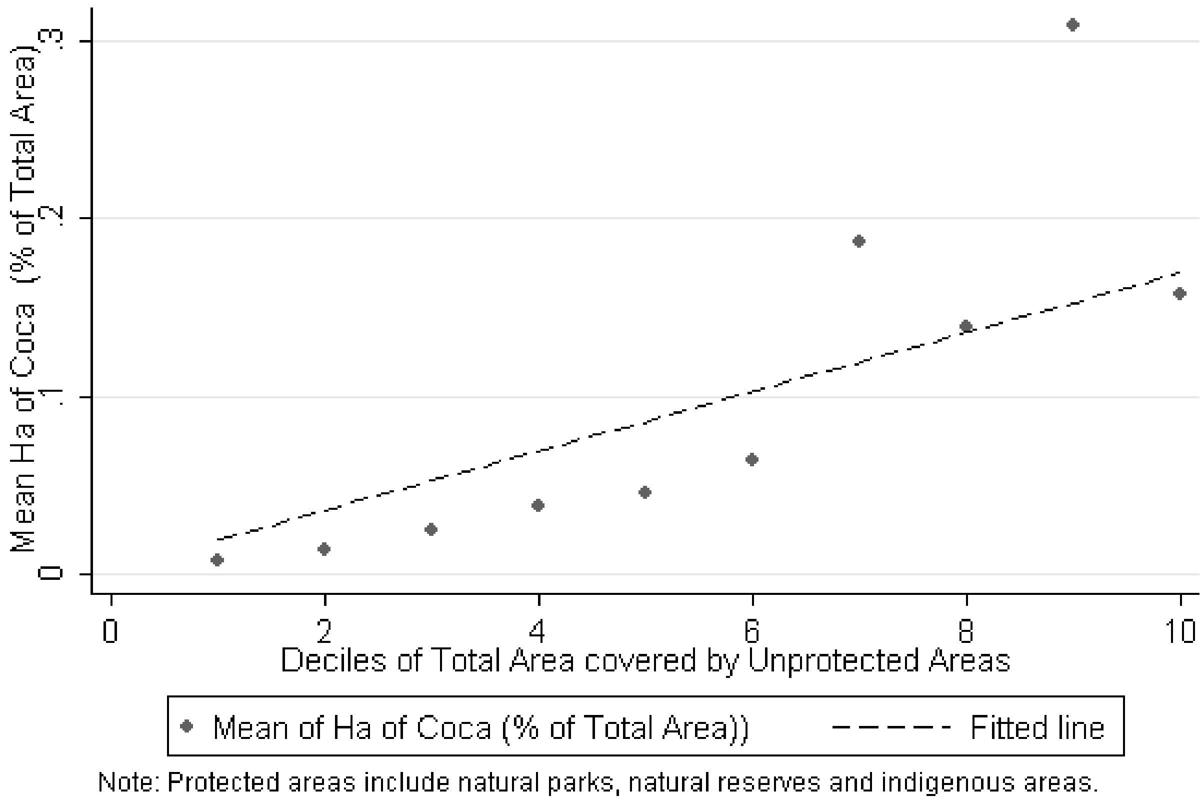

Figure V: Coca Cultivation in Unprotected Areas

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.

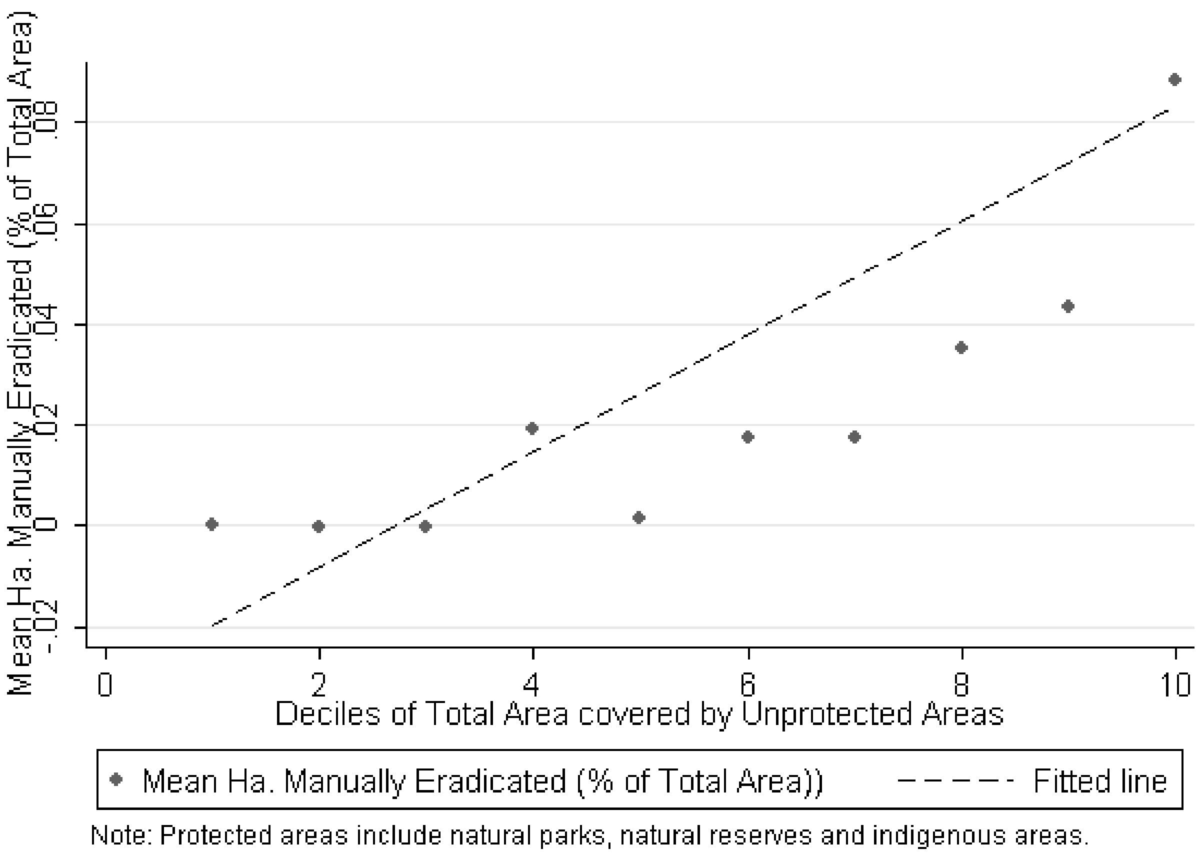

Figure VI: Manual Eradication in Unprotected Areas

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.

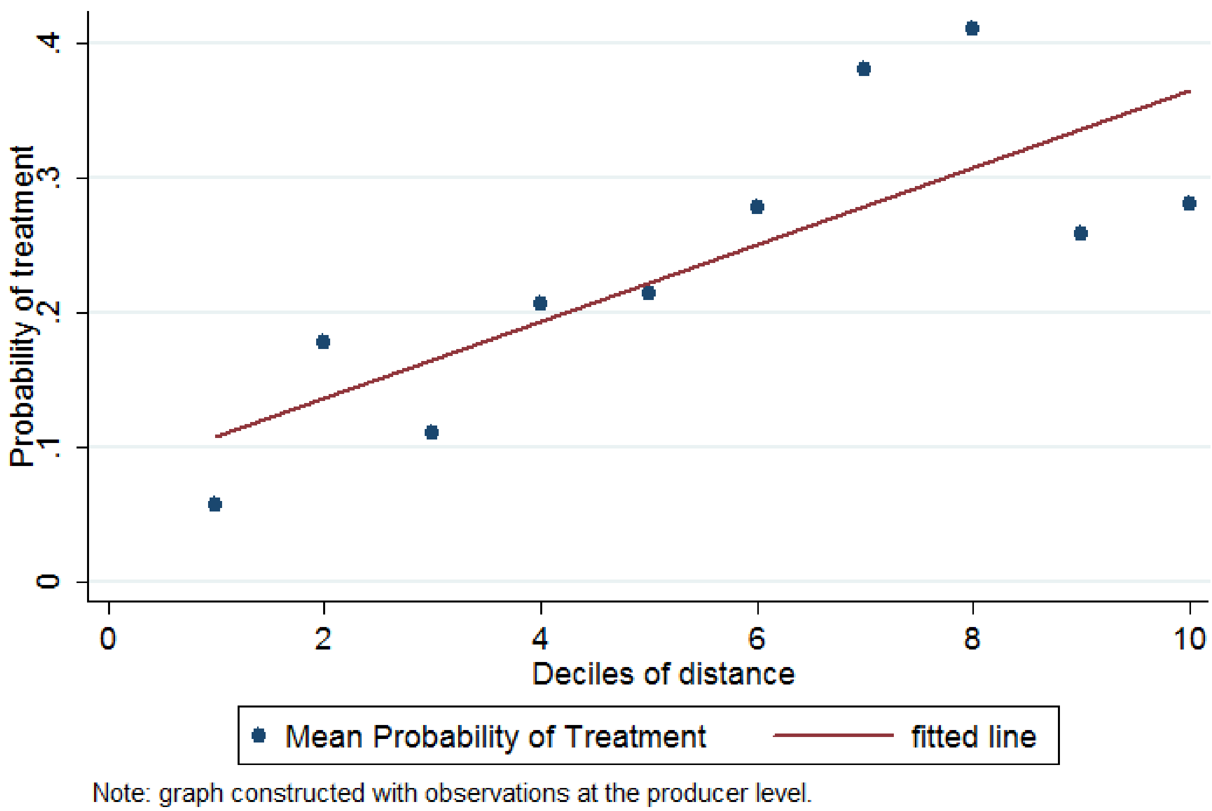

Figure VII: Distance to Nearest Protected Area and Probability of Treatment

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.