THE RISE AND PERSISTENCE OF ILLEGAL CROPS: EVIDENCE FROM A NAIVE POLICY ANNOUNCEMENT

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ABSTRACT. Well-intended policies often have negative unintended consequences if they fail to foresee the different ways in which individuals may respond to the new set of incentives. When widespread and persistent, these may lead to a net reduction of social welfare. Focusing on the case of anti-drug policies, in this paper we show that the recent unprecedented surge in the growing of illicit coca crops in Colombia was the result of a naive and untimely policy announcement during peace negotiations between the government and the FARC guerrillas. On May 2014, the parties' peace delegations issued a press release announcing that coca-growing farmers would receive material incentives for voluntary crop substitution once a final agreement had been reached. To evaluate the anticipation effect of this announcement we exploit the cross sectional variation on both the cost advantage of growing coca (using an ecological measure of coca suitability) and the expected benefits of doing so (using a predicted measure of where the material benefits would have been targeted). Coca plantations levels remained high even after the implementation of the announced incentives' scheme. We explain this persistence by documenting that the surge in coca growing is differentially higher in areas with presence illegal armed groups, that benefited financially from availability of a key input in the drug trade.

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1. Introduction

Well-intended policies often generate unintended consequences when policy makers fail to anticipate the equilibrium incentive structure generated by the policy change beyond the actual margin that the policy intends to affect. Unintended consequences, in turn, can largely affect the cost-benefit balance of these policies, potentially making them harmful from a social perspective. Price regulation and quotas are textbook examples used by economists to illustrate how policies can go wrong.

A paramount domain of this observation is drug policy. The evidence on the unintended consequences of prohibition policies and the "war against drugs" is abundant. Take for instance their effect on production and on violence. The traditional prohibition and interdiction approach may increase profits -thus inadvertently increasing supply- if the demand for drugs is inelastic, and can promote the creation of black markets in which disputes are often resolved violently.[1] Miron finds evidence that drug prohibition increases violent crime both in the U.S. (Miron, 1999) and across countries (Miron, 2001). In Mexico, Afghanistan, and Colombia different drug enforcement policies have resulted in more violence, respectively by creating violent power disputes (Dell, 2015; Calderón et al., 2015), by increasing the profits of the illegal sector (Clemens, 2013) and by generating retaliation from violent actors affected by the policy (Abadie et al., 2013). This mechanism also applies to integrated markets across different countries. For instance, Castillo et al. (2018) show that cocaine seizures in Colombia produce scarcity in downstream drug markets in Mexico and, by rising prices, it increases drug-related violence.

This paper expands this literature by showing how the anticipation effect generated by the announcement of a policy aimed at reducing the area cultivated with coca crops actually had the opposite effect. We focus on the case of Colombia, where coca growing surged starting in 2014 because of the announcement, remained high after the actual policy implementation started in 2017, and fueled new cycles of violence after a peace agreement was signed in 2016 to end a five-long civil conflict.

On October 2012 the government of Colombia and the *Revolutionary Armed Forces of Colombia* (FARC from the Spanish acronym) started formal peace negotiations in Havana. While a peace agreement would eventually be signed at the end of 2016,

[1] Becker et al. (2006) estimate the price elasticity of the demand for drugs to be around 0.5. Mejía and Restrepo (2016) show that an inelastic demand for drugs in the U.S. is one key reason why *Plan Colombia* was so ineffective in controlling coca production –the main input in the production of cocaine– in Colombia during the 2000s.

one of the most important milestones of the peace process was the partial agreement on illicit drugs. On the 16th of May 2014, the delegations of the negotiating parties announced in a joint press release that they had agreed upon the future creation –after the eventual signature of a final peace agreement– of an illicit crops substitution program that would provide the material incentives for coca-growing communities to voluntarily substitute coca for legal crops. The joint press release also pointed out that the implementation of the substitution program was going to be carried out preferably by local community organizations.

According to Bermúdez Liévano (2018) the government negotiating team was fully aware of the miss-information –and thus the perverse incentives– created by the announcement.[2] Indeed, for the rest of the peace negotiations the government team explicitly opposed the possibility of providing monetary incentives for peasants who would substitute away illicit crops and eventually, the final peace agreement –signed over two years after the announcement– did not explicitly include any reference to individualized monetary incentives. Nevertheless, not only was the seed planted in that the announcement did generate expectations about future rents for coca growers but also, upon the final agreement was signed, the Comprehensive National Program for the Substitution of Crops for Illicit Use (PNIS from its Spanish acronym) was launched, and coca growers did end up receiving direct cash transfers from the government, confirming, almost three years later, the expectations generated by the May 2014 announcement.

We empirically assess the anticipation effect of the announcement on coca growing by exploiting the time variation given by the press release, as well as two sources of cross sectional variation. First, we rely on an ecological time-invariant coca *suitability* measure to distinguish municipalities according to their differential cost-advantage of growing coca, and thus on their ability to respond to the anticipation of material benefits. Second, we predict the location of the areas that ended up being targeted with material incentives to substitute away coca crops using the same information that coca growers had at the time of the May 2014 press release. Specifically, the announcement clearly stated that incentives were to be targeted in areas that witnessed historical

[2] This was confirmed in several interviews that we conducted with people who where close to the peace negotiation: it *ex-post* became apparent that the inclusion of the wording "material welfare conditions for the people affected by illicit crops" in the 2014 press release could be interpreted as a promise of future direct cash transfers to coca growers. The qualitative evidence also supports the view that rural communities got the message that they should grow more coca to obtain government benefits (see e.g., Garzón, 2015).

coca crops and faced poverty conditions.[3] We thus complement our measure of actual ecological cost of growing coca with one of predicted material benefits, avoiding the use of the actual (endogenous) implementation of the coca substitution incentive scheme.

We exploit both the temporal and the geographical sources of variation in a *difference-in-differences* empirical framework, that also controls for municipality fixed effects, department-year fixed effects, and a large set of pre-determined municipal characteristics interacted with the post-announcement time dummy. We also estimate a non-parametric version of this model in order to test whether coca-growing trends were parallel in high vs low suitability areas and in areas where the probability of receiving the incentive scheme was high vs low before the press release. We confirm this is the case. This *event-study* empirical specification also allows us to study the dynamics of coca growing after the announcement.

We find a large differential increase in the area cultivated with coca in coca-suitable municipalities as well as in places with a higher probability of obtaining material incentives for substituting coca crops. Using our most demanding specification we find that a one-standard-deviation increase in coca suitability increases coca growing by almost one quarter of a standard deviation after the 2014 announcement, a magnitude that is equivalent to the mean of coca cultivation during our sample period. In other words, municipalities where the coca suitability index is one standard deviation above the average doubled their area cultivated with coca after the announcement. Moreover, if the estimated probability that a municipality will receive the substitution incentive scheme increases by 50 percent relative to the mean (from 5 to 7.5 percent), then the incidence of coca crops will increase in 0.57 standard deviations. Both of these magnitudes are substantial. Moreover, when the two sources of cross-sectional variation are included in the same specification both remain significant, and we find evidence of complementarity between both measures when we estimate a triple-differences model.

In contrast to the most common journalistic accounts of the recent unprecedented surge in coca growing, we show that this phenomenon is not explained by the prohibition in 2015 of areal spraying of coca crops with the herbicide glyphosate. This finding is of foremost policy importance, as the current administration has pushed to resume aerial spraying after the U.S government has exerted political pressure. Our findings add to a series of recent papers that show that aerial spraying is unlikely to

[3]The actual excerpt of the announcement stated that the incentives were going to be targeted on "the communities affected by illicit crops, particularly for the peasant communities that live in poverty." (our translation).

drive down coca crops (see Abadie et al., 2013; Mejía and Restrepo, 2015), while it can have negative effects on health (Camacho and Mejía, 2017) and violence (Abadie et al., 2013). Moreover, we then test if our main results are driven by preferential access to the substitution program of FARC-controlled areas, as has been suggested for instance by Lopez et al. (2019). We implement this test by interacting an indicator of FARC presence prior to the announcement with the full set of year fixed effects, we show that our results are robust to flexibly controlling for FARC's dominance.

Beyond these average estimates of the causal effect of the policy announcement on the areas cultivated with coca, our dynamic specification suggests that the differential increase in coca growing in coca-suitable municipalities or in places with a higher probability of obtaining material incentives from coca crops substitution programs increases over time and during our entire sample period (which goes until the end of 2018). This is a relevant finding given that the announced crop-substitution program started its implementation phase in 2017, after the final peace agreement was signed. Importantly, we show that violence inflicted by other armed groups which neither took part of the peace process nor signed the peace agreement increased substantially between 2013 and 2018 precisely in the areas in which we show effects of the 2014 announcement on coca growing. We posit that the surge in the availability of coca, together with the inability of FARC of continuing to handle the drug business in some of these areas, made it attractive for existing armed groups to control the business and its associated rents.

Also important for policy, we find that the differential increase in coca growing in coca-suitable areas and in municipalities with a higher probability of receiving the material benefits for voluntary substitution programs is to a large extent attenuated by the existence of National Parks and other protected areas. This result suggests that state presence and institutional monitoring are important factors to counteract the unintended negative consequences of policies such as the naive policy announcement that we study in this paper.

We contribute to several strands of the literature. First, we contribute to the literature on the determinants of coca cultivation. Several studies have associated the cultivation of coca to the presence of armed groups, which can manifest in violence and forced displacement (see Díaz and Sánchez, 2004; Vargas and Netherlands, 2005; Alvarez, 2001; Ruiz et al., 2013; and Ibáñez and Vélez, 2008), to the incidence of poverty and the lack of institutional and economic development (Angrist and Kugler, 2008; Ibanez and

Carlsson, 2010; Ibáñez, 2010; Rocha, 1997, 2000; and Thoumi, 2005a,b,c), and to environmental and ecological conditions (Dávalos et al., 2011 and Ruiz et al., 2013). We contribute to this literature by showing how the expectation of potential government benefits associated with illicit crops substitution programs may have induced farmers to cultivate more coca crops.

Second, we contribute to the literature that evaluates the effectiveness of anti-drug efforts in reducing illegal drug production and costs. This includes contributions that rely on the calibration of theoretical models of the "war on drugs" using aggregate data and that account for general equilibrium effects (e.g. Chumacero, 2010; Grossman and Mejía, 2008; and Mejía and Restrepo, 2011, 2016),[4] as well as empirical papers that use fine-grained data to evaluate different policies aimed at reducing illicit drugs production.[5] Our paper places in the second set of contributions and it is the first one to explore the unintended negative anticipation effects of a naive policy announcement and that at the same time has a causal interpretation.[6] We find that, because of these effects, the policy actually had results that went in the *opposite direction* than the intended effect.

The rest of the paper is organized as follows. Section 2 provides details on the dynamics of coca growing in Colombia and discusses the institutional context that led to the 2014 announcement that we study in the paper. Section 3 summarizes the data we use. Section 4 explains our empirical strategy and sections 5 and 6 review the main results and robustness, as well as the potential mechanisms respectively. Finally, section 7 concludes.

[4]A key result of these papers is that the low price elasticity of demand for cocaine is a key driving factor of the relative ineffectiveness of supply-side intervention policies, *vis-a-vis* demand reduction efforts through the implementation of prevention programs.

[5]Most of these studies have focused on the direct and collateral effects of aerial spraying campaigns aimed at reducing coca cultivation (see Abadie et al., 2013; Moya, 2005; Reyes, 2014; and Mejía et al., 2015). All of studies find very small (or negligible) effects of this supply-reduction strategy. In most cases, this is explained by the strategies used by coca growing farmers that mitigate the effects of aerial spraying campaigns, such as the spraying of molasses on the coca bushes to prevent the herbicide from penetrating the foliage and killing the plant; cutting the stem of the plant a few hours after the fumigation event, enabling the plant to grow back a few months later; and the reallocation of coca crops to areas less likely to be sprayed (Mejía et al., 2015).

[6]Lopez et al. (2019) assess the effect of the same announcement but using as cross-sectional variation the municipalities with presence of FARC even after the announcement. Instead, our sources of geographical variation are both predetermined and, in the case of the suitability measure, arguably exogenous. Moreover, our results are robust to controlling for the interaction of a measure of the pre-announcement FARC presence at the municipal level and the year fixed effects, and thus fully account for the variation exploited by these authors. Also, the authors use as temporal variation the start of the peace negotiations in 2012, not the release of the joint announcement.

2. Context

Coca crops are the main input in the production of cocaine, and Colombia has been the main cocaine producer for the last three decades. According to the latest figures available from the United Nations Office for Drugs and Crime (UNODC), coca cultivation in Colombia reached a historical peak in 2017, with 171,000 hectares of coca crops, and the potential cocaine production was estimated at 1,058 metric tons, also an all times record. Following the large increase in coca cultivation in Colombia after the main drug cartels were dismantled in the mid 1990s and the illegal armed groups became directly involved in the business, in September 1999 the governments of Colombia and the U.S. launched a joint strategy aimed at combating illegal drugs production and reclaiming control of large areas of the country that were under the control of guerrilla and paramilitary groups. This strategy was called *Plan Colombia*.[7]

The available figures on the magnitude of coca cultivation in Colombia reveal at least four distinct phases (see Figure 1).[8] During the first five years of the implementation of Plan Colombia, coca cultivation decreased rapidly from 163 thousand hectares in 2000 to 80 thousand hectares in 2004 (a 51 percent reduction). This was followed by a period of relative stability, and coca cultivation figures fluctuated between 80-100 thousand hectares until 2007. Starting in 2008 and through to 2013, coca cultivation halved again, going from 100 thousand hectares in 2007 to 48 thousand in 2012 and 2013 (the figure was identical in these two years).[9] The fourth period, from 2014 to 2017, shows an exponential increase in coca cultivation all to way to the aforementioned historical record in 2017.

What explains the unprecedented surge of the fourth period? Several analysts point to the ban of aerial spraying that was enacted in 2015. In April that year, the Colombia's Minister of Health recommended to the National Anti-drug Council to suspend the use of glyphosate in the aerial spraying of illicit crops. The Constitutional Court backed

[7]Different anti-drug strategies were implemented under *Plan Colombia*, such as the aerial spraying of herbicides to destroy illicit crops, manual eradication campaigns, alternative development projects and crop substitution programs, control of chemical precursors used in the transformation of coca leafs into cocaine, detection and destruction of cocaine-processing laboratories in the jungle, and seizure of drug shipments en route to foreign countries.

[8]These figures come from our dataset on coca growing, described in the section 3.

[9]This second reduction in coca cultivation responded to a major shift in the emphases of the country's anti-drug strategy. Instead of relying mainly in combating coca-leaf production, from 2007 onwards the emphasis shifted to attacking the main links of the production chain, for instance by significantly increasing seizures of large shipments of cocaine and by destroying laboratories used to process cocaine. Indeed, between 2007 and 2013 the number of hectares sprayed with herbicides decreased from 150 thousand to 48 thousand.

this recommendation on the grounds of the available evidence about the relationship between glyphosate and the incidence of cancer (International Agency for Research on Cancer, 2017). This led the National Anti-drug Council to ban the use of the herbicide on May 2015.

Despite the available evidence about both the health externalities of glyphosate (see International Agency for Research on Cancer, 2017; Camacho and Mejía, 2017; and Dias et al., 2019), as well as the relative ineffectiveness of the aerial eradication to reduce the incidence of coca crops (see papers cited in the Introduction), the banning of the spraying program ignited a heated debate in Colombia. As mentioned, the program defenders argue that the suspension of the spraying is the main cause behind the surge in coca cultivation during the most recent period. The current administration of the U.S. backs this view. In May 2017, during an official visit of the then president of Colombia –Juan Manuel Santos– to Washington, the White House said the increase in coca crops was worrisome and a month afterward the U.S. State Secretary stated that Colombia should resume aerial eradication. In September 2017, The U.S. President threatened to "decertify" Colombia in the war against drugs. Pressured by the U.S., shortly after its inauguration the current administration of Colombia announced its willingness to resume aerial spraying.

In the context of the government efforts to resume aerial spraying, on March 2019 Colombia's Constitutional Court convened a public hearing to gather the arguments of different actors about the convenience or inconvenience of resuming the program. Current President Iván Duque asked to lift the ban as a way to counteract "the threat and the risks that the country is currently facing because of the vertiginous growth of the illicit crop in the last years."[10]

Former president Santos was also requested by the Court to provide a statement. In it, Santos challenged the view that the surge in coca growing was explained by the suspension of aerial spraying, and instead, he mentioned some alternative explanations, including some retrospective self-criticism:

> '(...) And, I have to admit, the perverse stimulus generated by the announcement, during the peace negotiation with FARC, that we were

[10]Source: "Santos y Duque contrastan su política antidrogas ante la Corte Constitucional," published by newspaper *El País* on 03/07/2019. Available from: https://elpais.com/internacional/2019/03/07/colombia/1551970462_309935.html (last accessed 10/04/2019).

> going to create a program of incentives for the voluntary substitution of coca crops for legal crops."[11]

The evidence we provide in this paper confirms Santos' intuition. Importantly, we show that our results are not driven by the alternative explanations that have been put forward to explain the increase in coca cultivation observed since 2014, namely, the suspension of the aerial spraying program and/or the the possible pressure that the Farc may have exerted on the territories they controlled at the time for the peasants to grow more coca.

3. Data

3.1. **Area cultivated with coca.** Our main outcome variable is the share of the hectares of coca crops relative to the size of the municipality in thousands of hectares.[12] This is a satellite-based measure estimated annually since 1999 by the Integrated Monitoring System of Illicit Crops (SIMCI from its Spanish acronym) of the United Nations Office on Drugs and Crime (UNODC).[13] Table 1 shows that, during our sample period, the average municipality had 0.63 hectares of coca per thousand hectares of municipal land (standard deviation 3.78).

Using SIMCI's geo-referenced coca crops, we also construct four measures of coca concentration within a municipality and for every year. Specifically, we do so based on a raster of 1km^2 (i.e. 100 hectares) grids covering the full extent of Colombia's territory and for which we can identify the number of hectares within each grid cell. The first measure is a Herfindahl-Hirschman Index (HHI) and the second is a Gini coefficient. The third measure is the Moran's I, first formulated by Moran (1950), and widely used to compute the spatial autocorrelation (Bivand and Wong, 2018).[14] Larger numbers

[11]Juan Manuel Santos' statement in the public hearing on the use of glyphosate, March 7, 2019. Available from: https://www.insightcrime.org/wp-content/uploads/2019/03/IntervenciÃşn-de-Juan-Manuel-Santos-ante-la-Corte-Constitucional-07-03-19.pdf (last accessed 09/26/2019).

[12]1 hectare corresponds to about 2.5 acres.

[13]SIMCI's yearly estimates represent the incidence of coca crops at the end of each calendar year but, for accuracy, are based on satellite pictures from different periods. Most of them, however, are obtained between November of the year for which the estimate is produced and February of the next year. Next year's images are included purposefully to capture coca crops that are planted toward the end of the year and hence cannot be capture by the end-of-year pictures (UNODC, 2015).

[14]The Moran's I may be seen as an expanded correlation coefficient attaching a spatial weight matrix.The usual representation of the measure is as follows:

$$I = \frac{n}{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(y_i - \overline{y}\right)\left(y_j - \overline{y}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}$$

where y_i and $\bar{y}$ are, respectively, the value of interest in the grid i and the mean of y in the studied municipality. In our case the y_i is the number of hectares of coca plantations in each grid, and w_{ij}

of the Moran's I correspond to higher spatial autocorrelation. The fourth and final measure of coca concentration corresponds to Getis-Ord Global G (GG Index) (Getis and Ord, 1992).[15] Again, larger numbers of the GG Index correspond to higher spatial autocorrelation.

3.2. **Coca suitability.** We exploit cross sectional variation across municipalities on their average suitability to grow coca. This variable was constructed by Mejía and Restrepo (2015), and it is based on various rounds of a nationally representative household survey of coca farmers conducted by SIMCI/UNODC between 2005-2010. Surveyed coca growers were randomly selected using the satellite estimates described above to identify their location. In total, 1,678 farmers were surveyed in 64 municipalities scattered around the country.

The household survey provides self-reported data on coca crops' yields, which is then combined by Mejía and Restrepo (2015) with exogenous municipal geographic and weather characteristics to estimate an index of the extent of which each municipality is suitable for coca cultivation. These include the altitude of the municipality, a soil erosion index, a soil aptitude index based on soil nutrients, minerals and the topography of the municipality, and average rainfall levels.

3.3. **Predicted targeting of the incentive scheme.** Our second source of cross-sectional variation exploits the extent to which farmers could anticipate, at the time that the announcement about future incentives took place, the likelihood that they would benefit from the substitution program. In particular, the press release included the following information:

> "(...) we have agreed that the National Government will create and implement a new National Program for the Integral Substitution of Illicit Crops (...) with the goal of generating the material and intangible welfare conditions for the people affected by illicit crops, particularly for the peasant communities who live in poverty and that currently obtain

corresponds to the neighborhood matrix for studied municipality. For our analysis, we adopt the randomization assumption, a binary weights matrix and queen's contiguity definition, meaning that each grid can have up to 8 neighbors.

[15]The GG Index works similarly that the Moran's I, and is usually represented as follow:

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} y_i y_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} y_i y_j}$$

Notice that the sole difference between the numerator and denominator is the matrix of weights (which is the same used for the Moran's I), hence the measure changes following the level of spatial clustering in the data.

> their subsistence from such crops (...)" (Joint dispatch No. 36. Havana, May 16, 2014).[16]

We therefore construct –in the spirit of our coca suitability measure described above– a predicted probability of implementing the substitution program in a given municipality. To do this, we estimate a probit model using as dependent variable an indicator of the actual targeting of PNIS.[17] Following the press release, we use as regressors a poverty index and the historical incidence of coca crops, both measured before the announcement. We find that both variables are positively associated with the eligibility or the implementation of PNIS (see Table 2). Table 1 presents the summary statistics for the predicted probability, which has an average of 5%. In turn, 7% of the municipalities ended up being eligible to the program in 2017.

3.4. **Conflict data.** We examine violence as a potential mechanism of the dynamics of coca growing after the initial boost given by the anticipation behavior of coca growers following the announcement. To this end, we use a conflict dataset originally compiled by (Restrepo et al., 2004), and updated through 2018 by Universidad del Rosario. This dataset codes violent events recorded in the *Noche y Niebla* reports from the NGO *Centro de Investigación y Educación Popular (CINEP)* of the Company of Jesus in Colombia, which provides a detailed description of the violent event, its date of occurrence, the municipality in which it took place, the identity of the perpetrator, and the count of the victims involved in the incident.[18]

3.5. **Coca eradication.** The most important potential confounder that we examine is the ban on aerial eradication. To that end we construct municipal-level cumulative aggregates of the size of the area of illicit crops sprayed by Colombian authorities. The source of these data is the Anti-narcotic Unit of the Police (DIRAN from its Spanish acronym).

[16]Our translation from the original Spanish text. Available from: https://www.eltiempo.com/archivo/documento/CMS-13998996 (last accessed 10/04/2019).

[17]For our baseline results we use the 77 municipalities listed by the government as eligible to PNIS in 2017 in a kind of intent-to-treat approach (see Alta Consejería Presidencial, 2017). All our results are however robust to using only the 56 municipalities who actually received the program by the first half of 2019 (see UNODC, 2019).

[18] *Noche y Niebla* sources include "1. Press articles from more than 20 daily newspapers of both national and regional coverage. 2. Reports gathered directly by members of human rights NGOs and other organizations on the ground such as local public ombudsmen and, particularly, the clergy." (Restrepo et al., 2004, p. 404). Notably, since the Catholic Church is present in even the most remote areas of Colombia, we have extensive coverage of violent events across the entire country.

3.6. **Other data.** As we will explain in section 4, our preferred specification controls for a large set of predetermined municipal characteristics interacted with the post announcement period dummy. These control for differential changes across municipalities and over time, parametrized according to variables that characterize the municipal size, the degree of rurality, poverty, and geographical segregation. Specifically, our controls are the (logarithm of) population in 2010, the share of rural population, the poverty index, and the distance to the department capital. The first three variables are provided by Colombia's Statistics Bureau and the last has been computed by us using the municipal centroids on a shape file.

3.7. **Descriptive statistics.** Panels A and B of Figure 2 present the evolution of the share of coca cultivation for a discrete version of our two sources of cross-sectional variation, namely coca suitability and the predicted probability of receiving substitution benefits. In both cases we define as "high" (highly suitable or that obtained a high predicted probability) the municipalities above the median of the empirical distribution of these measures. We can see that in both cases the places with high suitability and high predicted probability of being targeted by the substitution program have more coca cultivation before the announcement. However, visual inspection suggests that despite this level difference the trends follow a similar trajectory. Because this speaks to the main identification assumption of our methodology, we will provide formals tests below. From the Figure it can also be observed that, after the press release, there is a differential increase in coca cultivation in areas highly suitable or with a high predicted probability.

Figure 3 further explores this relationship between the increase in coca and our two measures of what places could have been most affected by the anticipation effect generated by the policy announcement. In blue, we present the *change* in average coca cultivation between 2018-2014 and 2013-2011. Darker blue colors mean a larger interperiod *increase*. In turn, the red dots present suitability (Panel A) and predicted probability of receiving the incentive scheme (Panel B). For both cases larger dots represent higher suitability and a higher predicted probability. The patterns in both maps suggest that larger red dots tend to be placed in municipalities with darker blue colors, suggesting that the increase in coca cultivation was higher in places with lower costs of growing coca (because they had a high suitability) or with high potential benefits (because the predicted probability is high). In the rest of the paper we explore this relationship more formally.

4. Empirical Strategy

4.1. **Main specification.** Our identification strategy exploits the timing of the pre-announcement of future incentives to substitute away coca (on May, 2014), as well as the cross-sectional variation provided by a measure of the cost advantage of growing coca (the coca suitability index) and by a measure of the expected benefits of the crop substitution program (the predicted probability of benefiting from it). More formally, using the subindex m to denote municipalities, d to denote departments, and t to denote time, we estimate the following *difference-in-differences* model:[19]

$$y_{mdt} = \alpha_m + \lambda_{dt} + \beta(Announcement_t \times T_m) + \sum_{c \in \mathbf{X_m}} \gamma'(c \times Announcement_t) + \varepsilon_{mdt} \tag{4.1}$$

where y_{mdt} is measures the share of the municipality area with coca plantation per 1,000 hectares, T_m measures either the coca suitability of municipality m or the expected probability of receiving substitution benefits in municipality m, and $Announcement_t$ is a dummy that takes the value one after the press release where the peace delegations of the government and FARC announced the future implementation of the substitution program. α_m are municipality fixed effects and λ_{dt} are department-year fixed effects. These set of fixed effects control respectively for any observed or unobserved municipal-level time invariant heterogeneity, and for any time shocks that affects simultaneously all the municipalities of the same department. X_m is a vector of various municipality characteristics measured before the announcement that we interact with the time indicator that identifies the post-announcement period to flexibly control for differential changes parametrized by each one of the municipal attributes included in the vector. Finally, ε_{mdt} is the error term, which we cluster at the municipality level in the case of the treatment based on coca suitability.[20]

Our coefficient of interest, β, captures the average differential change of coca growing before and after the announcement in municipalities with high coca suitability or in municipalities with a high estimated probability of receiving the substitution program

[19]Municipalities are equivalent to U.S. counties and departments to U.S. states. There are around 1,100 municipalities in Colombia distributed in 32 mainland departments plus the Caribbean island of San Andrés. Our sample excludes the latter as well as the capital city, Bogota, which constitutes its own department. We thus end up with 31 departments, with the average department including 35 municipalities.

[20]When the cross sectional variation is given by the predicted probability of benefiting from the incentives scheme, we bootstrap the standard errors, given that this measure comes from the predicted values of a previously-estimated regression model. As a robustness we estimate equation 4.1 using a variance-covariance matrix that takes into account cross-sectional dependence in the error term. To that end we follow Conley (1999) and Conley (2016).

relative to municipalities with low suitability or a low estimated probability. Moreover, our estimation takes into account any municipality characteristics that do not vary over time, as well as any differential trends in coca cultivation that are different across departments.

4.2. **Identifying assumption.** The main assumption behind our *difference-in-differences* model is that in the absence of the announcement, the area cultivated with coca in municipalities with high coca suitability or with a high estimated probability of receiving benefits from coca substitution would have followed a similar trajectory to coca growing in municipalities with low coca suitability or a low estimated probability. The validity of this "parallel trends" assumption can be partially assessed by estimating the following non-parametric regression:

$$y_{mdt} = \alpha_m + \lambda_{dt} + \sum_{j \in J} \beta_j (T_m \times \delta_j) + \epsilon_{mdt} \tag{4.2}$$

where J includes all years in our sample except from 2013, which is the year before the announcement. Therefore the parameters β_j can be interpreted as the differential coca production in municipalities with high coca suitability or high predicted probability relative to municipalities with low suitability/probability, in year j relative to the year prior to that of the policy announcement.

4.3. **Potential mechanisms.** We can use municipal-level characteristics to estimate heterogeneous effects that can shed some light regarding the underlying mechanisms of the main effects of interest. To test for heterogeneous effects across municipal-level characteristics, we augment the main specification in equation (4.1) by adding a third interaction term. Specifically, let the municipal characteristic Z_m (measured prior to the May 2014 press release) be a potential mechanism of interest. We estimate:

$$\begin{aligned} y_{mdt} = {} & \alpha_m + \delta_{dt} + \beta_1 (Announcement_t \times T_m \times Z_m) + \beta_2 (Announcement_t \times Z_m) \\ & + \beta_3 (\mathrm{T}_m \times Announcement_t) + \mu_{mdt} \end{aligned} \tag{4.3}$$

Our coefficient of interest, β_1, captures the differential change in coca production in places with high coca suitability/predicted probability of the substitution program for municipalities with characteristic Z. Note that the results coming from this test are suggestive about *potential* mechanisms, but not necessarily causal. Hence, they have to be interpreted with caution.

Using the above specifications we estimate the causal effect of the May 2014 announcement of future material incentives on coca growing (equation 4.1), the dynamic persistence of this effect (equation 4.2), and heterogeneous effects which provide indirect evidence on potential mechanisms (equation 4.3). The next section reports the estimated results.

5. Results

5.1. **Main findings.** Table 3 reports the coefficients of interest obtained from estimating equation (4.1). Columns 1 to 3 present the differential effect of the announcement on coca growing for municipalities with high coca suitability. Columns 4 to 6 do so for municipalities with a high predicted probability of being targeted by the substitution program. Columns 1 and 4 include municipality and year fixed effects, while Columns 2 and 5 change the latter for department×year fixed effects, to capture any aggregate yearly shock at the department level. Finally, Columns 3 and 6 are equivalent to 2 and 5 but also control for differential changes in coca cultivation after the ceasefire due to several pre-ceasefire municipality characteristics.[21] The standard errors in parentheses are clustered at the municipality level in Columns 1 to 3 and bootstrapped in Columns 4 to 6. For robustness, in square brackets we report `p-values` that take into account the potential cross-sectional dependence in the error term Conley (1999, 2016).

Focusing on coca suitability as a measure of the relative cost advantage for coca cultivation, we find that, following the press release, a municipality with a coca suitability index one standard deviation higher than the average municipality experienced an increase in the share of the municipal area cultivated with coca of 0.30 hectares per 1,000 hectares (Column 1). This increase is statistically significant and economically large. It represents 24% of a standard deviation and 109% of the sample mean of coca-growing during the pre-announcement period. Results are of similar magnitude and significance once we add department-year fixed effects (Column 2) and control for differential changes in the outcome after the policy announcement parametrized by pre-announcement characteristic (Column 3). The results are also robust to accounting for spatial correlation in the error term.

Turning to the predicted probability of receiving material incentives to substitute coca for legal crops as a measure of the expected benefits of growing coca, we find similar results in terms of economic importance. In particular, following the press release, a municipality with a predicted probability 10% higher that the mean (which is equal to 5%) experienced an increase in the share of the municipal area cultivated with coca of 0.14 hectares per 1,000 hectares (Column 4). Again, this increase is statistically

[21] This set of municipality characteristics include the logarithm of population, the share of rural population, a poverty index, and the distance to the department capital.

significant and economically large. It represents 11% of a standard deviation and 49% of the sample mean of coca-growing during the pre-announcement period. As in the case of coca suitability, the results are of similar magnitude and significance once we add department-year fixed effects (Column 5), control for differential changes in the outcome after the policy announcement parametrized by pre-announcement characteristic (Column 3), or account for potential spatial correlation in the error term.

In Table 4 we asses the relative importance of our two sources of cross-sectional variation that account respectively for the cost advantage of growing coca and for the expected benefits of engaging in such activity. We do so by including in the same regression model (equivalent to specification (4.1)) the interaction of the post-announcement indicator with both variables simultaneously, as well as the triple interaction. Columns 1 to 3 of Table 4 have the same structure of the previous table (making the specification more demanding incrementally) but include the interaction of the post-announcement indicator with both the suitability index and the predicted probability of receiving incentives for substitution. Column 4, keeps the specification of Column 3 (which includes department-year fixed effects and controls for differential changes parametrized by various pre-determined municipal characteristics) but adds the triple interaction. The coefficient associated with it can be interpreted as the differential change of coca growing following the announcement on places with both high suitability and expected to be targeted by the substitution program.

We find that, when both the cost-advantage and the expected benefits of growing coca are included simultaneously, the coefficient associated with the effect of the estimated probability of receiving the substitution program remains quite stable in terms of magnitude and significance compared to the results reported in Table 3. In the case of the coefficient associated with the effect of coca suitability, it drops in magnitude (to a value between one half and one third of the equivalent coefficient of Table 3) but remain significant. This is important as it suggest that both margins independently, the cost-advantage for and the potential benefits of growing coca, are relevant in this context. Put differently, these results suggest that it is not the case that the two measures of exposure to the policy anticipation shock just capture the same spatial variation.[22]

This is also consistent with the results reported on Column 4, which add the interaction between coca suitability, predicted probability and the time variation given by

[22]Indeed, the correlation between the two measures is rather small: 0.05.

the announcement. We find that the coefficient associated with this triple interaction is positive and significant. In other words, places with both high coca suitability and expected to receive incentives to substitute coca for legal crops in the future react differentially to the incentive given by the policy announcement, making the coca surge even larger.

5.2. **Identifying assumption.** Panels C and D of Figure 2 report the coefficients that result from estimating equation (4.2). Panel C focuses on the effect of the press release on coca growing in municipalities with a higher coca suitability index. Instead, Panel D looks at the variation provided by the predicted probability of being targeted by the substitution program. In both cases it can be seen that there is no differential trend in 2011 and 2012 with respect to 2013, the year prior to the policy announcement. This evidence provides support for the main identifying assumption of the *difference-in-differences* empirical strategy that we use to estimate the effect of the policy announcement on the share of the coca cultivation in Colombia.

Importantly, in contrast to the estimated effects for the years prior to the announcement, starting in 2014 there is differential increase in the share of coca plantations in municipalities with high coca suitability or with a high estimated probability of being favored by material incentives. Moreover, the effect grows overtime and only slows down (but does not revert) in 2018, the final year of our sample.

We also conduct a more parametric test for the existence of differential trends during the pre-announcement period in the spirit of Muralidharan and Prakash (2017). In this test, we interact a linear trend with our measures of low cost of growing coca and of high potential benefits of doing so, and test for the significance of this coefficient prior to the announcement. Reassuringly, we find no evidence for differential trends before the ceasefire (see Table 5 Columns 1 and 5).

5.3. **Further robustness.** As an additional exercise to assess the robustness of our standard errors, we follow Bertrand et al. (2004) and collapse our data before and after the policy announcement to deal with potential serial correlation in the dependent variable. Table 5 Columns 2 and 6 report these results, which reassure the validity of the baseline estimates of Table 3.

Recall that the most demanding version of our baseline results (Columns 3 and 6 of Table 3) include a set of pre-determined municipal characteristics interacted with the post-announcement dummy to control for differential time changes across municipalities parametrized by these variables. For robustness, Columns 3 and 7 of Table 5 report a version of this specification in which, following Belloni et al. (2014), the controls are selected using machine learning techniques. In this way, we take an agnostic stance about which municipality characteristics are more related to coca cultivation and to our measures of coca suitability and the probability of benefiting from the substitution program.[23] Our results are robust to implementing this control-selection practice.

Finally, in Columns 4 and 8 we present a version of our main specification in which our estimates are weighted by the size of the municipality. By doing so, we give the same weight to every square kilometer of Colombia, instead of more weigh to larger municipalities. Our results are robust to this weighting strategy as well.

6. Mechanisms

We have documented a robust and large increase in the land cultivated with illegal coca crops in Colombia triggered by the anticipation effect that a pre-announced policy generated among potential coca growers. This boost concentrated in two types of areas in which the incentive provided by the announcement is expected to have a larger effect: areas with lower costs of growing coca given their soil and climate conditions, and areas that anticipated a higher return from growing coca given by the estimated probability of being targeted to receive incentives. We have also shown that the increase in coca growing is persistent over time and it does not reverse with the actual implementation of the announced crop-substitution program.

We interpret these two pieces of evidence as consistent with an unintended negative consequence of the naive policy announcement, as well as with the endogenous effect that a surge in coca growing has on the dynamics of the internal armed conflict in Colombia. In particular, we hypothesize that the persistence of the effect is consistent with active armed groups attempting to appropriate the output of these crops in order to obtain resources derived from the drug trade. Because of this, once coca growing areas were exposed to the presence of illegal groups, the effectiveness of the crop substitution campaign was reduced.

[23]The set of potential controls includes the logarithm of population, the size of the municipality, the distance to department capital, the share of rural population, a poverty index, the municipal tax revenue per capita, the municipal fiscal deficit, the average elevation of the municipality and the illiteracy rate. The model selects as relevant controls the municipal fiscal deficit in Column 3 and the poverty index and the illiteracy rate in Column 7.

In this section we provide further evidence in favor of our interpretation of the initial rise in coca crops as well as consistent with our explanation of its persistence. In particular, in the next two subsections we show that our results are not driven by alternative explanation such as the suspension of the aerial spraying program in 2015 or the possible pressure that the FARC may have exerted on the territories they controlled at the time so that the farmers could cultivate more coca and receive the future material benefits associated with illicit crops substitution programs. Moreover, the following subsection will formally explore the role of armed groups in the persistence of the upward shift in coca growing and the role of state presence in reducing the observed increase.

6.1. **Alternative accounts.** As discussed in section 2, several internal and external political actors, as well as most of the public opinion, blame the banning of the aerial spraying of coca crops with herbicide glyphosate as the most important factor driving the recent unprecedented surge in coca growing. Our findings are not consistent with this explanation.

Table 6 reports the estimated effect of the announcement on coca cultivation in areas with high vs low coca suitability (Columns 1 to 3) and in areas with high vs low estimated probability of receiving the substitution benefits (Columns 4 to 6). Columns 1 and 4 include the municipality and department-year fixed effects, thus *de facto* replicating Columns 2 and 5 of Table 3.[24] Columns 2 and 5 of Table 6 show the estimates from an equivalent specification, but adding as an additional control the cumulative share of the municipal area that was exposed to aerial eradication in 2011-2014, the period prior to its ban (see section 2) interacted with the year fixed effects. By doing so, we flexibly control for differential trends at the municipality level parametrized by their exposure to aerial spraying of glyphosate. Importantly, we show that the point estimate is largely unchanged both in terms of magnitude and significance. If anything, the differential effect of the announcement on coca growing in municipalities expecting a large benefit from growing coca increases slightly (Column 5).

A second alternative account does recognize the unintended negative effect of the 2014 policy announcement, but places the burden of responsibility on FARC. According to this interpretation, following the announcement of the creation of PNIS, but before the signature of the peace agreement, FARC went back to the territory to promote

[24]The results are unchanged if we use as a baseline the most demanding specification of that Table, that adds as controls pre-determined municipal characteristics interacted with the post-announcement time dummy.

coca plantations, assuring the rural communities in their area of influence that benefits would come downstream if they did so. This is the main variation exploited in a recent paper (Lopez et al., 2019).

Columns 3 and 6 of Table 6 add as an additional control an indicator of FARC presence, as described in Prem et al. (2019a) and Prem et al. (2019b), interacted with the time fixed-effects. Again, this flexibly controls for differential trends at the municipality level parametrized by FARC presence prior to the announcement. Our coefficient of interest is slightly smaller (but the difference is not statistically significant) for the case of the interaction of the post-announcement indicator and the coca suitability index, and virtually unchanged for the case of the interaction of the time variation and the probability of substitution. Therefore, our findings are not driven by this alternative interpretation.

As a final exercise, we conduct a rough horse race-like analysis to determine the relative importance in explaining the surge in coca cultivation of our measures of the differential exposure to the incentive generated by the announcement across municipalities *vis-a-vis* the eradication ban and the presence of FARC in some areas. Specifically, for each municipality we compute the difference in the share of areas cultivated with coca between 2018 (the final year of our sample period) and 2013 (the year prior to the press-release), and regress this result on each one of the potential mechanisms at play. Then we look at the R-square of each regression and determine which mechanism accounts for a larger fraction of the cross-sectional variation of the changes in coca growing between 2013 and 2018.

The results are reported on Figure 4. The R-squared of our measures of the cost advantage of growing coca plus the expected benefit of doing so is 0.596. The R-squared of FARC presence is 0.108 and that of the pre-ban share of the municipality affected by aerial spraying eradication is 0.060. Moreover, when we add the two alternative mechanisms to the regression of the municipal period change of coca growing on our proposed exposure measures, the R-squared increases only 4.6%, up to 0.64.

6.2. **Concentration.** We also look at the within municipal variation of the rise in coca crops and, in particular, we exploit geo-referenced data on coca crops on a yearly basis to compute a range of geographical concentration measures of coca growing by municipality/year. To do so we use the variables defined in section 3 as dependent variables in equation (4.1). This serves the purpose of exploring the patterns of coca growing associated with the documented surge following the policy announcement. In addition, this can also shed light on one of the mechanisms discussed above, by which the increase in coca cultivation is driven by FARCs territorial dissemination of the potential benefits of growing coca. In particular, if FARC spread the word about the future benefits among their already established base of coca growers, one would expect that the surge in coca plantations generates a higher concentration within-municipalities. Instead, if the growth of coca is decentralized across the rural areas independent of having previous experience in coca growing, one would expect an increase across the board and hence no effect on concentration.

On Table 7, we explore whether the increase in coca cultivation was driven by few areas within the municipality that expanded their production, or else by a scattered appearance of new plots with coca. Apart from Columns 2 and 3 (with opposite conclusion relative to one another) we do not observe any statistically significant coefficient, and they range their signs from positive to negative depending on the measure of concentration and spatial autocorrelation correction that we use. Again, this "no result" is consistent with the main mechanism not being the exploitation of the policy announcement by FARC to favor its constituency, but rather the general economic effect that we have unveiled: the new coca went either where its production cost was lower of where the money was expected. Simply put, people respond to incentives.

6.3. **Other armed groups.** Has the persistence in the surge of coca cultivation over time after the announcement been driven by its effect on the dynamics of the internal armed conflict in Colombia? We present two different pieces of evidence that suggests that this is indeed the case. First, on Table 8 we estimate a version of equation (4.3) where we use as the heterogeneous effect Z_m an indicator of the presence of (or the vicinity to) at least one illegal armed group in municipality m before the policy announcement.[25]

We find a positive coefficient in the triple-interaction term, suggesting that in places with low cost for growing coca (or with high potential benefits of the substitution program) and presence of armed groups before the policy announcement, the increase in

[25]Measuring the influence exercised by an armed group over a specific location is extremely challenging. Indicators of presence and non-violent coercion over a large set of municipalities cannot be systematically recorded in an objective way. Violence, on the other hand, while more easily observed, is only imperfectly correlated with territorial dominance. However, non-violent dominance is unlikely to occur without any violence inflicted in the past. It is thus reasonable to assume that the ability to inflict localized violence over a certain period could be expected to translate into influence in different ways. We thus follow a growing empirical literature on the Colombian conflict (see e.g. Acemoglu et al., 2013 and Ch et al., 2018), and use past violence over a period of years as an (imperfect) indicator of influence, as in Prem et al. (2019a).

coca was differentially larger after the policy announcement. Specifically, in Column 1 of Table 8 the triple interaction term doubles the magnitude of interaction term for coca suitability, while in Column 3 it increases the average effect of the probability of receiving substitution benefits by around 160%. These results suggest that the increase in coca growing in areas attractive to armed groups was not only larger, but also economically significantly. This is consistent with the persistence of the coca boom being (at least partially) driven by the endogenous dynamics of the conflict, whereby existing armed groups took advantage of the newly available coca rents to dominate the hosting territories.

To put more flesh into this hypothesized channel, and because territorial dispute is often violent in the context of an internal conflict –which has been the case of Colombia for over 5 decades–, we complement this evidence by exploring how armed conflict changed between 2013 (the year before the policy announcement) and 2018 for municipalities with high suitability/high probability substitution and municipalities with low suitability/low probability. For this purpose we use our digitized armed conflict data, discussed in section 3.

Specifically, for each municipality we take the difference between a dummy that takes the value one if the municipality faced an attack by an armed group other-than-FARC in 2018 minus the same dummy computed in 2013.[26] Thus this variable takes a value one if in 2018 there was at least one attack and there was no attack before, a value zero if the municipality faced an attack in both 2018 and 2013 or did not face any attack in neither year, and a value of minus one if the municipality faced an attack in 2013 but not in 2018. We split municipalities into high and low suitability and high and low probability using the median of the empirical distribution. It can be seen from all panels in Figure 5 that municipalities with low suitability and low probability faced a reduction in the probability of an attack by other armed groups, while municipalities with high suitability/high probability faced an increase in the probability of an attack, with the increase almost doubling the reduction. Moreover, the difference between the averages presented in the bars is statistically significant with `p-values` smaller than 3% in all the cases.

[26]We exclude FARC since they signed a peace agreement with the government in 2016, so they are excluded from the original dataset as perpetrators of conflict related events.

Table 9 shows a similar pattern in a regression framework that estimate the cross-sectional correlation between a dummy that takes the value one if a municipality experienced at least one violent event (Panel A) or at least one attack (Panel B) perpetrated by an armed group different from FARC in 2018 (dependent variable) and our two proxies of the differential incentive provided by the policy announcement, that account for the cost advantage of growing coca and for the expected benefits of doing so. Importantly, in addition to municipal characteristics we control for both department-level fixed effects, a set of municipality characteristics measured before 2013, and for the lagged dependent variable, as measured in 2013 (the year prior to the announcement). Looking at our preferred specification (even columns), the results suggest that a one standard deviation increase in the suitability index is associated with a probability of experiencing a violent event of one percentage point (Panel A, Column 2), which corresponds to an increase of 18% with respect to the average of the dependent variable. In the case of the estimated probability of receiving the substitution program, an increase in 10% in this probability relative to the mean is associated with an increase in 0.3 percentage points in the probability of experiencing a violent event in 2018 (Panel A, Column 4), which corresponds to an increase of 5% with respect to the average of the dependent variable. If we look at unilateral attacks instead of any type of violent events (Panel B) the results are virtually unchanged.

6.4. **State presence.** The last analysis that we undertake is to explore the extent of which state presence at the local level helps attenuate the negative unintended consequences of the policy announcement. In particular, we follow Bonilla-Mejía and Higuera-Mendieta (2019) and Prem et al. (2019b), and use protected areas within municipalities as places with higher relatively state presence to explore potential heterogeneous effects.[27] These areas are protected by the central government due to their environmental value and density of native as well as endangered species. Moreover, they are monitored by park rangers that report to the central government any illegal activity that takes place within the boundaries of these areas.

Table 10 presents a version of equation (4.1) that uses as dependent variable the share of the municipality with coca cultivation that is part of a protected area (Columns 1 and 3) and that is part of a non-protected area (Columns 2 and 4). We find that in non-protected areas an increase of one standard deviation in the suitability index increases the share of coca cultivation in 0.29 per 1,000 hectares. This increase represents

[27]Protected areas include national parks, indigenous lands, and communal lands, where either formal or informal –or traditional ethnic-like institutions– are more likely to be present and active.

a 152% increase with respect to the average share of coca before the announcement (Column 2). We also find a statistically significant increase in protected areas, with an increase of 72% with respect to the mean before the announcement (Column 1). The differences between both effects is statistically significant (`p-value` of 0.02). These results suggests that, within municipalities, areas with more state presence experienced a smaller increase in the area cultivated with coca after the incentives generated by the policy announcement. Also, the fact that we observe an increase in protected areas is reassuring that our results are not driven by the 2015 ban in aerial spraying, as in these areas aerial eradication was not allowed to begin with prior to the ban. We find similar patterns in the case of the potential benefits associated with the substitution program (see Columns 3 and 4).

7. Conclusion

This paper contributes to the recent literature on the unintended negative consequences of the war against drugs by exposing how the announcement of future policies can go wrong. We exploit the recent experience of Colombia, that witnessed an increase in coca growing from 48 thousand hectares in 2013 (the lowest figures since 1999) to 171 thousand hectares in 2017 (the historical record). We document that this large increase was to a great extent the result on a promise made in May 2014 that material benefits would be given to coca growers in the future. Importantly, we show that our results are not driven by alternative explanations such as the ban of aerial spraying of 2015, an explanation recently championed for political reasons by some political parties in Colombia (as well as by the U.S. administration).

Indeed, the increase in coca cultivation in the last five years has generated an intense technical and political debate about its causes and consequences. Our work contributes to this debate by showing how a naive and untimely policy announcement during the peace negotiations between the national government and the FARC generated perverse incentives that led to an unprecedented historical increase in coca cultivation in the country. Our most demanding specifications show that the announcement of material benefits for coca growers who decided to embark on substitution programs increased coca cultivation in some areas of the country that are suitable for coca cultivation by over 100%.

Our results highlight the importance of conducting well designed policy announcements that could minimize unintended consequences derived from the policy-generated incentives. Specifically, the design of illicit crop substitution programs should incorporate baseline estimations of illicit crop cultivation at very desegregated levels, and should impose conditions for the delivery of material benefits for growers who decide to substitute their illicit crops. Otherwise, the announcement of benefits may cause the opposite effect to that initially expected.

We conclude by emphasizing that our findings highlight the negative unintended consequences of a naive policy announcement. However, our research does not evaluate the actual effectiveness of the PNIS substitution program. Until mid-2019 more than 100 thousand families have been enrolled in the program, and recent estimates suggest that over 30 thousand hectares of coca have been eradicated with extremely low levels of recidivism. This question deserves future analysis.

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UNODC (2019): "Informe No. 18 - Programa Nacional Integral de Sustitución de Cultivos Ilícitos," .

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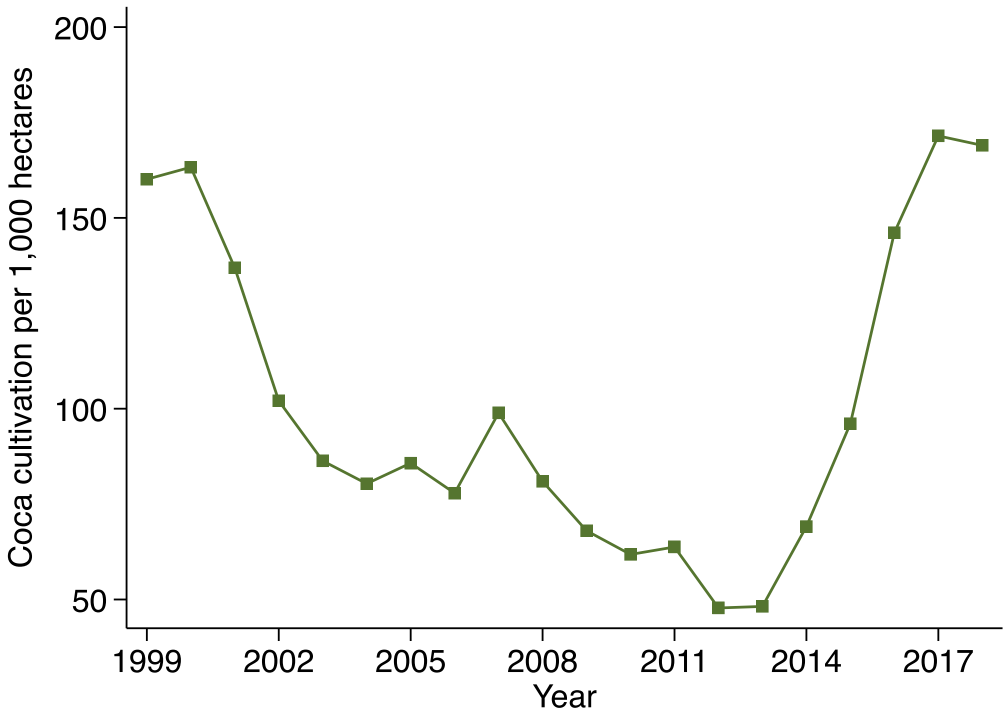
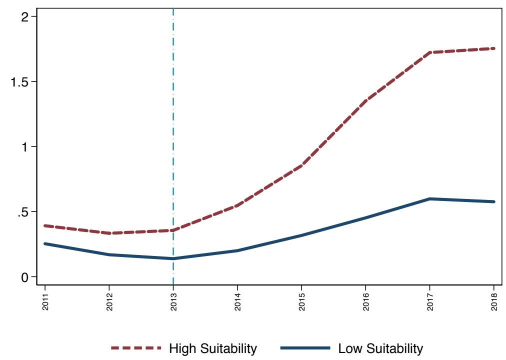
FIGURE 1. **Evolution of coca cultivation**

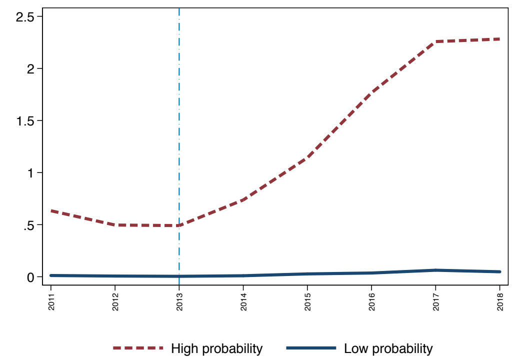


Notes: This figure presents the evolution of coca cultivation per 1,000 hectares in the entire country for the period 1999-2018.

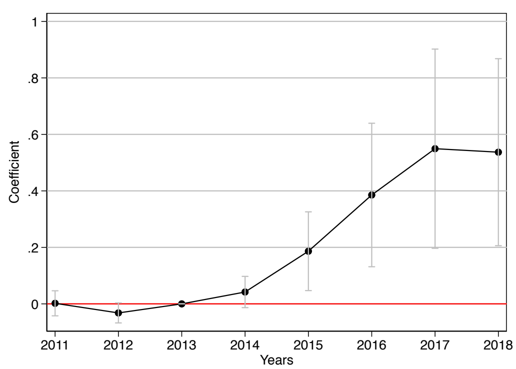
FIGURE 2. **Raw data dynamics and point estimates**



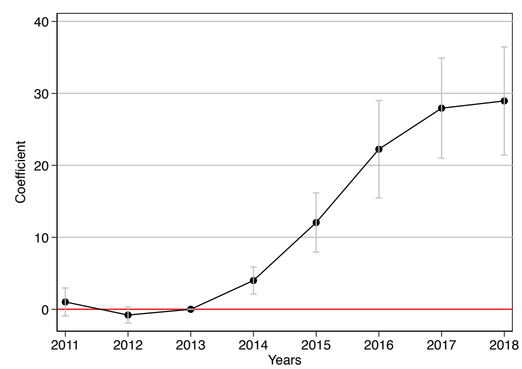
A. Raw data: Suitability



B. Raw data: Probability of substitution



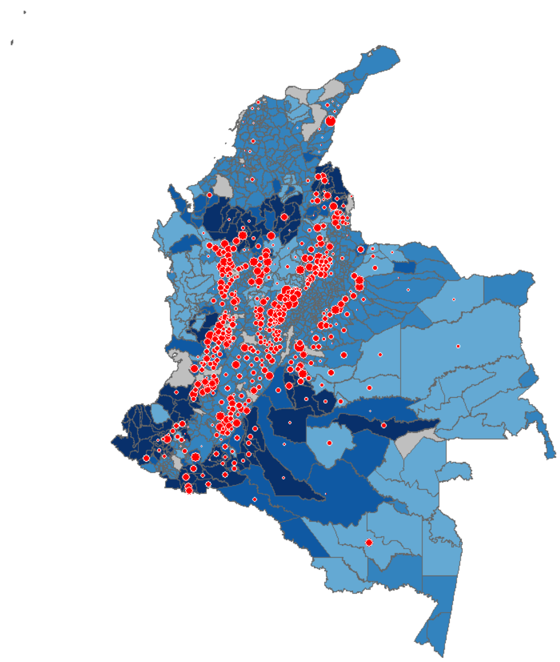
C. Point estimates: Suitability



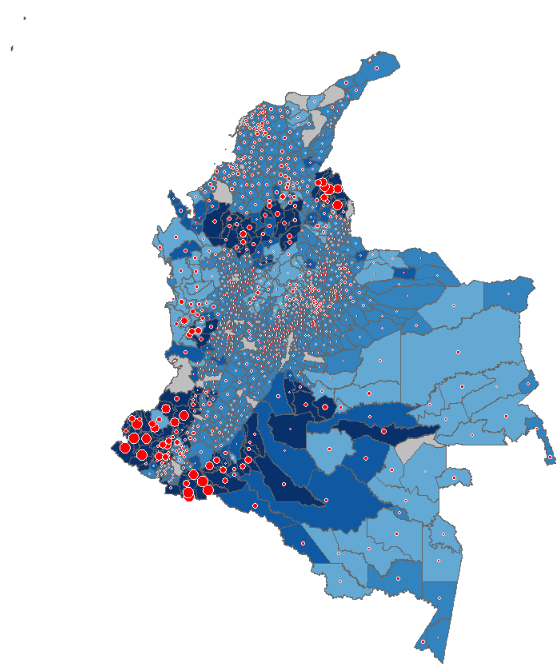
D. Point estimates: Probability of substitution

Notes: This figure presents the evolution of coca area for municipalities with high and low coca suitability and for municipalities with high and low probability of the substitution program. Panels A and B present the raw data. Panels C and D presents the coefficients from our dynamic specification presented in equation (4.2). Panel C uses our continuous treatment of coca suitability, while Panel D uses the probability of the substitution program. We present the point estimates of the regression and the confidence of interval at the 95%.

Figure 3. **Change in coca production, coca suitability, and substitution probability**



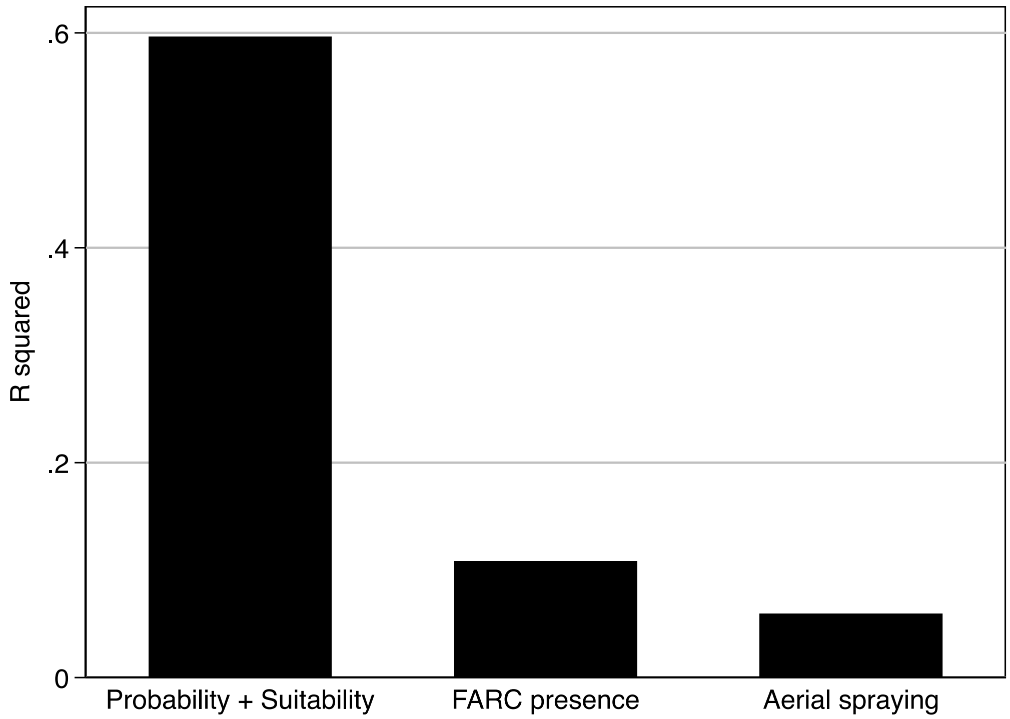
A. Suitability



B. PNIS probability

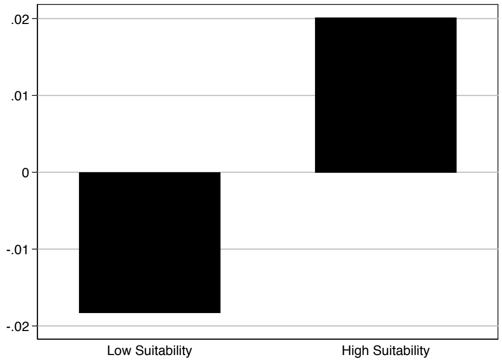
Notes: This figure presents the change in coca production after the announcement compare to before. Darker blues means a larger increase in coca production after the announcement. In panel A the red dots represent the coca suitability of the soil, larger dots means more suitability. In panel B the red dots represent the expected probability of the substitution program, larger dots means higher probability.

Figure 4. **Relative importance of different mechanisms in explaining the surge in coca growing**

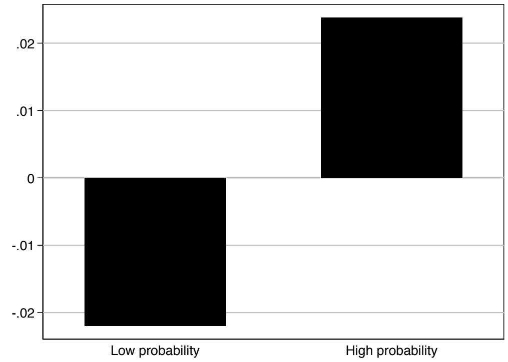


Notes: This figure presents relative importance of different mechanisms in explaining the surge in coca growing. Each column presents the R^2 from three different cross-sectional regressions of the change in the share of the municipality with coca in 2018 minus the same share in 2013 on the different mechanisms. The first regression includes the suitability index and the probability of substitution (Bar 1), the second includes a dummy for FARC presence (Bar 2), while the third includes the sum of all hectares affected by aerial spraying eradication between 2011 and 2014 over the municipality area.

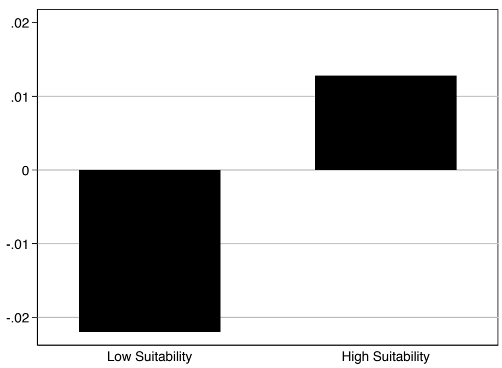
Figure 5. **Change in conflict-related events by coca suitability and substitution probability**



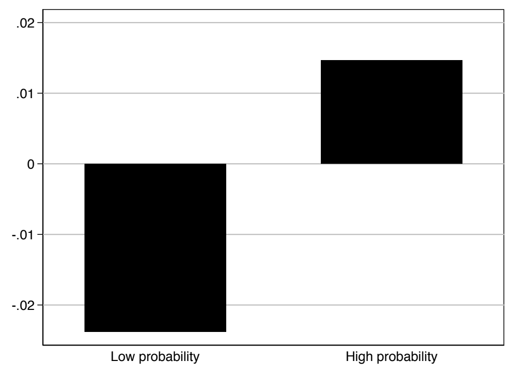
A. Violence: Suitability



B. Violence: Probability of substitution



C. Attacks: Suitability



D. Violence: Probability of substitution

Notes: This figure shows the average change in the occurrence of a conflict related event between 2018 and 2013 for municipalities with high and low coca suitability and with high and low predicted probability of the substitution program. Panels A and B define conflict related events as clash or attack, while Panels C and D only use attacks to define conflict related events. The p-values of the average difference between both groups are 0.005 (Panel A), 0.020 (Panel B), 0.015 (Panel C), and 0.028 (Panel D).

Table 1. Summary Statistics

	(1) Mean	(2) Standard deviation	(3) Median	(4) 90th percentile	(5) 10th percentile
Share of coca cultivation per 1,000 hct	0.63	3.78	0.00	0.45	0.00
Counties in substitution program	0.07	0.26	0.00	0.00	0.00
Probability of substitution program	0.05	0.10	0.03	0.06	0.01
Rural population	0.59	0.23	0.62	0.86	0.23
Poverty index	70.35	15.75	71.27	89.45	48.23
Distance to capital	83.32	60.12	68.81	158.13	24.82
Population	20883.16	26090.27	12567.50	44561.00	3768.00

Notes: This table presents summary statistics for the main variables of interest. See section 3 for variable description.

Table 2. Predicting PNIS

Dependent variable: Dummy for counties in PNIS program	
	(1)
Poverty index	0.15***
	(0.05)
Coca cultivation per 1,000 hct	0.31***
	(0.06)
Observations	1,092
Municipality FE	Yes
Mean DV	0.072

Notes: This table presents the results from a Probit regression on the probability of a county being part of the PNIS program. The table reports the marginal effects computed at the mean of the covariates. Robust standard errors are presented in parenthesis. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table 3. Coca production, coca suitability, substitution probability, and policy announcement

Dependent variable: Share of coca cultivation over 1,000 hectares

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment:	Coca Suitability			Probability of Substitution Program		
Suitability × Announcement	0.30**	0.35***	0.28**	26.99***	26.48***	27.38***
	(0.12)	(0.11)	(0.11)	(4.48)	(4.57)	(4.88)
	[0.002]	[0.002]	[0.006]	[0.000]	[0.000]	[0.000]
Observations	8,736	8,736	8,736	8,736	8,736	8,736
R-squared	0.683	0.736	0.749	0.366	0.438	0.441
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Dept-Year FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Municipalities	1092	1092	1092	1092	1092	1092
Mean DV	0.274	0.274	0.274	0.274	0.274	0.274
SD DV	1.240	1.240	1.240	1.240	1.240	1.240

Notes: This table presents the results from the main specification in equation (4.1). *Suitability* is an index of coca suitability constructed by Mejía and Restrepo (2015). *Probability of substitution* is a predicted probability of the substitution program estimated in Table 2. *Announcement* is a dummy that takes the value one for the period after 2013. Columns 3 and 6 add predetermined municipal controls interacted with the ceasefire dummy. This controls include logarithm of the population in 2010, share of rural population, poverty index, and distance to the department capital. Columns 1 to 3 present robust standard errors clustered at the municipality level in parenthesis, while Columns 4 to 6 present bootstrap standard errors. In square brackets we present the pvalues for standard errors control for spatial and first-order time correlation (see Conley, 1999, Conley, 2016). We allow spatial correlation to extend to up to 279 km from each municipality's centroid to ensure that each municipality has at least one neighbor. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table 4. Relative importance of treatments

Dependent variable: Share of coca cultivation over 1,000 hectares

	(1)	(2)	(3)	(4)
Suitability × Probability of substitution × Announcement				11.58**
				(5.23)
Suitability × Announcement	0.16***	0.10	0.13*	-0.31*
	(0.06)	(0.07)	(0.07)	(0.18)
Probability of substitution × Announcement	26.90***	26.39***	27.29***	24.62***
	(4.46)	(4.58)	(4.89)	(4.50)
Observations	8,736	8,736	8,736	8,736
R-squared	0.367	0.438	0.442	0.471
Municipalities	1092	1092	1092	1092
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dept-Year FE	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Mean DV	0.274	0.274	0.274	0.274
SD DV	1.240	1.240	1.240	1.240

Notes: This table presents the results from the main specification in equation (4.1). *Suitability* is an index of coca suitability constructed by Mejía and Restrepo (2015). *Probability of substitution* is a predicted probability of the substitution program estimated in Table 2. *Announcement* is a dummy that takes the value one for the period after 2013. Column 3 adds predetermined municipal controls interacted with the ceasefire dummy. This controls include logarithm of the population in 2010, share of rural population, poverty index, and distance to the department capital. Bootstrap standard errors are presented in parenthesis. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table 5. Robustness exercises

Dependent variable: Share of coca cultivation over 1,000 hectares

Treatment:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Coca Suitability				Probability of Substitution Program			
	Pre-trend	Collapse pre/post	Machine learning controls	Weighted by county area	Pre-trend	Collapse pre/post	Machine learning controls	Weighted by county area
Suitability × Announcement		0.35***	0.35***	0.34**		26.48***	27.42***	26.01***
		(0.11)	(0.11)	(0.17)		(4.57)	(4.82)	(3.55)
Treatment × Trend	0.01				-0.52			
	(0.02)				(0.70)			
Observations	3,276	2,184	8,736	8,736	3,276	2,184	8,736	8,736
R-squared	0.911	0.783	0.737	0.111	0.784	0.652	0.441	0.524
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dept-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipalities	1092	1092	1092	1092	1092	1092	1092	1092
Mean DV	0.274	0.274	0.274	0.274	0.274	0.274	0.274	0.274
SD DV	1.177	1.240	1.240	1.177	1.240	1.240	1.240	1.240

Notes: This table presents the results from the main specification in equation (4.1). *Suitability* is an index of coca suitability constructed by Mejía and Restrepo (2015). *Probability of substitution* is a predicted probability of the substitution program estimated in Table 2. *Announcement* is a dummy that takes the value one for the period after 2013. Columns 1 to 4 present robust standard errors clustered at the municipality level in parenthesis, while Columns 5 to 8 present bootstrap standard errors. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE 6. Was it eradication or FARC presence?

Dependent variable: Share of coca cultivation over 1,000 hectares	(1)	(2)	(3)	(4)	(5)	(6)
Suitability × Announcement	0.35***	0.34***	0.27***			
	(0.11)	(0.11)	(0.10)			
Probability of substitution × Announcement				26.48***	33.41***	25.47***
				(4.57)	(4.50)	(4.53)
Observations	8,736	8,736	8,736	8,736	8,736	8,736
R-squared	0.736	0.754	0.760	0.438	0.494	0.472
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Dept-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Announcement Eradication × Year FE	No	Yes	No	No	Yes	No
FARC Presence × Year FE	No	No	Yes	No	No	Yes
Municipalities	1092	1092	1092	1092	1092	1092
Mean DV	0.274	0.274	0.274	0.274	0.274	0.274
SD DV	1.240	1.240	1.240	1.240	1.240	1.240

Notes: This table presents the results from the main specification in equation (4.1). *Suitability* is an index of coca suitability constructed by Mejía and Restrepo (2015). *Probability of substitution* is a predicted probability of the PNIS program estimated in Table 2. *Announcement* is a dummy that takes the value one for the period after 2013. *Pre-Announcement Eradication Controls* is the total area eradicated via aerial spraying between 2011 and 2014 over the municipality area interacted with year dummies. Columns 1 to 2 present robust standard errors clustered at the municipality level in parenthesis, while Columns 3 to 4 present bootstrap standard errors. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table 7. Did concentration change?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HHI		GINI		Moran's I		GG Index	
Suitability × Announcement	-0.00		-0.01***		-0.03		0.00	
	(0.02)		(0.00)		(0.02)		(0.00)	
Probability of substitution × Announcement		0.05*		-0.01		0.05		0.00
		(0.03)		(0.02)		(0.04)		(0.00)
Observations	1,636	1,636	1,636	1,636	1,586	1,586	1,621	1,621
R-squared	0.711	0.711	0.939	0.937	0.713	0.712	0.327	0.326
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dept-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipalities	255	255	255	255	246	246	253	253
Mean DV	0.096	0.096	0.933	0.933	0.170	0.170	0.001	0.001
SD DV	0.176	0.176	0.085	0.085	0.233	0.233	0.018	0.018

Notes: This table presents the results from the main specification in equation (4.1) for coca concentration measures. *HHI* is defined as the Herfindahl-Hirshman index for the share of coca cultivation in square kilometer over the total cultivation in the municipality. *GINI* is a gini index based on the share of coca cultivation in each square kilometer. *Moran Index* and *GG Index* are measures of spatial autocorrelation based on Moran (1950) and Getis and Ord (1992) and described in section 3, respectively. *Suitability* is an index of coca suitability constructed by Mejía and Restrepo (2015). *Probability of substitution* is a predicted probability of the substitution program estimated in Table 2. *Announcement* is a dummy that takes the value one for the period after 2013. Even columns present robust standard errors clustered at the municipality level in parenthesis, while odd columns present bootstrap standard errors. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE 8. Heterogeneous effects by armed groups presence

Dependent variable: Share of coca cultivation over 1,000 hectares		
	(1)	(2)
Armed group presence × Suitability × Announcement	0.39*	
	(0.20)	
Armed group presence × Probability of substitution × Announcement		16.63***
		(6.47)
Suitability × Announcement	0.18**	
	(0.08)	
Probability of substitution × Announcement		10.60**
		(5.17)
Armed group presence × announcement	0.91***	-0.38*
	(0.20)	(0.23)
Observations	8,736	8,736
R-squared	0.739	0.818
Municipality FE	Yes	Yes
Dept-Year FE	Yes	Yes
Municipalities	1092	1092
Mean DV	0.274	0.274
SD DV	1.240	1.240

Notes: This table presents the results from the main specification in equation (4.1). *Suitability* is an index of coca suitability constructed by Mejía and Restrepo (2015). *Probability of substitution* is a predicted probability of the substitution program estimated in Table 2. *Armed group presence* is a dummy that takes the value one for municipalities with at least one attack by any armed group between 2011 and 2014. *Announcement* is a dummy that takes the value one for the period after 2013. Column 1 presents robust standard errors clustered at the municipality level in parenthesis, while Column 2 presents bootstrap standard errors. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table 9. Change in violence, coca suitability, and probability of substitution

Dependent variable: Dummy for any other armed group event in 2018

	(1)	(2)	(3)	(4)
Panel A: Any violent event				
Suitability	0.02**	0.01*		
	(0.01)	(0.01)		
Probability of substitution			0.69***	0.61***
			(0.15)	(0.17)
Other armed groups violent events in 2013	0.28***	0.24***	0.25***	0.22***
	(0.06)	(0.06)	(0.06)	(0.06)
Observations	1,092	1,092	1,092	1,092
R-squared	0.178	0.218	0.236	0.258
Department FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Mean DV	0.057	0.057	0.057	0.057
Panel B: Any attack				
Suitability	0.01**	0.01		
	(0.01)	(0.01)		
Probability of substitution			0.64***	0.55***
			(0.16)	(0.16)
Other armed groups violent events in 2013	0.29***	0.25***	0.26***	0.23***
	(0.06)	(0.06)	(0.06)	(0.06)
Observations	1,092	1,092	1,092	1,092
R-squared	0.174	0.221	0.230	0.258
Department FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Mean DV	0.050	0.050	0.050	0.050

Notes: This table presents the results from the main specification in equation. Panel A uses as dependent variable a dummy that takes the value one if in 2018 there was at least one clash or attack by an other-than-FARC armed group, while in Panel B takes the value one if there was at least one attack. *Suitability* is an index of coca suitability constructed by Mejía and Restrepo (2015). *Probability of substitution* is a predicted probability of the substitution program estimated in Table 2. *Announcement* is a dummy that takes the value one for the period after 2013. Columns 1 and 2 present robust standard errors in parenthesis, while Columns 3 and 4 present bootstrap standard errors. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table 10. Differential effects by protected areas

Dependent variable: Share of coca cultivation over 1,000 hectares

	(1) Protected	(2) Not Protected	(3) Protected	(4) Not Protected
Suitability × Announcement	0.06***	0.29***		
	(0.02)	(0.10)		
Probability of substitution × Announcement			6.65***	19.84***
			(2.02)	(5.22)
Observations	8,736	8,736	8,736	8,736
R-squared	0.805	0.712	0.309	0.345
Municipality FE	Yes	Yes	Yes	Yes
Dept-Year FE	Yes	Yes	Yes	Yes
Municipalities	1092	1092	1092	1092
Mean DV	0.0830	0.191	0.0830	0.191
SD DV	0.696	0.928	0.696	0.928
`p-value` Protected vs Non Protected	0.021		0.024	

Notes: This table presents the results from the main specification in equation (4.1). The dependent variable is the share of coca cultivation over 1,000 hectares in protected areas (Columns 1 and 3) and in non-protected areas (Columns 2 and 4). An area is defined as protected if the square kilometer is part of a national park or an indigeneous or communal land. *Suitability* is an index of coca suitability constructed by Mejía and Restrepo (2015). *Probability of substitution* is a predicted probability of the substitution program estimated in Table 2. *Announcement* is a dummy that takes the value one for the period after 2013. *`p-value` Protected vs Non Protected* is the `p-value` of the statistical difference between the coefficient from the Protected and the Non-Protected regression. Columns 1 and 2 present robust standard errors in parenthesis, while Columns 3 and 4 present bootstrap standard errors. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.