The Political Consequences of 'Source Country' Operations: Evidence from Crop Eradication in Mexico
Supplemental Information

March 11, 2024

Contents

Appendix A Military Geography

While Mexico is politically divided into 32 states, the Mexican Army is territorially organized around 13 military regions and 46 military zones. Each region is headed by a Division General and encompasses whole states, while military zones are headed by lower-ranking Brigade Generals and can incorporate municipalities from one, two, or three different states. Zone commanders have operational autonomy in the territory they head and can appoint the commanders of sectors and subsectors within their territory. In addition, the president has the prerogative to appoint both zone and region commanders directly for an indeterminate length of time. Figure A1 shows the overlap between military zones and regions.

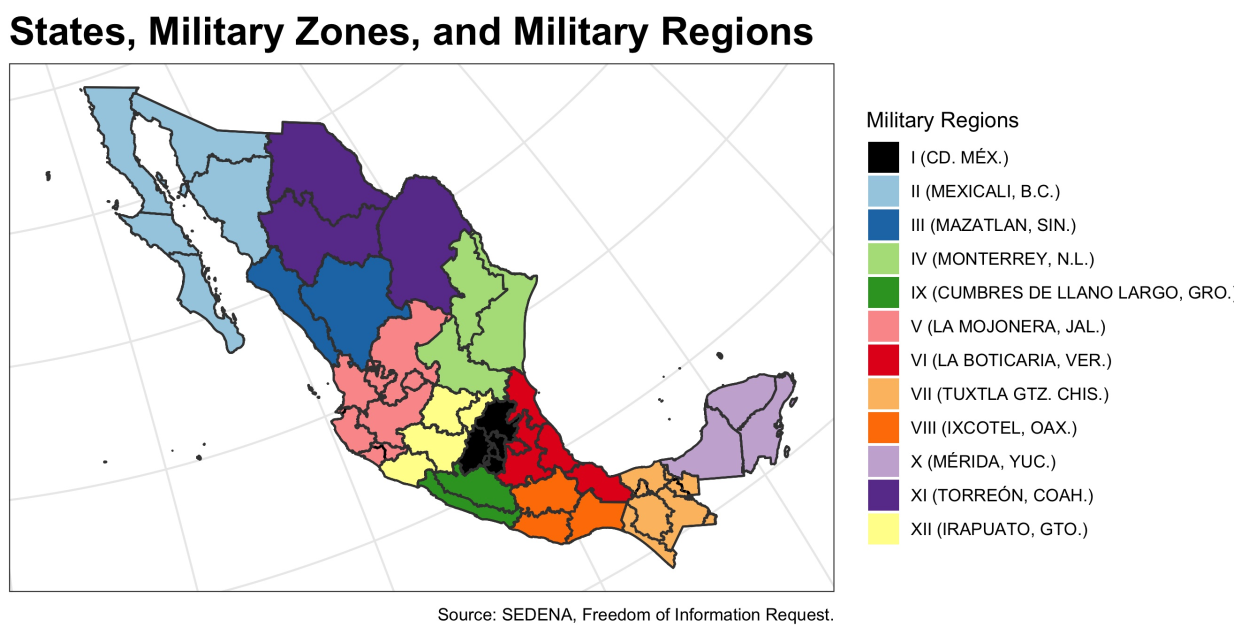


Figure A1: The map colors municipalities by the military region to which they belong, and shows the borders of military zones in black.

Appendix B The Drug-Trafficking Chain

Growers, not drug-trading organizations (DTOs), often own the illicit crops the army eradicates in Mexico. Thus, eradication operations do not affect DTOs economically, and the negative economic shock is absorbed by growers that, as Figure A2 shows, sell their crops to intermediaries.

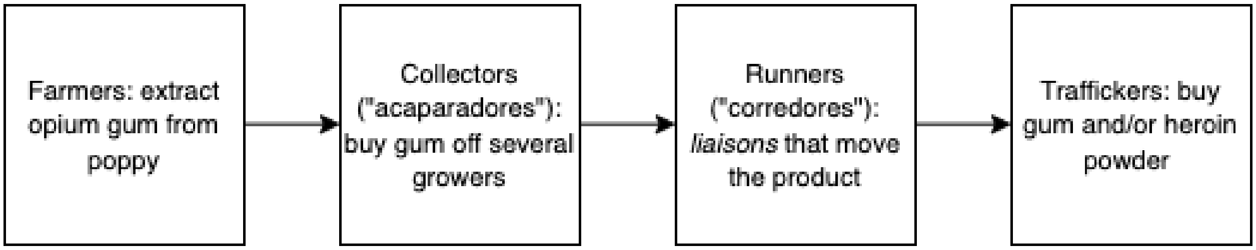


Figure A2: The figure describes the drug-trafficking process, starting from the selling of poppy farming in a town of the Sierra de Guerrero, as described in Álvarez Rodriguez (2021a).

Appendix C Municipal level results

The municipal level results rely on municipal fixed-effects for identification. Besides the absence of time-variant confounders, the effects must be constant across groups, periods, and dosages for the the effect estimated from the continuous mesure of eradication to recover the desired causal contrast. In figure A3 I plot the result of estimating a flexible ten-knot cubic regression spline with the same specification. The effects of eradication are plausibly constant across different dosages for the log number of eradicated hectares; however, the effects across dosages are heterogeneous for the log number of eradicated fields.

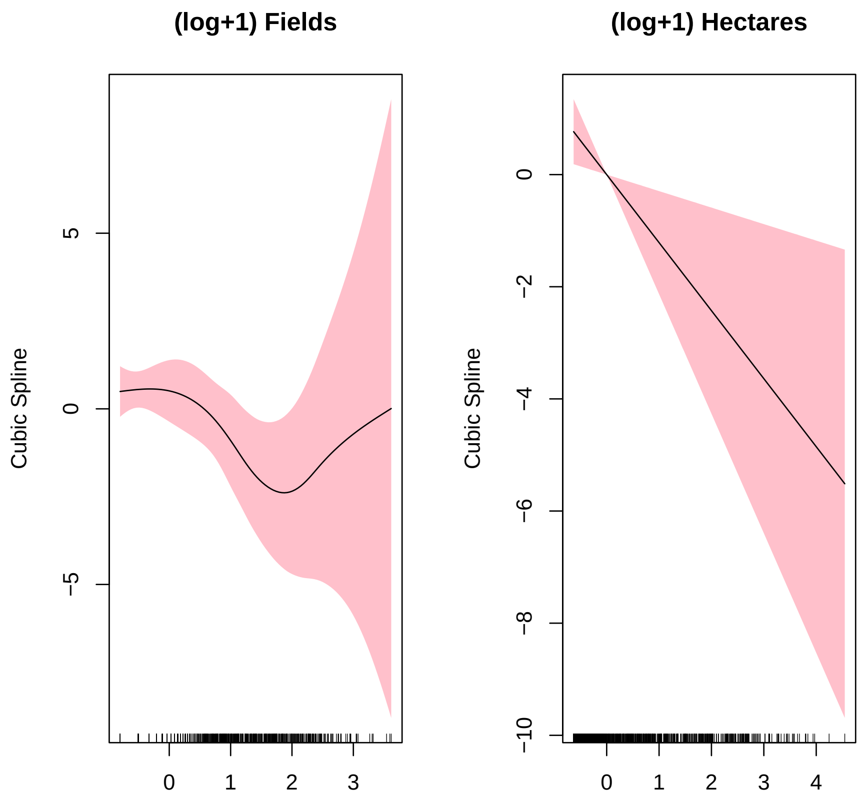


Figure A3: Figure shows the result of fitting smoothing cubic splines with 10 knots on a model with hectares or fields as the independent variable, and turnout as the dependent variable.

Appendix D Eradication: Precinct level results

A4.1 Sample

The sample I use for the precinct-level results consists of all precincts where the army detected an illicit field during a federal election year. To measure eradication, I combine data on all fires detected by NASA satellites with the geolocated information on detected fields. With these data, I construct a measure of precinct-level eradication as described in section 4.3 of the main paper. Table A1 provides basic summary statistics of the resulting precinct-level sample.

Predicted eradication?			No					Yes		
Variable	N	Mean	Min	Max	Sd	N	Mean	Min	Max	Sd
Turnout (%)	701	52.29	5.49	97.73	16.51	336	56.73	5.9	99.4	15.25
Detected fields (count)	701	8.46	1	206	17.15	336	29.24	1	417	46.27
Destroyed fields (count)	701	-	-	-	-	336	7.73	1	97	13.01

Table A1: Table shows basic summary statistics according to presence or absence of predicted eradication at the precinct level.

A4.2 Results with municipal fixed effects

Table A2 replicates the precinct-level analysis from section 6.1 in the main paper, but substitutes the military-zone fixed effects with municipal fixed-effects. While this specification is very stringent, as most of the variation comes from within military-zones, the magnitude and direction of the results corroborate that eradication depresses turnout, albeit estimated more imprecisely.

	Turnout (1)	Turnout (2)	Turnout (3)
Any eradication (dummy)	−0.503		
	(1.065)		
Destroyed hectares (log)		−0.496	
		(0.349)	
Destroyed fields (log)			−0.782
			(0.530)
Num.Obs.	1039	1039	1039
R2	0.596	0.597	0.597
R2 Adj.	0.530	0.531	0.531
Fixed effects: Year x Municipality	Yes	Yes	Yes

Cluster-robust standard errors shown in parentheses.
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table A2: Illicit-crop eradication and turnout in federal elections for deputies: precinct-level results. Dependent variable measures turnout as share of all registered voters in the precinct. Robust standard errors clustered at the precinct level.

A4.3 ICWa construction

I construct the following inverse covarance weighted average that synthesize a battery of sociodemigraphic characteristics. For each electoral precinct i, the ICW willl equal

$$ICW_i = (\mathbf{1}'\hat{\boldsymbol{\Sigma}}^{\mathbf{-1}}\mathbf{1})^{-1}(\mathbf{1}'\hat{\boldsymbol{\Sigma}}^{\mathbf{-1}}\boldsymbol{X_i})^{-1}$$

Where $\boldsymbol{X_i}$ is a vector of the following standardized precinct-level covariates: mean school achievement, share of employed residents, share of residents who can read and write, share of dwellings that have T.V., share of dwellings that have internet, share of dwellings without a dirt floor, share of homes headed by a man, share of residents with healthcare. $\hat{\boldsymbol{\Sigma}}^{\mathbf{-1}}$ is the inverted covariance matrix and $\mathbf{1}$ is a column vector of 1's (Anderson, 2008).

Appendix E Trust

A5.1 Trust in family and neighbors

In this paper, trust in law enforcement agencies is characterized as a belief that is updated when people acquire new information about the authorities through eradication operations. The results would be biased if trust operated not as a belief but as a personal proclivity, whose distribution in the population covaries with the timing of crop eradication operations. If individuals living in municipalities eradicated before survey collection were more trusting, generally, than people living in municipalities eradicated after, then the results would be biased. Figure A4 shows that trust in family or neighbors is not the case. The timing of eradication is not correlated with differences in trust in either of these groups.

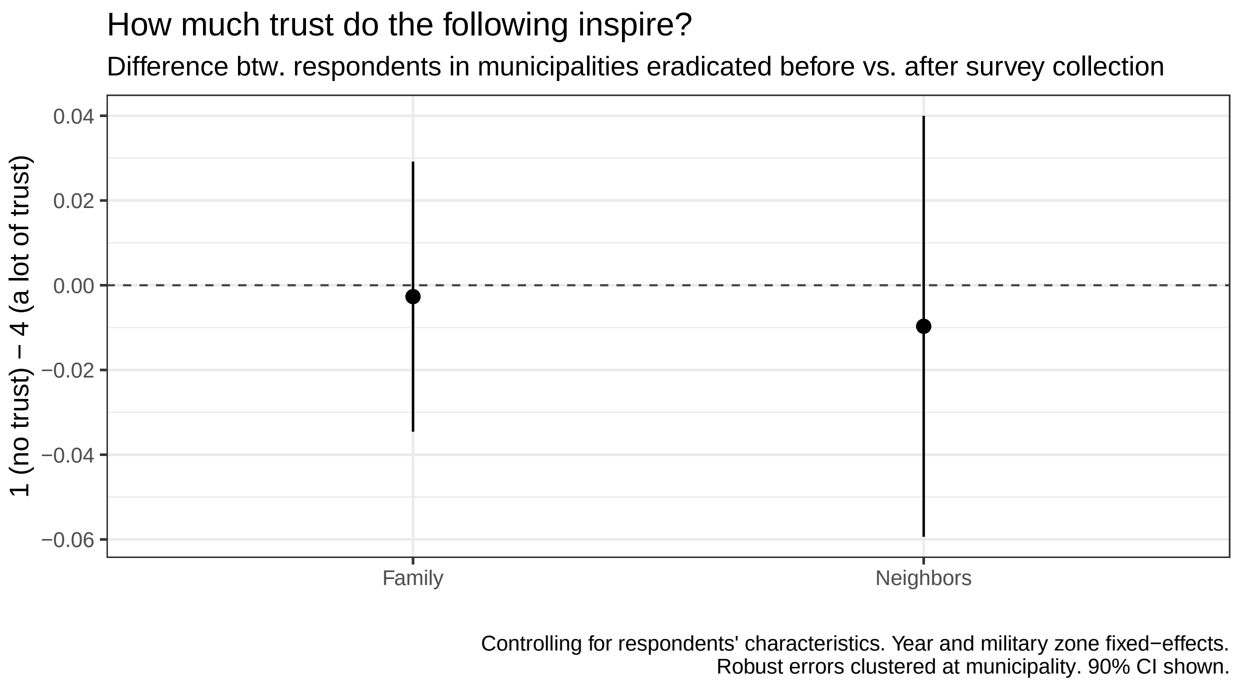


Figure A4: Difference-in-means in two measures of trust reported by ENVIPE respondents living in municipalities eradicated before vs after survey was collected.

A5.2 Figure 3: Figure 3: Full Results

Table A3 shows the full results of the difference-in-means in self-reported trust in law enforcement institutions, plotted in Figure 3.

DV:Trust in...	Diff-in-means rural	Female rural	Education rural	Age quintile rural	Diff-in-means urban	Female urban	Education urban	Age quintile urban
Army	-0.052 [0.028] n = 19520	-0.241 [0.016] n = 19520	0.005 [0.005] n = 19520	-0.014 [0.006] n = 19520	0.000 [0.041] n = 49970	-0.220 [0.017] n = 49970	-0.029 [0.003] n = 49970	-0.010 [0.005] n = 49970
Navy	-0.067 [0.041] n = 12443	-0.238 [0.023] n = 12443	0.012 [0.005] n = 12443	-0.020 [0.008] n = 12443	0.021 [0.068] n = 35792	-0.192 [0.0156] n = 35792	-0.015 [0.002] n = 35792	-0.018 [0.005] n = 35792
Federal police	-0.057 [0.039] n = 12418	-0.111 [0.022] n = 12418	-0.010 [0.005] n = 12418	-0.0351 [0.008] n = 12418	-0.001 [0.035] n = 42468	-0.108 [0.0132] n = 42468	-0.030 [0.002] n = 42468	-0.0419 [0.004] n = 42468
State police	-0.004 [0.038] n = 12774	0.040 [0.018] n = 1277	-0.022 [0.005] n = 12774	-0.038 [0.007] n = 12774	-0.003 [0.039] n = 42215	0.041 [0.015] n = 42215	-0.035 [0.003] n = 42215	-0.0189 [0.007] n = 42215
Attorney General	-0.000 [0.041] n = 7632	-0.058 [0.025] n = 7632	-0.010 [0.007] n = 7632	-0.040 [0.010] n = 7632	0.050 [0.058] n = 32612	-0.100 [0.020] n = 32612	-0.034 [0.003] n = 32612	-0.040 [0.008] n = 32612
Public Ministry	-0.047 [0.036] n = 6943	0.000 [0.021] n = 6943	-0.030 [0.006] n = 6943	-0.050 [0.009] n = 6943	-0.020 [0.044] n = 2507	0.052 [0.015] n = 2507	-0.036 [0.003] n = 2507	-0.057 [0.005] n = 2507
Judges	-0.045 [0.057] n =3658	-0.017 [0.029] n =3658	-0.025 [0.009] n =3658	-0.040 [0.014] n =3658	0.069 [0.039] n = 12846	0.027 [0.015] n = 12846	-0.023 [0.004] n = 12846	-0.035 [0.009] n = 12846

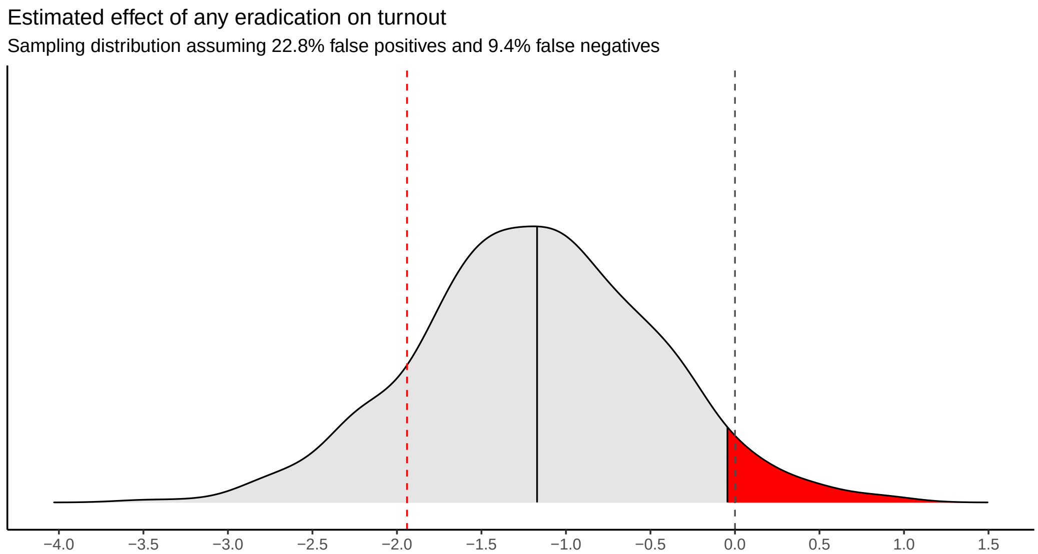
Table A3: Table corresponds to Figure 3 in the main paper. Robust standard errors clustered at the municipality are shown in brackets. The dependent variable is the standardized response to the question "How much trust do the following authorities inspire?" measured on 1-4 scale. Columns show the estimated coefficients for each of the individual-level covariates used in the adjustment, along with the difference-in-means in self-reported trust in each authority for people living in municipalities eradicated before vs. after the survey was collected. Columns labeled "rural" show the results of models fitted only with rural respondents, while columns labeled "urban" show the results of models fitted exclusively with urban respondents. All models include year and municipality fixed effects.

Appendix F Measurment and Selection Issues

A6.1 Missclasification

To benchmark a plausible proportion of misclassified units in the precinct-level analysis, I compare the estimated eradication measure with official geolocated data from the army on all eradication operations for 2019 and 2020. For each field detected between 2019 and 2020, I replicate the algorithm described in Section 4.3 but use reported eradication instead of NASA fire data to measure eradication. I compare the classification of all fields when eradication is predicted with NASA fire data to the classification when it is predicted with official army data. Importantly, the army eradicates fields it detected with all techniques, not only via satellite. Thus, the estimated proportion of false positives is likely overstated. Benchmarking the fire-based measure of predicted eradication to reported eradication, I estimate the former measure to be 61% accurate. When aggregated into electoral precincts, I estimate a conservative proportion of 9.45% of false negative and 22.8% of false positive units.

To test the robustness of the results to the inclusion of false negatives and false positives, I first assess the sensitivity of the results to each, independently and then simultaneously. To start, I assign control/treatment units to treatment/control probabilistically by sampling 500 new outcomes from Bernoulli processes with a probability of success equal to the hypothesized shares of each type of misclassified units. Next, I re-estimate the model 500 times, each using one of the 500 new probabilistically-drawn outcomes. Figure A7 shows the results of the simulation. The top panel shows the sampling distribution of the difference-in-means estimator, assuming the benchmarked proportions of false positives and negatives: 9.45% and 22.8%, respectively. Results show that the difference-in-means, although overstated, is still statistically significant under this assumed misclassification proportion. The left panel shows the sampling distributions of the difference-in-means estimator under different assumptions of the "true" proportion of false negatives, holding false positives fixed. The right panel shows the corresponding distributions as the "true" proportion of false positives changes, holding the proportion of false negatives fixed. Results show that the "true" estimated effect is statistically different from zero with up to 40% of misclassified control units or 45% of misclassified treatment units.



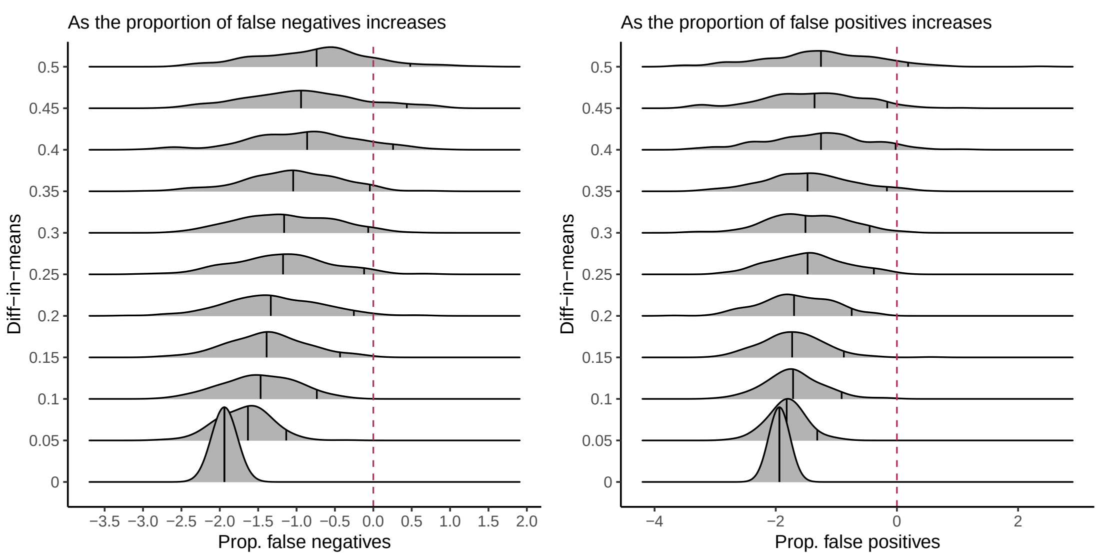


Figure A5: The top panel plots the estimated sampling distribution of the effect of eradication on turnout, assuming 22.8% of the observations classified as 'eradicated' are false positives and 9.4% of the observations classified as 'not eradicated' are false negatives. The bottom left panel show the sampling distribution of the difference-in-means estimator as the proportion of false negatives changes, holding false positives fixed. The bottom right panel show the sampling distribution of the difference-in-means estimator as the proportion of false positives changes, holding false negatives fixed.

A6.2 Geographic determinants of eradication

In this subsection, I present the results of the predictive exercise detailed in section 6.1.2 of the main paper. To test for the possibility of strategic eradication, motivated by geographic characteristics, I model the probability θ that illicit field i in electoral precinct p was counted as eradicated as follows:

$$\theta_{i[p]} = g^{-1}(\gamma DistanceToArmy_i + \beta \boldsymbol{X}_p + \mu_t + \theta_z)$$

Where $DistanceToArmy_i$ is the distance from illicit field i to the corresponding military zone's headquarters in decimal degrees, X_p is a vector of precinct-level covariates, including the proportion of precinct p's surface area that is occupied by grassland, agriculture, forest, and human settlements, and a dummy variable that takes the value of one if any paved roads pass through the electoral precinct and zero otherwise, μ_t are year fixed-effects, θ_z are military zone fixed-effects, and $g(.)$ is the logistic link function.

Table A4 shows this model's confusion matrix. Geographic characteristics do a very poor of predicting eradication: only 0.13% of all eradicated fields are correctly predicted to be eradicated, lending credence to the identifying assumption.

	Destroyed (DV)	Not destroyed (DV)
Destroyed (Fitted)	9	13
Not destroyed (Fitted)	6507	27338

Table A4: Do geographic characteristics predict field eradication? Confusion table from predicting eradication using the geographic characteristics of detected fields.

Appendix G Alternative Explanations

A7.1 Income

In this subsection I consider the possibility that eradication operates on participation mechanically through changes in people's income. To test, I use the 2017 collapse of poppy prices. While poppy was selling for record prices between 2014 and 2017, its price fell by around 50% in 2018. I subset the precinct-level data on eradication and keep only elecotral precincts detected illicit poppy fields. I define the treatment as the $(log+1)$ number of poppy fields the algorithm predicts were eradicated before the elections or the $(log + 1)$ number of destroyed hectares.

I plot the marginal effect of eradication on turnout for each of the two years in Figure A6. The effect is more precisely estimated for 2018 than 2015 because the army detected many more poppy fields in the former year than in the latter. However, the estimated effects are of comparable magnitude, and we cannot reject the null that the coefficients are the same with 95% confidence. Further, contrary to what we would expect if the loss of income drove the effects, the point estimates for 2015 are less negative than in 2018 for both cases, suggesting that the negative economic shock of eradication cannot explain the results, at least in isolation.

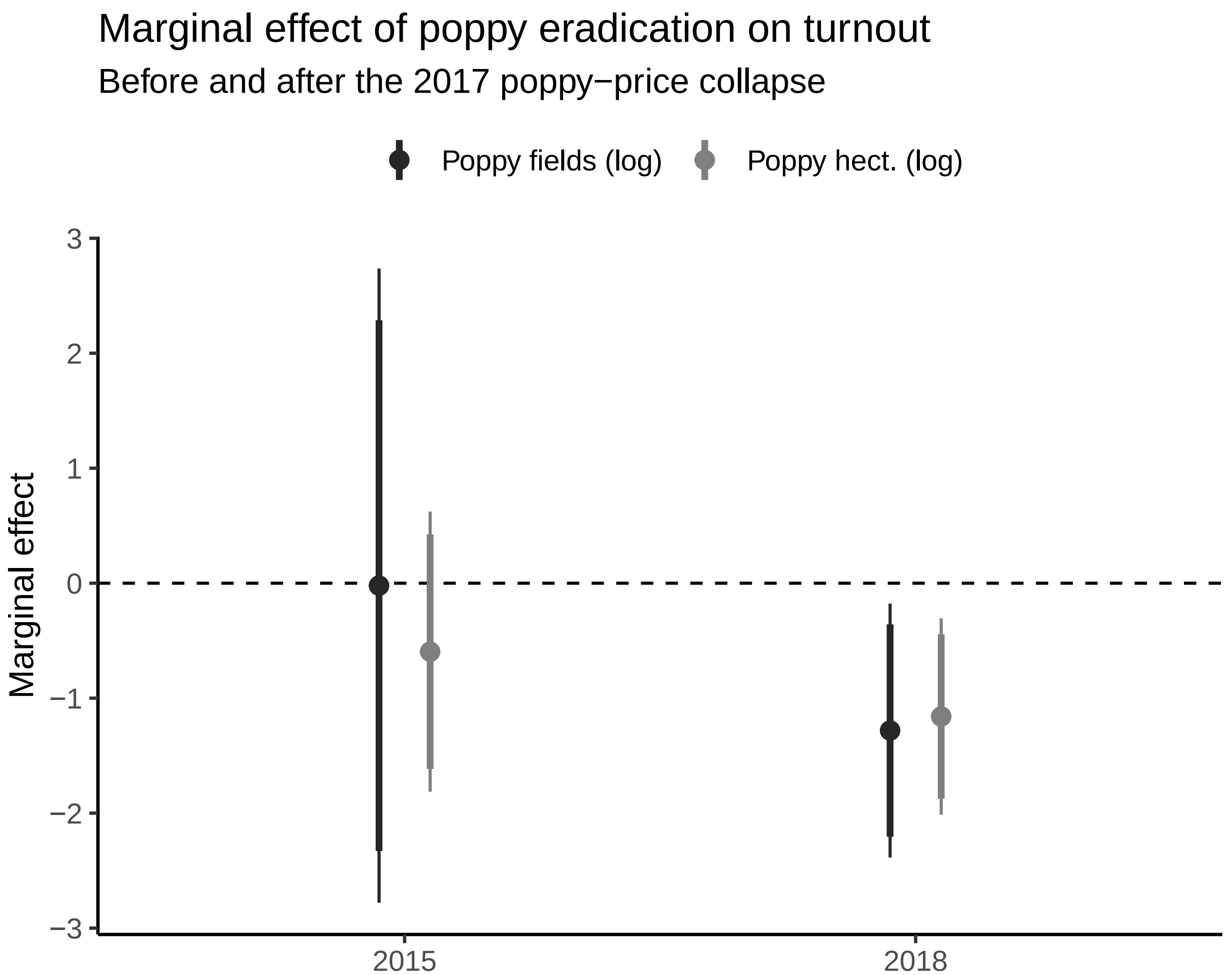


Figure A6: Figure plots the marginal effect per year of a model with turnout as a dependent variable, and the log+1 number of eradicated poppy fields/hectares as the main independent variable. All controls and fixed-effects are included. Only electoral precincts with detected poppy fields are included in the control group.

A7.2 Lethal violence

In this subsection, I consider the possibility that eradication operates on participation by changing the intensity of violence perpetrated by drug trading organizations (DTOs). If, for instance, DTOs respond to eradication by trying to capture new territory, or if eradication weakens DTOs and incentivizes competitors to attack, then eradication might increase violence, which then might depresses electoral participation. To test descriptively, I analyze whether eradication operations predict downstream violence.

Table A5: Homicide rate and eradication

	Change (t-t+1)	Homicide rate t+1 (log)	Homicide rate t+2 (log)
Eradicated hectares (log)	-0.016	0.017**	0.015**
	(0.028)	(0.005)	(0.005)
Num.Obs.	17008	187421	186259
R2 Adj.	0.097	0.201	0.202
Fixed effects: Year	Yes	Yes	Yes
Fixed effects: Municipality	Yes	Yes	Yes

Robust errors clustered at the municipality
+ p < 0.1, * p < 0.05, ** p < 0.01

I estimate the following two-way fixed-effects model:

$$Violence_{mt} = \gamma Eradication_{mt} + \mu_t + \theta_m + \varepsilon_{mt} \tag{1}$$

where $Violence_{mt}$ is a measure of lethal violence in municipality m during month t and $Eradication_{mt}$ is the (log+1) count of fields or hectares eradicated manually in the same period. μ_t are year fixed-effects, and θ_m are municipality fixed-effects. Robust standard errors are clustered at the municipality. Results show a weak, but statistically significant positive association between eradication and the (log) municipal homicide rate one and two months after eradication. However, Figure A7 shows how eradication is a very poor predictor of lethal violence.

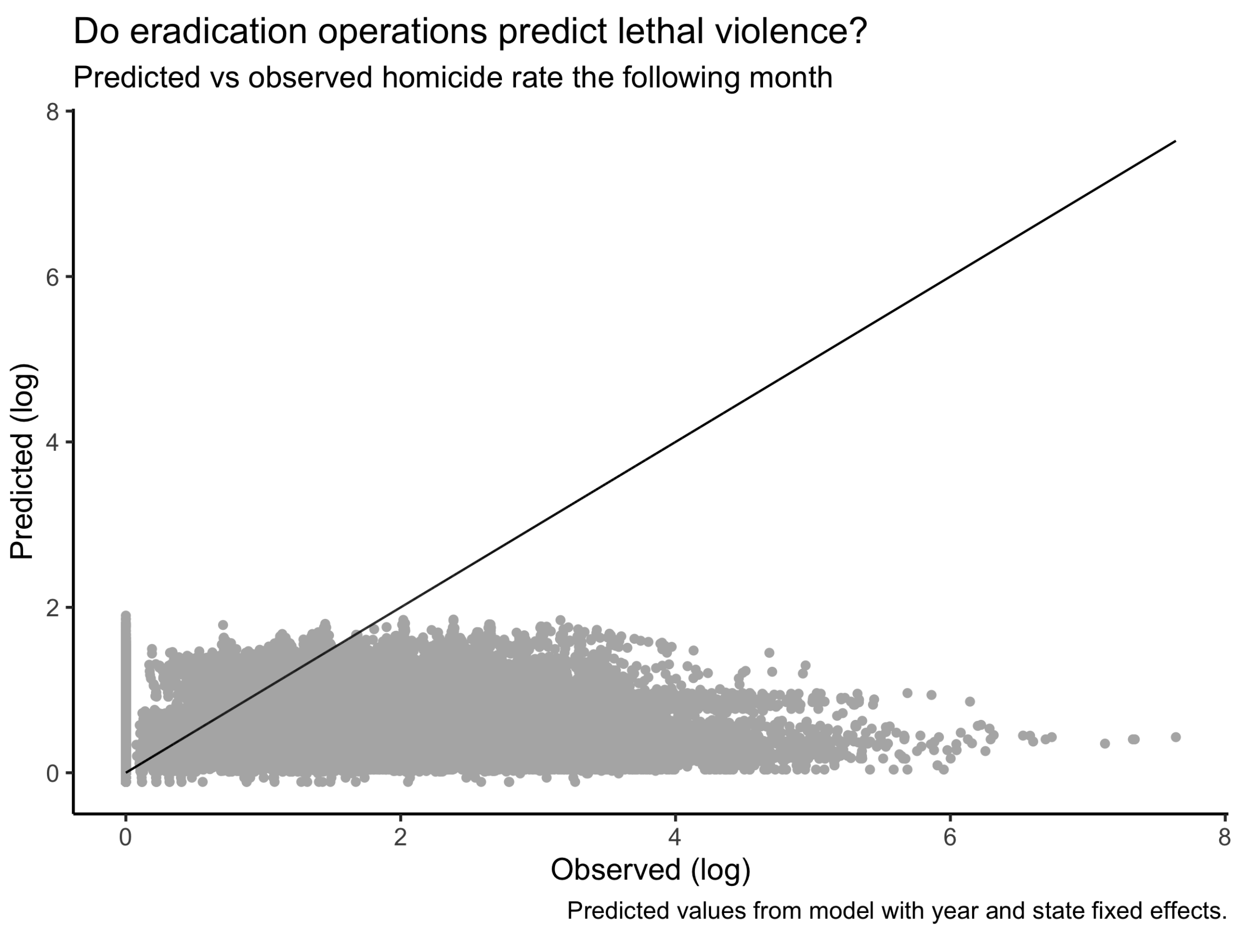


Figure A7: Figure plots the observed homicide rate per municipality (x axis) vs the predicted (log+1) number of eradicated hectares in the municipality (y axis). As can be seen, lethal violence is a poor predictor of eradication.