Abril 2022

WP3-2022-SS1

N° de serie

DOCUMENTO DE TRABAJO

The response of illegal mining to revealing its existence

Autores

Santiago Saavedra

COLOMBIA CIENTÍFICA
Conocimiento Global para el Desarrollo

ALIANZA EFI
Economía Formal e Inclusiva

The response of illegal mining to revealing its existence*

Santiago Saavedra†

April 28, 2022

Abstract

New monitoring technologies can help curb illegal activities by reducing information asymmetries between enforcing and monitoring government agents. I created a novel dataset using machine learning predictions on satellite imagery that detects illegal mining. Then I disclosed the predictions to government agents to study the response of illegal activity. I randomly assigned municipalities to one of four groups: (1) information to the observer (local government) of potential mine locations in his jurisdiction; (2) information to the enforcer (National government) of potential mine locations; (3) information to both observer and enforcer, and (4) a control group, where I informed no one. The effect of information is relatively similar regardless of who is informed: in treated municipalities, illegal mining is reduced by 11% in the disclosed locations and surrounding areas. However, when accounting for negative spillovers — increases in illegal mining in areas not targeted by the information — the net reduction is only 7%. These results illustrate the benefits of new technologies for building state capacity and reducing illegal activity.

JEL classification: H26, K42, O13, O17, Q53

Keywords: Illegal mining, Monitoring Technology, Colombia

*This study is registered in the AEA RCT Registry, unique identifying number: "AEARCTR-0002397. I acknowledge support from Google's Artificial Intelligence Impact Challenge. Thanks Alianza EFI-Colombia Científica grant with code 60185 and FP44842-220-2018. I am grateful to Teniente Calixto Rodriguez and Colombia's Air Force for invaluable help in this project, and Stanford University's Computing Cluster for access to their capabilities. This paper was enriched by comments from Achyuta Adhvaryu, Agustin Bergeron, Arun Chandrasekhar, Pascaline Dupas, Melanie Morten, Robert Fletcher, Mauricio Romero; and seminar participants at PacDev 2022, CU Denver, CU Boulder environmental lunch, ESA Antigua, Rosario-Andes Taller Applied. Ivan de las Heras, Sergio Perilla, Juan Pablo Martinez, Carolina Velez, Juan Andres Russy, Carlos Beltran, Oscar Garcia, Santiago Fernandez, Andres Pabon and Manuela Gallego provided instrumental assistance in constructing and validating the predictions.

†University of Colorado, Denver and Universidad del Rosario, Department of Economics, santisaap@gmail.com.

1 Introduction

Illegal activity is widespread around the world, in part because of corruption and asymmetric information. Weak law enforcement is usually fueled by a lack of monitoring technologies and unaligned incentives of local bureaucrats. Monitoring technologies have the potential to reduce asymmetries by providing objective and independent measures (de Rochambeau, 2020). The monitoring technologies can add new information and/or the threat that information is widely available. The effect of monitoring will then depend on how government officials use the information to enforce the law. In addition, reducing illegal activity in some areas may have positive or negative spillovers to other zones. In this paper, I study the direct and spillover effects of revealing the location of illegal activity to government officials from a new monitoring technology in the context of illegal mining in Colombia.

Throughout the literature on illegal activity, the main challenge is measuring its extent (Banerjee, Mullainathan, & Hanna, 2012). In order to overcome this obstacle, I use a machine learning model on satellite imagery to detect mining activity (Saavedra & Romero, 2021). The model is highly accurate: For every 100 pixels it labels as mined, 78 are actually mined according to a testing sub-sample. I used the model to predict mined areas and disclosed some of the predictions to Government entities in a randomized control experiment. I measure illegal mining following the definition of Colombia's national government as "mining activity without a mining title registered with the National Mining Registry" (Ministerio de Minas y Energia, 2003, p. 108).

The intervention is a 2x2 randomized control trial. In half of the municipalities, I informed local authorities (mayors) of five locations predicted as mines in their municipality. For another random half of the municipalities, I informed the National Government (the Air Force) of five locations predicted as mined in each of those municipalities. By disclosing this information to the authorities, I address three research questions: (1) Does revealing the existence of illegal activity reduce the extent of the activity?; (2) Does the agent I informed matter for effect?; (3) Does illegal activity relocate to neighboring areas not treated? As I only disclosed five mined locations per municipality, there are mined areas in treated municipalities that are not revealed in the information letters, and therefore I can study spillovers. There might be positive spillovers if the local authorities increase monitoring and reporting overall. But there might be negative spillovers if illegal activity relocates from disclosed locations to other areas.

I first study how authorities respond to the information treatment. Given that I disclosed unverified model predictions, some of these predictions might not actually be mined. To decide if the machine learning model was accurate, a group of students did double-blinded validation of the disclosed locations with high-resolution images.[1] I find that when the prediction model is wrong, local officials accurately respond that there is not a mine in the disclosed location. However, when the model is correct, local officials are less likely to confirm the existence of a mine, especially when the mine is illegal. The results are robust to municipality fixed effects, meaning that the same local official responds differentially when the disclosed mine is illegal. By contrast, the differential response accuracy by the legality of the mine is not present in the National Government verifications. These results point to the possible collusion between local government officials and illegal miners, and the importance of incentives when implementing new monitoring technologies. I discard alternative explanations like local officials not knowing because illegal mines are possibly newer or further from the town hall.

[1] I did not verify the model predictions before sending the letters. The predictions were not based on high-resolution images ($1x1$ meters resolution) because they were only sporadically available and only in certain locations at the time of treatment.

After analyzing the responses to the information letters, I study what happened in treated municipalities with the share of the mined area mined illegally after I disclosed the predicted locations. I find a reduction in illegal mining in the exact disclosed locations, regardless of which level of government is informed. There is also a reduction of similar magnitude in surrounding areas of disclosed locations (areas less than $1km$ away). However, there is an increase in illegal mining in other areas of the municipality away from disclosed mines. Without the negative spillovers, the reduction in illegal mining due to the treatment would have been 11%, but due to the spillovers, the net reduction is only 7%.

Finally, I investigate whether the treatment had effects on other socio-economic and environmental variables. I find a reduction in coca cultivation, which makes sense given the monitoring of illegal activity by government authorities. However, I do not find statistically significant effects on homicides or deforestation. A final concern is that the reduction in illegal mining might have affected the population that depended economically on mining. I do not find statistically significant effects on poverty or child labor. This is in line with the mayors' survey, where around 80% state that workers from a closed mine switch to other occupations or migrate.

I contribute to the literature on enforcement and the incentives of local bureaucrats (Balán, Bergeron, Tourek, & Weigel, 2022; Amodio, Choi, De Giorgi, & Rahman, 2021; Khan, Khwaja, & Olken, 2016), and the use of technology to improve monitoring (Callen, Gulzar, Hasanain, Khan, & Rezaee, 2018; Dal Bó, Finan, Li, & Schechter, 2018; Dhaliwal & Hanna, 2017; de Rochambeau, 2020). The answer to the existence of spillover effects speaks directly to the important question of "How much do improvements in enforcement generate displacement in wrongdoing?" (Dal Bo & Finan, 2016). De Andrade, Bruhn, and McKenzie (2013) performed a randomized control trail where in one treatment arm an auditor visited informal firms. In another arm, the auditor visited a neighbor firm. De Andrade et al. (2013) did not find evidence of spillover effects on formalization if a neighbor firm was visited. My context is different because the machinery of illegal mines could be transported to nearby areas, in contrast to the firms studied in their paper.

The literature on remote sensing monitoring (Ferreira, 2021; Moffette, Alix-Garcia, Shea, & Pickens, 2021; Zou, 2021; Greenstone, He, Jia, & Liu, 2020; Assunção, Gandour, & Rocha, 2022) has shown the usefulness of these technologies in reducing deforestation and pollution. My results complement the usefulness of these technologies in the context of illegal mining, and in addition, exploit randomized within-country variation in access to the information.

In the Colombian context, illegal mining is defined as the absence of a registered title, which can be framed as informality. The literature on formalization has generally shown that "the sticks are more effective than the carrots". For example, threats of tax audits are more effective than exhortative messages (McGraw & Scholz, 1991; Blumenthal, Christian, Slemrod, & Smith, 2001; Castro & Scartascini, 2015). Also, lowering costs and offering information to formalize business are ineffective (McKenzie & Sakho, 2010). My results complement the findings that enforcement is effective and add the estimation of spillovers.

The remainder of the paper is organized as follows: Section 2 presents details of the information intervention. Section 3 presents results for the responses to the information intervention. Section 4 studies the response of illegal mining to the intervention. The final section is devoted to conclusions and recommendations.

2 Mining context, details of the intervention and data

2.1 Illegal mining in Colombia

Illegal mining is very common around the world: 67% of the companies in the United States could not identify the origin of the minerals used in their supply chain (GAO, 2016). Illegal mining has both social, environmental, and fiscal impacts on host countries. It is estimated that around 1 million children work in mines around the world (ILO, 2019). On the environmental side, illegal mining is associated with greater levels of pollution (TGIATOC, 2016). On the fiscal side, illegal mines typically evade taxes. Illegal mining is defined by Colombia's national government as "mining activity without a mining title registered with the National Mining Registry" (Ministerio de Minas y Energia, 2003, p. 108). In Colombia, 82% of the area mined is mined without a legal title, which means it is illegally mined Saavedra and Romero (2021).

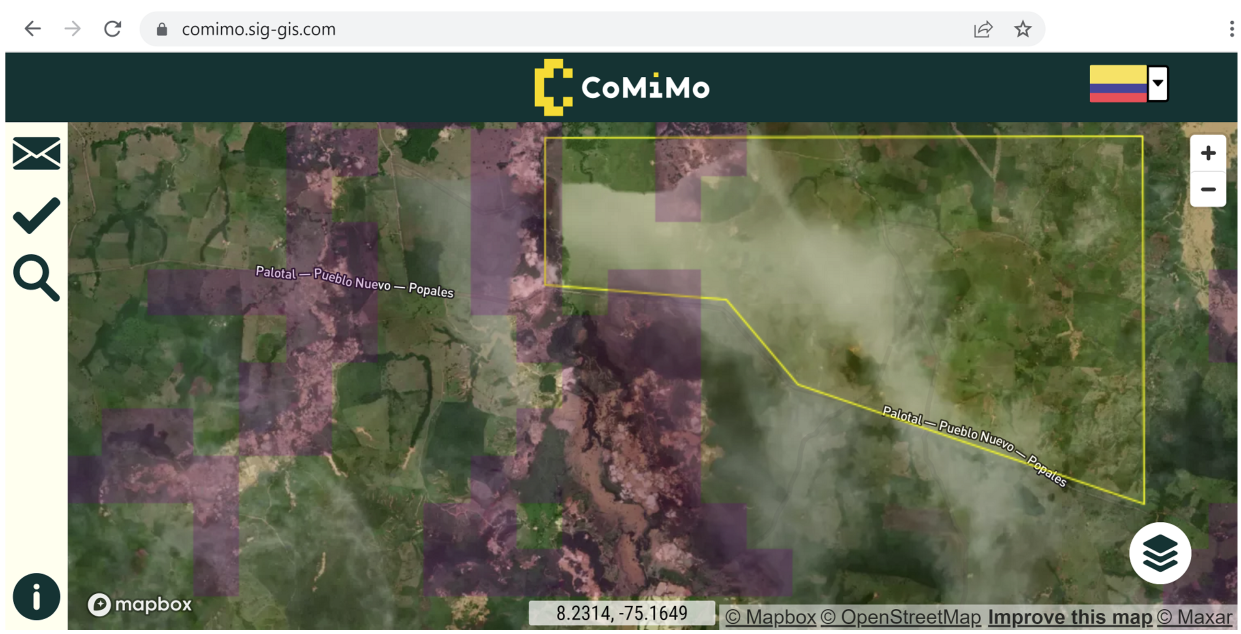
Local authorities in Colombia are responsible for applying mining laws in their jurisdiction. This responsibility includes suspending any mining activity in their municipality carried out without a title (Law 685 of 2001). If the illegal mining activity continues after the suspension order, local authorities must inform national authorities. The national authorities will do strict enforcement, like confiscating or destroying machinery and starting a judicial process.

According to the National Constitution, the Colombian Air Force is in charge of protecting the integrity of the national territory. One of the duties is to provide aerial photography and surveillance for joint operations with the Army and the National Police to confiscate or destroy illegal mining machinery.[2]

[2] See for example https://www.fac.mil.co/fuerza-a%C3%A9rea-colombiana-apoya-operaci%C3%B3n-en-contra-de-la-miner%C3%ADa-ilegal

Saavedra and Romero (2021) constructed a machine learning model using satellite imagery to detect mining activity. The model is highly accurate: For every 100 pixels it labels as mined, 79% are actually mined according to the testing sub-sample. The dimension of each pixel is 30x30 meters. I used this model for the information revealing treatment in the first two rounds. Subsequently, I improved the model using higher resolution imagery (5x5 meters) and a convolutional neural network, achieving a precision of 90%.[3] This improved model is the one I used in the last round of information treatment. After finding mining activity, I assess its legality with georeferenced mining permits issued by the National Government. Figure 1 presents one example of identified mines (highlighted purple squares) and a legal mining title (the yellow polygon).

Figure 1: Example of detected mines and mining titles



Notes: Highlighted purple squares represent identified mines and the yellow polygon a mining title.

[3]The predictions are available in https://comimo.sig-gis.com/

2.2 The information intervention

The intervention is a 2x2 randomized control trial revealing the location of some of the predicted mines to local and/or national authorities. I selected treated municipalities using computer random number generation, stratified by department (state). In half of the municipalities, I informed the local authority (the mayor) of five locations predicted as mined by the machine learning model in the municipality. For an orthogonal random half of the municipalities, I informed the Air Force, as a body of the National Government, of the location of five points predicted as mines in those municipalities. That is, each municipality is assigned to one of four groups: (1) the observer (local government) was informed of five potential mine locations in his jurisdiction; (2) the enforcer (National Government) was informed of five potential mine locations; (3) both observer and enforcer were informed, and (4) control group, where no agent was informed of mine predictions in those municipalities.[4] See Figure A.1 for the distribution of treatment and control municipalities in the Colombian territory.

Within each municipality, the five disclosed locations were randomly chosen, also using random number generation. For municipalities where I inform both local and national authorities, I send the same five predictions to both parties but did not mention I had also shared the predictions with the other authority. I sent the information letters in September 2017, February 2019, and August 2021.

I sent the information letters as "Freedom of Information Act" requests (Derechos de Peticion). The letters contained Universidad del Rosario's logo to add credibility. More than a quarter of Colombia's presidents graduated from Rosario, so the University's rep-

[4]In audit studies, the control group knows that there will be an increase in enforcement. In my case, control municipalities do not know other municipalities received predictions or that the Air Force received predictions. Although the Air Force is informed of the technology so it could affect control municipalities; my coefficients would be a lower bound.

utation is well known to the authorities. The letter I sent contained unverified predictions of the model; therefore, the location might not actually have a mine, and the mined locations might be legal or illegal. Consequently, in the letter, I asked local governments and the National Government for confirmation on whether there is mining activity in each of the five disclosed locations. See Figure A.2 for an example of the personalized information letter I sent to local officials disclosing the model's predictions. Figure A.3 is an example of the letter to the National authority. After I sent the letters, I had students do double-blinded manual validation with high-resolution images to assess whether the model found a mine or not in each disclosed location.[5]

Figure A.4 presents a visual representation of the experiment and the predictions data I have. The municipalities are divided into four groups (columns), and I have five data sources. The United Nations Office on Drug and Crime produces mining data for municipalities with gold mining. I have model predictions for all municipalities, indicated in dark blue. I only have the local government's responses for half of the municipalities where I sent the letters. Similarly, for the National Government, I only have responses from another half of the municipalities. Finally, the high-resolution verification that I will be using as the truth is available only for the five selected locations in each municipality. As an intermediate outcome of the intervention, I study the accuracy of municipalities' responses in Section 3. To assess the effectiveness of the intervention, I study in Section 4 the response of area illegally mined.

One of the main concerns with this study is that illegal activity could react to the information, as in Olken (2009). I am able to detect if illegal mining moves to another location. It is also theoretically possible that some illegal mines will start operating underground to avoid being detected from space. Given that with satellite data it is only possible to

[5] The high-resolution images have a 1x1meter or finer resolution. The model cannot be trained in these images because they are not continuously available through time and space.

detect open-pit mining, I would overestimate the effect of the intervention. However, I expect this underground hiding not to happen because it is a costly strategy.

2.3 Data sources

Illegal mining

The main outcome of interest is what happens to illegal mining after the information intervention. I use the database constructed by the United Nations Office on Drug and Crime (UNODC). This database is available for the years 2014, 2016 (pre-treatment), 2018, and 2019 (post-treatment). The UNODC data is constructed by experts' validation of satellite imagery, so it does not have the errors that a machine learning algorithm could have. UNODC database is restricted to gold mining areas only, which represents approximately two-thirds of open-pit mining in Colombia. For each municipality, I calculate the percentage of mining area that is mined illegally. That is, I calculate the total mined in each municipality-year, and then assess what percentage of that area is outside legal mining titles. According to the UNODC data, 83.7% of the gold mining area was illegally mined in 2014, and it fell to 79.5% in 2019.

Municipality survey 2021

In order to understand how local authorities deal with illegal mining, Innovations for Poverty Action collected data from local authorities. I sent the last information treatment letter in August 2021, and the survey took place in September 2021.[6] The survey asks about legal and illegal mining, operation of the mayor's office, deforestation, and fires.

Table 1 Column 1, shows that 73% of the municipalities answered the survey. Importantly, municipalities where I informed the mayor are equally likely to answer the mu-

[6] I could not do a baseline survey because I did not have funding in 2017, and could not do the survey in 2020 given the COVID-19 pandemic.

Table 1: The information doubled the number of illegal mining complaints

Dependent variable:	Answered	Complaints	Mining POT	Muni Area	% mined area mined illegaly
	(1)	(2)	(3)	(4)	(5)
Sent to local	-0.0087	0.72***	-0.056	-6.92	0.52
	(0.031)	(0.27)	(0.041)	(83.5)	(1.68)
Mean Dep.Var. Control	.726	.753	.67	619	82.9
N. Obs	842	139	541	830	827
R^2	0.00	0.05	0.00	0.00	0.00

Notes: (1) Dummy if municipality answered 2021 survey. (2) N of illegal mining complaints received by the mayor. (3) dummy if municipality has mining in territorial plan (POT). (4) Municipality Area in Km^2. Robust standard errors. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

nicipality survey. Column 2 then shows that in municipalities where I sent the letter, I doubled the number of illegal mining complaints. The coefficient should theoretically be one, because I asked about complaints in the last two months, a period that includes the last information letter. I cannot reject the statistically that the coefficient is equal to one. Columns 3, 4 and 5 of Table 1 show that municipalities where I informed the mayor are similar to municipalities where I did not inform the mayor. Municipalities are equally likely to have mining in the municipality development plan (column 3), area (column 4) and percentage of mined area mined illegally (column 5). Tables A.1 and A.2 in the Appendix present additional balance tests between treated and control municipalities, separating by whether I informed local and national authorities. As expected with the randomization, treated and control municipalities have similar area illegally mined, number of illegal mines, and population.

Authorities responses to treatment

I sent information letters in 2017, 2019, and 2021. The National authority responded in 2017 but then stopped responding because it was time-consuming (400x5=2,000 validations), and they changed the original point of contact. The response rate of local authorities varied through the years: 50% in 2017, 25% in 2019 and 40% in 2021. I focus on 2017 to compare the responses of local and national authorities. Table A.3, columns 1 and 2 present summary statistics of the responses I obtained from local authorities in 2017. Around 40% of the local governments responded with verifications on whether the disclosed coordinates are mines or not. Close to 5% responded that they did not have resources for the verification, and interestingly a couple expressed they could not visit the points because of armed groups' presence. Columns 3-6 present summary statistics for the 2019 and 2021 information rounds. The response rate was lower during those years.

Table A.4 studies whether the decision of majors to respond depends on the content of the letter. Importantly, whether the disclosed locations are legal or illegal mines did not change the likelihood I obtained a response with verifications. The more accurate the disclosed predictions for the municipality are, the more likely the local authority is to verify. Finally, when the reported points are further away from the mayor's office, the less likely municipalities were to verify. Tables C.1 and C.2 present robustness to logit and probit specifications.

Table A.5 presents the accuracy of the verifications I obtained from municipality authorities, separated by panels according to the legality of the disclosed points. Recall, I am taking as the truth the result of the double-blinded validation by students. So I classify as accurate a local authority response if it coincides with the double-blinded validation. In all the panels, when the prediction model was wrong, most of the local officials responded accurately that the point was not a mine. However, when the model was accurate identifying a mine, the majors most of the time responded there was not a mine. In addition, when the predicted point was an illegal mine, the local governments were less likely to confirm the model was accurate. I will explore this fact further with regression analysis in Section 3.

Other data

I also use different dependent variables to estimate the effect of treatment on different outcomes such as coca cultivation, deforestation, violence, and poverty. Coca cultivation data is provided in a municipality panel by the Ministry of Justice and Law. Deforestation is computed from (Hansen et al., 2014), which uses satellite imagery to detect forest clearance. In order to assess what happens with violence, I compute the number of homicides per capita. I obtain homicides per municipality and year from the National Police database and divide them by population in 2013. Finally, I use the Colombian National Census 2018 data to study the intervention effects on poverty and child labor data.

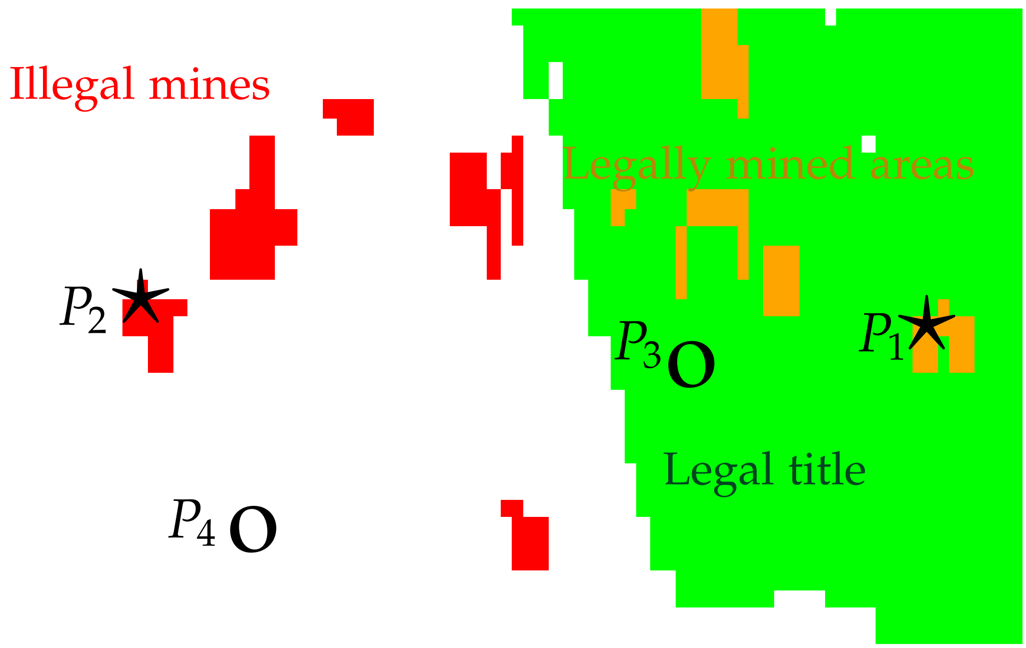
3 Responses to the information intervention

In order to study the responses of government entities to the information treatment, I divide this section into two sub-sections. First, I present the equation I estimate with the responses data. Then, I present the estimation results. The main message is that local authorities are less likely to confirm the model was accurate when the mine is illegal. This differential response is not present in the National authority data.

3.1 Estimating equation

I want to investigate if the response of government authorities differs by the legality of the identified mine. Recall that I disclosed model predictions without verifying if they were actual mines, and without checking if the predictions were located inside or outside legal titles. Figure 2 presents an example of machine learning predictions and disclosed locations. The dark pixel areas in red and orange are mined. The light green area on the right represents a mining title. The four points P_i illustrate the four possible types of disclosed predictions. P_1 and P_2 are marked with stars because the model correctly identified a mine. P_1 is a legal mine, that is, a prediction of the model that is accurate and inside a legal mining title. P_2 is an illegal mine because the model was accurate, and the mine is outside a mining title. P_3 and P_4 were predicted by the model as mined, but they are not mined, according to the high-resolution validation. These two points are consequently called False Positives. P_3 is inside a legal title, while P_4 is outside a title.

Figure 2: Types of disclosed predictions



Notes: The areas in red and orange illustrate are mined. The light green area indicate a mining title. P_1 is a legal mine, while P_2 is an illegal mine. P_3 and P_4 were predicted as mined, but they are not according to the independent validation, consequently I called them False Positives. They differ on whether they fall inside our outside a legal title.

I explore whether the response of government authorities is different for illegal mines, by estimating the following equation:

$$Accurate_{im} = \beta_0 + \beta_1 Illegal\ Mine_i + \beta_2 False\ Positive_i\ x\ Title_i + \beta_3 False\ Positive_i\ x\ (1 - Title_i) + \gamma_m + \varepsilon_{im} \quad (1)$$

Where $Accurate_{im}$ indicates whether the government's response is accurate for disclosed point i in municipality m. That is, if the predicted point is truly mined according to the independent verification, and the government official confirms it. Or if the prediction is wrong and the local official accurately indicates that it is not mined in the response. $Illegal\ Mine_i$ indicates whether the point is an illegal mine (P_2 in Figure 2). $FalsePositive_i$ indicates whether the point was predicted as mined by the model, but in the independent verification it was not. $Title_i$ indicates whether the prediction is inside an area titled for mining (P_3 in Figure 2). The omitted category is thus an accurate prediction of a legal mine. Finally, γ_m are municipality fixed effects, which allows me to compare the responses of the same authority for different predictions. I cluster the standard errors at the municipality level.

3.2 Regression results

Table 2 presents the results of estimating equation (1). Even columns include municipality fixed effects, and odd columns do not include them. Columns 1-2 include only the local governments' responses, and columns 3-4 only the responses of the National Government. Columns 5-6 restrict the sample to the municipalities where I informed both local and national authorities so that I am comparing the responses to the same points. When the predicted point is an illegal mine, local officials were less likely to confirm the model was accurate. In the case of the National Government's responses, in contrast to the local governments' responses, I do not find a differential accuracy in whether the mine is illegal or not. The differential accuracy of the response is confirmed in this sub-sample. These results point to the possible collusion between local government officials and illegal miners, but I present below alternative explanations.[7] Table A.6 has the results with all the coefficients of equation (1) reported. Table A.7 shows results for the local authority responses in all years. The differential response for illegal mines is of similar magnitude. Finally, Table C.3 presents the results restricting to municipalities with gold mining according to the UNODC data. The coefficients of the differential response for illegal mines by local authorities are of similar magnitude, although they are not statistically significant because there are not many observations.

Table 2: Determinants of local and national government's accuracy and pixel characteristics (2017)

Dependent variable:	Accurate Response=1					
Responses by	Local		National		Local & National	
	(1)	(2)	(3)	(4)	(5)	(6)
IllegalMineXLocal	-0.15**	-0.16**			-0.32	-0.44**
	(0.071)	(0.066)			(0.19)	(0.19)
IllegalMineXNational			-0.17*	-0.058	-0.028	-0.058
			(0.095)	(0.087)	(0.12)	(0.20)
N. of obs.	752	748	512	457	270	254
Mean of Dep. Var.	0.64	0.64	0.64	0.63	0.68	0.68
R^2	0.51	0.74	0.72	0.88	0.60	0.85
Municipality FE	No	Yes	No	Yes	No	Yes

Notes: Clustered standard errors at the municipality level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Alternative explanations

The theoretical bargaining model in Saavedra and Romero (2021) assumes that local authorities perfectly know where illegal mining occurs and allow it to operate in exchange for a bribe. It is difficult for the national authority to enforce titling because they do not have the information on where firms are located, unless the local authorities report

[7]See Table A.5 for the responses of mayors by prediction type.

them. But it is possible that the local authority's capacity to fully observe all illegal mining is limited, especially in remote areas. Thus an alternative explanation for the lower accuracy is that illegal mines are newer or further from the local authority's office. Although they should not have confirmed whether the prediction was accurate if they did not visit the location, I can still test if the age or the distance of the mine affects the accuracy results. Another alternative explanation for the differential accuracy results is that majors got tired of verifying. This is unlikely because the disclosed predictions were randomized, but I can still control for the order in the regression.

Tables A.8 and A.9 presents the regression results of testing for alternative explanations. In all cases, the coefficient of the differential accuracy of local authorities for illegal mines is stable, and similar to the ones in Table 2. On Columns 1 and 4, I test whether the differential results could be explained because illegal mines are more recent, and therefore local authorities are less likely to know about their existence. The coefficients are similar to those of The coefficient of Age of the Mine is significant at the 10% in Column 1 and not statistically significant in Column 4. In addition, it has the opposite sign as it would be expected that local authorities are more accurate for older mines. Next, on Columns 2 and 5, I test whether the reduction in accuracy for the responses for illegal mines is because these mines are further from the municipality town hall, and consequently, local officials monitor them less. The coefficient on the dummy for illegal mines is basically unchanged, and the distance variable is not statistically significant. Finally, on Columns 3 and 6, I test whether the results are because the accuracy of local authorities' responses decreases during the verification process I asked them to perform. Although this is unlikely, given that I randomize the selection of the mines, I find that the order in which I listed the prediction does not affect the accuracy.

4 Response of illegal mining and other variables to the information intervention

4.1 Estimating equations

Municipality level

I study the response to the information intervention by estimating the following equation at the municipality level:

$$y_{mdt} = \beta_L After_t \times OnlyLocal_m + \beta_N After_t \times OnlyNat_m + \beta_{LN} After_t \times Local_m \times Nat_m + \gamma_m + \gamma_{dt} + \varepsilon_{m,dt}, \quad (2)$$

Where y_{mdt} is the percentage of mined area mined illegally or other variable in municipality m, department d, at time t. $After_t$ is a dummy indicating that t is after I sent the first treatment information letters in 2017. $Local_m, Nat_m$ are dummies that indicate whether I informed the local authorities or the National Government for municipality m. Finally, γ_m, γ_{dt} are municipality and department-time fixed effects, respectively. The municipality fixed effects control for time-invariant characteristics like the type of minerals available in the subsoil, terrain, and municipality size. Theoretically, I should include department fixed effects because that is the strata of randomization. However, they are absorbed by the municipalities' fixed effects. But I include department-year that captures any weather shocks or clouds presence in a given area. I cluster the standard errors two-way at the municipality level and at the department-year level.

Grid level

Within treated municipalities, I have three types of mining locations: (i) some locations that are disclosed in the letters, (ii) some neighbor the disclosed points, and (iii) other locations that are further away from disclosed points. The mining data is available at the $1kmX1km$ grid square level. Therefore if grid square g was one of the five locations actually disclosed in the information letter, I use the dummy ($Disclosed_{gm} = 1$). If grid g is one of the eight neighboring squares surrounding a disclosed grid (see Figure 3), I use the dummy ($Neighbor_{gm} = 1$). Finally, if grid g is in a treated municipality but farther than $1km$ away from disclosed locations, I use the dummy ($MuniTreated_{gm} = 1$). To facilitate the interpretation of coefficients I set $(MuniTreated_{gm} = 0)$, when $Disclosed_{gm} = 1$ or $Neighbor_{gm} = 1$.

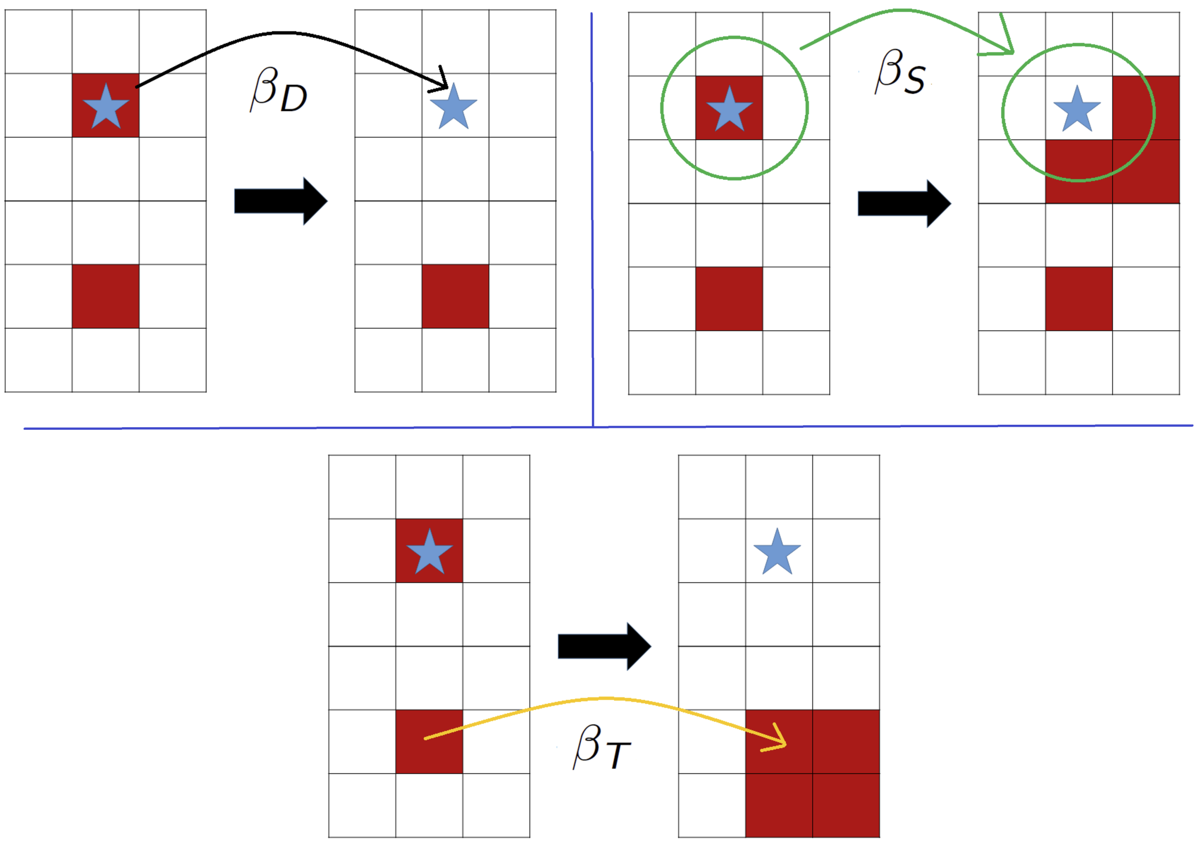
I estimate the following equation:

$$\begin{aligned}\widehat{y_{gmdt}} = \beta_D After_t \times Disclosed_{gm} + \beta_S After_t \times Neighbor_{gm} \\ + \beta_T After_t \times MuniTreated_{gm} + \gamma_m + \gamma_{dt} + \varepsilon_{m,dt} \quad (3)\end{aligned}$$

Where y_{gmdt} is the percentage of mined area mined illegally in grid g municipality m, department d in year t. $Disclosed_g$ is a dummy variable that indicates if grid g is one of the five disclosed points in the letter. $Neighbor_g$ is another dummy variable that indicates if grid g neighbors disclosed points. $MuniTreated_{gm}$ is an indicator that takes the value of one if mines were disclosed in municipality m, but g is far from disclosed points. I separate the effect of informing the national government, the local government, or both. Finally, $After_t$ indicates if time t is after the intervention and γ_m and γ_{dt} are municipality and department-time fixed effects.

The coefficients of interest are three: (i) β_D: the effect on illegal mining of including a grid in the information letter; (ii) β_S: the effect on illegal mining in grids that neighbor a disclosed grid; and (iii) β_T: the effect on illegal mining in grids in a treated municipality, but located far from disclosed mines. Figure 3 illustrates what I try to measure with β_D, β_S, and β_T. Note that each of these three coefficients may vary by each of the three types of treated municipalities that I have: (i) only the local authority was informed; (ii) only the National authority was informed; (iii) both authorities were informed. That is, I will present estimates for $3x3 = 9$ coefficients.

Figure 3: Visual representation of the spillovers



Notes: Visual representation of the three coefficients of interest. The blues star represents a disclosed grid, and dark squares a mining area. β_D is the effect of including a grid square in the information letter. β_S is the effect on the neighbors that surround a disclosed grid. Finally, β_T is the effect in other grids of treated municipalities farther than $1km$ from disclosed grids.

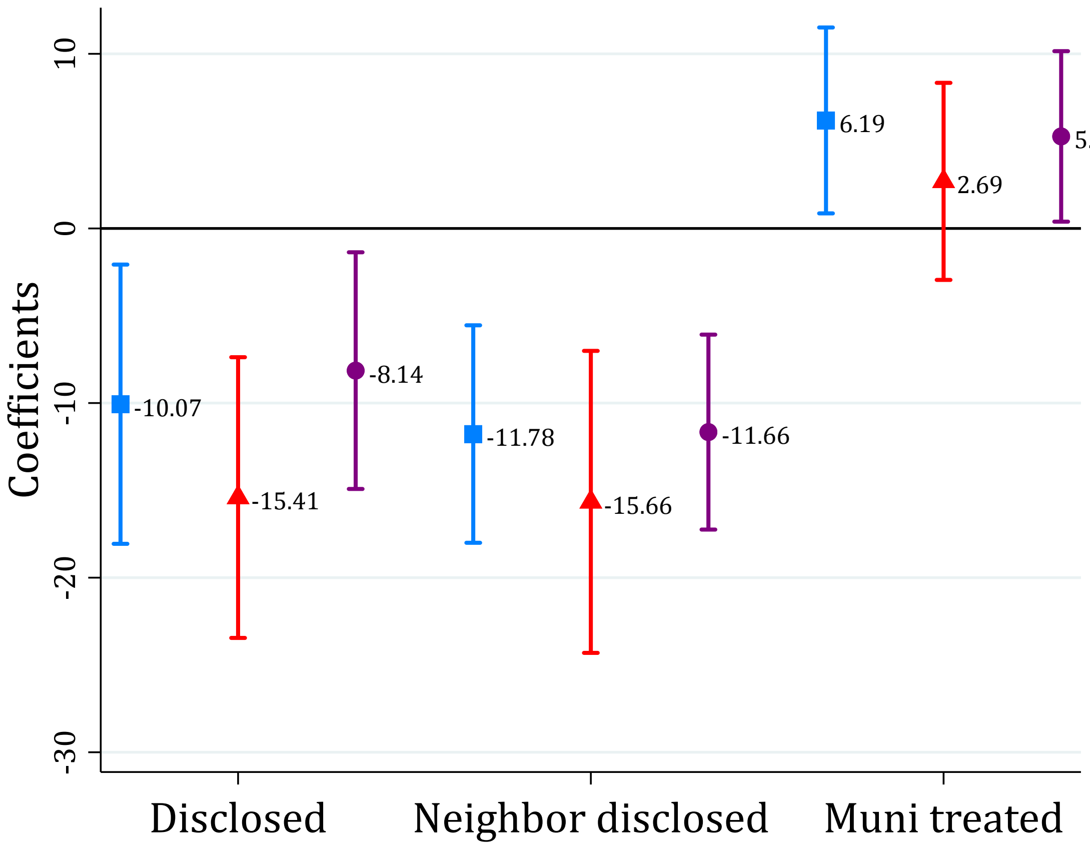
4.2 Regression results

Figure 4 plots graphically the estimated coefficients of equation (3). Table A.11 presents these results in table form. The first three coefficients are the estimated effects of disclosing a grid in the information letter (β_{Dj}). The three coefficients in the middle are the estimates of spillovers to direct neighbors (β_{Sj}). The last three coefficients are the effect in grids in treated municipalities far from disclosed points β_{Tj}. Within each group, I use colors to distinguish who was informed. The blue coefficient on the left of each group is the effect in municipalities where I only informed the local authority (β_{iL}). The red coefficient in the middle of each group is the estimate for municipalities where I only informed the National government (β_{iN}). Finally, the purple coefficient on the right of each group is the effect in municipalities where I informed both local and national authorities (β_{iB}).

I find a reduction in illegal mining in disclosed grids of treated municipalities. The effect varies from -8.14 in municipalities where I informed both authorities to -15.41 for municipalities where I only informed the National authority. But statistically, I cannot reject the effect is the same for all three types of treated municipalities at the 5% level (the p-value for the test that $\beta_{DN} < \beta_{DB}$ is 7.5%). Interestingly the effect is of similar magnitude in neighboring grids. This could happen because when local authorities visit the disclosed location, they observe or have a deterrence effect in the surrounding areas. Alternatively, neighboring mines might be owned by the same person or group, or the owners share information.

Finally, in grids in treated municipalities far from disclosed locations, there is an increase in illegal mining (negative spillovers). The effect varies from an increase of 6 percentage points in municipalities where I only informed the local authority to 2.69 when I only informed the National authority. But again, statistically, I cannot reject the three estimated coefficients are equal. Without the negative spillovers, the reduction in illegal mining due to the treatment would have been 11%, but due to the spillovers, the net reduction is only 7%.[8]

Figure 4: Effect of the intervention by grid type and treatment type



Notes: Graphical representation of the estimated coefficients of equation (3) presented in Table A.11. The first three coefficients are estimates of β_D, the middle estimates of β_S, and the last three β_T. In each group, the blue coefficient on the left is the effect in municipalities where I only informed the local authority. The red coefficient in the middle of each group is the estimate for municipalities where I only informed the National government. The purple coefficient on the right of each group is the effect in municipalities where I informed both authorities. [p-value] for selected hypothesis tests: $\beta_{DN} < \beta_{DB}$ [0.076], $\beta_{TN} < \beta_{TL}$ [0.17]

Robustness

[8]These calculations take into account that there are more grids with negative spillovers than disclosed or neighboring grids.

The reduction in the percentage of the mined area mined illegally could happen because there is less area illegally mined, or because an area that was mined without title was legalized. To study this issue, column (2) of Table A.11 presents the results when holding the mining titles before the information intervention constant. The results are similar to those in column (1), so I conclude they are driven mostly by reductions in the illegal mining area. This result makes sense, given that the titling process takes time. Finally, in Table A.12 I present robustness to doing a cross-section comparison instead of the difference-in-differences specification and using illegal mining in squared kilometers as the dependent variable.

Heterogeneity

Table 3 presents heterogeneous effects of disclosing the predictions to local authorities. It follows equation (3), but I only report the coefficient of disclosing the prediction to the local authorities and its heterogeneous effects for clarity. Column 1 repeats the estimation without interactions, the blue square coefficient on the left of Figure 4. In column 2, I interact with an indicator on whether the local authority responded to the information letter with verifications of the predictions. I find that when the local authority verified the predictions, the reduction in illegal mining is larger. This makes sense given that it confirmed by itself the presence of illegal mines in its municipality. In column 3, I study heterogeneity by whether the responses with verifications are accurate. I find that the effect is larger when the authority responds accurately. As the accuracy of the responses is a proxy for honest behavior, these mayors are more likely to act on the disclosed predictions. Column 4 shows that when the letter disclosed more illegal mines, the reduction in illegal mining is larger, although the effect is not statistically significant at the 5% level. Finally, in column 5, I find that when the letter contains more accurate predictions, there is a larger reduction. However, the coefficient is small and not statistically signifi-

Table 3: Spillovers heterogeneous effects

Dependent variable:	% gold mined area mined illegally				
	(1)	(2)	(3)	(4)	(5)
Local X After X Disc	-10.1**	-7.47	-7.04	-0.45	-9.89***
	(3.97)	(4.79)	(4.48)	(17.2)	(3.54)
Local X After X Disc X Verified		-8.86*			
		(5.22)			
Local X After X Disc X Local Accuracy			-18.0**		
			(7.26)		
Local X After X Disc X Letter Share Illegal				-10.9	
				(17.0)	
Local X After X Disc X Letter Accuracy					-0.56
					(9.33)
N. of obs.	72,876	72,876	72,876	72,876	72,876
Mean of Dep. Var.	35.8	35.8	35.8	35.8	35.8
R^2	0.24	0.24	0.24	0.24	0.24

Notes: Heterogeneous effects of disclosing the predictions to local authorities. Results following equation (3), with heterogeneous effects. Verified: dummy equal to one if the local authority responded to the letter with verifications for the disclosed points. Local accuracy: what share of the verified responses by the local authorities are accurate according to independent validation. Letter share illegal: the share of the disclosed points that are located outside legal mining titles. Letter Accuracy: share of disclosed points that are actually mined according to independent verifications. Clustered standard errors at the municipality level are in parentheses. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

cant. The fact that a letter that contained five erroneous predictions also reduces illegal mining illustrates the importance of disclosing the monitoring technology.

Mechanisms

Ideally, I would have detailed information on the judicial process at each of the disclosed points. However, for legal reasons, they do not disclose information on the coordinates and status of these processes. However, I have information from the municipality survey on the number of judicial processes and mine closures. Table 4 column 1 shows that there is an increase in illegal mining investigative processes with the mining authority. In column 2, I do not find a significant effect in processes with the Police. In columns 3 and 4, I find large effects on mine closures compared to the mean, but they are not

Table 4: Mechanisms

Dependent variable:	Processes Mining auth. (1)	Processes Police (2)	Mines Closed 2020 (3)	Mines Closed 2021 (4)
Sent to local	0.13***	0.051	0.39	0.22
	(0.049)	(0.14)	(0.26)	(0.19)
Mean Dep.Var. Control	.0576	.366	.287	.251
N. Obs	555	548	552	581
R^2	0.03	0.06	0.03	0.03

Notes: Column (1) refers to the number of processes started with mining authorities. Column (2) to number of processes started with Police and columns (3) and (4) number of closed mines in 2020 and 2021. Robust standard errors. Significance level: $^{*}p < 0.10$, $^{**}\ p < 0.05$, $^{***}p < 0.01$

statistically significant.

4.3 Effects of the intervention in other outcomes

Table 5 presents the effect of the information treatment on outcomes other than illegal mining. These outcomes are at the municipality level, so I estimate equation (2). In column 1, I assess what happened with another illegal activity: coca cultivation. I find a reduction that is statistically significant, especially when the National authority was informed. These results make sense, given that the monitoring of authorities dissuades illegal activity in general. However, in column 2, I do not find statistically significant effects for the deforestation rate. A possible explanation is that mining and coca cultivation have a more permanent footprint than deforestation. That is, the coca plants and the mining pits are evidence of illegal activity stable through time, while the timber is removed and there is not material left to confiscate.

In column 3, I investigate whether the intervention and the reduction in illegal mining had any effect on the homicide rate. I cannot reject in any of the three treatments that

Table 5: Results for outcome other than mining

Dependent variable:	Coca % (1)	Defo rate (2)	Homicides (3)	Poverty (4)	Child labor (5)
After X Only Local	-0.098	-0.045	9.18	3.49	0.43
	(0.066)	(0.089)	(6.38)	(2.97)	(0.46)
After X Only Nat	-0.16***	-0.092	12.8	-4.06	0.13
	(0.053)	(0.072)	(13.3)	(3.79)	(0.52)
After X Nat X Local	-0.14**	0.061	4.72	0.10	-0.014
	(0.054)	(0.088)	(6.19)	(3.20)	(0.43)
Mean Dep. Var. Before	0.07	0.35	44.37	61.02	3.48
Obs.	880	880	880	110	110
N. Munis	110	110	110	110	110
R^2	0.46	0.81	0.68	0.35	0.25

Notes: Column (1) uses the percentage of municipality area with coca crops. Column (2) is deforestation rate computed as deforested area divided by municipality area. Column (3) is the number of homicides per 100,000 population. Columns (4) and (5) are in terms of percentages of population. Robust standard errors. Significance level: $*p < 0.10$, $**\ p < 0.05$, $***p < 0.01$

homicides did not change. Finally, the reduction of illegal mining could affect the population that depended economically on it. However, I do not find statistically significant effects on poverty (column 4) or child labor (column 5) in the short term.[9] This is in line with the mayors' survey, where around 80% state that workers from a closed mine switch to other occupations or migrate.

5 Conclusions

Illegal activity is widespread around the world. Weak law enforcement is usually fueled by a lack of monitoring technologies and unaligned incentives of local bureaucrats. Technology has the potential to change this by providing objective and independent measures of illegal activity. I use machine learning predictions on satellite imagery features to detect illegal mining activity, and disclosed the predictions to the Government in a Randomized Control Experiment. I find that in treated municipalities, illegal mining

[9] The information intervention started in 2017, and the poverty and child labor measurements are from 2018.

is reduced by 11% in the disclosed locations and surrounding areas. However, when accounting for negative spillovers — increases in illegal mining in areas not targeted by the information — the net reduction is only 7%.

These results illustrate the benefits of new technologies for building state capacity and reducing illegal activity. I released all the predictions for public access in September 2021, and have constantly been updating them every month.[10] A technology similar to the one I released for Colombia could be extended to all the countries. Its success will depend on the credibility of the source, and the use bureaucrats make of the information. Besides mining, these monitoring technologies are available for deforestation, fires, and fishing. The continuous use by government authorities will be key to controlling environmental degradation and achieving the Sustainable Development Goals.

References

Amodio, F., Choi, J., De Giorgi, G., & Rahman, A. (2021). Bribes vs. taxes: Market structure and incentives. *Journal of Comparative Economics*. Retrieved from https://www.sciencedirect.com/science/article/pii/S0147596721000627 doi: https://doi.org/10.1016/j.jce.2021.09.006

Assunção, J., Gandour, C., & Rocha, R. (2022). Deterring deforestation in the amazon: environmental monitoring and law enforcement. *American Economic Journal: Applied Economics (forthcoming)*.

Balán, P., Bergeron, A., Tourek, G., & Weigel, J. L. (2022). Local elites as state capacity: How city chiefs use local information to increase tax compliance in the dr congo. *American Economic Review*.

Banerjee, A., Mullainathan, S., & Hanna, R. (2012, April). *Corruption* (Working Paper No. 17968). National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w17968 doi: 10.3386/w17968

Blumenthal, M., Christian, C., Slemrod, J., & Smith, M. G. (2001). Do normative appeals affect tax compliance? evidence from a controlled experiment in minnesota. *National Tax Journal*, 125–138.

Callen, M., Gulzar, S., Hasanain, A., Khan, Y., & Rezaee, A. (2018, May). *Personalities and public sector performance: Evidence from a health experiment in pakistan* (Working

[10] https://comimo.sig-gis.com/

Paper No. 21180). National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w21180 doi: 10.3386/w21180

Castro, L., & Scartascini, C. (2015). Tax compliance and enforcement in the pampas evidence from a field experiment. *Journal of Economic Behavior & Organization*, *116*, 65–82.

Dal Bo, E., & Finan, F. (2016). At the intersection: A review of institutions in economic development.

Dal Bó, E., Finan, F., Li, N. Y., & Schechter, L. (2018). *Government decentralization under changing state capacity: Experimental evidence from paraguay* (Tech. Rep.). National Bureau of Economic Research.

De Andrade, G. H., Bruhn, M., & McKenzie, D. J. (2013). A helping hand or the long arm of the law? experimental evidence on what governments can do to formalize firms.

de Rochambeau, G. (2020). Monitoring and intrinsic motivation: Evidence from liberia's trucking firms.

Dhaliwal, I., & Hanna, R. (2017). The devil is in the details: The successes and limitations of bureaucratic reform in india. *Journal of Development Economics*, *124*, 1 - 21. Retrieved from http://www.sciencedirect.com/science/article/pii/S0304387816300669 doi: https://doi.org/10.1016/j.jdeveco.2016.08.008

Ferreira, A. (2021). *Satellites and fines: Using monitoring to target inspections of deforestation.*

GAO, U. S. G. A. O. (2016). *Sec conflict minerals rule.*

Greenstone, M., He, G., Jia, R., & Liu, T. (2020). *Can technology solve the principal-agent problem? evidence from china's war on air pollution* (Tech. Rep.). National Bureau of Economic Research.

Hansen, M., Potapov, P., Margono, B., Stehman, S., Turubanova, S., & Tyukavina, A. (2014). Response to comment on “high-resolution global maps of 21st-century forest cover change”. *Science*, *344*(6187), 981-981. Retrieved from https://www.science.org/doi/abs/10.1126/science.1248817 doi: 10.1126/science.1248817

ILO. (2019). *Child labour in mining and global supply chains.*

Khan, A., Khwaja, A., & Olken, B. (2016). Tax farming redux: experimental evidence on performance pay for tax collectors. *Quarterly Journal of Economics*, 219-271.

McGraw, K. M., & Scholz, J. T. (1991). Appeals to civic virtue versus attention to self-interest: Effects on tax compliance. *Law and Society Review*, 471–498.

McKenzie, D., & Sakho, Y. S. (2010). Does it pay firms to register for taxes? the impact of formality on firm profitability. *Journal of Development Economics*, *91*(1), 15–24.

Ministerio de Minas y Energia. (2003). *Glosario tecnico minero.*

Moffette, F., Alix-Garcia, J., Shea, K., & Pickens, A. H. (2021). The impact of near-real-time deforestation alerts across the tropics. *Nature Climate Change*, *11*(2), 172–178.

Olken, B. (2009). Corruption perceptions vs. corruption reality. *Journal of Political Economy*, *93*(7-8), 950-964.

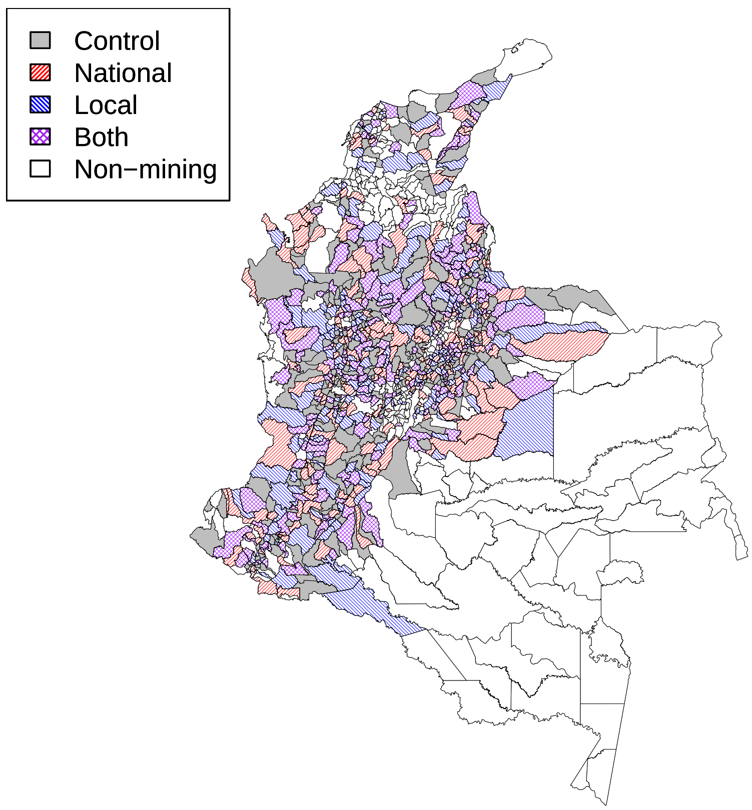
Saavedra, S., & Romero, M. (2021). Local incentives and national tax evasion: The response of illegal mining to a tax reform in colombia. *European Economic Review*, *138*, 103843.

TGIATOC, T. G. I. A. T. O. C. (2016). *Organized crime and illegally mined gold in latin america.*

Zou, E. Y. (2021). Unwatched pollution: The effect of intermittent monitoring on air quality. *American Economic Review*, *111*(7), 2101–26.

Appendix A Additional Figures and Tables

Figure A.1: Distribution of treatment and control municipalities

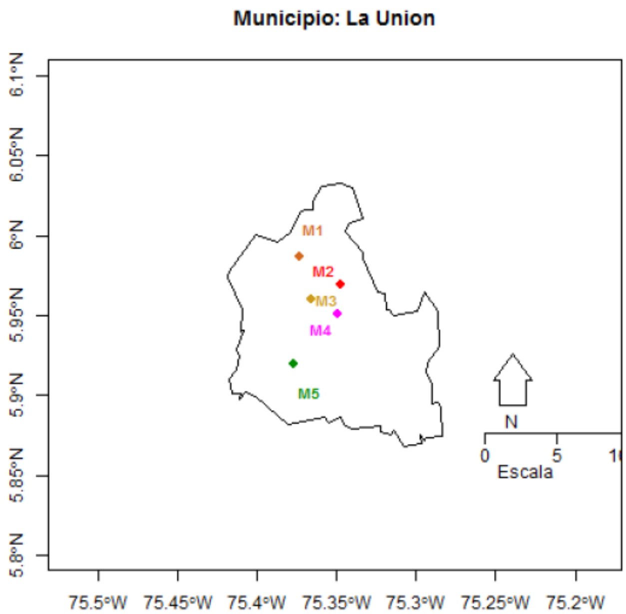


Notes: Map of Colombian municipalities. Municipalities in solid gray are control municipalities. Municipalities in red upward to the right diagonal pattern are municipalities where I disclosed predictions only to the National government. Municipalities in blue downward to the right diagonal pattern are municipalities where I disclosed predictions only to the local government. Municipalities in the purple squared pattern are municipalities where I disclosed predictions to both National and local authorities. White municipalities were not included in the study because they do not have mineral resources in the subsoil, or there were not four municipalities in the state to do the stratification.

Figure A.2: Example of letter sent to local authorities

1 Hechos

Como parte de mi investigación en la Universidad del Rosario hemos desarrollado un modelo de machine learning para detectar actividad minera usando imágenes satelitales. Para su municipio en particular, predecimos que en los siguientes puntos hay actividad minera.



Predicción	Latitud	Longitud	SI hay mineria	NO hay mineria
Punto 1	5.98675938	-75.37384951		
Punto 2	5.96967942	-75.34754535		
Punto 3	5.95989764	-75.36597077		
Punto 4	5.95068128	-75.34943074		
Punto 5	5.91999683	-75.37678574		

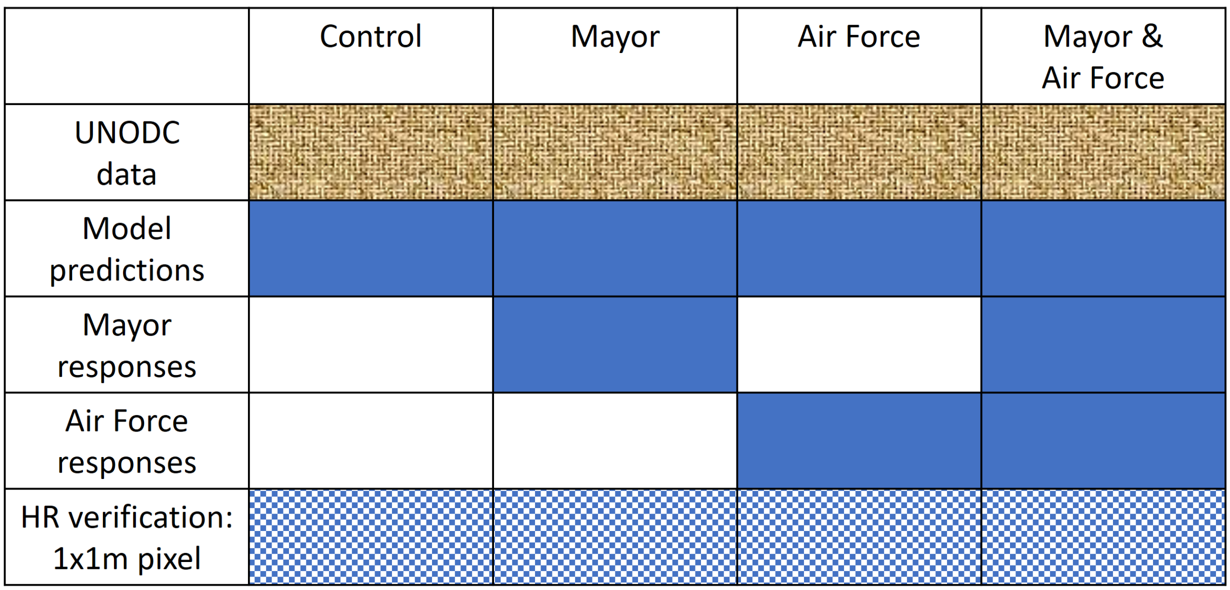
Notes: I sent to each of the local authorities of the 400 selected municipalities a personalized letter like the one shown above. It include a map and the coordinates of five points predicted as mined.

Figure A.3: National authority treatment

Código Divipola Mpio	Departamento	Municipio	Longitud	Latitud
54003	Norte de Santander	Abrego	-73,02930109	8,08612853
54003	Norte de Santander	Abrego	-73,18639958	7,94771262
54003	Norte de Santander	Abrego	-73,12553243	7,93116889
54003	Norte de Santander	Abrego	-73,01482651	8,09663557
54003	Norte de Santander	Abrego	-73,09220015	7,78374356
27006	Chocó	Acandí	-77,34937030	8,46752252
27006	Chocó	Acandí	-77,18134244	8,42104209
27006	Chocó	Acandí	-77,34366791	8,47026820
27006	Chocó	Acandí	-77,26301260	8,46315159
27006	Chocó	Acandí	-77,11376477	8,36364958
25001	Cundinamarca	Agua de Dios	-74,73182195	4,38098266
25001	Cundinamarca	Agua de Dios	-74,70452168	4,35926036
25001	Cundinamarca	Agua de Dios	-74,66016595	4,39072386
25001	Cundinamarca	Agua de Dios	-74,68937707	4,36793904
25001	Cundinamarca	Agua de Dios	-74,70966485	4,34352115
20011	Cesar	Aguachica	-73,63099118	8,03405840
20011	Cesar	Aguachica	-73,62747928	8,02617925
20011	Cesar	Aguachica	-73,65285667	8,00645864
20011	Cesar	Aguachica	-73,66394898	8,02684184
20011	Cesar	Aguachica	-73,64959251	8,00590538

Notes: I sent to the National authority (the Air Force) a letter with 2,000 coordinates, 5 points for each of the 400 selected municipalities.

Figure A.4: Visual representation of the experiment and data



Notes: The columns indicate the four treatments and the rows the information I have for each one. For all the municipalities, I have predictions of the machine learning model. In a quarter of the municipalities, I only informed local authorities of five locations in their municipality predicted as mined. In another quarter of the municipalities, I only informed the National Government of five predicted mines in the municipality. In the third quarter, I informed both the local and the National governments. The remaining quarter of the municipalities forms the control group. For the disclosed predictions of the four treatments, we were able to do manual verification using high-resolution images. We cannot verify all because it is time consuming and the imagery is not available.

Table A.1: Balance table local authorities treatment

	Tell to Local	Control	Difference	t-stat
Area of municipality (km2)	612.41	619.33	6.9	0.08
Area predicted as illegally mined (km2)	7.55	6.94	-0.6	-0.21
% mined area mined illegaly	83.44	82.93	-0.5	-0.31
Population	25,013.19	26,196.48	1,183.3	0.41
Number of ilegal mines (2010 Census)	27.79	24.63	-3.2	-0.77
Observations	400	442		

Area and percentage illegally mined calculated with the machine learning model. Number of mines according to the Mining Census of 2010. The Census was the starting point to train the machine learning model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Balance table National authority treatment

	Tell to National	Control	Difference	t-stat
Area of municipality (km2)	600.20	630.46	30.3	0.37
Area predicted as illegally mined (km2)	6.53	7.86	1.3	0.46
% mined area mined illegaly	84.58	81.89	-2.7	-1.60
Population	27,114.23	24,296.80	-2817.4	-0.97
Number of ilegal mines (2010 Census)	24.51	27.59	3.1	0.75
Observations	400	442		

See Notes from Table A.1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Local responses to the information letters

	2017		2019		2020	
	Frequency	%	Frequency	%	Frequency	%
Verified	165	41.25	75	18.75	113	28.25
Lack resources	21	5.25	17	4.25	36	9.00
Fear armed groups	2	0.50	2	0.50	1	0.25
Other response	26	6.50	6	1.50	11	2.75
No response	186	46.50	300	75.00	239	59.75
Total	400	100.00	400	100.00	400	100.00

Notes: We classify the response of the local authorities into five categories: (1) Verified: if they answered whether there was mining or not on the disclosed coordinates; (2) Doesn't have resources: if they answered that they could not visit the coordinates because they did not have money or personnel to reach the disclosed locations; (3) Fear of armed groups: if they expressed concern on visiting the coordinates because of armed groups presence there; (4) Other response: if they contacted us and gave a different answer of the ones above (5) No response: if after six months I did not receive a response.

Table A.4: Determinants of local authority's verifying the coordinates

Dependent variable:	Verified			
	(1)	(2)	(3)	(4)
Model accuracy	0.16**			0.16**
	(0.069)			(0.068)
Share illegal		-0.084		-0.019
		(0.11)		(0.12)
Distance (Km)			-0.0081***	-0.0081***
			(0.0018)	(0.0019)
N. of obs.	389	400	400	389
Mean of Dep. Var.	0.41	0.41	0.41	0.41
R^2	0.013	0.0013	0.033	0.046

Notes: Verified= 1: if the municipality answered whether there was mining or not on the disclosed coordinates. Accuracy: is the fraction of the disclosed coordinates that are actually mines according to the high-resolution verification. Distance is the average distance from the disclosed coordinates to the municipality office. There are less observations when including the model accuracy variable, because there are no high resolution images available for all the municipalities. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Tabulation of local authority responses by accuracy of predictions

(a) All the predictions

	Mine NO	Mine YES	Total
Local NO	369	263	632
Local YES	9	111	120
Total	378	374	752

(b) Only predictions inside legal titles

	Mine NO	Mine YES	Total
Local NO	28	44	72
Local YES	1	31	32
Total	29	75	104

(c) Only predictions outside legal titles

	Mine NO	Mine YES	Total
Local NO	341	219	560
Local YES	8	80	88
Total	349	299	648

Notes: Panel A includes all the points for which we obtained local authorities responses and high resolution verification. Panel B has only the disclosed points inside legal titles and Panel C points outside titles. Each panel presents the tabulation of local government responses (Local NO/ Local YES) against the high resolution verification (Mine NO / Mine YES), what I consider the "truth".

Table A.6: Determinants of local and national government's accuracy and pixel characteristics (2017)

Dependent variable: Responses	Accurate response = 1					
	Local		National		National & Local	
	(1)	(2)	(3)	(4)	(5)	(6)
IllegalMineXLocal	-0.15**	-0.16**			-0.32	-0.44**
	(0.071)	(0.066)			(0.19)	(0.19)
FPxTitleXLocal	0.55***	0.57***			-0.028	-0.26
	(0.079)	(0.11)			(0.29)	(0.37)
FPxNOTitleXLocal	0.56***	0.62***			0.21	0.36*
	(0.068)	(0.074)			(0.16)	(0.21)
IllegalMineXNational			-0.17*	-0.058	-0.028	-0.058
			(0.095)	(0.087)	(0.12)	(0.20)
FPxTitleXNational			0.62***	0.79***	0.89***	0.77***
			(0.12)	(0.098)	(0.11)	(0.16)
FPxNOTitleXNational			0.71***	0.85***	0.83***	0.84***
			(0.096)	(0.086)	(0.12)	(0.21)
N. of obs.	752	748	512	457	270	254
Mean of Dep. Var.	0.64	0.64	0.64	0.63	0.68	0.68
R^2	0.51	0.74	0.72	0.88	0.60	0.85
Municipality FE	No	Yes	No	Yes	No	Yes

Notes: Estimates of equation (1) for government responses in 2017. False positive (FP) is a prediction of the model that was not a mine according to independent verification. Clustered standard errors at the municipality level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Results for accuracy of local's aggregate responses (2017-2019-2021)

Dependent variable:	Accurate	
Illegal Mine	-0.16***	-0.11***
	(0.032)	(0.033)
False Positive x Title	0.43***	0.47***
	(0.071)	(0.087)
False Positive x NO Title	0.54***	0.65***
	(0.046)	(0.051)
N. of obs.	1,071	1,052
Mean of Dep. Var.	0.69	0.69
R^2	0.41	0.68
Municipality FE	No	Yes

Notes: Estimates of equation (1) for local government responses in 2017, 2019, 2021. The National government did not respond in 2019 and 2021, so it is not included in this Table. Clustered standard errors at the municipality level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Alternative determinants of local government's accuracy and pixel characteristics

Dependent variable:	Accurate					
Sent to:	Local			Local & National		
	(1)	(2)	(3)	(4)	(5)	(6)
Illegal Mine	-0.17**	-0.16**	-0.15**	-0.45**	-0.49**	-0.43**
	(0.066)	(0.066)	(0.063)	(0.19)	(0.19)	(0.18)
False Positive x Title	0.57***	0.57***	0.58***	-0.26	-0.24	-0.22
	(0.11)	(0.11)	(0.11)	(0.38)	(0.34)	(0.37)
False Positive x NO Title	0.61***	0.62***	0.62***	0.36*	0.34	0.39*
	(0.074)	(0.074)	(0.071)	(0.21)	(0.21)	(0.19)
Age of the Mine	-0.0098*			-0.012		
	(0.0051)			(0.012)		
Distance (Km)		0.037			0.12	
		(0.031)			(0.11)	
Location 2			-0.0079			-0.080
			(0.028)			(0.073)
Location 3			0.078**			-0.032
			(0.032)			(0.069)
Location 4			0.054			0.035
			(0.036)			(0.093)
Location 5			0.020			-0.018
			(0.033)			(0.061)
N. of obs.	748	748	748	127	127	127
Mean of Dep. Var.	0.64	0.64	0.64	0.78	0.78	0.78
R^2	0.74	0.74	0.75	0.75	0.76	0.76

Notes: "Age of the Mine" as the first year our model detect the pixel as mined. "Distance" is the distance from the disclosed coordinate to the municipality office. All estimations include municipality fixed effects. Clustered standard errors at the municipality level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Alternative determinants of National Government's accuracy and pixel characteristics

Dependent variable:	Accurate					
Sent to:	National			National & Local		
	(1)	(2)	(3)	(4)	(5)	(6)
Illegal Mine	-0.060	-0.059	-0.056	-0.059	-0.052	-0.051
	(0.088)	(0.085)	(0.086)	(0.20)	(0.20)	(0.21)
False Positive x Title	0.79***	0.79***	0.80***	0.77***	0.81***	0.79***
	(0.098)	(0.10)	(0.099)	(0.16)	(0.15)	(0.17)
False Positive x NO Title	0.85***	0.85***	0.85***	0.85***	0.85***	0.85***
	(0.086)	(0.084)	(0.085)	(0.21)	(0.21)	(0.22)
Age of the Mine	-0.0030			-0.0091		
	(0.0041)			(0.0074)		
Distance to Bogota (Km)		0.0029			-0.042	
		(0.028)			(0.053)	
Location 2			-0.038*			-0.015
			(0.022)			(0.029)
Location 3			0.00094			0.036
			(0.026)			(0.071)
Location 4			-0.023			0.010
			(0.028)			(0.061)
Location 5			-0.028			0.00084
			(0.037)			(0.049)
N. of obs.	457	457	457	127	127	127
Mean of Dep. Var.	0.63	0.63	0.63	0.57	0.57	0.57
R^2	0.88	0.88	0.88	0.90	0.90	0.90

Notes: All estimations include municipality fixed effects. Clustered standard errors at the municipality level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B Online Appendix (For Online Publication)

I present the machine learning model used to detect mining activity using satellite data. The data is available on https://comimo.sig-gis.com/. I present the description of the latest model used for the data posted on CoMiMo and on the dependent variable. The details of the random forest model used for the first rounds of treatment are in Appendix D of Saavedra and Romero (2021).

Colombian Mining Monitoring (CoMiMo) aims to detect illegal mining using satellite data and machine learning. I train the model with thousands of examples of images with mines, and also of images without mines. The goal of the machine learning algorithm

Table A.10: Evolution of illegally mined area in response to the treatment

Dependent variable:	% gold mined area mined illegally			
	(1)	(2)	(3)	(4)
After X Local	-4.30*		-2.77	
	(2.29)		(3.72)	
After X Nat		-4.30*	-2.41	
		(2.51)	(2.74)	
After X Nat X Local			-1.91	-7.09**
			(4.81)	(3.30)
After X Only Local				-2.77
				(3.72)
After X Only Nat				-2.41
				(2.75)
Mean Dep. Var. Before	85.07	85.07	85.07	85.07
Obs.	363	363	363	363
N. Munis	110	110	110	110
R^2	0.87	0.87	0.87	0.87

Notes: The percentage of gold mined area mined illegally is calculated from data of the United Nations Office on Drug and Crime. There are four years of data: 2014, 2016, 2018 and 2019. All regressions include municipality and department-year fixed effects. Two-way clustered standard errors, by municipality and department-year, are in parentheses. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

Table A.11: Spillovers effect

Dependent variable:	% gold mined area mined illegally	
	(1)	(2)
Local X After X Disc	-10.1**	-11.7***
	(3.97)	(4.16)
National X After X Disc	-15.4***	-17.0***
	(3.99)	(4.19)
Both X After X Disc	-8.14**	-9.47***
	(3.36)	(3.30)
Local x After x Neighbour disclosure	-11.8***	-13.4***
	(3.09)	(3.23)
National x After x Neighbour disclosure	-15.7***	-17.3***
	(4.29)	(4.59)
Both x After x Neighbour disclosure	-11.7***	-13.0***
	(2.77)	(2.81)
Local X After X Treated	6.19**	4.67*
	(2.64)	(2.59)
National X After X Treated	2.69	1.05
	(2.80)	(2.37)
Both X After X Treated	5.27**	3.93
	(2.42)	(2.40)
N. of obs.	72,876	72,876
Mean of Dep. Var.	35.8	36.1
R^2	0.24	0.25
Mining titles fixed 2016	No	Yes

Notes: (1) % of gold area mined illegally using mining titles of each year. (2) % of gold area mined illegally keeping constant 2016 mining titles. Clustered standard errors, by municipality, are in parentheses. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

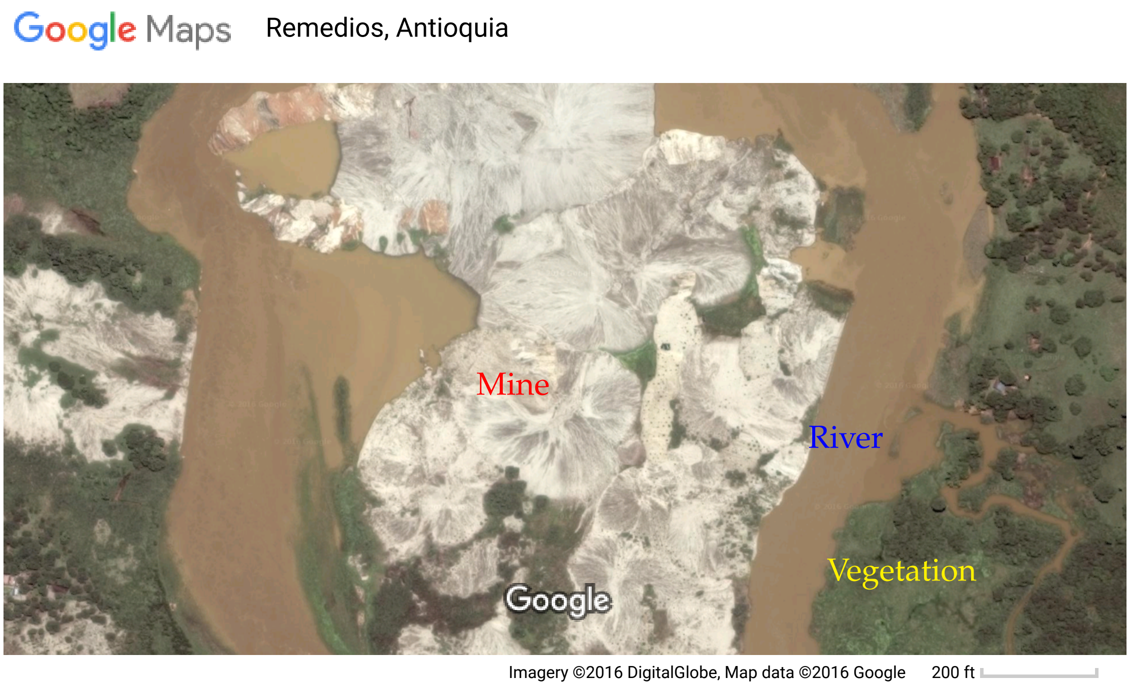
Table A.12: RCT specifications

Dependent variable:	Gold area mined illegally (Km2)			% Gold area mined illegally		
After X Grid disclosed	-0.011**	-0.015**	-0.014	-20.1***	-25.6***	-20.8***
	(0.0055)	(0.0064)	(0.011)	(2.34)	(2.54)	(5.13)
After X Neighbor disclosed		-0.021***	-0.019**		-27.0***	-22.2***
		(0.0048)	(0.0095)		(2.02)	(4.84)
After X Muni treated			0.0023			6.94
			(0.0097)			(5.13)
Mean Dep. Var. Control	0.05	0.05	0.05	36.23	36.23	36.23
Obs.	18,219	18,219	18,219	18,219	18,219	18,219
N. Munis	110	110	110	110	110	110
R^2	0.042	0.047	0.047	0.073	0.11	0.12

Notes: Clustered standard errors at the municipality level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

is to detect the footprint of an open-pit mine (e.g., the white part in Figure B.1). One could impose a rule for declaring an image as mined or allow the machine to "learn" the optimal rule based on the characteristics of known mines. For example, we could impose the following rule: Every image without forests and with a color close to white is a mine. Instead, I let the computer find the characteristics that differentiate images with mines from those without mines.

Figure B.1: Image of a mine in the municipality of Remedios



Notes: The white portion of the image is the mine footprint, in contrast to the river (brown) and vegetation (green). Source: Digital Globe-Google Maps.

I divide this section into four sub-sections. First, I present the satellite data used as input for training and predictions. Second, I present the labeled data of examples of mining and no-mining areas. Third, I present the model architecture and other specifications. Finally, I present the performance metrics of the best model used for the predictions available in CoMiMo.

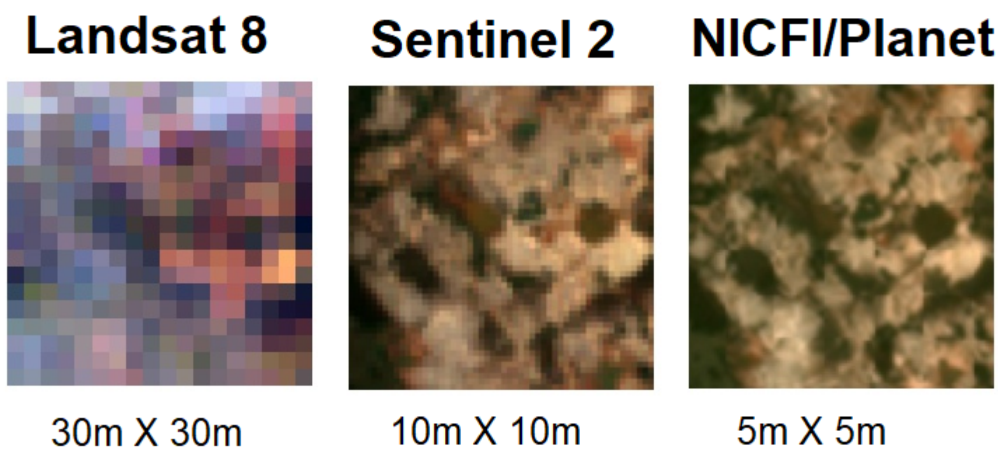
B.1 Satellite data

I use three different satellite sources: NICFI, Sentinel 1, and Sentinel 2. Although the satellites have different resolutions, each satellite imagery is divided into common 540mx540m grid squares that will be the basis of the analysis. That is, in the training data, I have an indicator on whether the 540mx540m grid square has a mine or not. From now on, if the text mentions a grid square, I am referring to these 540mx540m grid squares. The images are processed in Google Earth Engine.

NICFI-Planet data The image is provided for free by Norway's International Climate and Forest Initiative (NICFI), from Planet's constellation of satellites. There are four variables that can be used as predictors: The red band, green band, blue band, and the fourth band (near-infrared). Available every six months since December 2015 and monthly since September 2020. The resolution is 4.77m per pixel.

Sentinel 1 data This imagery is created using radar, so it is not affected by the presence of clouds. Provided by the European Space Agency daily since October 2014. I use the two bands (VV, VH) and a combination of these two (VH-VV). The resolution is 10m per pixel.

Figure B.2



Sentinel 2 data It is also provided by the European Space Agency, but it is affected by clouds. Available daily since March 2017. I use the red, green, and blue bands. The resolution is 10m per pixel.

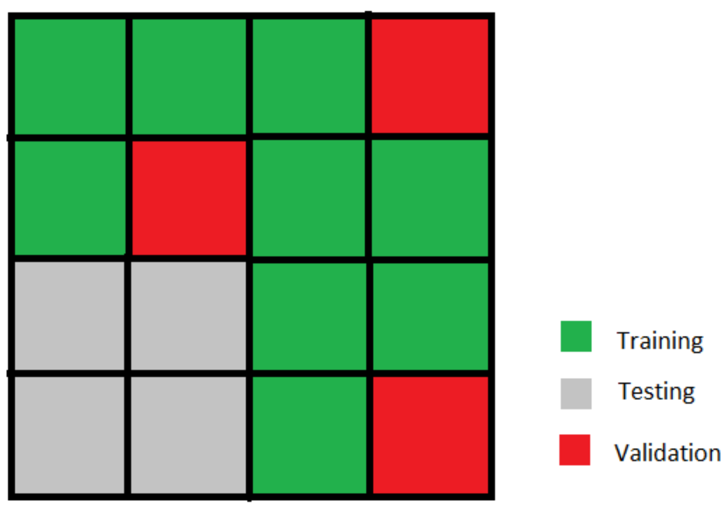
B.2 Training, validation and testing data

The labels on whether a grid square has a mine or not are derived from many sources. The first source is the Colombian Mining Census of 2010, the source used for the random forest model described below. The second source is The United Nations Office on Drugs and Crime (UNODC) map of open pit gold mining from 2014. The final source is our own validation of three different kinds of points. The first kind is a random sample of grid squares in Colombia, and a random sample from mining regions. The second kind is from grids belonging to mining titles. The final kind is validation from previous models. This allows me to present the model examples of imagery that is difficult to classify. We have 5,602 images classified as mines and 12,517 images classified as no mined. I can expand this set of images with rotations, reflections, and extracting on different dates.

Besides the label on whether there is a mine, each image extracted from a given satellite needs to be inspected in case there are clouds. For example, even though a given grid might have a mine, a satellite image of the grid might have a cloud, so the label needs to be adjusted for that satellite. The labels were done by students in double-blinded validation using the extracted image and Google Maps, Digital Globe, and Planet for additional context.

I divided the country into 100kmX100km data squares. Each data square is divided into four equal sub-squares. One of these sub-squares was randomly assigned to testing. The remaining sub-squares were each split again into four, assigning randomly a fourth for validation. See the figure below for an example. That is, I have 56.25% of the area for training, 18.75% for validation, and 25% for testing. The reason for not doing fully random splitting is to avoid geographical correlation between training and testing. In fully random splitting, I might train in a grid and test in its neighbor, which is easy to predict, overstating performance metrics.

Figure B.3



B.3 Model architecture

We have a trade-off between having a large image with more pixels that provides more information for classification and a small image that would be more certain of the location for field verification. We decided on 540mx540m images because half a kilometer is a reasonable distance to walk on the field.

- Architecture: ResNet-50, ResNet-18, ResNet-34, ResNet-101, EfficientNet-B1, DenseNet-

101

- Satellite: NICFI-Planet, Sentinel-1, Sentinel-2, Landsat 8
- Bands: RGB, add Infrared
- Learning rate: 0.0001, 0.0002, 0.0005
- Epochs: 30, 15, 45, 60
- Dropout: 0.5, 0.25, 0.75
- Data augmentation: simple, rotation, reflection, multiple periods
- Hybrids of the models above: hierarchy, arithmetic or geometric average of predictions

B.4 Metrics

The validation metrics of the best performing model used for the August 2021 predictions are presented below. The precision is 90.54%. I do not yet use the testing data because I think there is still room for improvement.

Table B.1: Confusion matrix for the model currently in CoMiMo

	Non-Mined	Mined
Predicted Non-Mined	1647	923
Predicted Mined	14	134

Notes: The confusion matrix presents the accuracy of the prediction model in classifying mined images using the optimal threshold. The columns show the actual mined status of the images according to the validation data, while the rows show what the model predicts. The precision is 90.54%.

Appendix C Online Appendix (For Online Publication)

Table C.1: Determinants of response - Logit model

Dependent variable:	Verified			
	(1)	(2)	(3)	(4)
Model accuracy	0.66**			0.70**
	(0.29)			(0.30)
Share illegal		-0.34		-0.064
		(0.47)		(0.49)
Distance (Km)			-0.045***	-0.045***
			(0.013)	(0.013)
N. of obs.	389	400	400	389
Mean of Dep. Var.	0.41	0.41	0.41	0.41

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: Determinants of response - Probit model

Dependent variable:	Verified			
	(1)	(2)	(3)	(4)
Model accuracy	0.41**			0.43**
	(0.18)			(0.18)
Share illegal		-0.22		-0.055
		(0.29)		(0.30)
Distance (Km)			-0.026***	-0.026***
			(0.0073)	(0.0074)
N. of obs.	389	400	400	389
Mean of Dep. Var.	0.41	0.41	0.41	0.41

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: Determinants of local and national government's accuracy gold mining municipalities

Dependent variable:	Accurate Response=1				
Responses by	Local		National		Local & National
	(1)	(2)	(3)	(4)	(5)
IllegalMineXLocal	-0.17	-0.14			-0.33
	(0.16)	(0.18)			(0.27)
IllegalMineXNational			-0.13	0.0065	0.44
			(0.14)	(0.19)	(0.27)
N. of obs.	68	68	100	87	42
Mean of Dep. Var.	0.68	0.68	0.58	0.57	0.57
R^2	0.11	0.50	0.13	0.60	0.34
Municipality FE	No	Yes	No	Yes	No

Notes: This table is the equivalent of Table 2 but restricted to municipalities with gold mining area according to the UNODC data. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$