Local incentives and national tax evasion:
Unintended effects of a mining reform in Colombia *

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Abstract

There is a growing trend in developing countries towards decentralizing spending. However, the tax revenue sources remain unchanged. The share of tax revenue transferred back for the locality where the taxed economic activity takes place could affect the incentives of local authorities to curb tax evasion. In this paper, we document that a reduction in the share of mining royalties transferred back to the mining municipalities in Colombia led to an increase in illegal mining. Although tax evasion might not have a welfare cost if it is just a transfer of resources, we show that illegal mining causes worse health outcomes for newborn children.

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1 Introduction

There is a growing trend in developing countries towards decentralizing spending, without changing the sources of tax revenue sources. The share of tax revenue transferred back for the locality where the economic activity taxed takes place could affect the incentives of local authorities to curb tax evasion (Banerjee, Mullainathan, & Hanna, 2012). In this paper, we document that a reduction in the share of mining royalties transferred back to the mining municipalities in Colombia led to an increase in illegal mining. Although tax evasion may not have a welfare cost (if it is just a transfer of resources (Chetty, 2009)), illegal mining causes worse health outcomes for newborn children than legal mining.[1]

Throughout the literature on illegal activity, the main challenge is measuring its extent (Banerjee et al., 2012). To overcome this obstacle, we construct a novel dataset using machine learning predictions on satellite imagery features to detect illegal mining activity. We predict mining activity using the satellite images, and assess its legality with the map of legal titles produced by the National Government.[2] Not holding a mining title is highly correlated with evading royalty taxes.

We use the mining predictions to study the effect of a reform that sharply reduced the share of taxes transferred back to the municipality where the mine is located. The remaining revenue is distributed among all municipalities according to socioeconomic indicators. The reform altered the income local authorities receive from legal mining and consequently their incentives to monitor miners' compliance with national regulations.

We formalize our intuition regarding how incentives for local authorities are

[1] Previous literature (Aragón & Rud, 2015; von der Goltz & Barnwal, 2016; Tolonen, 2015) has shown the pollution effects of mining, but we are the first to show differential effects of legal versus illegal mines.

[2] We 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).

affected by the reform with a simple theoretical framework in which a miner decides whether to operate legally. The local authority observes mining activity in its municipality. To operate illegally, the miner has to pay a bribe, the amount of which is determined by bargaining with the local authority. The reform does not affect the cost of operating legally. However, since the reform causes the municipality to receive less of the tax revenue paid by legal miners, it changes the payout for the local authority if the mine is in compliance with regulations. Consequently the bribe to operate illegally is smaller after the reform, and therefore mines are more likely to operate illegally. The model also predicts that the effect of the reform is larger in areas where the national government's presence is weak. Intuitively, larger mines can operate illegally in these areas, because the probability of the national government confiscating its capital is smaller.

We test these predictions by looking at the change in illegal mining in Colombia before and after the reform. In addition, to estimate the effect of the reform in a difference-in-differences framework, we also apply the mining prediction model to municipalities in the neighbor country of Peru. The simple difference (event study) and the difference-in-differences estimates suggest that the reform increased the share of the total mined area that is mined illegally. After the reform, we estimate this share increases in Colombia by 1.63 -4.47 percentage points. As predicted in the theoretical framework, the effect of the reform is greater in municipalities where the national government's presence is weak. These results are economically significant. Approximately USD 45-138 million in potential government revenue was lost as a result of the increase of illegal mining with the reform. This is equivalent to 7-21% of the USD 660 million in mining royalties in 2015.

Besides the lost tax revenue, illegal mining could have differential environmental impacts for at least two reasons. First, since the machinery of illegal mines would be destroyed if found, illegal mines may have less efficient machinery. This machinery requires using more variable inputs which potentially pollute the environment to a greater degree. Second, legal mines have to present an

environmental management plan. To test this hypothesis we study the effect of legal and illegal gold mines on newborns' health, using the data on mines we detected. We instrument the presence of illegal mines with the heterogeneous effect of the reform. As predicted, babies born downstream from illegal mines have a 0.69 -2.26 percentage points smaller probability of being born with high APGAR.[3] This health cost of the reform is between 4-13 cents per dollar redistributed.

To the best of our knowledge, this is the first paper to quantify the response of tax evasion to the formula used to distribute tax revenue across municipalities. Cai and Treisman (2004) provide examples of cases where regional governments help firms evade national taxes and regulations. A closely related paper by Khan, Khwaja, and Olken (2016) presents experimental evidence that performance pay for tax collection increased both tax revenue and reported bribes. Although local authorities in our context are not direct "tax collectors", the royalties reform reduces their incentives to monitor the legality of mines. We also contribute to the developing body of literature on natural resources and political economy. Similar to Burgess, Hansen, Olken, Potapov, and Sieber (2012) and Lipscomb and Mobarak (2013) we study a national interest resource whose regulation depends on local authorities. Those papers find that greater decentralization increased deforestation and water pollution. In addition, we show that the associated environmental damage has worse effects on human capital. Previous literature (Aragón & Rud, 2015; von der Goltz & Barnwal, 2016; Tolonen, 2015) has shown the pollution effects of mining, but given our data, we are the first to show differential effects of legal versus illegal mines.

Methodologically this paper uses machine learning both for prediction of the dependent variable and to estimate causal effects. We use applications of machine learning techniques for causal inference (Belloni, Chernozhukov, &

[3]This is an indicator of good health that measures: Appearance, Pulse, Grimace, Activity and Respiration.

Hansen, 2014; Athey & Imbens, 2016) and join the growing body of literature that uses satellite observations to study economic outcomes including Foster, Gutierrez, and Kumar (2009); Jayachandran (2009); Henderson, Storeygard, and Weil (2012); Guiteras, Jina, and Mobarak (2015); Faber and Gaubert (2016). Previous papers studying illegal mining used static measures in their analysis (Idrobo, Mejia, & Tribin, 2014; Romero & Saavedra, 2015). Thus, our panel dataset on illegal mining by municipality is a contribution in itself, as are the codes used to create the dataset, which could potentially be used to create similar datasets for other countries.

The remainder of the paper is organized as follows: Section 2 describes the context of mining in Colombia and details of the reform. Section 3 presents the theoretical framework. Section 4 describes the data, in particular the construction of the illegal mining panel. Section 5 presents the identification strategies and main results for area illegally mined. Section 6 presents the estimation of differential health effects from legal and illegal mines, and the final section concludes.

2 Mining context and details of the reform

The mining and hydrocarbon industry is important for the Colombian economy, representing 8-11% of GDP from 2012-2016.[4] Although mineral mining represents a small portion (20%) of royalty revenue (compared to hydrocarbon extraction, which amounts to 80%), it has a large footprint — large enough that its environmental impacts can be tracked from space (Asner, Llactayo, Tupayachi, & Luna, 2013). Within mineral mining, 77% of the royalties come from coal, 12% from nickel, 10% from precious metals (e.g., gold and silver) and the remaining fraction from salt, emeralds and construction materials.

According to Colombia's Constitution, subsoil and mineral resources are owned by the national government. This is different from other countries, such as

[4]The share was 11% in 2012 but has fallen in recent years due to the reduction in commodity prices. http://www.banrep.gov.co/es/pib

the United States, where the owner of the land is entitled to its mineral resources. Colombia's national government allocates mining permits and sets royalty taxes for mineral extraction. The title holder pays a fee that depends on the size of the mine and is equivalent to a legal daily minimum wage per hectare per year.[5] Additionally, mining companies pay royalties based on the gross value and type of minerals extracted.[6]

Before 2012, a mining municipality would receive around 55% of the royalties paid by mines operating in its territory. But, Legislative Act 05 of 2011 changed the allocation formula dramatically, such that only 10% of the royalties are transferred directly to the mining municipality. 40% are earmarked for regional funds, while the rest of the royalties revenue must be used for savings.[7] The resources allocated to the regional funds are distributed according to population, poverty and unemployment; thus, the net impact of the reform in each municipality varies depending on these characteristics.

When the Colombian national government introduced the reform, it stated that its main objectives were to reduce poverty and regional inequality, save part of the expected increase in mining revenue and improve the management of royalties resources.[8] Illegal mining was neither mentioned as a motivation for the reform nor were the impacts of the reform on illegal mining contemplated.[9] Therefore we take the timing of the reform as exogenous to the evolution of

[5]If the title area is between 2,000 and 5,000 hectares, the title holder pays the equivalent of two times the legal minimum wage per hectare and holders of title to areas larger than 5,000 hectares pay three times the minimum wage per hectare (Agencia Nacional Minera, 2013).

[6]The price used to calculate the gross value is the average monthly price on the London Metal Exchange. Colombia is considered a price taker in all of these markets given the size of its production (Fedesarrollo, 2014b). The royalties tax varies across minerals and depends on the quantity extracted. For example, construction materials are taxed at a 1% rate, gold and silver at a 4% rate, and nickel at a 12% rate. See Table C1 in the Online Appendix

[7]10% of royalties must be allocated to a science, technology and innovation fund; 10 % go to under-budgeted pensions and (up to) 30% are placed in a savings and stabilization fund.

[8]See `https://www.sgr.gov.co/LinkClick.aspx?fileticket=bsf8qrvGVOg%3D&tabid=181`

[9]The reform was approved six months before it was implemented, so we cannot rule out some anticipation by local governments of its effects.

illegal mining.

Local authorities are responsible for monitoring illegal mining. According to the Law 685 of 2001 "Mining Code" majors should suspend any mining activity without title. In addition, they should confiscate any mineral that does not have a certificate of origin from a legal mine and inform the national penal authority.

During 2010 the government of Colombia conducted a census of all mines, regardless of whether they held a mining title, in half of the municipalities. According to the census 62% of the surveyed mines did not have a title. There have been three attempts to legalize illegal mines in Colombia, with little success.[10] Government attempts to provide incentives to legalize illegal mines, have also been accompanied by stricter enforcement rules. At the end of 2012 the Andean Community of Nations (which includes Colombia and Peru) signed a decree allowing the destruction of all machinery used in mines that do not have a registered title.[11]

While some illegal producers pay production taxes, the majority doesn't. According to the Mining Census, 19% of the mines without a title paid royalties to "legalize production" and in the national government's official production data, 30% of the production takes place in municipalities without any registered mining titles. The reported production in municipalities without mining titles is usually the result of collusion between miners and local authorities in which the former "launders" its illegal production and the latter obtains additional funds from royalties revenue (Masse & Camargo, 2012). More importantly, there is evidence of production that does not pay royalties: between 2009 and 2011, an excess of 28.6 tons of gold were found in export records over

[10]The Mining Code of 2001 contained difficult requirements for legalization and of the 2,845 legalization requests received only 23 were approved. Similarly, the Mining Code of 2010 generated 700 requests, but only one title legalization was approved. Finally, a pilot legalization program that started with 150 mining operations in 2012 only has 25 still in the process after three years, and none have complied with all the requisites (TGIATOC, 2016)

[11]Before the decree the machinery was supposed to be confiscated, which was difficult to implement in remote regions.

the reported amount on which royalties were paid; this "excess" production amounts to 20 % of the value of gold royalties value (Rudas & Espitia, 2013).

3 Theoretical framework

3.1 Setup

We present a framework for understanding a miner's decision to operate legally or illegally. This decision depends on the cost of operating legally and the probability of being detected by the National Government. The "surplus" of illegal mining for a mine with capital K is the difference between the payoffs for the miner and the local authority when legal/illegal (see the Appendix for the derivation of this expression):

$$S(K) = \underbrace{T + pq(K)\alpha}_{Legality\ fees} + \underbrace{f(B) - f(pq(K)\alpha\beta + B)}_{Foregone\ revenue} - \underbrace{Pr(K)(p_K K + V)}_{Expected\ punishment} - \underbrace{q(K)(\gamma_I - \gamma_L)}_{Additional\ pollution}$$

Where T are the title fees; p is the international price of the mineral; $q(K)$ the quantity extracted; α the royalty taxes; β is the share of royalties allocated to the mining municipality, B is the municipality's budget aside from mining royalties, γ_i is the local environmental damage associated with each type of mining, and V is the cost to the local authority if the national government discovers the illegal mine and confirms the existence of collusion in a trial. $Pr(K)$ is the probability of the illegal mine being detected by the National Police, increasing in the size of the mine. The function f reflects the valuation of the local municipality's budget by the local authority. We assume $f' > 0$, either because the local authority gets a share of the contracts or because it altruistically cares more about investing in local projects than in projects outside the municipality. The shape of f will play an important role when studying the income effect of the reform. Denote by K^* the value of capital such that $S(K^*) = 0$. Any firm with capital K such that $S(K) \geq 0$ will pay the bribe and operate illegally. Given the punishment (destruction of capital) if caught operating illegally, any firm with $K > K^*$ will operate legally.

3.2 The effect of the reform on illegal mining

The reform did not change the "legality fees": neither the cost of the title fee nor the royalties paid by the firm changed. Regarding the "Foregone Revenue" term: irrespective of the shape of $f(\cdot)$, a reduction in the share of royalties transferred back to the mining municipality (β), reduces the payout from legal mining to the local authority. Therefore the surplus of illegal mining is larger for every level of capital. In particular, the threshold size of illegal mines (K^*) increases and the share of area illegally mined increases. This reasoning leads to the following prediction:

Prediction 1. The reform increases the share of mined area that is mined illegally.

This model applies not only to a miner opening a new mine, but also to an existing illegal mine deciding whether or not to legalize each period. Consequently in the empirical section we will test this hypothesis both in the stock of mined area and the new area mined each year.

3.3 Heterogeneous effects of the reform

The effect of the reform in municipalities with lower national oversight Consider a municipality where the probability of detecting illegal mines is small, either because of weak presence of the national government or where armed groups (AG) provide protection for illegal miners ($Pr_{AG}() < Pr()$).[12] With a smaller probability of detection, the surplus of illegal mining is higher in these municipalities for any mine size ($S_{AG}(K) \geq S(K), \forall K$). When the reform reduces the share of royalties for mining municipalities, the surplus of illegal mining is positive for larger mines. Consequently we should observe a larger effect of the reform on the share of area illegally mined. [13]

[12] We abstract from an endogenous response of armed groups. Table C2 in the online Appendix show that there is no evidence of armed group relocation in response to the reform.

[13] In the extreme case in which armed groups have total control and the national government is unable to destroy illegal mine machinery in those places, then all the mines should

Prediction 2. The increase in illegal mining is larger in municipalities with lower probability of illegal mines being detected.

The income effect of the reform The effect of the reform on the budget depends on the transfer/loss (B_1) based on socioeconomic criteria. The change in illegal mining surplus due to revenue lost with the reform can be written as:

$$\Delta S(K) = (f(B + B_1) - f(pq(K)\alpha\beta_1 + B + B_1)) - (f(B) - f(pq(K)\alpha\beta_0 + B))$$

The sign of $\Delta S(K)$ depends on the concavity of $f(\cdot)$. To see this, we separate $f(\cdot)$ in two components: $f(B) = \delta(B)B + g((1 - \delta(B))B)$, where the first term is the share of the budget that the local authority captures for itself and the second term is the valuation of the budget actually invested in public goods. If we assume the local authority captures a constant share of the budget $\delta(B) = \delta$ and $g(\cdot)$ is linear, then $f(\cdot)$ is linear. In such case, $\Delta S = pq\alpha(\beta_0 - \beta_1)$, which does not depend on B_1, and the effect of the reform on illegal mining is the same for all municipalities regardless of whether they win or lose in net with the reform (i.e., there is no income effect).

However, when the local authority has a convex function $f(\cdot)$, the surplus of illegal mining for any size K is now larger for municipalities whose budget decreased with the reform.[14] Consequently, the average size of illegal mines is larger for municipalities negatively affected by the reform and there should be a larger increase in illegal mining in these municipalities. The converse holds if the function is concave: the increase in illegal mining is larger in municipalities whose budget increased with the reform. The function $f(\cdot)$ can be convex either because local authorities capture an increasing share of the

be illegal ($S_{AG}(K) \geq 0, \forall K$), no royalties would be paid in those places and the national government reform should have no effect. This, however, is not what we observe in the data: There are legal mines and royalties taxes paid in municipalities with armed groups.

[14] The same happens with a function with a reference point based on what the municipality received before the reform.

budget (Brollo, Nannicini, Perotti, & Tabellini, 2013), or because $g(\cdot)$ is convex. An illustration of this last point is the case of discrete investments: For example, with a small budget only a vaccination campaign could be funded, while with a large budget a hospital could be built which is politically more visible. In Colombia the median municipality spent 86 % of the revenue on "lumpy" projects like construction of a hospital or a bridge. Figure A1 in the Appendix illustrates the predictions regarding the shape of f and the differential effect on the reform depending on the size of the budget transfer. In short, the income effect of the reform depends on the concavity of f.

This simple model has some limitations. First, it does not consider the location decision of the miner, because the mineral resources are fixed in the subsoil. However, one could imagine a miner moving his capital to a neighboring municipality where conditions are more favorable a la Burgess et al. (2012). Second, we abstract away from any possible interactions with a local authority receiving bribes from multiple miners. These two limitations affect the level and location of illegal activity, but not the direction of change after the reform. Finally, we are modeling the decisions to obtain a legal title and pay royalty taxes as a single choice, but some legal mines may evade a percentage of production taxes. To explore this possibility, we assess the effect of the reform on the produced quantity reported by legal mines.

4 Data

We rely on four main sources of data for our analysis. The first source is the panel of illegal mining by municipality we constructed—details will be explained in the next subsection. The secondd database is from Colombia's governments mineral information system SIMCO[15] on reported production and prices. We also use a municipality panel from the Center for Studies of Economic Development (CEDE) at Universidad de los Andes (Acevedo & Bornacelly, 2014) with information on royalties, municipal budgets, homicides

[15] http://www.simco.gov.co/

committed by armed groups, and other characteristics of Colombian municipalities. Finally, we use the Vital Statistics of Colombia's Statistics Department (DANE) for information on newborn's health.

Summary statistics for the Colombian municipalities are presented in Table 1. We exclude from the analysis municipalities without mining potential in the subsoil, because, tautologically, there can be no mining in those municipalities. Of the 927 municipalities with minerals in the subsoil, 84% had a net increase in budget due to the reform (we will refere to these municipalities as the "winners"). Most of the mines are open pit and therefore can, in principle, be observed from space and detected with our prediction model.

Table 1: Summary statistics for municipalities used in the analysis

	Mean	Median	Std. Dev.	Min	Max
Population	25,279.99	13,226.00	40,628.42	984.00	394,627.00
Area of municipality (km2)	638.15	264.50	1,330.73	15.44	17,266.03
Produced precious metals	0.29	0.00	0.45	0.00	1.00
Change in royalties % budget if loser	-16.79	-12.77	15.05	-62.50	-0.02
Change in royalties % budget if winner	8.11	8.24	3.80	0.03	49.55
% illegal mines (Census)	47.02	50.00	40.24	0.00	100.00
% open pit mines (Census)	77.88	100.00	35.28	0.00	100.00

An observation is a Colombian municipality. The sample consists of 927 municipalities, of which 148 experienced a budget loss with the reform. There are 1,123 municipalities in Colombia but we exclude those without minerals in the subsoil. Source: Panel CEDE and 2010 Mining Census where indicated.

4.1 Constructing the illegal mining panel

There are four main steps taken to construct the panel of illegal mining by municipality. First, we prepare the satellite data so it can be used in the prediction model. Second, we construct a model to predict whether a certain pixel is mined. With the model we then predict mining presence in all pixels for the years 2004 to 2014. Finally we assess the legality of each mined pixel with the map of legal titles, and collapse the results at the municipality level for the regression analysis.

We use data from NASA's LANDSAT 7 satellite for the years 2004-2014 at a

resolution of 30m × 30m pixels (squares).[16]

The Mining Census published by the Colombian Ministry of Mines has the location of mines in 2010 for half of the municipalities.[17] In Figure 1, the white portion is the footprint of an open pit mine. Our final dataset has the following information for each pixel: a label denoting whether the pixel is mined, six satellite surface reflectance measures for different bands,[18] deforestation year (Hansen et al., 2013) and ecosystem type (Etter, 2006). We split the sample, allocating 75% of the observations for training (learning) and 25% for testing. Given this dataset one could impose a rule for declaring a pixel as mined or allow the machine to "learn" the optimal rule based on the characteristics of the known mines. For example, we could impose the following rule: Every pixel with deforestation, not in a desert and with a color close to white is a mine. Instead, we let the computer try different nested binary decision rules (trees[19]) and find one that accurately predicts mined pixels (i.e., it labels true mined pixels as mined), but with a low false positives rate (i.e., it does not label non-mined pixels as mined). We expect the relationship between the existence of a mine and the satellite bands measurements to be highly non-linear and complex, and use random forests which are suitable for this type of problem (James, Witten, Hastie, & Tibshirani, 2014). A random forest, as its name indicates, is a collection of many binary decision trees where in each node the candidate subset of explanatory variables to be used in the binary partition is random.

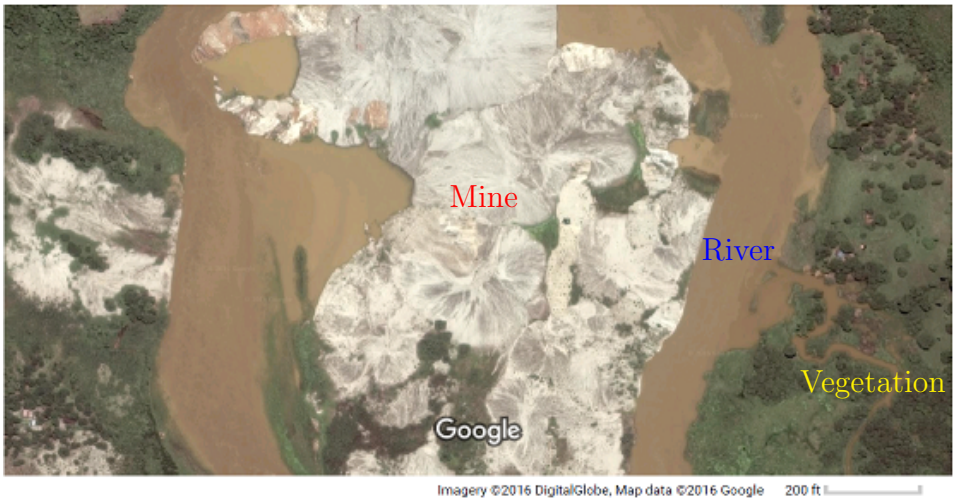
[16]These data are distributed by the Land Processes Distributed Active Archive Center (LP DAAC), located at USGS/EROS, Sioux Falls, SD. http://lpdaac.usgs.gov

[17]Although there might be a concern that the municipalities sampled by the Census were selected based on certain characteristics, we show in the on-line appendix Table C3 this is not the case. Municipalities included and not included in the Census are balanced in terms of change in royalties due to the reform, production of different minerals, institutional presence of the national government and presence of armed groups.

[18]Different wavelengths are captured in different bands. Specifically we use Band 1 (blue), Band 2 (Green), Band 3 (Red), Band 4 (Near infrared), Band 5 (Shortwave infrared 1) and Band 7 (Shortwave infrared 2)

[19]The name "tree" comes from the graphical representation of the nested binary decision rules.

Figure 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.

The random forest prediction attaches to each pixel in each year a probability that it is mined. We then need to determine the optimal cutoff at which we declare a pixel to be mined.[20] For each cutoff we plot in Figure A2 the associated true positive rate (TPR) and false positive rate (FPR) in the testing sample. Ideally we want to have 100% TPR and 0% FPR (upper left corner). As we lower the cutoff, we improve the TPR but also increase the FPR. In the literature it is standard to choose the cutoff ρ such that $TPR(\rho) - FPR(\rho)$ is maximized (marked with a blue star in the Figure). There are two important aspects of our analysis and data that make this standard cutoff inappropriate. First, we are using the predictions as dependent variables. Second, our sample includes many non-mined pixels. We discuss both issues in sub-section C.1 in

[20]The downside of using the raw probabilities is that the measure of fraction of area mined will be affected by the probability the model assigns to non-mined pixels. Nowadays, as a robustness we present results using the raw probability.

the Appendix. In a nutshell, the formula we use to choose the optimal cutoff assigns more weight to a lower FPR, given that most pixels in the country are not mined. Although we use this optimal cutoff in our main regressions, we will present robustness of our results to using the standard cutoff.

In Table 2 we present the confusion matrix for the optimally chosen cutoff. This matrix presents the number of correctly/incorrectly classified mined/non-mined pixels. The precision is 79% that is, of the pixels we predict as mined, almost four-fifths are truly mines according to the testing data. Our model correctly classifies 32.45% of true mine pixels (TPR), and wrongly classifies as mines 0.29% of pixels without a mine.[21] The area under the curve of our prediction model is 87%, much higher than the 50% of a random classifier and close to the 95% of very good classifiers (James et al., 2014).

Table 2: Confusion matrix for optimal threshold

	Non-Mined	Mined
Predicted Non-Mined	131,747	2,972
Predicted Mined	382	1,428

Notes: The confusion matrix presents the accurracy of the prediction model in classifying mined pixels. In the columns we have the true mined status of the pixels according to the training data. In the rows we have what the model predicts. The precision is 79% that is, of the pixels in the row Predicted Mined, what percentage are actually Mined (lower-right cell).

4.2 From pixel predictions to municipality panel

After predicting whether a given pixel in each year is mined,[22] we overlap the map of legal titles that year to declare the pixel as legally or illegally mined. Locations and exact shapes of Colombian legal mines were obtained

[21]The TPR is similar (26%) when testing our model in the illegal gold mines manually identified by (UNODC, United Nations Office on Drug and Crime, 2016).

[22]We smooth our predictions to prevent having pixels that switch back and forth from mined to not mined due to prediction error. We do this by calculating the monotonic sequence of 0's (not-mined) and 1's (mined) that is closer to the vector of each pixel predictions through time.

from Tierra Minada.[23] The data for Peru was obtained from the Peruvian Geology, Mining and Metallurgy Institute.[24] Finally, we aggregate the predictions at the municipality level for use in the regression analysis. The measure of illegal mining can be expressed as a fraction of either total municipality area, or only municipality mining area. We report both for completeness, but we focus on the fraction of mined area which captures the evolution of illegal compared to legal mining.

Table 3 presents the summary statistics of our predictions and a preview of our results. 89% of the mining area in Colombia is exploited without a title. Although this number seems high, it is close to the 78% estimated for gold mining in 2014 by (UNODC, United Nations Office on Drug and Crime, 2016).

Table 3: Summary statistics, illegal mining panel

% of mined area mined illegally	Peru	Colombia	Difference
Before the reform	87.65	87.74	.09
	(21.54)	(23.9)	(.35)
After the reform	77.22	82.18	4.96***
	(27.08)	(25.3)	(.63)
Difference	-10.43***	-5.56***	4.87***
	(.39)	(.56)	(.67)

Notes: Table 3 presents the mean percentage of a municipality area that is mined illegally. In the columns the results are presented by country, and in the rows before (2004-2011) and after the reform (2012-2014). An observation is a municipality-year. There are 2,738 municipalities in both countries, 927 in Colombia. Calculations: Authors.

[23] A nonprofit organization that digitized official records contained in the Catastro Minero Colombiano (Colombian mining cadastre). The full data set can be downloaded from `https://sites.google.com/site/tierraminada/`

[24] Accessed through Global Forest Watch on May 22nd 2016. www.globalforestwatch.org

5 The effect of the reform on illegal mining

5.1 Identification strategies

We want to identify how illegal mining responds to the share of mining taxes transfered back to the host municipality. In an ideal experiment, we would randomize the levels of marginal change and the net change in royalties returned to different municipalities. This is politically infeasible, so we rely on differences and difference-in-differences strategies to approximate the ideal experiment. Our estimating equation using only Colombian data is:

$$\widehat{y_{mt}} = \beta_A After_t + \beta_P PriceIndex_{mt} + \gamma_m + \delta * t + \varepsilon_{mt}, \quad (1)$$

where $\widehat{y_{mt}}$ is our constructed measure of illegal mining in municipality m at time t. $After_t$ is an indicator variables for after the reform. $Price_{mt}$ is an index of the price of the minerals available in the subsoil of that municipality. δ is the pre-reform linear trend and γ_m are municipality fixed effects.

The identification for β_A in the equation above comes from changes in illegal mining before and after the reform, netting out the pre-reform trend. This identification method may not be satisfactory if other national or international events, beyond the price changes we control for, occurred at the same time as the reform. Of particular concern here are two such concurring events. First, in Colombia the national government's system for receiving mining title requests was closed from the end of 2011 to July 2013. Although one might expect that the firms that wanted to obtain a title would wait or legalize once requests were being accepted again, we cannot fully separate these two effects. In order to address this first concern, we conservatively define illegal mining as mining areas outside the legal titles at the end of the study period, eighteen months after the system reopened. That is, if a miner could not register the title while the office was closed it will not count as illegal mining in our data. The second event occurring at the same time of the reform was a change in the law that allowed destruction of illegal mining machinery on site, instead of

being confiscated and processed in court. This law likely deters illegal activity, and consequently our event study coefficient will be underestimating the effect of the reform.

The change in illegal mining caused by the reform can alternatively be identified in a difference-in-differences framework. We use Peru as the control for several reasons. It is a neighbor country that is also highly affected by illegal mining. Peru also has levels of gold production in the same order of magnitude as Colombia (see Table A1 in the Appendix). Finally, Peru adopted the law on destruction of machinery on site as the same time as Colombia.[25] The estimating equation in the standard framework difference-in-differences framework is:

$$\widehat{y_{mt}} = \beta_A After_t \times Col_m + \gamma_m + \gamma_t + \varepsilon_{mt}, \quad (2)$$

In Figure A3 we empirically check the parallel trend assumption. As mentioned before, the reform was approved on July 2011 and took effect on the royalties paid starting January 2012. Colombia and Peru had similar levels of illegal mining before the reform. After the reform it increases in Colombia. There is some anticipation in 2011, but we conservatively define the period "After the reform" starting in 2012.

5.2 Main results

The results of estimating the effect of the reform on the share of mining area that is mined illegally are presented in Table 4. The first column shows the results of estimating equation (1) only with Colombian data. The second column incorporates the data from Peru and estimate equation (2), respectively. As expected, illegal mining increased after the reform in Colombia. The magnitude is 1.63 percentage points as a share of the mined area, using

[25] Although Brazil was another candidate, it is not part of the Andean Community of Nations, thus it is not affected by the mentioned law that allows the destruction of illegal mining machinery.

a before-after comparison controlling for the trend in Colombia (Column 1). The increase is 4.47 in the differences-in-differences estimator using Peru as the control (Column 2). In Columns 3-4, we include the results when using as the dependent variable the fraction of newly mined area that is illegally mined. The effect of the reform is larger, because this measure excludes the stock of existing mines.[26]

Another way of confirming our results is to estimate an analogous regression using titled area as the dependent variable. This measure does not depend on our mining area predictions, and is calculated from the government's data. Results are presented in Columns 5-6. They show a reduction in area titled in Colombia after the reform. However, we cannot tell apart the effect of the reform from the closure of the mining system.

[26]There numbers of observations drops in Columns 3-4 since the estimation needs a cloud free image in consecutive years and we cannot use observations from 2004, because we do not have satellite images from the previous year.

Table 4: Effect of the reform on illegal mining

Dependent variable:	% mined area mined illegally				Area mining titles (ha)	
	Stock		New			
	Colombia	DD Peru	Colombia	DD Peru	Colombia	DD Peru
	(1)	(2)	(3)	(4)	(5)	(6)
After x Colombia	1.63***	4.47***	2.30***	5.35***	-0.41**	-1.22***
	(0.45)	(0.62)	(0.51)	(0.75)	(0.16)	(0.31)
Mineral price index	0.0058		0.011**		0.0028	
	(0.0071)		(0.0047)		(0.0037)	
Time FE-Trend	Trend	TimeFE	Trend	TimeFE	Trend	TimeFE
N. of obs.	8,796	26,355	5,156	11,608	10,204	30,021
Municipalities	927	2,733	816	1,552	940	2,748
Mean of Dep. Var.	86.04	85.13	92.21	88.63	3.53	4.7
R^2	0.78	0.73	0.66	0.72	0.81	0.86

Notes: The entries in Table 4 are the coefficients estimates of 1 in the odd columns, and equation 2 in the evn columns. In the first two columns the dependent variable is the percentage of the stock of area mined that is mined illegaly. In columns 3 and 4, we calculate this percentage only in the new area mined that year. In the last two columns the dependent variable is the area of mining titles measured in hectares. All regressions include municipality fixed effects. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Tables A2-A4 we present different robustness checks of the main results. Column 1 of Table A2 repeats the main specification with Peru to facilitate comparison. We run again this specification but only with municipalities close to the border in column 2. The measure of illegally mined area that we use in columns 1-2 is calculated using the optimal threshold described in Sub-Section C.1. We investigate whether the results are robust to using a different cutoff. In particular we use the point closest to the ideal of 100% TPR and 0% FPR. For our model it is a cutoff associated with a 80% TPR and a 20% FPR. Results are presented in column 3 of Table A2. The magnitudes of the estimated coefficient is almost double the coefficients with the optimal threshold. This is because the new cutoff has almost double the difference between TPR and FPR compared to our conservative optimal threshold (60% compared to 32%). The difference between the TPR and the FPR is the factor that appears in equation (4). In column 4 of Table A2 we adjust the raw measure of fraction

of the municipality area that is mined, using the formula in equation (4). Finally, we use as regression weights the fraction of the municipality area that is analyzed (column 5).

In the theoretical model we assumed the miner could legalize if he paid the title fees and royalty taxes. However, not all illegal mines can be legalized. For example, if they are extracting minerals in a National Park. We assess whether the increase in the share of area illegally mined after the reform is in areas that could be legalized. For this we exclude illegal mining inside national parks in our calculations. The results are presented in column 1 of Table A3. The coefficient is in fact the same and also significant at 5%. In column 2 we present the results using the raw probabilities that a pixel is mined, instead of a dummy. The magnitude of the coefficient is smaller, partially because of the noise added by the probability of non-mined pixels. We include state trends in column 3 of Table A3) and use different measures of illegal mining (columns 4-5 Table A3). In all cases the results remain significant at 5%.

We assess whether our results are robust when controlling for other covariates in the regression. In our basic specification for Colombia we include the mineral price index, but other variables could also affect the evolution of illegal mining. As the set of possible controls is large, we rely on another machine learning technique to select the optimal controls. We use a Lasso procedure that selects controls that are relevant from a statistical point of view and are not chosen ad-hoc by the researcher. The Lasso procedure is like an ordinary least squares regression where the sum of squared residuals is minimized, but there is also a penalty for the number of controls used (James et al., 2014). In the set of possible candidates we include the price index, population, homicides by armed groups and these variables squared, lagged, interacted among them, interacted with a linear trend, and interacted with a quadratic trend. We use the Stata program provided by (Belloni et al., 2014) to implement their Double Lasso procedure (see Table A4 in the Appendix for the results). The procedure selects among others the lagged price index, which makes sense given the time it takes to start mining. The coefficient of "After the reform"

is smaller when including the optimal controls, but still significative at 5%. Finally, to alleviate concerns that the results are driven by unobservables we perform tests based on Altonji, Elder, and Taber (2005) using Oster (2013)'s procedure. We impose the most stringent parameters of perfect prediction if unobservables were observed ($R_{max} = 1$) and equally important unobservables ($|\delta| = 1$), and find that zero is not in the identification set. The identified set for the coefficient of β_A, the coefficient of After the reform is (0.11 ,3.32) percentage points.

Analysis of evasion in reported quantity produced

So far we have looked at the extensive margin of evasion, but it is possible that evasion is also present on the intensive margin through under-reporting to the national government of quantity produced. Consequently, we estimate the equivalent of equation (1) using reported production per area as the dependent variable.[27] Results are presented in Table 5. We do not find a significant effect for any of the products analyzed, and in fact for two of them the sign is positive. This could be explained by at least two facts: First, compared to area mined, it is harder for the local government to monitor the quantity extracted. Second, it is difficult to misreport production in oil and gas pipelines monitoring systems. Although the magnitude of some coefficients is large relative to the mean, we prefer to be conservative and assume there is no increase in under-reporting when monetizing the increase in evasion with the reform.

[27]For gas and oil we normalize production of each municipality to 100 in the first year of positive production.

Table 5: Effect of the reform on reported quantity

Dependent variable: Reported production by area	Coal	Gas	Oil	Gold	Silver	Platinum
	(1)	(2)	(3)	(4)	(5)	(6)
After	0.34	-0.44	-0.036	9.94	-0.45	-0.24
	(2.06)	(0.37)	(0.16)	(12.0)	(5.30)	(1.59)
N. of obs.	733	714	772	1,413	1,203	405
Municipalities	105	80	84	229	197	63
Mean of Dep. Var.	4.20	2.22	1.88	17.6	6.53	1.54
R^2	0.32	0.34	0.59	0.35	0.27	0.74

Notes: The entries in Table 5 are the coefficients estimates of 1 where the dependent variable is the reported production of each mineral by area. For gas and oil is just the raw production. All regressions include municipality fixed effects and control for the price index. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Heterogeneous effects of the reform

The effect of the reform in municipalities with lower national oversight

The theoretical framework predicts a larger effect of the reform in municipalities with low probability of illegal mines being detected. Empirically, municipalities with low probability of detection could be those with presence of armed groups or those with weak institutional presence of the national government. The former is measured with a dummy indicating if there was an homicide committed by an armed group. We measure the later as the number of institutions (e.g. tax collection or notary's office) per capita (Acevedo & Bornacelly, 2014). Although the two measures are correlated, the data indicates that the effect of the reform is larger in municipalities with weak institutional presence of the national government, but not in municipalities with armed groups (see Figure A5).[28] These results could be explained by at least two reasons. First, the National Police has targeted its efforts against illegal mining to areas that finance armed groups. Consequently the probability of detection might not be smaller in these municipalities. Weak institutional

[28]We only have the data for the heterogeneity analysis for Colombian municipalities.

presence would capture better the fact that the national government does not monitor these municipalities that often.[29] Another reason is that the measure of homicides committed by armed groups is not a good measure of their presence. Where armed groups have strong control, they do not need to resort to homicides to exert control.

Income effect of the reform

We also study whether a larger or smaller municipal budget affects the extent of illegal mining. The income effect of the reform is well identified; it relies on the assumption that, after controlling for municipality fixed effects and trends, the extent of illegal mining is only affected differentially by the impact of the reform on the municipality budget. In the theoretical framework section we showed that the differential increase in illegal mining for the municipalities that lost revenue depends on the concavity of the valuation of public funds. In Table 6 column 1 we present results including the dummy of "After the reform" interacted with the percentage of budget loss (negative if the budget increased). A 10-percentage-point decrease in the budget is associated with an additional 0.7 -percentage-point increase in the share of mined area that is illegally mined.

Through the lens of our model, these results suggest that the valuation of public funds by local authorities is convex. Alternative explanations are that loser municipalities are inherently different from winner municipalities, or that miners have less motivation to pay taxes after the reform. This last point is based on the evidence presented in Gadenne (2016) that grant revenue has no impact on local infrastructure, in contrast to tax revenue that is spent more carefully. However, in Colombia more than 75% of the title owners are from a different municipality than where the mine is located. Consequently the interest of the miners on where the taxes are spent cannot explain our results in their entirety.

[29] We asked for data on National Police operations to study these conjectures, but were denied access.

In addressing the possibility that the losers are inherently different from the winners, there are three points to consider. First, our regressions include only Colombian municipalities with mining potential in the subsoil. That is, there can be mining activity in any of the municipalities studied because there are resources underground. Second, we show in Table 1 that winners and losers have similar levels of mining activity. The main difference is the presence of oil resources, which can be considered random. Finally, we can re-run our main regression, exploiting a discontinuity in the post-reform formula for determining the transfer based on socioeconomic indicators.

The formula to determine post-reform lump sum transfers gives access to a special fund for municipality with poverty rates above 30%. Consequently a municipality with poverty below 30% is more likely to be a net loser with the reform. We re-estimate the income effect of the reform using only municipalities with poverty rates between 25 and 35%. These municipalities are more similar and their winner/loser status is determined by the sharp cutoff. The results are presented in Table 6 (column 2). The magnitudes of the coefficients are smaller and the results are not significative, so we cannot discard the function $f()$ is linear. In columns 3-4 we repeat the specifications used in columns 1-2 respectively, but we use as the dependent variable the fraction of the total area of the municipality that is illegally mined. The results are qualitatively similar confirming that $f()$ is convex.

Table 6: Results with percentage of budget loss

Dependent variable:	% mined area mined illegally		% total area illegally mined	
	All	Poverty 25-35%	All	Poverty 25-35%
	(1)	(2)	(3)	(4)
After	1.88***	1.11	0.20***	0.16***
	(0.43)	(1.09)	(0.032)	(0.036)
After x % Budget Loss	0.066***	0.043	0.0068*	0.014**
	(0.024)	(0.052)	(0.0040)	(0.0062)
N. of obs.	8,796	1,753	10,204	2,049
Municipalities	927	187	940	188
Mean of Dep. Var.	93.7	91.6	0.49	0.27
R^2	0.78	0.75	0.74	0.81

Notes: Poverty 25-35%, refers to municipalities with a poverty rate in this range, centered around the sharp cutoff of 30% for the post-reform transfer. All regressions include municipality fixed effects, linear time trend and control for the price index. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We estimate the dollars lost trough evasion in three steps. First we convert our coefficient of the effect of the reform into area illegally mined. Then we calculate the dollars lost in titles fees and finally the dollars lost in royalty taxes. The coefficient of "After the reform" when illegal mining is measured as percentage of municipality area is 0.12 (Column 4, Table A3). The analyzed area is $457,840km^2$, consequently illegal mining increased by $549km^2$. The coefficient of "After X Loser" in that specification is 0.31. The analyzed area in loser municipalities is $136,170km^2$. This represents additional $422km^2$ in the losers, for a total of $971km^2 = 97,100ha$ increase in illegal mining due to the reform.

The title fee per year is equivalent to a daily legal minimum wage ($10.5) per ha, for a total of $\$1M$ lost title fees. Around half a kilo of gold is extracted per ha,[30] the price of gold per kg is $ 44,000, and the royalties rate for gold is 5%. Multiplying these quantities we get $ 1,100 lost in revenue per hectare. Around 40% of the area illegally mined extracts gold, therefore at least $\$44M$

[30] http://phenomena.nationalgeographic.com/2013/10/28/gold-mining-in-peru-is-much-worse-than-anyone-thought/

of royalties revenue are lost with the reform. Compared to the total mining royalties of $\$660M$, this is equivalent to 7 cents per dollar. Recalling the formula for the estimated share of area illegally mined (equation 4), the coefficient underestimates the true effect by a factor of $TPR - FPR$. Consequently, there are $7(TPR - FPR) = 21$ cents lost to evasion per dollar redistributed.

6 Differential health effects of illegal mines

In this section we asses whether illegal mines have different health externalities than legal mines. Ideally we could do it for every type of mineral, but we focus on gold for two main reasons. First, over half of the total area of mining titles held is devoted to precious metals extraction (Agencia Nacional Minera, 2013). Second, the channels of exposure are well known, as we describe below.

Mercury is used to bind gold particles together apart from silt. After obtaining gold, mercury is released to the air or nearby water bodies. Besides drinking water, mercury is ingested by humans through fish consumption. In Colombia the EPA limits for mercury in water and mercury consumption are exceeded near mining areas (Guiza & Aristizabal, 2013; Olivero & Johnson, 2002).

Mercury is harmful to the heart, kidneys, and central nervous system, with women and children being the most sensitive to its effects. The fetal brain is especially susceptible to damage from exposure to mercury (Davidson, Myers, and Weiss (2004), Environmental Protection Agency (2013), Black, Bütikofer, Devereux, and Salvanes (2013). Babies born to women poisoned with methylmercury are more likely to develop cerebral palsy (Center for Disease Control, 2009), and in turn a low APGAR[31] score at birth is associated with an 81-fold increase in the risk of cerebral palsy (Moster, Lie, Irgens, Bjerkedal, & Markestad, 2001). APGAR scores have been found to be a significant predictor of health, cognitive ability, and behavioral problems later in life, even after controlling for family background and low birth weight (Almond, Chay, &

[31] Appearance, Pulse, Grimace, Activity and Respiration.

Lee, 2005). For further detail see (Romero & Saavedra, 2015).

6.1 Identification strategies

The health effects of illegal mines are potentially worse for two main reasons. First, since the capital of illegal mines would be destroyed if detected, illegal mines are likely to have less efficient machinery. This machinery requires using more variable inputs that potentially pollute the environment. Second, legal mines are required by law to present an environmental management plan. We expect that the population living downstream from mines are negatively affected by the pollution generated by the mines. Consequently for each municipality and year we estimate whether the population lives adjacent to a river that has a mine upstream ($DownstreamFromMine_{mt}$). Our dependent variable is an indicator of whether a baby is born with high APGAR score, a measure of good health.

$$HighAPGAR_{imt} = \beta_1 DownstreamFromIllegalMine_{mt} + \beta_2 DownstreamFromLegalMine_{mt} + X_{imt}\alpha + \gamma_m + \gamma_t + \lambda_{r(m)} \times t + \varepsilon_{imt} \quad (3)$$

Where X_{imt} are individual level controls: mother's age, education level and marital status. γ_m are municipality fixed effects. γ_t are year and week of the year fixed effects and $\lambda_{s(m)} \times t$ are state dummy variables interacted with a time trend to allow for differential time trends for each state. To test whether illegal mines have different health effects than legal mines, we test whether $\beta_1 < \beta_2$.

It is possible that in the specification above the timing of an illegal mine opening coincides with a reduction in the health of newborns for an alternative factor. We include municipality fixed effects so it has to be a time varying factor. For example, if an armed group took control of the municipality, reduced funding for the hospital and started illegal mining operations. To alleviate

this concerns, we instrument the opening of an illegal mine upstream with the heterogeneous effect of the reform. Specifically we use as instrument "After X Weak Institutions Municipality Upstream". We use the effect of the reform in the municipality located upstream, because there might be health effects associated with the budget change of the reform.

6.2 Results

We first present the results of the first stage, regressing "Downstream from Illegal mine" with "After X Weak Institutions Municipality Upstream". This variable predicts an increase in illegal mining as we showed in the previous section, as confirmed in Column 1 of Table 7. In Column 2, we invert the flow of the river to show this relationship is not driven by spatial correlation.[32]

Table 7: First stage predicting illegal mining upstream with the reform

Dependent variable: Downstream from illegal mining	(1)	(2)
After X Weak Institutions Municipality Upstream	0.14***	
	(0.051)	
After X Weak Institutions Municipality Downstream		-0.027
		(0.030)
N. of observations	2'866,390	598,003
Municipalities	573	122
Mean of Dep. Var.	0.79	0.92
R^2	0.76	0.73
F-stat	3.23	1.09

Notes: The dependent variable is an indicator on whether a baby was born downstream from an illegal mine. Data are for the period 2004-2014. All regressions include municipality FE, year FE, and state trends. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 present the results of the estimation of equation 3. In Column 1 we present the OLS results, and in Column 2 the instrumental variable regression. The p-value for the test of equality between the coefficient of legal and illegal

[32]There are less observations because the municipalities are not perfectly paired upstream/downstream, but there are more municipalities downstream from a single municipality.

mines are .04 and .07 respectively. Therefore, illegal mines have worse health effects than legal mines

Table 8: Differential health effects

Dependent variable: High APGAR	(1)	(2)
Downstream from illegal mine	-0.68*	-2.53
	(0.39)	(1.70)
Downstream from legal mine	0.0054	-0.27
	(0.13)	(0.26)
Method	OLS	IV Inst
N. of observations	2'866,390	2'866,390
Municipalities	573	573
Mean of Dep. Var.	95.2	95.2
R^2	0.014	0.014
p-value (H_0:Legal≥Illegal)	0.04	0.07

Notes: All regressions include mother characteristics, municipality FE, week FE, year FE, and state trends. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To conver the APGAR results into dollars, we first estimate the cost per affected baby and then we estimate the number of affected babies. The effect of being born with low APGAR is a reduction of -2.6 IQ points (Ehrenstein, 2009). The association between IQ points and wages is 0.53% per IQ point (Psacharopoulos & Velez, 1992). The minimum monthly wage in Colombia in 2011 was $ 240 and we assume each person works for 40 years. Multiplying these quantities we obtain that the estimated cost per affected baby is $1,590.

The differential APGAR effect from illegal mining ($\beta_1 - \beta_2$) is 0.69 -2.26 percentage points for the OLS and IV regressions, respectively. We estimate there are $269,398$ babies born downstream from mines in 2011. Therefore the number of affected babies is 1,859, with a total of $\$3M$ in newborn health costs. The gold royalties were $\$66M$, so a lower bound is for every dollar redistributed there are $4 - 13$ cents of health costs are accrued.

7 Conclusions

In this paper, we studied a reform in Colombia that reduced the share of tax revenue allocated to mining municipalities. The reform dramatically lowered the revenue local governments receive from legal mining in their territory and consequently their incentives to report illegal mining. Studying tax evasion and illegal activities is difficult as, almost by definition, these activities are hard to observe and the data is often scant and unreliable. We overcome this obstacle by using machine learning algorithms applied to satellite data to measure illegal mining over time.

Illegal mining increased in Colombia by 4.47 percentage points as a share of the mined area. Of every dollar redistributed, 7-21 cents are lost through evasion. Although tax evasion might not have welfare costs if it is just a transfer of resources, we document larger negative effects of illegal gold mines on newborn's health. These are equivalent to additional 4-13 cents on human capital costs per dollar redistributed.

The increase in illegal mining illustrates the difficulties of redistributing resources. Given the trend towards decentralized budgeting of local public goods, our results point to the importance of connecting tax revenue and spending. Local authorities should have incentives aligned with their tax revenue and the national government monitor the externalities. Another straightforward recommendation is to increase monitoring of illegal activity, especially using the satellite techniques illustrated in this paper. For example, India recently announced a policy along these lines.[33] However, illegal miners could respond by resorting to more underground mining, rendering monitoring more difficult.

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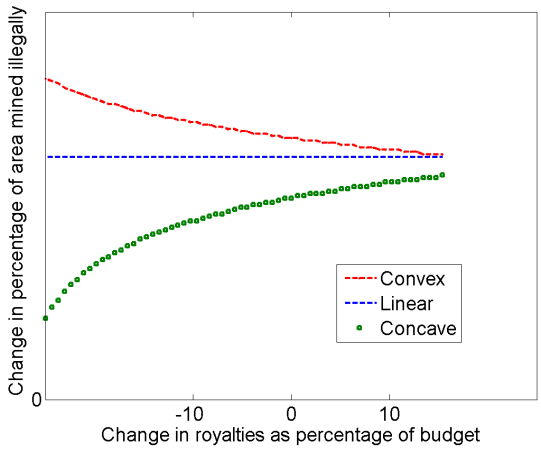
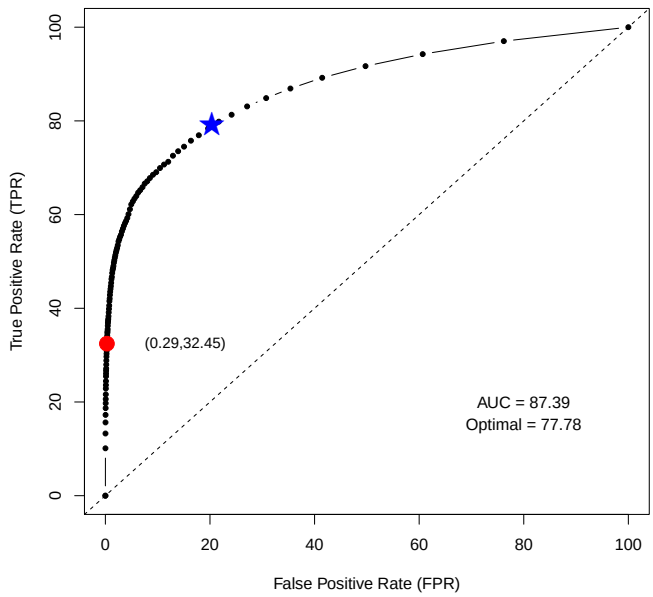
Appendix A Additional Figures and Tables

Figure A1: Theoretical predictions of the income effect of the reform



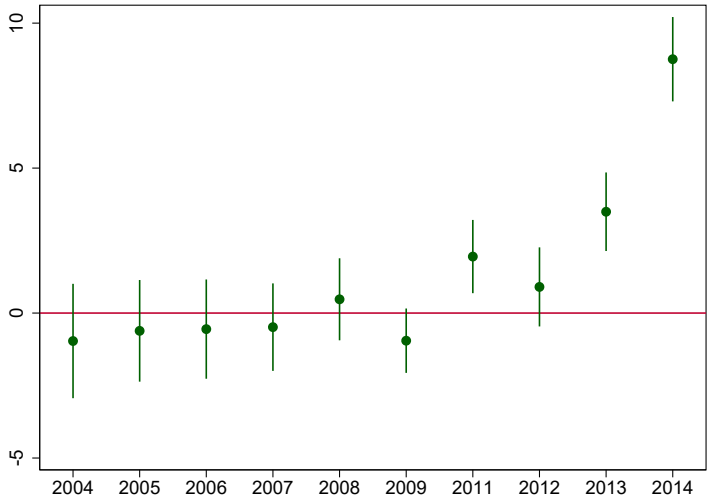
Change in percentage of area mined illegally before and after the reform, depending on the function the local authority uses to value the local municipality budget.

Figure A2: ROC curve for the mining prediction model.



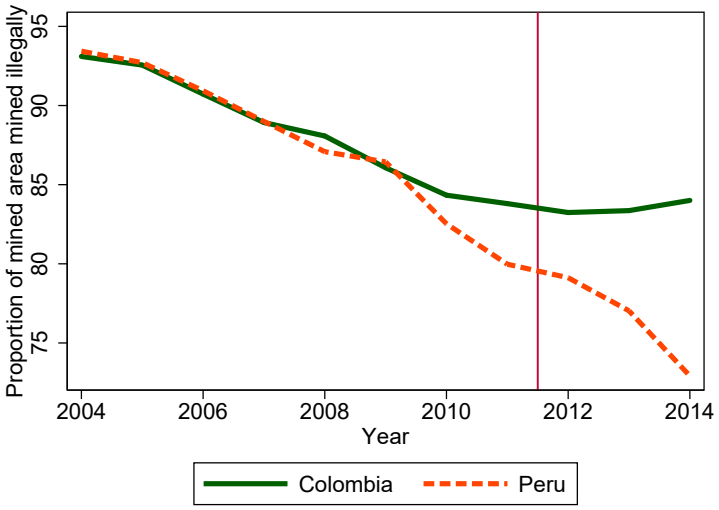
Notes: The receiver operating characteristic- ROC curve plots the performance of a binary classification model when varying the cutoff threshold. The false positive rate (FPR)–the percentage of true no-mined pixels incorrectly classified as mined pixels–is on the x-axis. The true positive rate (TPR)–the percentage of correctly classified true mine pixel–is on the y-axis. As we decrease the cutoff to declare a mine, we accurately classify more true mined pixels as mined, but also increase the number of no-mined pixels incorrectly classified as mined.

Figure A3: Visual representation of parallel trends assumption



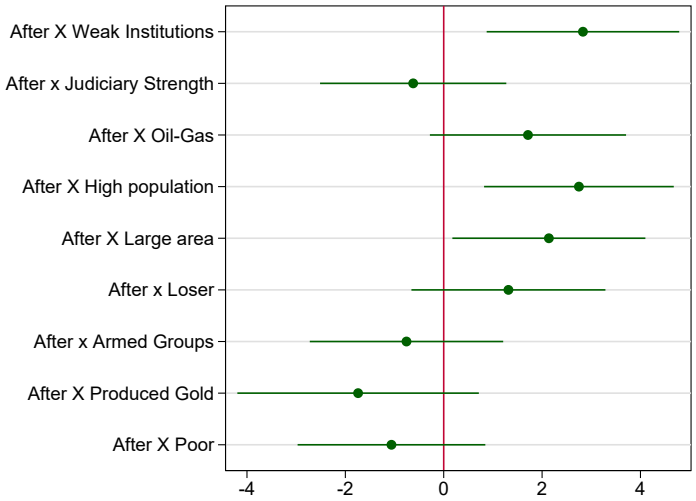
Notes: The estimates in Figure A3 are from an event study regression for the percentage of mined area mined illegally. The x-axis plots time in years and the y-axis the coefficient of the indicator of Colombia interacted with the respective year. 2010 is the excluded year. The drop in 2012 is due to our conservative assumption of including as legal titles all those registered by 2014. See C7 where we use the titles from each year.

Figure A4: Evolution of illegal mining in Colombia and Peru



Notes: The x-axis plots time in years, with a vertical line indicating when the reform happened. The y-axis represents our estimate of percentage of area mined illegally as percentage of total mined area in the municipality.

Figure A5: Heterogeneous effects of the reform by different municipal characteristics



The regression results of this Figure are presented in Tables C4 and C5 in the online Appendix.

Table A1: Production of mineral commodities in 2013

Country	Aluminum	Copper	Gold	Iron ore	Steel	Lead	Nickel	Silver	Tin
Brazil	34,171	271	79,573	386,270	34,163	19	105	–	16,830
Colombia	–	1	55,745	710	1,297	–	70	14	–
Ecuador	–	–	2,800	–	562	–	–	1	–
Panama	–	–	2,099	–	–	–	–	–	–
Peru	–	1,286	151,486	10,126	1,069	266	–	3,407	23,688
Venezuela	2,312	–	1,691	10,583	2,250	–	6	–	–

Gold production in kilograms. Silver and Tin production in metric tons. Other minerals in thousand metric tons. Source: USGS http://minerals.usgs.gov/minerals/pubs/country/sa.html.

Table A2: Robustness of the results to different specifications

Dependent variable:	% of mined area mined illegally				
	All	$< 1,000km$	Cutoff	Adjusted	Weights
	(1)	(2)	(3)	(4)	(5)
After x Colombia	4.47***	1.98***	7.54***	6.59***	5.80***
	(0.62)	(0.75)	(0.44)	(0.70)	(0.61)
N. of obs.	26,355	15,609	28,952	17,759	1673601
Municipalities	2,733	1,718	2,748	2,183	2,732
Mean of Dep. Var.	85.1	86.0	82.4	83.7	85.0
R^2	0.73	0.73	0.77	0.79	0.77

Column (1) is the main specification. Column (2) restricts to municipalities close to the border. Column (3) changes the cutoff of the mining predictions. Column (4) adjust the measure of area mined according to formula (4). Column (5) weights each observation by the fraction of the municipality analyzed (i.e. cloud free). All regressions include municipality and year fixed effects. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Results using other measures of illegal mining

Dependent variable:	% of mined area mined illegally			% area illegal	Log(Area ille
	NO Natl Parks	Probability	State Trends		
	(1)	(2)	(3)	(4)	(5)
After x Colombia	1.41***	1.40***	1.66***	0.12***	0.023*
	(0.54)	(0.25)	(0.53)	(0.037)	(0.012)
After x Loser	1.26	0.89	0.75	0.31**	0.28***
	(1.05)	(0.65)	(1.03)	(0.13)	(0.046)
N. of obs.	8,705	10,187	8,763	10,204	10,204
Municipalities	926	940	924	940	940
Mean of Dep. Var.	85.73	92.37	85.99	.49	.49
R^2	0.78	0.79	0.77	0.74	0.89

Column (1) excludes mined areas in national parks, that couldn't be legalized even if they paid the title fees. Column (2) uses the probability a pixel is mined instead of the dummy of mined. Column (3) includes state trends. Column (4) uses as dependent variable the percentage of the total area of the municipality that is illegally mined. Column (5) uses as dependent variable the logarithm of the area illegally mined. All regressions include municipality fixed effects and linear trend. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Results selecting optimal controls with Lasso style procedure

Dependent variable:	% of mined area mined illegally			% area illegal		
	(1)	(2)	(3)	(4)	(5)	(6)
After	1.65***	1.34***	1.27**	0.20***	0.14***	0.13***
	(0.45)	(0.50)	(0.49)	(0.036)	(0.026)	(0.028)
Controls	Main	All	DLasso	Main	All	DLasso
N. of obs.	8,152	8,044	8,044	9,283	9,166	9,166
Municipalities	927	927	927	940	940	940
Mean of Dep. Var.	85.58	85.58	85.58	.52	.52	.52
R^2	0.79	0.80	0.80	0.76	0.75	0.75

"Basic" repeats the main specification controlling only for the price index, columns 1 and 4 respectively. The number of observations is different because when lagged variables are included, we lose the first year in the sample. "All" includes the price index, population, armed groups homicides and all these variables squared, lagged, interacted among them, interacted with linear trend, and interacted with quadratic trend. "DLasso" includes the variables from the "All" selected from a Double Lasso procedure: in this case the model selects population, lagged population, price squared, lagged price and lagged price squared. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B Theoretical Framework

Consider a miner with capital K who must decide whether to operate legally. If he operates legally (L), he has to pay the associated royalties α and title fees $T(Area(K))$ to the national government. But if he decides to operate illegally (I) he makes a side-payment $b(K)$ to the local authority[34] and faces a probability of the illegal mine being detected by the National Police $Pr(K)$. This probability is increasing in the size of the mine. The expected profits, in each case, can be expressed as:

$$\Pi_L = pq(K)(1-\alpha) - C(q(K)) - T(Area(K))$$

$$\Pi_I = pq(K) - C(q(K)) - Pr(K)p_K K - b$$

where p is the international price of the mineral, $q(K)$ the quantity extracted as a function of K, α is the production tax paid by the firm, $C(\cdot)$ the associated cost of extraction, and p_K the price of capital. The cost of illegality is $Pr(K)p_K K$, because when an illegal mine is detected, its capital is confiscated or destroyed in accordance with the law (see Section 2). The side-payment is determined endogenously by each miner bargaining with the local authority depending on the payoffs for both when legal/illegal.[35] We model the local authority as a single agent who values the budget of the municipality, the local externalities from mining and the bribe he can obtain.[36] The local authority's

[34]We are assuming the local authority observes all mining activity in its municipality without cost. Empirically this is supported by a survey of 18 local authorities, where all of them confirmed that they were aware of the presence of illegal mining within their jurisdictions (Fedesarrollo, 2014a). For a detailed case see Giraldo (2013) and http://www.elpais.com.co/elpais/colombia/noticias/informe-exclusivo-denuncian-mafia-detras-mina-san-antonio-santander-quilichao. Theoretically, in a model with endogenous effort to observe illegal mines the level of illegal mining is higher but the change in illegal mining with the reform is of similar magnitude.

[35]The predictions on the surplus of illegal mining increasing do not require assumptions on the bargaining model. In Figure A1 in the Appendix we are assuming Nash bargaining with constant bargaining power before and after the reform.

[36]If the bribe was paid to an agent whose payoff does not depend on the municipal budget then the reform would not have an effect on illegal mining under this framework.

payouts in each case are

$$G_L = f(pq\alpha\beta + B) - \gamma_L q$$

$$G_I = f(B) - \gamma_I q - Pr(K)V + b$$

where β is the share of royalty taxes allocated to the mining municipality, B is the municipality's budget aside from mining royalties, γ_i is the local environmental damage associated with each type of mining, and V is the cost to the local authority if the national government discovers the illegal mine and confirms the existence of collusion in a trial. This cost would be a monetary sanction or a prison sentence, if evidence of the local authority receiving a bribe is found.[37] The function f reflects the valuation of the local municipality's budget by the local authority. We assume $f' > 0$, either because the local authority gets a share of the contracts or because it altruistically cares more about investing in local projects than in projects outside the municipality.

The "surplus" of illegal mining is the difference between the payoffs for the miner and the local authority when legal/illegal:

$$S(K) = \Pi_I - \Pi_L + G_I - G_L =$$

$$\underbrace{T + pq(K)\alpha}_{Legality\ fees} + \underbrace{f(B) - f(pq(K)\alpha\beta + B)}_{Foregone\ revenue} - \underbrace{Pr(K)(p_K K + V)}_{Expected\ punishment} - \underbrace{q(K)(\gamma_I - \gamma_L)}_{Additional\ pollution}$$

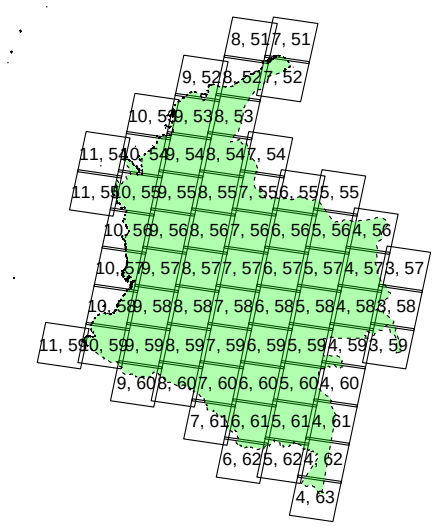
[37] In most cases the National Police destroys the machinery but does not conduct further investigation. Thus, we model V as zero.

Appendix C Constructing the illegal mining data (For Online Publication)

The area of Colombia and Peru combined is 2.42 million square kilometers, so we have a total of 2.7×10^{10} pixels to analyze for illegal mining.

- Identify images from the Landsat7 satellite that cover Colombia for the years 2004-2014, on the web page of the U.S. Geological Survey http://earthexplorer.usgs.gov/ . The satellite takes a picture of each square ("path-row") of the earth every two weeks.

Figure A6: Scenes (Path,row) from LANDSAT 7 covering Colombia

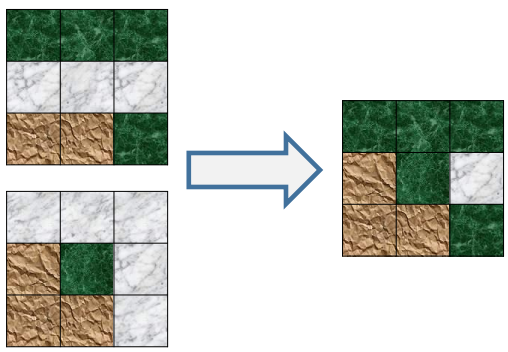


- Download the necessary surface reflectance images from http://espa.cr.usgs.gov/ using UTM-18 projection. There are on average 550 images per year,

each one around 230MB when compressed. That is a total of around 1.5TB of raw data.

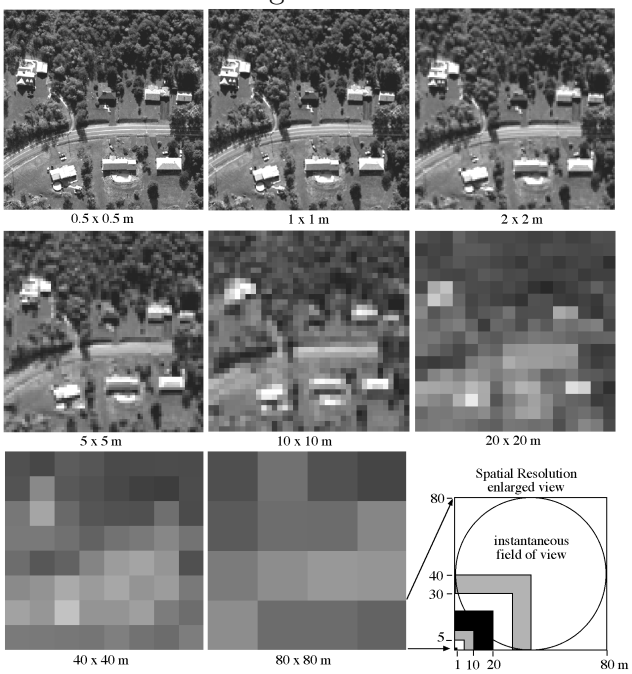
- We use the program teamlucc (http://azvoleff.com/teamlucc.html), with slight modifications we encountered on the process, to remove clouds and adjust for topography so that the data can be used in the prediction model.

- Given the presence of clouds, we need to construct a cloudless composite for every year. That is we look for a cloudless image of each pixel and create a new image with information from the image when the pixel was cloud free. This process takes around 120 days of computer time.



- The resolution of Landsat is 30x30m so we cannot use shape recognition. See below for an illustration.

Figure A7:



Source: (Jensen, 2007)

- In order to train the prediction model we need to label pixels as mined or not mined. For this we use the 2010 Mining Census that give us the location and area of all the mines in half the municipalities of the country. Before using the Census data we have to remove mines whose coordinates are not inside the indicated municipality, or have missing values, or have values for minutes or second not between 0 and 60. We only include open pit mines, because those are the ones we expect to observe evidence of mining using the satellite images.

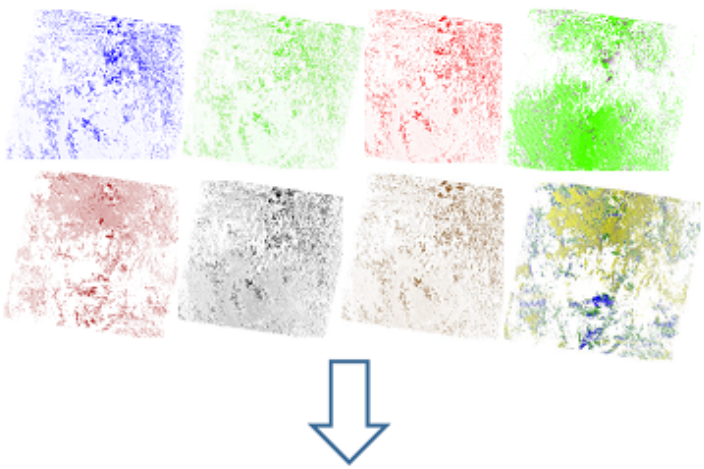
- We validate the presence of mines on the coordinates stated on the Census by using high-resolution images from Digital Globe (https://www.digitalglobe.com/). This allows us to draw the exact shape of the mine.

- We also use the identified shape of mines in Open Street Map to com-

plement the mining census.[38]

- Our training data frame consist of a matrix with 9 columns (variables) and 168,000 rows (observations or pixels). The columns are the 6 bands of the satellite information [39], the information on how long ago the pixel was deforested ((Hansen et al., 2013)), ecosystem type (Etter, 2006) and an indicator of whether the pixel is a mine or not (from the validated images of the Census).

Figure A8: Visual representation of transforming the satellite data into a data frame



Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Loss year	Ecosystem
207	246	211.5	0	0	364	10	25
204	247	209	0	0	362.5	10	25
205.5	246.5	210.5	0	0	362	10	25
99	147	77.5	1227	495	197.5	0	25

- We exclude from the analysis pixels with forests using Hansen's deforestation data (Hansen et al., 2013)

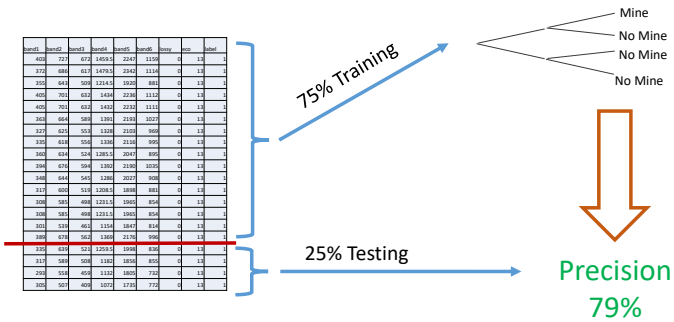
- We split the sample into training and testing sets, by dividing the country into $40km \times 40km$ squares. We further subdivide each square into 4

[38] https://www.openstreetmap.org

[39] Band 1 (blue), Band 2 (Green), Band 3 (Red), Band 4 (Near infrared), Band 5 (Shortwave infrared 1) and Band 7 (Shortwave infrared 2)

squares and randomly choose one for testing and the other three for training. We do not take a random 25% sample for testing because each pixel is fairly similar to its neighbors, so it is better to stratify this way.

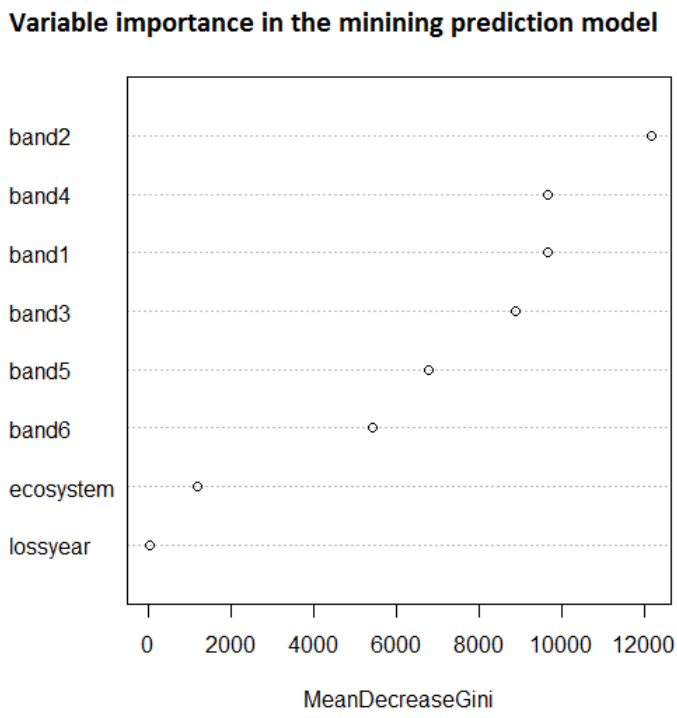
Figure A9: Visual representation of training and testing data



- We try boosting, support vector machines with radial kernels and random forest models in a small subsample of the data. For all three models we try down-sampling and smote. The best parameters for each case where chosen by 10-fold cross validation. Based on the results in the subsample we decide to fit a random forest by down-sampling in the whole dataset.

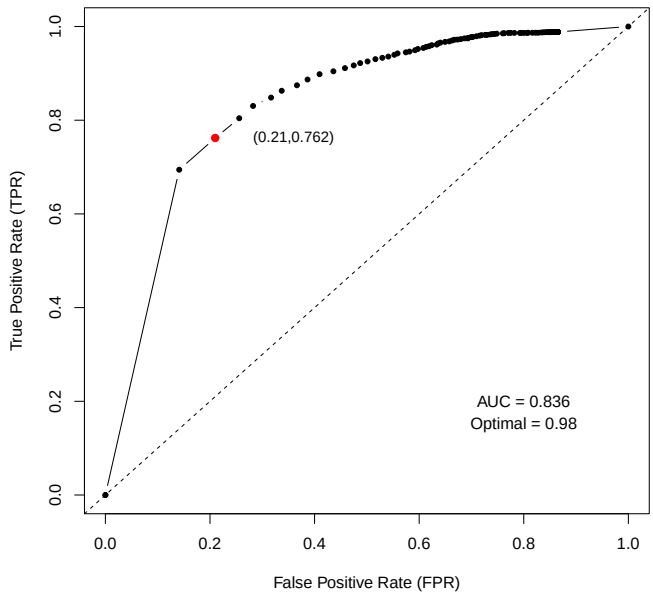
- The random forest consists of 100 trees so it is difficult to represent its structure. However we can consider the "importance" of each variable for the prediction.

Figure A10:



When we train the model using UNODC data only for gold mines the classification is not good. Classifying some gold mined pixels as mines immediately miss-classifies non-gold-mined pixels as mined. In other words the FPR is high, and the formula of optimal cutoff obtains that is best not to do any prediction unless one assign less weight to the FPR.

Figure A11: ROC curve for the mining prediction model trained with UNODC data.



The receiver operating characteristic- ROC curve plots the performance of a binary classification model when varying the cutoff threshold. The false positive rate (FPR)–the percentage of true no-mined pixels incorrectly classified as mined pixels–is on the x-axis. The true positive rate (TPR)–the percentage of correctly classified true mine pixel–is on the y-axis. As we decrease the cutoff to declare a mine, we accurately classify more true mined pixels as mined, but also increase the number of no-mined pixels incorrectly classified as mined.

C.1 Econometric analysis of the error term and implications for the optimal cutoff

It is important to analyze how the errors in the individual pixel prediction might affect our estimation of the effect of the reform on illegal mining. In this subsection we explain how errors at the pixel level aggregate to our measure of illegal mining area by municipality, and in turn how this might affect the coefficient estimates in the regression. Our estimated measure of mining area

($\widehat{y_{mt}}$) in municipality m at time t can be expressed as the sum of correctly identified true mined pixels plus the misclassified true no-mined pixels:

$$\widehat{y_{mt}} = \sum_{i \in Mines} (Pred(pix_i) = 1) + \sum_{i \notin Mines} (Pred(pix_i) = 1)$$

In each true mined pixel the probability of predicting a mine is equal to TPR and in each pixel that is truly mine-free the probability of predicting a mine is the FPR, where TPR and FPR are the true and false positive rates of the prediction model respectively. In each pixel the random variable can be modeled as a Bernoulli, and, assuming independence and identical distribution, their sum is binomial.[40] As the number of pixels is large, we can approximate the sum with a normal. Thus $\widehat{y_{mt}} = y_{mt}TPR + y_{Nmt}FPR + \epsilon_{mt}$, where y_{mt} is the true number of mined pixels, y_{Nmt} the true number of no-mine pixels and $\epsilon_{mt} \sim N(0, y_{mt}TPR(1-TPR) + y_{Nmt}FPR(1-FPR))$. Finally, since the total area of the municipality (Y_m) is fixed ($y_{Nmt} = Y_m - y_{mt}$) we can obtain the fraction of the municipality's area that is predicted to be mined as:

$$\frac{\widehat{y_{mt}}}{Y_m} = \frac{y_{mt}}{Y_m}(TPR - FPR) + FPR + \upsilon_{mt} \tag{4}$$

Where

$$\upsilon_{mt} \sim N\left(0, \frac{y_{mt}TPR(1-TPR) + y_{Nmt}FPR(1-FPR)}{Y_m^2}\right)$$

The raw predicted fraction of the total municipality area that is mined underestimates the true fraction that is mined by a factor of (TPR-FPR) plus an additive error term of FPR. Therefore the coefficient in the regression will underestimate the effect of the reform. When we use the predictions as the dependent variable in our regression analysis, a constant FPR will be absorbed by the municipality fixed effects. To minimize the sum of squared errors, using

[40] We do not need to assume independence to prove a weaker version of the law of large numbers if we assume that the correlation between pixels far apart decays geometrically with distance. See Appendix C.2 for details.

formula (4), the optimal cutoff for declaring a pixel as mined is:

$$\rho^* = \arg\min_{\rho} \sum_m \left(TPR(\rho)\frac{y_{m,2010}}{Y_{m,2010}} + FPR(\rho)\left(1 - \frac{y_{m,2010}}{Y_{m,2010}}\right) - \frac{y_{m,2010}}{Y_{m,2010}} \right)^2$$

since 2010 is our training year from the mining Census. Since the fraction of total municipality area that is mined is around 1%, the error of our predictions is approximately $1\%TPR + 99\%FPR$. This is why our cutoff (shown as the big dot in figure A2) prioritizes having a small FPR. For completeness in the results section we present regressions with both the raw predictions and the adjusted predictions using formula (4).

C.2 Weak law of large numbers for correlated Bernoulli's random variables among pixels

In this subsection we show that the independce assumption is not necessary to prove a weaker version of the law of large numbers. Let's assume that $|cov(X_i, X_j)| \leq c^{dist(i,j)}$. We need to find a bound for $\sum_{j=1}^{n} cov(X_i, X_j)$. The largest sum of covariances will be for a pixel right in the center, because it will have the shortest distances to other pixels. For ease of exposition let's assume $n = (2k+1)^2$, and consider pixel i in the center. This pixel will have its 8 neighbors, the 16 pixels surrounding them, and so on. The exact expression is:

$$\sum_{j=1}^{n} cov(X_i, X_j) \leq c + 8c^2 + 16c^3 + \ldots + 8kc^{k+1}$$

With some manipulation it can be shown that

$$\sum_{j=1}^{n} cov(X_i, X_j) \leq c + \frac{8c^2(1-c^k)k}{1-c}$$

Consequently using Chebyshev's inequality

Table C1: Royalty taxes and municipality share by mineral

Mineral	Royalty tax (α)	Municipality share (β)
Clay	1%	65%
Coal (0-3 Tons)	5%	2%
Coal (>3 Tons)	10%	2%
Construction materials	1%	65%
Copper	5%	65%
Emeralds	3%	65%
Gems	2%	65%
Gold	4%	65%
Gold (Alluvial)	6%	65%
Gravel	1%	65%
Iron	5%	65%
Limestone	1%	65%
Metallic mineral	5%	65%
Nickel	12%	2%
Non-metalic minerals	3%	65%
Plaster	1%	65%
Platinum	5%	65%
Radioactive minerals	10%	60%
Salt	12%	65%
Silver	4%	65%

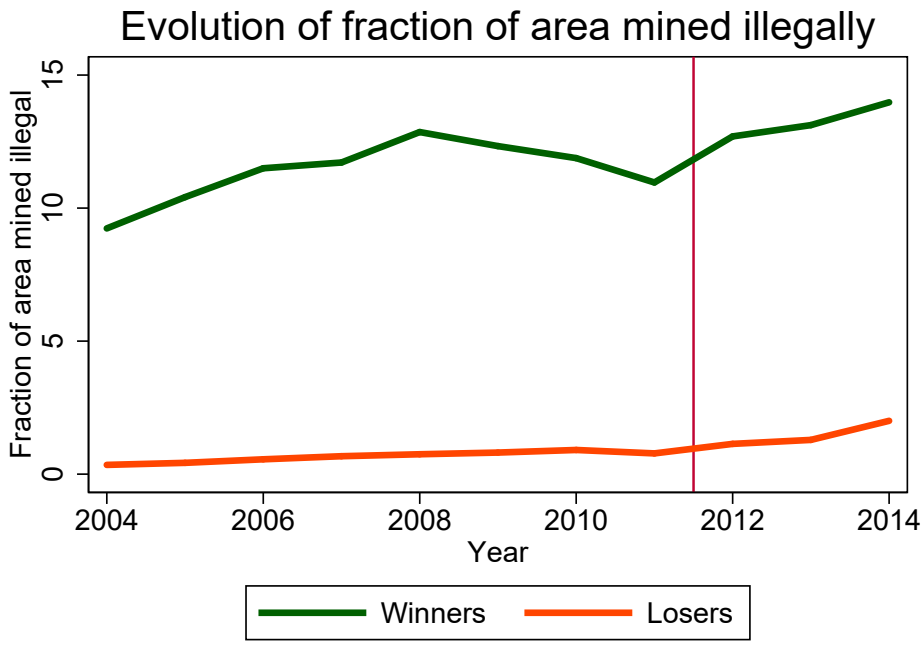
Appendix D Online Appendix (For Online Publication)

Table C2: Change in armed groups homicide rate

Dependent variable: Armed Group Homicides Rate			
	All	No AG Bef Reform	AG Bef Reform
	(1)	(2)	(3)
After x % Budget Loss	0.026	-0.078	0.29
	(0.22)	(0.064)	(0.44)
Mineral price index	0.12	0.0078	0.26
	(0.12)	(0.024)	(0.31)
Time FE	Yes	Yes	Yes
N. of obs.	10,204	6,171	4,033
Municipalities	940	568	372
Mean of Dep. Var.	24.4	1.65	59.3
R^2	0.24	0.11	0.23

Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C2: Evolution of illegal mining by winners and losers with the reform



The x-axis plots time in years, with a vertical line when the reform happened. The y-axis represents our estimate of percentage of area mined illegally as percentage of total municipality area.

Table C3: Summary statistics for municipalities separated by whether it was censused

	All	Censused	Not Censused	Difference
% Loss	-4.03	-5.14	-3.10	2.04***
	(11.6)	(10.3)	(12.5)	(0.76)
Royalties from precious metals	0.32	0.34	0.31	-0.032
	(0.47)	(0.47)	(0.46)	(0.031)
Royalties from oil-gas	0.14	0.11	0.16	0.051**
	(0.35)	(0.31)	(0.37)	(0.023)
Armed group presence before reform	0.40	0.39	0.40	0.0074
	(0.49)	(0.49)	(0.49)	(0.032)
Population	25280.0	23160.5	27072.4	3911.9
	(40628.4)	(41049.0)	(40223.3)	(2685.3)
Area (km2) of municipality in raster	638.1	633.1	642.4	9.30
	(1330.7)	(1348.7)	(1316.7)	(88.1)

Summary statistics for municipalities used in the analysis. An observation is a municipality. All data comes from CEDE's municipalities panel, except the row that indicates is from the 2010 Mining Census. Calculations: Authors.

Table C4: Heterogeneous effects of the reform

Dependent variable:	% mined area mined illegally					
	Only Colombia					
	(1)	(2)	(3)	(4)	(5)	
After x Colombia	1.63***	0.87	1.96***	1.36***	0.23	0.39
	(0.45)	(0.56)	(0.63)	(0.51)	(0.72)	(0.77)
After X Weak Institutions		2.83***				
		(1.00)				
After x Judiciary Strength			-0.62			
			(0.96)			
After X Oil-Gas				1.71*		
				(1.02)		
After X High population					2.75***	
					(0.98)	
After X Large area						2.14**
						(1.00)
N. of obs.	8,796	8,455	8,796	8,796	8,796	8,796
Municipalities	927	890	927	927	927	927
Mean of Dep. Var.	86.04	85.92	86.04	86.04	86.04	86.04
R^2	0.78	0.79	0.78	0.78	0.78	0.78

All regressions include municipality fixed effects and control for the price index. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C5: Heterogeneous effects of the reform

Dependent variable:	% mined area mined illegally				
	Only Colombia				
	(1)	(2)	(3)	(4)	(5)
After x Colombia	1.63***	1.40***	1.94***	2.05***	2.16***
	(0.45)	(0.52)	(0.60)	(0.51)	(0.71)
After x Loser		1.32			
		(1.00)			
After x Armed Groups			-0.76		
			(1.00)		
After X Produced Gold				-1.74	
				(1.25)	
After X Poor					-1.06
					(0.97)
N. of obs.	8,796	8,796	8,796	8,796	8,796
Municipalities	927	927	927	927	927
Mean of Dep. Var.	86.04	86.04	86.04	86.04	86.04
R^2	0.78	0.78	0.78	0.78	0.78

All regressions include municipality fixed effects and control for the price index. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table C6 we compare the results of this paper using the predicted illegal mines and our previous paper ((Romero & Saavedra, 2015)), that used only legal titles. Column 1 uses only the information on the location of legal mines titles from the Colombia's mining cadastre. In column 2 we recalculate the measures of near mine and downstream from a mine, including the locations of illegal mines we found. For the next three columns we restrict our attention only to the mines we detect with the prediction model. Those are open pit mines detectable via satellite, and consequently exclude mining titles without evidences of open pit mining. Column 3, presents the results of excluding mining titles without evidence of open pit extraction. Column 4 separates the downstream measure by the legality of the mine and in Column 5 we separate the near measure by legality of the mine. Note that when we include the illegal mines, in Column 2, the magnitude of the coefficient of downstream from mine almost doubles. When we separate by legality of the mine the

Table C6: Differential health effects of legal and illegal mines

	Dependent variable: High APGAR				
	(1)	(2)	(3)	(4)	(5)
Near Mine	0.49	0.63*	0.72	0.63	
	(0.36)	(0.34)	(0.48)	(0.50)	
Downstream from mine	-0.30*	-0.71*	-0.56		
	(0.16)	(0.38)	(0.49)		
Downstream from legal mine only				0.17	-0.17
				(0.50)	(0.60)
Downstream from illegal mine only				-0.68	-0.64
				(0.52)	(0.48)
Downstream from both types of mines				-0.71	-0.58
				(0.55)	(0.53)
Near legal mine only					1.30
					(0.84)
Near illegal mine only					0.17
					(0.46)
Near both types of mines					-0.012
					(0.51)
Mines	Titles	All	Open pit	Open pit	Open pit
N. of observations (babies)	3'632,569	3'632,569	3'129,368	3'129,368	3'129,368
Mean of Dep. Var.	95.2	95.2	95.2	95.2	95.2
p-value (H_0:Legal=Illegal)				0.028	0.17

p-values for tests of coefficients for downstream from illegal equal to downstream from legal are .028 and .166 , respectively. All regressions include mother characteristics, municipality FE, week FE, year FE, and state trends. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

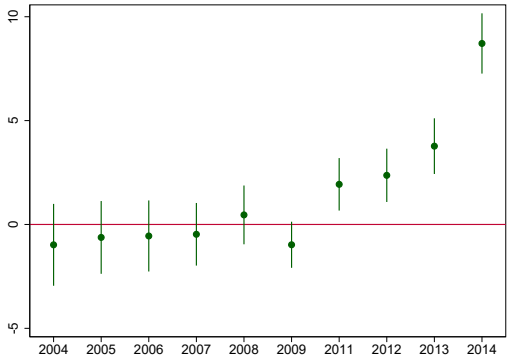
coefficients indicate that the impacts are larger in illegal mines: The p-value of a test of equality is .028 . In Table C7 in the Appendix we repeat the specification in Column 4 separating by size of the mines, and we find that for all sizes the magnitude of the coefficients for illegal mines are at least five times larger. These results point to another unintended effect of the reform: larger health effects.

Table C7: Differential health effects of legal and illegal mines

	Dependent variable: High APGAR	
	(1)	(2)
Near open pit mine	0.72	0.77
	(0.60)	(0.58)
Downstream from open pit mine q1	-0.42	
	(0.59)	
Downstream from open pit mine q2	-0.55	
	(0.57)	
Downstream from open pit mine q3	-0.39	
	(0.56)	
Downstream from open pit mine q4	-0.20	
	(0.64)	
Downstream from legal open pit mine q1		-0.10
		(0.14)
Downstream from illegal open pit mine q1		-0.82
		(0.56)
Downstream from legal open pit mine q2		-0.17
		(0.17)
Downstream from illegal open pit mine q2		-0.97*
		(0.53)
Downstream from legal open pit mine q3		-0.065
		(0.26)
Downstream from illegal open pit mine q3		-0.64
		(0.50)
Downstream from legal open pit mine q4		0.12
		(0.41)
Downstream from illegal open pit mine q4		-0.63
		(0.54)
N. of observations (babies)	2'585,545	2'585,545
Municipalities	614	614
Mean of Dep. Var.	95.5	95.5
R^2	0.017	0.017

All regressions include mother characteristics, municipality FE, week FE, year FE, and state trends. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C7: Visual representation of parallel trends assumption



Notes: The estimates in Figure A3 are from an event study regression for the percentage of mined area mined illegally. The x-axis plots time in years and the y-axis the coefficient of the indicator of Colombia interacted with the respective year. 2010 is the excluded year.