SIEPR Discussion Paper No. 17-009

Local incentives and national tax evasion: The response of illegal mining to a tax reform in Colombia

By

Santiago Saavedra, Mauricio Romero

Local incentives and national tax evasion:
The response of illegal mining to a tax reform in Colombia *

Santiago Saavedra† (Job Market Paper)

Mauricio Romero‡

February 17, 2017

Latest version available in: `http://web.stanford.edu/~santisap/`

Abstract

National governments can only tax the economic activity they either directly observe or that is reported by municipal authorities. In this paper we investigate how illegal mining, a very common phenomenon in Colombia, changed with a tax reform that reduced the share of revenue transferred back to mining municipalities. To overcome the challenge of measuring illegal activity, we construct a novel dataset using machine learning predictions on satellite imagery features. Theoretically we expect illegal mining to increase because the amount required to bribe the local authority is smaller after the reform. Using a difference-in-differences strategy, with Peru as the control, we find that illegal mining increased by 4.47 percentage points as share of the mining area. In addition, we provide suggestive evidence that illegal mines have more harmful health effects on the surrounding population than legal mines. These results illustrate unintended effects of tax revenue redistribution.

JEL classification: H26,O13,O17,Q53

*We are grateful to Prashant Bharadwaj, Arun Chandrasekhar, Pascaline Dupas, Larry Goulder and Melanie Morten for invaluable guidance. This paper was enriched by comments from Juan Castillo, Thomas Ginn, Marcel Fafchamps, Mounu Prem, Mark Rosenzweig, Jeff Weaver and seminar participants at LACEA, NEUDC, Stanford University, UC San Diego and Universidad del Rosario. Francisco Barrera, Muhammad Islam, Fabian Latorre and Michael Wang provided excellent assistance constructing the illegal mining data. This study was carried out with support from the Latin American and Caribbean Environmental Economics Program (LACEEP) and Policy Design and Evaluation Lab (PDEL). Saavedra acknowledges support of the Stanford Institute for Economic Policy Research through the Kohlhagen Fellowship Fund.

†Stanford University Department of Economics, *e-mail:* `santisap@stanford.edu`.

‡University of California - San Diego Department of Economics, *e-mail :* `mtromero@ucsd.edu`.

1 Introduction

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 economic activity is located 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 costs if it is just a transfer of resources, we show that illegal mining causes worse health outcomes for newborn children.

Illegal mining is very common around the world: The origin of the minerals used in their supply chain could not be identified by 67% of the companies in the United States (GAO, 2016). Illegal mining has both environmental and fiscal impacts for host countries. On the environmental side, illegal mining is associated with greater levels of pollution (TGIATOC, 2016). On the fiscal side, illegal mines typically evade taxes.

Throughout the literature on illegal activity, the main challenge is measuring its extent (Banerjee, Mullainathan, & Hanna, 2012). To overcome this obstacle, we construct a novel dataset using machine learning predictions on satellite imagery features to detect illegal mining activity. 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). We predict mining activity using the satellite images, and assess its legality with the map of legal titles produced by the National Government. Not holding a mining title is highly correlated with evading royalty taxes.[1]

In order to study how evasion responds to the share of taxes transferred back to the local municipality, we exploit a reform that changed the formula for tax revenue distribution. The reform sharply reduced the share of taxes transferred back to the municipality where the mine is located, while 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.

[1] 19% of mines without a title report paying royalty taxes on production. This will be discussed further in the context section.

We formalize our intuition regarding how incentives for local authorities are affected by the reform with a simple theoretical framework in which a miner decides whether to operate legally or illegally. The local authority observes mining activity in its municipality. Therefore to operate illegally, the miner pays a bribe 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 a miner would pay to operate illegally is smaller after the reform, and therefore mines are more likely to operate illegally. We also predict that this effect of the reform is amplified in areas of the country where the national government's presence is weak. The model delivers two main predictions: (i) illegal mining increases after the reform; (ii) this effect is greater in municipalities where the national government's presence is weak.

To conduct this study, we need to obtain a precise observation of the mined area that is not registered with the national government. To this end, we first apply machine learning algorithms to satellite imagery to detect the presence of mining activity. We train a prediction model using the geographical location of legal and illegal mines reported in the 2010 Mining Census. Specifically, we calibrate a random forest model using the information from different layers of Landsat satellite images to predict whether each 30x30m pixel of the country is being mined. We split the sample, allocating 75% of the observations for training (learning) and 25% for testing. The model is accurate: For every 100 pixels it labels as mined, 79% are actually mined according to the testing sub-sample. We use this model to predict which pixels were mined, year by year, for the period 2004 to 2014. Finally we check whether the pixels predicted as mined are inside the boundaries of legal titles registered with the National Government. The predicted mined area outside active mining titles enables us to identify illegally mined areas. We also apply the mining prediction model to the neighbor country of Peru to estimate the effect of the reform in a difference-in-differences framework.

The simple difference (event study) and the difference-in-differences estimates suggest that the reform, which took place amidst a mining boom, increased the share of the total mined area that is mined illegally. The challenge of using time variation is that other events affecting illegal mining happened at the same time as the reform. In our case: The system to register legal titles was closed at the time of the reform and there was an increase on the stringency of prosecution. In order to address the first concern, we define illegal mining as activity outside the legal titles at the end of the study period. That is, if a miner could not register the title while the office was closed it will not count as illegal mining. The second event was a change in the law that allow destruction of illegal mining machinery on site, instead of being confiscated and processed in court. This law applies both in Colombia and Peru, and probably deters illegal activity. Consequently our event study coefficient will be underestimating the effect of the reform.

We find that after the reform, illegal mining as share of the mined area increased in Colombia by 1.63 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. Besides changing the share of local royalties kept locally, the reform also changed the size of the local budget: Some "gained" from the reform (they received more from the redistribution than what they lost in local royalties) and some "lost" with the reform. Theoretically, the relationship between municipal budget size and illegal mining is ambiguous: Mayors with smaller budgets may have less incentives to curb illegal mining because they can appropriate less public resources. Comparing the effects of the reform on "loser" municipalities with respect to that of "winner" municipalities, we find evidence that illegal mining increases more when the local budget shrinks. Our results indicate that a 10-percentage-point decrease in the budget is associated with an additional 0.7 -percentage-point increase in the share of total mined area that is mined illegally. In order to alleviate concerns that "winner" and "loser" municipalities are inherently different, we exploit a sharp poverty cutoff for the lump sum transfer after the reform.

These results are economically significant. We estimate that 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. These results illustrate the importance of thinking beyond efficient spending to avoid perverse incentives when redistributing resources.

It is possible that, besides evasion on area mined, there is also evasion on the quantity reported for royalties taxes by legal mines. However, we do not find an effect of the reform, be it overall or specifically for "losers", on the reported production of legal mines in Colombia. In other words, evasion through under-reporting of production does not seem to be a margin of adjustment after the reform. Since it is more difficult for local authorities to observe production than mining area, it is not surprising that the latter responds more to the reform.

Besides the lost tax revenue, illegal mining could have differential environmental impacts for two main reasons. First, given that the machinery of illegal mines would be destroyed if found, illegal mines may have less efficient machinery. This machinery requires using more variable inputs that 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. We find evidence that, as predicted, babies born downstream from illegal mines have a lower probability of being born with high APGAR (an indicator of good health).

Related Literature

To the best of our knowledge, this is the first paper that quantifies the response of tax evasion to the formula that distributes the 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); 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, respectively. Our setting is different since mining operations cannot be moved to a different municipality, in contrast to the logging firms or industrial plants studied in those papers. In addition we show that the associated environmental damage has an impact on human capital. In a related setting, Eynde (2015) studied a reform in India that increased royalty rates, thereby boosting local government incentives to control illegal mines, which led to a rise in state violence. Unlike local governments in Colombia, Indian states are in charge of military operations and therefore can directly control illegal mines.

Methodologically this paper is among the first, together with Burlig, Knittel, Rapson, Reguant, and Wolfram (2016), to use 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, & 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 rest of the article 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. We then present the identification strategy, and in Section 6 the main results. Section 7 presents the estimation of differential health effects from legal and illegal mines, and the final section concludes.

2 Colombian context and details of the reform

The mining and hydrocarbon industry is important for the Colombian economy, representing 8-11% of Colombian GDP over the last five years.[2] 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, and 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. While only one-tenth of mining royalties come from precious metals, over half of the total area of mining titles held is devoted to precious metals extraction (Agencia Nacional Minera, 2013).

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

[2]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

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.[3] Additionally, mining companies pay royalties based on the gross value and type of minerals extracted.[4]

Before 2012, a municipality would receive around 55% of the royalties paid by mining companies operating in its territory, while the rest was allocated to a National Fund.[5] Legislative Act 05 of 2011 changed the allocation formula dramatically, such that only 10% of the royalties are transferred directly to the mining municipality and 40% are earmarked for regional funds, while the rest of the royalties revenue must be used for savings.[6] 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. The reform also reduced the resources received by regional environmental authorities by 80%, since their funding is directly linked to the royalties transferred (directly) to municipalities.

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.[7] Illegal mining was neither mentioned as a motivation for the reform nor were the impacts of the reform on illegal mining contemplated.[8]

During 2010 the government conducted a census of all mines, regardless of whether they held a mining title, in half of the municipalities in Colombia. The census found that 62% of the surveyed mines did not have a title. There have been three attempts to legalize illegal mines, but with very little success.[9] Government attempts to provide favorable

[3] 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).

[4] 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 large oil fields are taxed at a 25% rate.

[5] The amount varied across minerals. For example, before 2012 the fraction transferred to a municipality with a gold mine was 87%.

[6] 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.

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

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

[9] 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

conditions to illegal miners ("carrots") have also been accompanied by an increase in "sticks". For example, at the end of 2012 the Andean Community of Nations (which includes Colombia and Peru) signed a decree that allows the destruction of all machinery used in mines that do not have a registered title.[10]

In the model, and as reported in some cases,[11] the local authorities know of the existence of the mines and receive side payments. Also, when we model the miners' decisions to extract illegally, we assume they simultaneously decide to operate while evading both title fees and production taxes. However, it is important to note that some illegal producers pay production taxes. 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 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 illegally depending on the cost of operating legally (e.g., title fees and taxes), probability of being detected by the National Government and side-payment to the local authority if operating illegally. The framework illustrates how the side-payment depends on the share of revenue the local municipality receives from taxes paid by the firm and consequently, the response of illegal mining to the 2012 reform.

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)

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

[11]See, for example, (Giraldo, 2013) http://www.elpais.com.co/elpais/colombia/noticias/informe-exclusivo-denuncian-mafia-detras-mina-san-antonio-santander-quilichao

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[12] 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:

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

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

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. Note that when an illegal firm is detected its capital is destroyed, in accordance with the law (see Section 2). The side-payment is determined endogenously by bargaining with the local authority depending on the payoffs for both when legal/illegal.[13] We model the local authority as a single agent[14] that values the budget of the municipality, the local externalities from mining and the bribe it can obtain. The local authority's payouts in each case are

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

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

where β is the share of royalty taxes allocated to the mining municipality, B is the municipality's budget aside from mining royalties, γ is the local environmental damage associated with 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

[12]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). Theoretically, in a model with endogenous effort the level of illegal mining is higher but the change in illegal mining with the reform is of similar magnitude.

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

[14]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.

a bribe is found.[15] The function $f(\cdot)$ reflects the valuation of the local municipality's budget by the local authority. We assume $f'(B) > 0$, 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 in the next sub-section.

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

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

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

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 capital) if caught operating illegally, any firm with $K > K^*$ will operate legally.

3.2 The effect of the reform on illegal mining

Consider the possible effects of the royalties reform. First, the reform did not change the "legality fees": neither the cost of the title fee nor the royalties paid by the firm changed. Second, the reform did change the allocation of royalties directly transferred to the municipalities and their budgets by redistributing the royalties according to socioeconomic criteria. Finally, the reform might have changed the "expected punishment" through the probability of detection. The national government might have a greater incentive to monitor illegal mining, but the regional environmental authority has fewer resources and incentives to monitor (since its budget is directly proportional to the royalties assigned directly to the municipality). Thus, the effect of the reform on the probability of detection may be ambiguous.

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 ($\beta_1 < \beta_0$) reduces the payout from legal mining to the local authority and therefore increases the surplus of illegal mining for every level of capital. In particular, the average size of illegal mines increases ($K^*(\beta_1) > K^*(\beta_0)$) and illegal mining increases (as a proportion of total mining).

[15] In most cases the National Police destroy the machinery but do not conduct further investigation. Thus, we model V as zero.

This reasoning leads to the following prediction:

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

Note that this model applies to the decision of a new mine and existing illegal mines to legalize each year. Consequently in the empirical section we will test this hypothesis both in the stock of mined area and the new mines each year. For a legal mine the titles are allocated for 30 years, so the decision to evade legislation will take the form of under-reporting of quantity produced.

This simple model has some limitations. The first one is that we do 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 are modeling the decisions to obtain a legal title and pay royalty taxes as a single decision. But it is possible that some legal mines evade a certain percentage of the production taxes. Finally, we abstract away from any possible interactions with a local authority receiving bribes from multiple miners.

The effect of the reform in municipalities with lower national oversight

The probability of the national government detecting an illegal mine and destroying its capital is smaller in municipalities where armed groups (AG) provide protection for illegal miners ($Pr_{AG}() < Pr()$).[16] Note that in our model, this is equivalent to small probability of detection because of weak presence of the national government. Given the smaller probability of detection, the surplus of illegal mining is higher in these municipalities for a given size K. So when the reform reduces the payoff when the mine is legal, the average size of illegal mines is larger and we see a larger effect of the reform on illegal mining. In the extreme case that armed groups have total control and the national government is unable to destroy illegal mine machinery in those places, then all the mines should 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.

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

[16]We abstract from an endogenous response of armed groups. Tables 29 - 32 in the online Appendix show that there is no evidence of armed group relocation in response to the reform.

The income effect of the reform The effect of the reform on the revenue lost depends on the lump sum transfer (B_1), which is based on socioeconomic criteria. The change in illegal mining surplus due to revenue lost with the reform can be written as:

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

The above expression has the form of increasing differences so its sign will depend on the concavity of $f(\cdot)$. 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 that the local authority captures a constant share of the budget $\delta(B) = \delta$ and $g(\cdot)$ is linear, then $f(\cdot)$ is linear. In that case, $\Delta S = pq\alpha(\beta_0 - \beta_1)$, which does not depend on B_1. Consequently 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, the surplus of illegal mining for a given mine size K is now larger for those negatively affected by the reform.[17] Consequently, the average size of illegal mines is larger for municipalities negatively affected by the reform and we should observe a larger increase in illegal mining in these municipalities. The function $f(\cdot)$ can be convex either because local authorities capture an increasing share of the 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 the data for Colombia we have that the median municipality spent 86 % of the revenue on "lumpy" projects like construction of a hospital or a bridge. Figure 4 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, we have that the income effect of the reform depends on the concavity of f.

Before turning to the data section recall the three predictions from this simple framework. First, illegal mining increases after the reform. Second, the reform is larger in municipal-

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

ities with low probability of detection. Finally, the income effect of the reform depends on the shape of the function the local authorities use to value the municipality budget.

4 Data

We rely on three main sources of data for our analysis. The first source is the panel of illegal mining by municipality we constructed, whose details will be explained in the next subsection. The second data is from Colombia's governments mineral information system SIMCO[18] on reported production and prices. Finally, we 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 committed by armed groups, and other characteristics of Colombian municipalities. Note that we construct the illegal mining panel for Peruvian municipalities, but do not have socio-economic characteristics for them.

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. We observe that of the 927 municipalities with minerals in the subsoil, 84% had a net increase in budget ("winners") due to the reform. Losers tend to be bigger and more populous, as well as more likely to receive royalties from oil and gas. Most of the mines are open pit and therefore can, in principle, be observed from space. Finally, note that 40 % of the municipalities had some presence of armed groups before the reform.

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

Table 1: Summary statistics for municipalities used in the analysis

	All	Winners	Losers	Difference
Change in royalties as percentage of budget	4.03	8.11	-16.8	-24.9***
	(11.6)	(3.80)	(15.1)	(0.62)
Royalties from precious metals	0.32	0.31	0.37	0.059
	(0.47)	(0.46)	(0.48)	(0.042)
Royalties from oil-gas	0.14	0.060	0.56	0.50***
	(0.35)	(0.23)	(0.50)	(0.026)
% open pit mines (Census)	0.78	0.77	0.80	0.021
	(0.35)	(0.35)	(0.35)	(0.040)
Armed group presence before reform	0.40	0.39	0.44	0.047
	(0.49)	(0.49)	(0.50)	(0.044)
Population	25280.0	22539.8	39252.9	16713.1***
	(40628.4)	(35257.3)	(59297.3)	(3575.7)
Area (km2) of municipality in raster	631.7	597.5	1198.2	600.7***
	(1535.4)	(1495.9)	(2007.6)	(128.2)

An observation is a Colombian municipality. There are 927 municipalities, of which 148 are negatively affected. There are 1,123 municipalities in Colombia but we exclude those without minerals in the subsoil. All data comes from CEDE's municipalities panel, except the row that indicates the presence of open pit mining, which is from the 2010 Mining Census. Calculations: Authors.

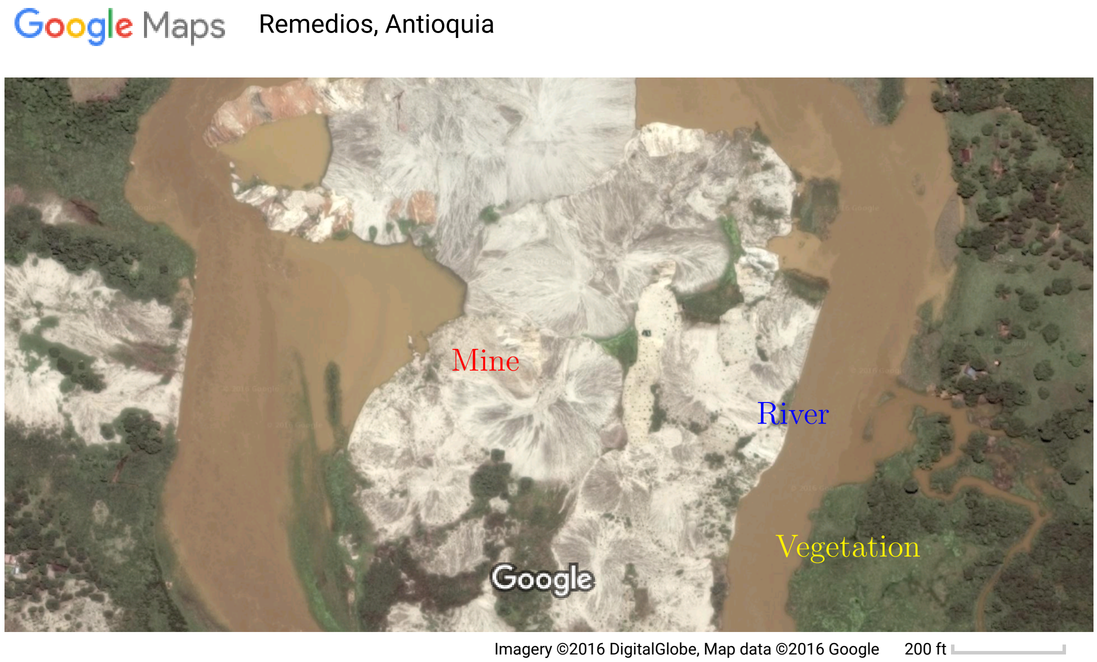
4.1 Constructing the illegal mining panel

There are three 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. And finally, we predict mining presence in all pixels for the years 2004 to 2014. We then 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[19] for the years 2004-2014 at a resolution of 30m $\times$ 30m pixels (squares). 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. The satellite captures every point on the earth's surface every two weeks, but due to the presence of clouds we need to create cloudless composites at the year level.[20] We exclude from the analysis pixels with forests using Hansen's deforestation data (Hansen et al., 2013).

[19]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

[20]We use Alex Zvoleff's open source algorithms http://azvoleff.com/teamlucc.html, which also apply topographic correction to each image to adjust for the relative position of the satellite.



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 Mining Census published by the Colombian Ministry of Mines shows one point of the location of the mines in 2010 for half of the municipalities.[21] We validate this information using manual inspection of high-resolution images to draw the exact shape of each mine. We also use the identified shape of mines in Open Street Map [22] to complement the mining census. 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 [23], deforestation year and ecosystem type (Etter, 2006).

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 a rule that 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 [24]) 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 split the sample, allocating 75% of the observations for

[21] 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 26 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 and presence of armed groups.

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

[23] 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)

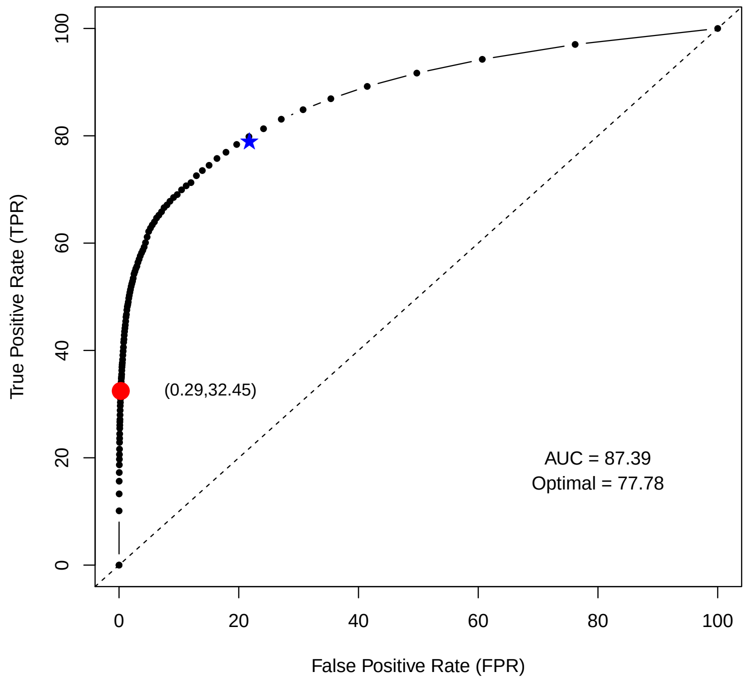
[24] The name "tree" comes from the graphical representation of the nested binary decision rules.

training (learning) and 25% for testing. 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 names 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.

The random forest prediction attaches to each pixel in each year a probability that it is mined. We then need to determine the cutoff at which we declare a pixel to be mined.[25] For each cutoff we plot in Figure 2 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 here. First, we are using the predictions as dependent variables. Second, our sample includes many non-mined pixels. We discuss these two issues in turn below. 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.

[25] 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.

Figure 2: ROC curve for the mining prediction model.



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.

4.2 Econometric analysis of the error term

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. In each pixel the random variable can be modeled as a Bernoulli, and, assuming independence[26] and identical distribution, their sum is binomial. 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, using the fact that 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:

$$\frac{\widehat{y_{mt}}}{Y_m} = \frac{y_{mt}}{Y_m}(TPR - FPR) + FPR + \upsilon_{mt} \tag{1}$$

Where

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

That is, 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. 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 formula (1), the optimal cutoff 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. Note that 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 2) 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 (1).

Two more points to note: First, the variance is smaller for municipalities with larger area, and, when we measure illegal mining as the fraction of the predicted mining area (instead of total municipality area), we do not know exactly the behavior of the error term because we are taking the ratio of two terms measured with error.

[26] 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 for details.

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),[27] and wrongly classifies as mines 0.29 % of pixels without a mine. 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	131747	2972
Predicted Mined	382	1428

4.3 From pixel predictions to municipality panel

We also want to construct a panel of illegal mining by municipality for Peru to better identify the coefficient of after the reform in a difference-in-differences framework. We use the respective satellite images, and deforestation data, as we have done for Colombia. Because we do not have data on location of mining activity to train or validate a model, we use the same prediction model trained in Colombian data. This required inputing the ecosystem type. See Appendix B for further details on our procedure.

We smooth our predictions over time to prevent having pixels that switch back and forth from mined to not mined due to prediction error.[28] After predicting whether each pixel is mined, we compare with the map of legal titles to declare the pixel as legally or illegally mined. Locations and exact shapes of Colombian legal mines were obtained from Tierra Minada[29], a nonprofit organization that digitized official records contained in the Catastro Minero Colombiano (Colombian mining cadastre). The data for Peru was obtained from the Peruvian Geology, Mining and Metallurgy Institute.[30] Finally, we collapse the predictions at the municipality level for use in the regression analysis.

[27] The TPR is similar (26%) when testing our model in the illegal gold mines manually identified by (UNODC, 2016).

[28] 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.

[29] The full data set can be downloaded from `https://sites.google.com/site/tierraminada/`

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

Table 3 presents the summary statistics of our predictions and a preview of our results. Our estimates imply that 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, 2016). In Table 11 in the appendix we present the results of illegal mining as fraction of total municipality area. We estimate that in the average municipality in Colombia, less than 1 % of its total area is illegally mined. The portion of total municipality area that is illegally mined in Peru seems high, but is in line with the 13.6% reported in (Maldonado, 2014). Anyway, the year-to-year variation could reasonable be used in a difference-in- differences framework, because the fixed effects will absorb the areas constantly misclassified every year.

Table 3: Summary statistics, illegal mining municipality panel

	Peru	Colombia	Difference
% of mined area mined illegally, 2004-2011	87.7	90.0	2.32***
	(21.5)	(22.1)	(0.34)
% of mined area mined illegally, 2012-2014	77.2	85.5	8.25***
	(27.1)	(23.3)	(0.62)
Difference	-10.43***	- 4.49***	5.93***
	(0.39)	(0.52)	(0.58)

An observation is a municipality-year. There are 2,738 municipalities in both countries, 932 in Colombia. Calculations: Authors.

5 Identification strategies

We want to identify how evasion responds to the share of 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:

$$\widehat{y_{mt}} = \beta_A After_t + \beta_P PriceIndex_{mt} + \gamma_m + \delta * t + \varepsilon_{mt}, \quad (2)$$

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 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.

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 is not well identified because of other national or international events, beyond the price changes we control for, occurring at the same time as the reform. In particular, in Colombia the system to register legal titles was closed at the time of the reform and there was an increase on the stringency of illegal mining prosecution in both countries. The national government's system for receiving mining title requests was closed from the end of 2011 to July 2013.[31] 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 in 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 applied to both Colombia and Peru, and likely deters illegal activity. Consequently our event study coefficient would be underestimating the effect of the reform.

The coefficient for the increase of illegal mining after the reform can also be identified in a difference-in-differences framework. Ideally we could use many countries but the process of generating the illegal mining panel by municipality is extremely computing time intensive. We decided to use Peru as the control for several reasons. It is a neighbor country that is also mentioned in the media with regions highly affected by illegal mining. Peru also has levels of gold production in the same order of magnitude as Colombia (see Table 10 in the Appendix). 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. The estimating equation using also the predictions of illegal mining in Peru is:

$$\widehat{y_{mt}} = \beta_A Aft_t \times Col_m + \beta_U Aft_t \times Per_m + \gamma_m + \delta_C t + \delta_P t + \varepsilon_{mt}, \quad (3)$$

[31] http://repository.urosario.edu.co/bitstream/handle/10336/8987/52378961-2014.pdf?sequence=1

Or in the standard framework without the linear trends:

$$\widehat{y_{mt}} = \beta_A After_t \times Col_m + \gamma_m + \gamma_t + \varepsilon_{mt}, \quad (4)$$

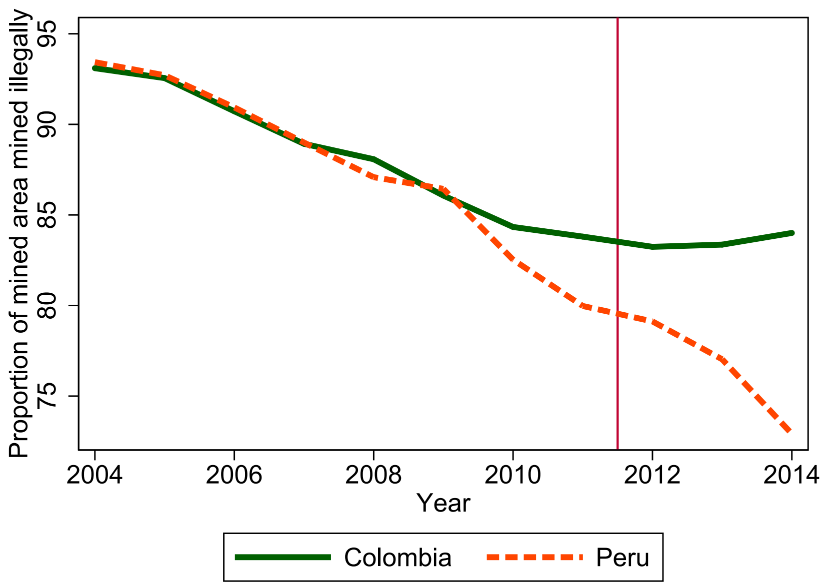
In Figure 5 in the Appendix we empirically check the parallel trend assumption.

6 Results

6.1 Main results

Before proceeding to the regression analysis we provide a visual representation of our results. Figure 3 plots the evolution of illegal mining in Colombia and Peru. We observe that illegal mining as a fraction of mined area was decreasing in both countries, but after the reform in Colombia it increased slightly.

Figure 3: Evolution of illegal mining in Colombia and Peru



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.

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 (2) only with Colombian data. The last two columns incorporate the data from

Peru and estimate equations (3) and (4), 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 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 3). We repeat this specification with municipalities closer to the border in Table 13.

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 4-6. 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. Finally in Table 12 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. There are less observations because we need a cloud free image in consecutive years and we lose observations for the year 2004, because we do not have satellite images for the previous year.

Table 4: Effect of the reform on illegal mining

Dependent variable:	% mined area mined illegally			Area mining titles (ha)		
	Colombia	Peru (DD)		Colombia	Peru (DD)	
	(1)	(2)	(3)	(4)	(5)	(6)
After x Colombia	1.63***	1.84***	4.47***	-6.02***	-8.88***	-1.22***
	(0.45)	(0.49)	(0.62)	(0.46)	(0.48)	(0.31)
Mineral price index	0.0058			-0.082***		
	(0.0071)			(0.0074)		
After x Peru		-2.36***			-13.8***	
		(0.38)			(0.38)	
Time FE	No	No	Yes	No	No	Yes
Linear Trend	Yes	Yes	No	Yes	Yes	No
N. of obs.	8796	26355	26355	8796	26355	30021
Municipalities	927	2733	2733	927	2733	2748
Mean of Dep. Var.	93.7	92.7	85.1	82.9	82.0	4.70
R^2	0.78	0.72	0.73	0.78	0.71	0.86

All regressions include municipality fixed effects. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The measure of illegally mined area that we use in Table 4 is calculated using the optimal threshold described in Sub-Section 4.2. 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 Table 14 with the same specifications by columns as Table 4. Note that the magnitudes of the estimated coefficients are almost double the coefficients with the optimal threshold. This fact is explained 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 (1). In Table 15 we present the results using the raw probabilities that a pixel is mined. The magnitude of the coefficient is smaller, probably because of the noise added by the probability of non-mined pixels.

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 16 in the Appendix for the results). The procedure selects only the lagged price index for the fraction of mined area that is illegally mined. The coefficient of "After the reform" is fairly similar when including this optimal control. 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.

In Table 17, we present robustness of the results to adjusting the raw measure of fraction of the municipality area that is mined, using the formula in equation (1). The coefficients are larger, because according to the formula our raw predictions underestimate the true fraction by a factor of $TPR - FPR$. Note that we have less observations using the adjusted measure, because in some cases the adjusted formula gives negative values of mined area: When the predicted mined area is not larger than the expected number of false positives. Table 18 presents results using different measures of illegal mining: The share of the total municipality area that is illegally mined, the area in square kilometers illegally mined and the logarithm of area illegally mined. Finally, we present regressions using as weights the fraction of the municipality area that is analyzed (Table 19), and including state trends (Table 20). In both cases the results remain significant at 5%.

Analysis of evasion in reported quantity produced

So far we have looked at the extensive margin of evasion, but it is also 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 (2) using reported production per area[32] as the dependent variable. 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.

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	0.64	-0.44	-0.036	4.52	-1.71	-1.08
	(1.92)	(0.37)	(0.16)	(10.4)	(5.15)	(1.33)
N. of obs.	733	714	772	1401	1191	401
Municipalities	105	80	84	228	196	63
Mean of Dep. Var.	4.26	2.22	1.88	15.4	6.12	1.34
R^2	0.33	0.34	0.59	0.33	0.27	0.77

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

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

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 detecting illegal mines. 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 6).[33] These results could be explained by at least two different 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 presence would capture better the fact that the national government does not monitor these municipalities that often.[34] 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 can 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). We find that 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

[33] We only have the data for the heterogeneity analysis for Colombian municipalities.
[34] We asked for data on National Police operations to study these conjectures, but were denied access.

(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.

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) and (4) we repeat the specifications used in (1) and (2) respectively, but we use as the dependent variable the fraction of the total area of the municipality that is illegally mined.

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.	8796	1753	10204	2049
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

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Health externalities

Besides the lost tax revenue, illegal mining could have differential environmental impacts for two main reasons. First, given that the capital of illegal mines would be destroyed if detected, illegal mines will 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. To test this hypothesis we study the effect of legal and illegal gold mines on newborns' health. Recall that half of the total area of mining titles held is devoted to precious metals extraction. We use the data on newborn's health for the years 2004-2014 from the Vital Statistics database provided by the government statistics department. We provide evidence that illegal mining has worse health effects on surrounding population.

Gold mining is known to contaminate the environment with mercury used in the process of amalgamation. The main channel of human exposure to mercury is through contaminated fish consumption. Consequently we expect that the population living downstream from mines are negatively affected by the pollution generated by the mines. In contrast, those living in the vicinity of the mine may benefit from the mine presence through an income effect. For each municipality and year we estimate whether the population lives within $20km$ of a mine ($NearMine_{mt}$) and 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.

$$HighAPGAR_{imt} = \beta_1 NearMine_{mt} + \beta_2 DownstreamFromMine_{mt} + X_{imt}\alpha + \gamma_m + \gamma_t + \lambda_{r(m)} \times t + \varepsilon_{imt} \quad (5)$$

In Table 7 we present the results of estimating equation (5). 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 coefficients indicate that the impacts are larger in illegal mines: The p-value of a test of equality is .028 . In Table 21 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.

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. Recall that 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 reform. Specifically we use as instrument "After X Weak Institutions Municipality Upstream". These variables predict an increase in illegal mining as we showed in the previous section, and confirm in Column 1 of Table 8. In Column 2, we invert the flow of the river to show this relationship is not driven by spatial correlation.[35] Table 9 present the results of the instrumental variable estimation. It shows

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

Table 7: 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)	3632569	3632569	3129368	3129368	3129368
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: First stage predicting illegal mining upstream with the reform

Dependent variable: Downstream from illegal mining		
	(1)	
After X Weak Institutions Municipality Upstream	0.14***	
	(0.051)	
After X Weak Institutions Municipality Downstream		-0.033
		(0.030)
N. of observations	2861263	593096
Municipalities	572	121
Mean of Dep. Var.	0.79	0.92
R^2	0.75	0.73
F-stat	7.57	1.21

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 9: Instrumental variable estimation with the reform

Dependent variable: High APGAR		
	(1)	(2)
Downstream from illegal mine	-0.73*	-2.46*
	(0.39)	(1.44)
Method	OLS	IV Inst
N. of observations	2861263	2861263
Municipalities	572	572
Mean of Dep. Var.	95.2	95.2
R^2	0.012	0.012

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

that the effect of illegal mining upstream is even larger than the ordinary least squares coefficient from before.

8 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.

We find that illegal mining increased in Colombia by 4.47 percentage points as a share of the mined area. This implies imply that of every dollar redistributed, 7-21 cents are lost through evasion. We rationalize our results in a model of bribe bargaining between the local authority and the miner. In addition, 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.

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.[36] However, illegal miners could respond by resorting to more underground mining, rendering monitoring more difficult.

References

Acevedo, K. M., & Bornacelly, I. D. (2014, July). *Panel Municipal del CEDE* (DOCUMENTOS CEDE No. 012223). UNIVERSIDAD DE LOS ANDES-CEDE. Retrieved from `https://ideas.repec.org/p/col/000089/012223.html`

Agencia Nacional Minera. (2013). *Exploring opportunities: the answer is colombia.* (http://www.anm.gov.co/sites/default/files/Documentos/exploringopportunities.pdf)

Altonji, J. G., Elder, T. E., & Taber, C. R. (2005). Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. *Journal of Political Economy*, *113*(1), 151.

Asner, G. P., Llactayo, W., Tupayachi, R., & Luna, E. R. (2013). Elevated rates of gold mining in the amazon revealed through high-resolution monitoring. *Proceedings of the National Academy of Sciences*, *110*(46), 18454-18459. Retrieved from `http://www.pnas.org/content/110/46/18454.abstract` doi: 10.1073/pnas.1318271110

[36]http://articles.economictimes.indiatimes.com/2016-04-12/news/72266895_1_minor-minerals-major-minerals-sand-mining

Athey, S., & Imbens, G. (2016). Recursive partitioning for heterogeneous causal effects. *Proceedings of the National Academy of Sciences*, *113*(27), 7353–7360.

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

Belloni, A., Chernozhukov, V., & Hansen, C. (2014). High-dimensional methods and inference on structural and treatment effects. *Journal of Economic Perspectives*, *28*(2), 29-50. Retrieved from `http://www.aeaweb.org/articles.php?doi=10.1257/jep.28.2.29` doi: 10.1257/jep.28.2.29

Brollo, F., Nannicini, T., Perotti, R., & Tabellini, G. (2013). The political resource curse. *The American Economic Review*, *103*(5), 1759–1796.

Burgess, R., Hansen, M., Olken, B. A., Potapov, P., & Sieber, S. (2012). The political economy of deforestation in the tropics. *The Quarterly Journal of Economics*. Retrieved from `http://qje.oxfordjournals.org/content/early/2012/10/04/qje.qjs034.abstract` doi: 10.1093/qje/qjs034

Burlig, F., Knittel, C., Rapson, D., Reguant, M., & Wolfram, C. (2016). Learning from schools about energy efficiency.

Cai, H., & Treisman, D. (2004). State corroding federalism. *Journal of Public Economics*, *88*(3), 819–843.

Ehrenstein, V. (2009). Association of apgar scores with death and neurologic disability. *Clinical epidemiology*, *1*, 45.

Etter, A. (2006). *Ecosistemas generales de colombia.* (Downloaded from http://capacitacion.siac.ideam.gov.co/SIAC/home/Catalogo_mapas.html)

Eynde, O. V. (2015). *Mining royalties and incentives for security operations: Evidence from india's red corridor.*

Faber, B., & Gaubert, C. (2016). *Tourism and economic development: Evidence from mexico's coastline* (Tech. Rep.). National Bureau of Economic Research.

Fedesarrollo. (2014a). *Mineria informal aurifera en colombia.*

Fedesarrollo. (2014b). *Mineria y medio ambiente en colombia.*

Foster, A., Gutierrez, E., & Kumar, N. (2009). Voluntary compliance, pollution levels, and infant mortality in mexico. *American Economic Review*, *99*(2), 191-97. Retrieved from `http://www.aeaweb.org/articles.php?doi=10.1257/aer.99.2.191` doi: 10.1257/aer.99.2.191

Gadenne, L. (2016). Tax me, but spend wisely? sources of public finance and government accountability. *Accepted American Economic Journal: Applied Economics*.

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

Giraldo, J. (2013). *El gobierno del oro en el bajo cauca, una lectura weberiana sobre la explotación aurífera aluvial no legal.* (Economía Criminal y Poder Político, Medellín: Universidad EAFIT)

Guiteras, R., Jina, A., & Mobarak, A. M. (2015, May). Satellites, self-reports, and submersion: Exposure to floods in bangladesh. *American Economic Review*, *105*(5), 232-36. Retrieved from http://www.aeaweb.org/articles?id=10.1257/aer.p20151095 doi: 10.1257/aer.p20151095

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., ... Townshend, J. R. G. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, *342*(6160), 850–853. Retrieved from http://science.sciencemag.org/content/342/6160/850 doi: 10.1126/science.1244693

Henderson, J. V., Storeygard, A., & Weil, D. N. (2012, April). Measuring Economic Growth from Outer Space. *American Economic Review*, *102*(2), 994-1028. Retrieved from https://ideas.repec.org/a/aea/aecrev/v102y2012i2p994-1028.html

Idrobo, N., Mejia, D., & Tribin, A. (2014). Illegal gold mining and violence in colombia. *Peace Economics, Peace Science and Public Policy*, *20*, 83-111.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2014). *An introduction to statistical learning with applications in r.* (Springer)

Jayachandran, S. (2009). Air quality and early-life mortality evidence from indonesia's wildfires. *Journal of Human Resources*, *44*(4), 916–954.

Jensen, J. (2007). *Remote sensing of the environment: an earth resource perspective.* Pearson Prentice Hall.

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

Lipscomb, M., & Mobarak, A. M. (2013). Decentralization and pollution spillovers: evidence from the re-drawing of county borders in brazil. *Unpublished Manuscript, University of Virginia and Yale University*.

Maldonado, S. (2014). *The political effects of resource booms: Political outcomes, clientelism and public goods provision in perul.*

Masse, F., & Camargo, J. (2012). *Actores armados ilegales y sector extractivo en colombia.* (CITPax-Observatorio Internacional)

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

Oster, E. (2013). *Unobservable selection and coefficient stability: Theory and validation*

(Tech. Rep.). National Bureau of Economic Research.

Psacharopoulos, G., & Velez, E. (1992). Schooling, ability, and earnings in colombia, 1988. *Economic Development and Cultural Change*, *40*(3), 629–643.

Romero, M., & Saavedra, S. (2015). The effect of gold mining on the health of newborns.

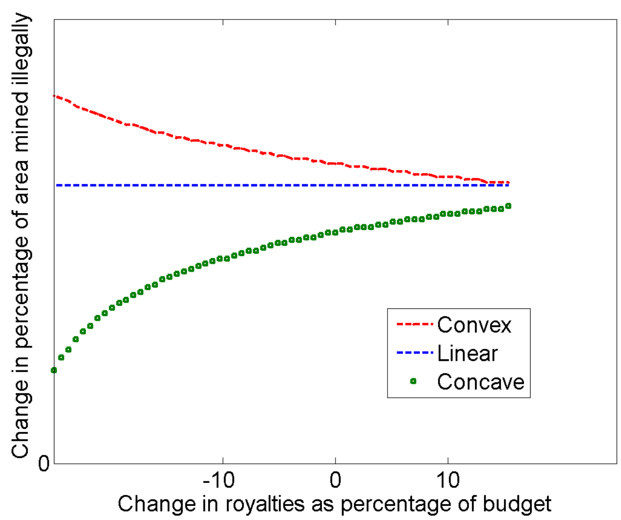
Rudas, G., & Espitia, J. (2013). *Participacion del estado y la sociedad en la renta minera.* (On Contraloria Genreal de la Republica "Mineria en Colombia")

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

UNODC, U. N. O. o. D. a. C. (2016). *Colombia: Explotacion de oro de aluvion. evidencias a partir de percepcion remota.*

Appendix A Additional Figures and Tables

Figure 4: 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.

Table 10: 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	–	–

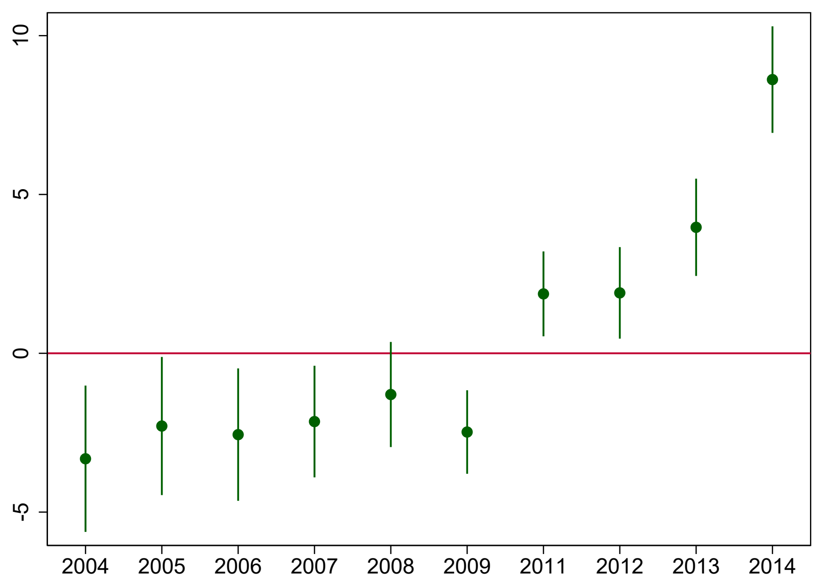
Gold production in kilograms. Silver and Tin production in metric tons. Other minerals in thousand metric tons. Source: USGS http://minerals.usgs.gov/minerals/pubs/country/sa.html.

Table 11: Summary statistics illegal mining as fraction of total municipality area

	All	Winners	Losers	Difference
Pct. of area illegal Colombia before	0.35	0.29	0.66	0.37***
	(1.24)	(0.95)	(2.15)	(0.039)
Pct. of area illegal Colombia after	0.88	0.77	1.47	0.71***
	(2.47)	(2.24)	(3.37)	(0.13)
Pct. of area illegal Peru before	16.4	16.4	.	-16.4***
	(23.8)	(23.8)	(.)	(0.20)
Pct. of area illegal Peru after	18.9	18.9	.	-18.9***
	(24.4)	(24.4)	(.)	(0.34)

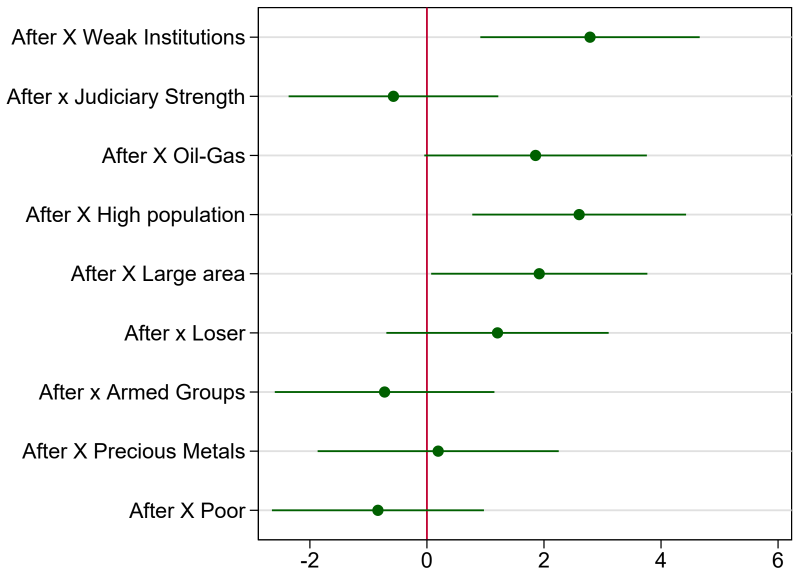
An observation is a municipality-year. Calculations: Authors.

Figure 5: Visual representation of parallel trends assumption



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.

Figure 6: Heterogeneous effects of the reform by different municipal characteristics



Regression results are presented in Table 27 and 28 in the online Appendix.

Table 12: Results selecting optimal controls with Lasso style procedure

Dependent variable:	% of new mined area mined illegally		
	(1)	(2)	(3)
After x Colombia	2.29***	2.00***	5.35***
	(0.61)	(0.59)	(0.75)
After x Peru		-0.86	
		(0.64)	
Time FE-Trend	Trend	Trend	TimeFE
N. of obs.	5156	11568	11608
Municipalities	816	1549	1552
Mean of Dep. Var.	92.2	88.6	88.6
R^2	0.67	0.72	0.72

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 13: Results municipalities closer to the Colombian-Peru border

Dependent variable:	% of mined area mined illegally		
	All	$< 1,000km$	$< 500km$
	(1)	(2)	(3)
After x Colombia	1.48***	1.29**	0.80
	(0.51)	(0.54)	(0.85)
After x Peru	-1.35***	-1.86***	-1.00
	(0.39)	(0.68)	(1.67)
N. of obs.	26355	15609	2511
Municipalities	2733	1718	279
Mean of Dep. Var.	85.2	86.1	90.0
R^2	0.73	0.73	0.72

All regressions include municipality fixed effects and country linear trends. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Results using different cutoff for mining predictions

Dependent variable:	% of mined area mined illegally		
	Only Colombia	With Peru	
	(1)	(2)	(3)
After x Colombia	3.02***	2.76***	7.55***
	(0.31)	(0.29)	(0.44)
After x Peru		-0.95***	
		(0.29)	
Time FE-Trend	Trend	Trend	TimeFE
N. of obs.	10207	28904	28971
Municipalities	940	2748	2748
Mean of Dep. Var.	75.9	82.4	82.4
R^2	0.79	0.77	0.77

The cutoff for declaring a pixel as mined in this regressions has a TPR of 80% and a FPR of 20%. All regressions include municipality fixed effects. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Results using pixels mined probabilities

Dependent variable:	% of mined area mined illegally	
Mined:	Dummy	Probability
	(1)	(2)
After x Colombia	1.48***	1.18**
	(0.53)	(0.49)
N. of obs.	8796	9952
Municipalities	927	940
Mean of Dep. Var.	86.2	84.1
R^2	0.79	0.76

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 16: Results selecting optimal controls with Lasso style procedure

Dependent variable:	% area illegal			% mined illegal		
	(1)	(2)	(3)	(4)	(5)	(6)
After	0.17***	0.054*	0.16***	1.88***	1.13**	1.74***
	(0.031)	(0.030)	(0.023)	(0.49)	(0.53)	(0.49)
After x Pctg Budget Loss	0.0058	0.0046	0.0051	0.044*	0.033	0.036
	(0.0038)	(0.0037)	(0.0037)	(0.023)	(0.022)	(0.022)
Controls	Main	All	DLasso	Main	All	DLasso
N. of obs.	9342	9225	9225	8211	8103	8103
Municipalities	944	944	944	932	932	932
Mean of Dep. Var.	0.56	0.55	0.55	88.2	88.2	88.2
R^2	0.79	0.78	0.78	0.81	0.81	0.81

"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 only selects lagged price. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Results using the adjusted measure of illegal mining

Dependent variable:	% of mined illegal adjusted		
	(1)	(2)	(3)
After x Colombia	3.20***	3.31***	6.59***
	(0.54)	(0.58)	(0.70)
After x Peru		-2.37***	
		(0.40)	
N. of obs.	2801	17759	17759
Municipalities	495	2183	2183
Mean of Dep. Var.	92.2	92.2	83.7
R^2	0.94	0.77	0.79

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 18: Results using other measures of illegal mining

Dependent variable:	% municipality area	Area illegal	Log (Area+1)
	(1)	(2)	(3)
After x Colombia	0.17***	1.26***	0.068***
	(0.029)	(0.33)	(0.0099)
N. of obs.	10204	10204	10204
Municipalities	940	940	940
Mean of Dep. Var.	0.49	2.90	0.49
R^2	0.74	0.56	0.89

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 19: Results using weights by fraction of municipality analyzed

Dependent variable:	% mined area mined illegally			
	(1)	(2)	(3)	(4)
After x Colombia	1.48***	1.51***	1.48***	1.52***
	(0.53)	(0.49)	(0.51)	(0.48)
After x Peru			-1.35***	-1.62***
			(0.39)	(0.34)
Weights		Yes	No	Yes
N. of obs.	8796	704106	26355	1673601
Municipalities	927	927	2733	2732
Mean of Dep. Var.	86.2	86.0	85.2	85.1
R^2	0.79	0.80	0.73	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 20: Results using state trends

Dependent variable:	% mined area mined illegally			
	(1)	(2)	(3)	(4)
After x Colombia	1.48***	1.33**	1.48***	1.47***
	(0.53)	(0.52)	(0.51)	(0.51)
After x Peru			-1.35***	-1.35***
			(0.39)	(0.39)
State trends	No	Yes	No	Yes
N. of obs.	8796	8796	26355	26355
Municipalities	927	927	2733	2733
Mean of Dep. Var.	86.2	86.2	85.2	85.2
R^2	0.79	0.79	0.73	0.73

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

Appendix B Constructing the illegal mining data

As illegal mining is not observable in government records, we use satellite images and a statistical model to detect the evolution of illegal mining through time. This requires many steps and computing time, as described below:

- 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/

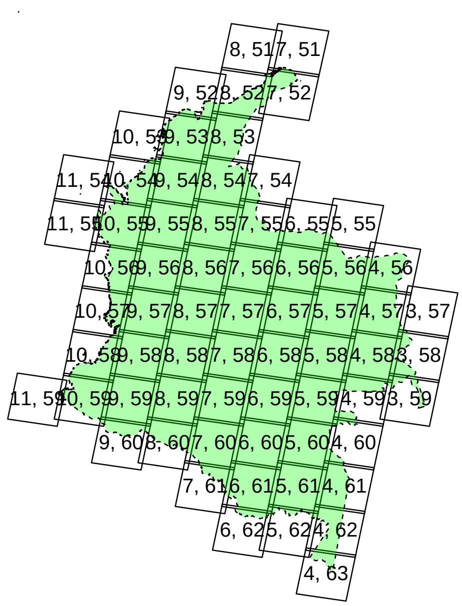
Table 21: Differential health effects of legal and illegal mines

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)	2585545	2585545
Municipalities	614	614
Mean of Dep. Var.	95.5	95.5
R^2	0.017	0.017

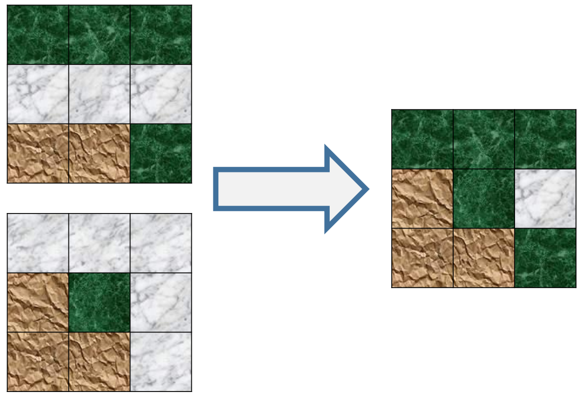
All regressions include mother characteristics, municipality FE, week FE, year FE, and state trends. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

. The satellite takes a picture of each square ("path-row") of the earth every two weeks.

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

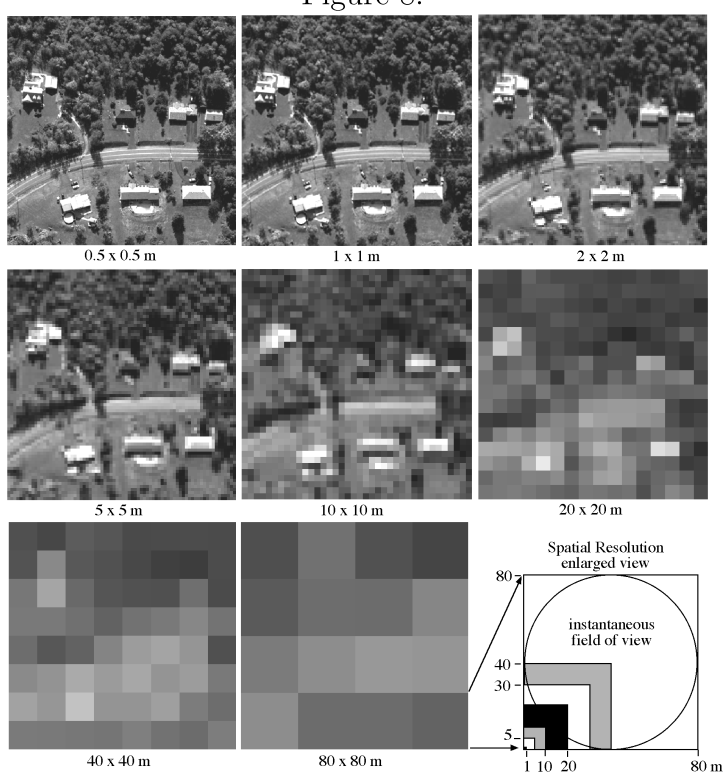


- Download the necessary surface reflectance images from http://espa.cr.usgs.gov/ using UTM-18 projection. There are on average 550 images per year, each one around 230MB when compressed. That is a total of around 1.5TB of raw data.
- We use the program teamlucc (http://azvoleff.com/teamlucc.html), with 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 8:



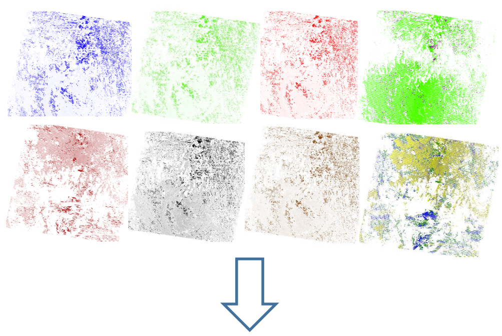
Source: (Jensen, 2007)

- 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.

- 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 [37], 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 9: Visual representation of transforming the satellite data into a data frame

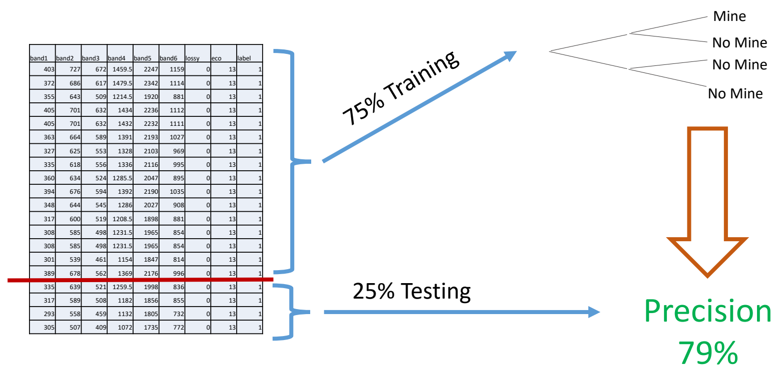


Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Loss year	Ecosystem
207	246	211.5	0	0	364	10	25
204	247	209	0	0	362.5	10	25
205.5	248.5	210.5	0	0	362	10	25
99	147	77.5	1227	495	197.5	0	25

- 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 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.

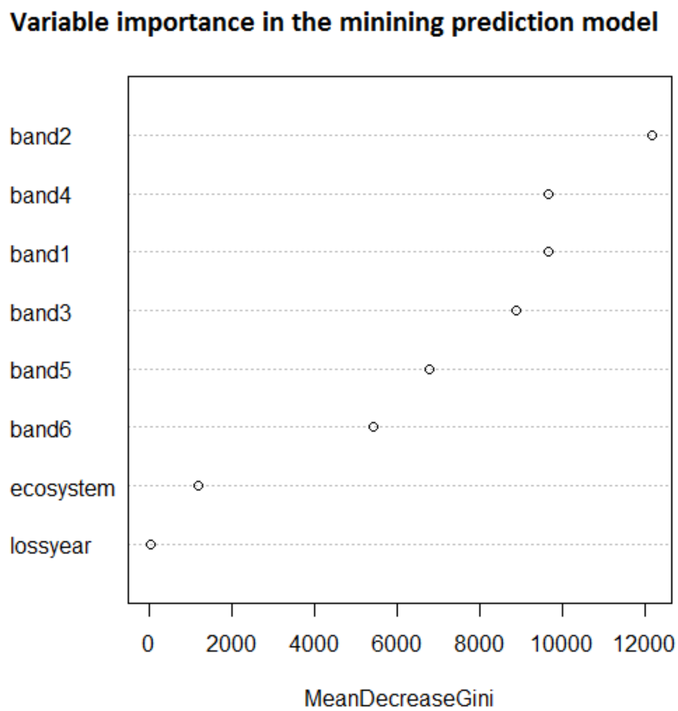
[37] Band 1 (blue), Band 2 (Green), Band 3 (Red), Band 4 (Near infrared), Band 5 (Shortwave infrared 1) and Band 7 (Shortwave infrared 2)

Figure 10: Visual representation of training and testing data



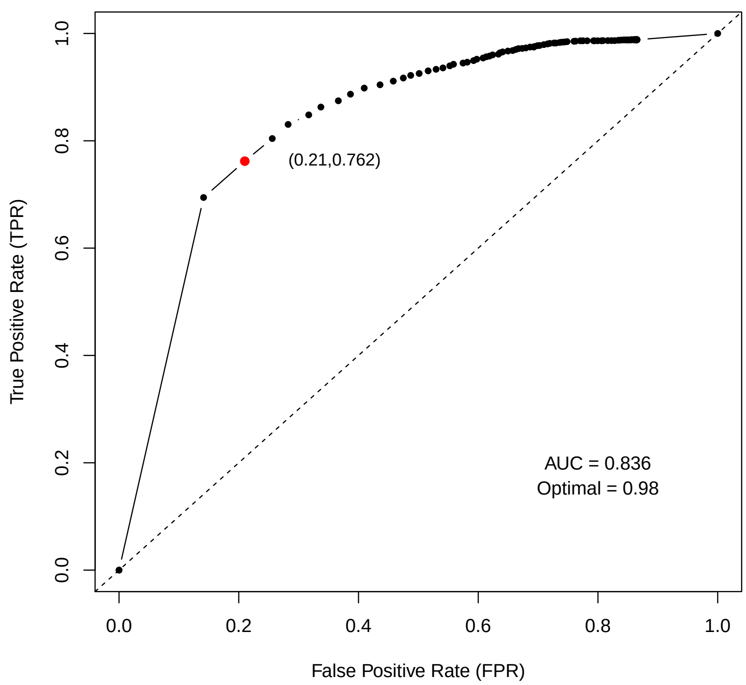
- We try boosting, support vector machines with radial kernels and random forest models in a small subsample of the data. For all three models we try down-sampling and smote. The best parameters for each case where chosen by 10-fold cross validation. Based on the results in the subsample we decide to 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 11:



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 12: 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.

B.1 Weak law of large numbers for correlated Bernoulli's random variables among pixels

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

Appendix C Further analysis

C.1 Estimate dollars lost to evasion and health costs

Dollars lost trough evasion

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 0.13 (Column 2, Table 18. The analyzed area is $457,840km^2$, consequently illegal mining increased by $595km^2$. The coefficient of "After X Loser" in that specification is 0.29. The analyzed area in loser municipalities is $136,170km^2$. This represents additional $395km^2$ in the losers, for a total of $990km^2 = 99,000ha$ 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,[38], 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. We estimate that around 40% of the area illegally mined extracts gold, therefore at least $\$44M$ of royalties revenue are lost with the reform. Compared to the total mining royalties of $\$660M$, this is equivalent to 7 cents per dollar.

Additional health cost

We would like to have information on the health effects of mining on the surrounding population. Unfortunately we only have estimates for newborns so our estimates are a lower bound for the total health effects. We proceed in two steps. First, we 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

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

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 is -0.7 percentage points. We estimate there are $269,398$ babies born downstream from mines in 2011. Therefore the number of affected babies is 1,886, with a total of $\$3M$ in newborn health costs. The gold royalties were $\$66M$, so a lower bound is for every dollar redistributed at least 4 cents of health costs are accrued.

C.2 Heterogeneous treatment effects in loser municipalities

It is possible to analyze heterogeneous effects in the loser municipalities. Instead of choosing a particular variable to present heterogeneous effects, we use another machine learning technique to let the data highlight the most relevant variable. Athey and Imbens (2016) introduces "honest causal trees" to identify subgroups with heterogeneous treatment effects. The "honest" part is because it incorporates in the objective function that there is out-of-sample estimation, and the "causal" part reflects that we are in the potential outcomes framework so municipalities are observed as winners or losers. The idea is to divide the data into three sub-samples: one sub-sample (A) to create the tree-splitting structure of similar sub-groups; sub-sample (B) to estimate the treatment effects; and the last sub-sample (C) to validate the results. If the same sample were to be used for the tree partition and the estimation of treatment effects, the confidence intervals would not be valid.

The results are presented in Table 22. In Column 1 we repeat our main specification in the whole sample for ease of comparison, in Column 2 we do the same specification in sub-sample C and in the last column we present the specification with the sub-groups identified. In this case the variable chosen to partition the data is the number of institutions per capita in the municipality. Here, we are underpowered because only 148 municipalities are losers, so splitting the municipalities into three sub-samples and two sub-groups results in only around 25 treated observations per sub-group. Although the results are not statistically significant, they suggest the effect of the reform was larger in municipalities with weak national government presence. Finally, in an Altonji test, the identified set for the coefficient of "After X Pct. Budget Loss", β_L, is (.05 ,.07) percentage points.

Table 22: Heterogeneous effects of the reform in loser municipalities

Dependent variable:% of total area mined illegally	(1)	(2)	(3)
After	0.13***	0.15*	0.095
	(0.037)	(0.085)	(0.098)
After x Loser	0.29**	0.31	0.19
	(0.13)	(0.21)	(0.16)
After x Group			0.25
			(0.22)
After x Loser x Group			0.34
			(0.61)
Sample			
N. of obs.	10267	3299	3299
Municipalities	944	302	302
Mean of Dep. Var.	0.53	0.53	0.53
R^2	0.77	0.77	0.77

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

C.3 Positive effects of the reform?

The reform was mainly intended to reduce regional inequality. Therefore, we examine whether the unintended increase in illegal mining is compensated by an improvement in socioeconomic indicators in municipalities that won with the reform. We lack information to conduct a complete cost-benefit analysis but we can look at infant mortality, given that health is one of the items royalties should be spent on. Results are presented in Table 23. Columns 1 and 2 are our standard specifications using infant mortality as the dependent variable. In Column 3 we use the percentage of budget loss, and in Column 4 we try to separate the effects of winning and losing with the reform. Finally in Columns 5 and 6 we repeat the specification of Column 4 separated by municipalities without and with armed groups. We find evidence that infant mortality in municipalities that lost with the reform did not improve as much as it did in those that won. When we decompose the results in Column 4, we observe that in municipalities that won more the improvement is greater. Surprisingly, the improvements are concentrated in municipalities with armed groups. We were expecting more budget capture in those municipalities, however the coefficient could also be capturing reduced pollution of less illegal mining.

Table 23: Change in infant mortality rate

Dependent variable:	Infant Mortality Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
After	-0.30***					
	(0.044)					
After x Loser	-0.24*	-0.24*				
	(0.14)	(0.14)				
After x Pctg Budget Loss			-0.0040			
			(0.0051)			
After x Pctg Budget Loss if Loss				-0.024***		
				(0.0077)		
After x Pctg Budget Win if Won				-0.039***		
				(0.011)		
Time FE						
Linear Trend						
N. of obs.	8398	8398	8398	8398		
Municipalities	944	944	944	944		
Mean of Dep. Var.	21.4	21.4	21.4	21.4		
R^2	0.99	0.99	0.99	0.99		

All regressions include municipality fixed effects. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.4 Effects on municipalities with mineral resources and prone to satellite detection

We expect to detect the effects of the reform mostly in municipalities where mining is open pit given that we use satellite data to construct our measure. To check this, we run our main specification separating by satellite-prone municipalities. In our definition, satellite-prone municipalities are those where the Census indicates there is open-pit extraction, or if they were not included in the Census, where there is extraction of minerals that in most municipalities are mined using open-pit methods. Results are presented in Table 24. The results suggest that most of the effects are in satelliteprone municipalities.

Table 24: Results by satellite-prone municipalities

	Dependent variable:Pctg of mined area mined illegally		
	All	Satellite-prone	Not satellite-prone
	(1)	(2)	(3)
After	0.13***	0.16***	0.052
	(0.037)	(0.043)	(0.032)
After x Loser	0.29**	0.15	0.18
	(0.13)	(0.15)	(0.18)
Time FE			
Linear Trend			
N. of obs.	10267	7031	2838
Municipalities	944	645	262
Mean of Dep. Var.	0.53	0.47	0.47
R^2	0.77	0.72	0.72

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

C.5 Endogenous response of municipalities to budget change

There are concerns that municipalities could have adjusted their local taxes in response to the royalties reallocation. To study this possibility, we run our main regressions using as the dependent variable one of two measures of local taxes. In Table 25, columns 1 and 2 use local taxes as a percentage of the municipal budget and columns 3 and 4 use local taxes normalized to the value of local taxes in the municipality in 2004. We do not find evidence of municipalities adjusting local taxes.

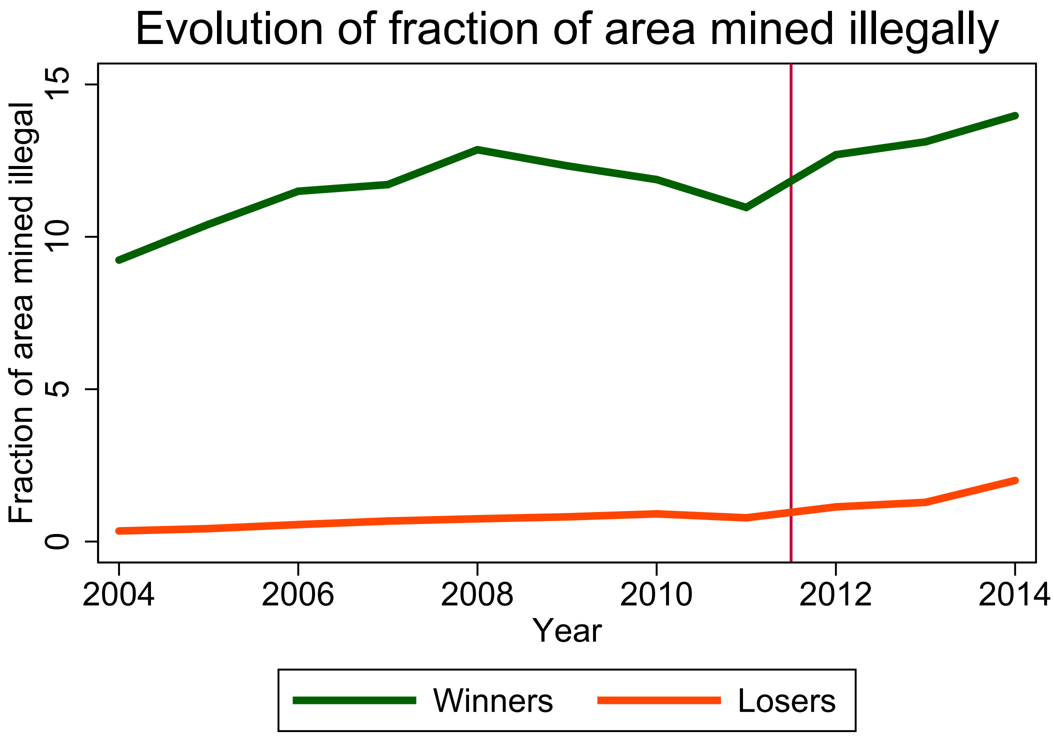
Table 25: Endogenous response of municipalities to budget change

Dependent variable:	Pctg own tax budget		Normalized own tax budget	
	(1)	(2)	(3)	(4)
After	-1.52***		19.0	
	(0.17)		(14.1)	
After x Loser	2.57***	2.57***	198.6	198.8
	(0.55)	(0.55)	(128.6)	(128.7)
Time FE	No	Yes	No	Yes
Linear Trend	Yes	No	Yes	No
N. of obs.	9282	9282	9220	9220
Municipalities	944	944	934	934
Mean of Dep. Var.	13.7	13.7	248.2	248.2
R^2	0.91	0.91	0.41	0.41

All regressions include municipality fixed effects. Standard errors, clustered by municipalities, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix D Online Appendix

Figure 13: 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 26: 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 27: 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.	8796	8455	8796	8796	8796	8796
Municipalities	927	890	927	927	927	927
Mean of Dep. Var.	93.7	93.6	93.7	93.7	93.7	93.7
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 28: 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***	1.68***	2.16***
	(0.45)	(0.52)	(0.60)	(0.54)	(0.71)
After x Loser		1.32			
		(1.00)			
After x Armed Groups			-0.76		
			(1.00)		
After X Precious Metals				-0.16	
				(1.11)	
After X Poor					-1.06
					(0.97)
N. of obs.	8796	8796	8796	8796	8796
Municipalities	927	927	927	927	927
Mean of Dep. Var.	93.7	93.7	93.7	93.7	93.7
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 29: 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 Loser	1.21	-3.50	10.6
	(11.0)	(2.91)	(25.4)
Mineral price index	0.13	0.0074	0.27
	(0.12)	(0.023)	(0.30)
Time FE			
N. of obs.	10267	6184	4083
Municipalities	944	568	376
Mean of Dep. Var.	24.5	1.65	59.1
R^2	0.24	0.11	0.23

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

Table 30: 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 Pctg Budget Loss	0.032	-0.078	0.29
	(0.22)	(0.064)	(0.44)
Mineral price index	0.13	0.0078	0.26
	(0.12)	(0.023)	(0.31)
Time FE			
N. of obs.	10267	6184	4083
Municipalities	944	568	376
Mean of Dep. Var.	24.5	1.65	59.1
R^2	0.24	0.11	0.23

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

Table 31: Change in armed groups homicide rate

Dependent variable: Armed Group Homicides			
	All	No AG Bef Reform	AG Bef Reform
	(1)	(2)	(3)
After x Loser	0.084	-0.018	0.25
	(0.36)	(0.085)	(0.84)
Mineral price index	0.0041	0.00027	0.0089
	(0.0028)	(0.00058)	(0.0072)
Time FE			
N. of obs.	10267	6184	4083
Municipalities	944	568	376
Mean of Dep. Var.	0.49	0.029	1.20
R^2	0.27	0.11	0.26

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

Table 32: Change in armed groups homicide rate

	Dependent variable: Armed Group Homicides		
	All	No AG Bef Reform	AG Bef Reform
	(1)	(2)	(3)
After x Pctg Budget Loss	0.0023	-0.00074	0.0069
	(0.0060)	(0.0012)	(0.012)
Mineral price index	0.0041	0.00027	0.0088
	(0.0028)	(0.00059)	(0.0073)
Time FE			
N. of obs.	10267	6184	4083
Municipalities	944	568	376
Mean of Dep. Var.	0.49	0.029	1.20
R^2	0.27	0.11	0.26

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