The Effects of Gold Mining on Newborns' Health

Mauricio Romero and Santiago Saavedra^{*}

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Abstract

Mining can propel economic growth, but often results in heavy metal releases, that could negatively impact human health. Using a differencein-differences strategy we estimate the impact of gold mining on the health of newborns in Colombia. We find heterogeneous effects depending on where mothers are located with respect to a mine. Mothers living in the vicinity of a mine are positively affected experiencing a reduction of 0.51 percentage points in the probability of having a child with low APGAR score at birth (from a basis of 4.5%). However, we find a negative effect on mothers living downstream from a mine, whose probability of having a child with a low APGAR score at birth increases by 0.45 percentage points. We provide suggestive evidence that contaminated fish consumption in the first weeks of gestation is the mechanism behind our results using an exogenous increase in fish consumption caused by a religious celebration.

1 Introduction

The surge in mineral prices over the last decade has propelled mining and economic growth in many low- and middle-income, mineral-rich countries (McMahon & Moreira, 2014). However, mining is usually accompanied by environmental degradation. The net impact of gold mining on human well-being is unclear, as more income could potentially expand opportunities for people (e.g., access to more and better food), while environmental degradation could negatively affect human health (e.g., respiratory infections and heavy metal poisoning).¹ Additionally, environmental degradation and its impact on human health could have

^{*}Romero: University of California - San Diego, *e-mail contact:* mtromero@ucsd.edu. Saavedra: Stanford University, *e-mail contact:* santisap@stanford.edu. This study was carried out with support from the Latin American and Caribbean Environmental Economics Program (LACEEP) grant IDEA-302. We are grateful to Prashant Bharadwaj, Pascaline Dupas, Thomas Ginn, LACEEP and seminar participants at PACDEV, Stanford and UC San Diego. Abraham Ibanez provided excellent research assistance.

 $^{^{1}}$ There is ample debate in the literature about the existence of the so-called environmental Kuznets curve, which predicts that the relationship between pollution and income has an

a detrimental effect on future income growth by reducing human capital. In particular, if newborns are negatively affected by environmental degradation, this could lead to lower future productivity as in-utero insults, birth outcomes, and early-life shocks have been shown to have long-term negative impacts on educational attainment (e.g., see Almond (2006)), learning outcomes (e.g., see Bharadwaj, Løken, and Neilson (2013)), cognitive ability (e.g., see Almond and Currie (2011)) and wages (e.g., see Black, Devereux, and Salvanes (2007)).

In this article, we study the effect of gold mining on newborns' health in Colombia. Although gold mining provided \$ 100 million (USD) in royalties in 2012, it often results in the release of heavy metals (mercury in particular) that affect the health of the surrounding population and especially infant brain development.² In fact, recent legislation to control and regulate the use of mercury (with an explicit goal to phase-out its use in mining by 2018) was set in place to "protect human health and preserve natural resources" (Congreso de la Republica, 2013). It is know that the main channel of mercury exposure is through fish consumption. However, there is scant evidence on the magnitude of the effect of mercury on surrounding populations, and whether the benefits of mining could compensate for any damage.

Our identification strategy is a difference-in-differences style estimator that compares births near mines with those far from them, before and after mining activity begins. The main dependent variable is whether the newborn has a low APGAR (Appearance, Pulse, Grimace, Activity and Respiration) score, which captures the presence of possible brain damage (Moster, Lie, Irgens, Bjerkedal, & Markestad, 2001) and is a significant predictor of health, cognitive ability, and behavioral problems later in life (Almond, Chay, & Lee, 2005). We use a rich data set with all births between 2001 and 2012, and administrative records on the location, shape and boundaries of the mines.

We find heterogeneous effects depending on where the mothers are located with respect to a mine. Babies born to mothers living near a mine are positively affected by mining activities and experience a reduction of 0.51 percentage points in the probability of having low APGAR score (from a basis of 4.5%). However, we find a negative effect on mothers living in municipalities located downstream from a mine, whose probability of having a child with a low APGAR score at birth increases by 0.45 percentage points.

The toxicology literature points to fish as the main channel of mercury expo-

inverted U shape, reflecting that pollution initially rises along with income but eventually reaches a turning point and starts to decline. However, the general consensus is that growth is accompanied by environmental degradation in developing countries. For a recent review of the literature on the environmental Kuznets curve see Carson (2010) and Harbaugh, Levinson, and Wilson (2002).

 $^{^{2}}$ The recent surge in gold mining has been accompanied by an increase in heavy metal poisoning (see Figure 4 in Appendix B).

sure to humans. Thus, we provide suggestive evidence that contaminated-fish consumption is the mechanism behind our results. We do this by studying an exogenous increase in fish consumption during pregnancy caused by Holy Week, a religious celebration during which fish consumption rises throughout the country. An overlap of Holy Week with the first trimester of gestation increases the likelihood of low APGAR at birth. We provide a number of robustness checks. In particular we show that our treatment effects decrease as we move away from the source of treatment (i.e., the mine or the river) and show that using the international gold price as an additional source of variation provides similar results.

We contribute to the growing body of literature on the effects and externalities of mining, and specifically to the literature on mining in developing countries and its effect on health outcomes. Although there has been an active literature on the health effects of pollution, most of it has been using developed countries? data (Greenstone & Jack, 2015). Previous studies have found that mining has negative effects on the environment and agricultural productivity (McMahon & Remy, 2001; Aragón & Rud, 2015), while others have found positive income effects on local communities (Aragón & Rud, 2013; von der Goltz & Barnwal, 2014). The indirect effect of mining on human health has rarely been considered in the literature; with the exception of von der Goltz and Barnwal (2014) and Tolonen (2015). An advantage of our data is that we have the exact shape of the mine, while von der Goltz and Barnwal (2014) and Tolonen (2015) only have one coordinate point to identify the location of the mines. We show that our main results are similar whether we use all the information on the mines' shape, or just its centroid. However, the heterogeneity with respect to the distance from the mine is different if we use only one point to identify the location instead of the exact shape of the mine. Finally, although previous studies have use other religious celebration (e.g., Ramadan) as a source of exogenous variation (e.g., see Almond and Mazumder (2011) and Schofield (2015)), we are not aware of any study that exploits Holy Week as a source of variation.

The rest of the article is organized as follows: Section 2 contains a review of the effects of mercury on human health and Section 3 describes the context of mining in Colombia and the data. Section 4 presents the identification strategy and the construction of the variables. Section 5 presents the main results, while Section 6 presents robustness checks. The final section contains concluding remarks and a discussion of avenues for further research.

2 Mercury and human health

A number of papers have identified a strong correlation between mining and adverse environmental and health outcomes. For example, Swenson, Carter, Domec, and Delgado (2011) find that increases in gold prices have boosted small-scale gold mining in Peru and led to increased deforestation in the Amazon jungle. Hilson (2002) finds that small-scale gold mining in Ghana led to socioeconomic growth but also mercury pollution and land degradation. Most studies linking health to mining also focus on correlation and, due to confounding effects, cannot imply causation (Fernández-Navarro, García-Pérez, Ramis, Boldo, & López-Abente, 2012; Attfield & Kuempel, 2008; Chakraborti et al., 2013). The few papers that have attempted to tease out the causal component have focused on the effect of mining on agricultural productivity: Aragón and Rud (2015) estimate that mining in Ghana reduced agricultural productivity in nearby areas by almost 40%; and on spillovers to non-mining activities Aragón and Rud (2013) find a positive effect of mining on real income for non-mining workers in Peru. However, the extent to which mining affects health is still unclear.

We are only aware of one article, by von der Goltz and Barnwal (2014), that credibly identifies the effect of mining on health. In their article, von der Goltz and Barnwal (2014) use mine locations (mine centroids) and the year a mine start operations to identify the effect of mines on wealth and health. They find that communities near mines in Africa have higher asset wealth but also higher rates of anemia. Our study is similar in spirit, but differs in three important dimensions. First, we have information on size and shape of the mines which allow us to calculate intensive margin effects (we find that there are none). Second, we study the impact of mining on cognitive development using as a proxy the APGAR score at birth. Third, we are able to separate the effects of increased income and increased pollution by exploiting the fact that water pollution flows downriver, while the economic gains accrue to all surrounding areas.

2.1 Mercury and amalgamation in gold mining

Metallic mercury is used in mining for amalgamation, the process of separating gold particles from other minerals (Mol, Ramlal, Lietar, & Verloo, 2001). For every kilogram of gold produced, on average 9 kilograms of mercury are released into the environment (Pfeiffer, Lacerda, Salomons, & Malm, 1993; da Veiga, 1997; Guiza & Aristizabal, 2013). Miners add mercury to silt in order to create an amalgam, a bond between mercury and gold. The remaining silt is then washed away. The amalgam is heated in smelters, where the mercury evaporates and the gold nuggets are separated. 55% of the mercury used enters the atmosphere, while 45% infiltrates bodies of water (Pfeiffer & de Lacerda, 1988). Aquatic microorganisms transform metallic mercury into methyl-mercury (Morel, Kraepiel, & Amyot, 1998). The microorganisms are eaten by fish, and in turn humans are exposed to methyl-mercury by consuming contaminated fish (for a more detailed explanation see Mol et al. (2001)). In the U.S., the EPA limits for metallic mercury in drinking water and for methyl-mercury consumption are 0.002 mq/L and 0.1 $\mu g/kg$ body weight/day, respectively. There is evidence that those limits are exceeded in Colombia near mining areas (Guiza & Aristizabal, 2013; Olivero & Johnson, 2002).

Artisanal and small-scale gold mining is the largest contributor to atmospheric mercury emissions at 727 tons annually, or 35% of anthropogenic emissions. In addition, discharges into water bodies from small-scale mining are estimated at 800 tons each year, representing 63% of anthropogenic releases (United Nations Environment Programme, 2013). Large-scale gold mining is classified as unintended mercury emission, because it is assumed that mercury is either captured and stockpiled or sold for other uses. This sector accounts for 97 tones, or 5% of emissions. In short, the two main sources of human exposure to mercury are through methyl-mercury in fish and mercury vapor from smelters. In the data section, to possibly account for the air channel, we use the proportion of area mined in the municipality and the proximity of the population to the mines. For the water channel we use exposure of the population to river pollution.

2.2 Health effects of mercury

Mercury is one of the top ten chemicals of major public health concern according to the World Health Organization (World Health Organization, 2013). There are five factors that determine the intensity of mercury health effects: the type of mercury; the dose; duration of exposure; route of exposure; and the age of the person (World Health Organization, 2013). An advantage of studying the health effects on newborns is that the age, type, duration, and route of exposure are known. Dosage, on the other hand, depends on fish consumption during pregnancy, as well as to mercury levels (if any) in the fished consumed.

The medical literature consistently points out that exposure to methyl-mercury in high doses can be fatal (Davidson, Myers, & Weiss, 2004), but there is no consensus on how variation in the dosage affects health.³ Mercury is harmful to the heart, kidneys, and central nervous system, with women and children being the most sensitive to its effects. There is evidence that the fetal brain is especially susceptible to damage from exposure to mercury (Davidson et al. (2004), Environmental Protection Agency (2013), Black, Bütikofer, Devereux, and Salvanes (2013). Babies born to women poisoned with methyl-mercury are more likely to develop cerebral palsy (Center for Disease Control, 2009), in turn a low APGAR score at birth is associated with an 81-fold increase in the risk of cerebral palsy (Moster et al., 2001). APGAR scores have been found to be a significant predictor of health, cognitive ability, and behavioral problems later in life, even after controlling for family background and low birth weight (Almond et al., 2005). We are not aware of literature discussing mercury effects on height, birth weight or length of gestation (the other newborn outcomes we have information for).

 $^{^3 \}rm See$ Mergler et al. (2007) , Davidson et al. (2004), Counter and Buchanan (2004), and Clarkson, Magos, and Myers (2003) for reviews of the literature.

3 Colombian context and data

Colombia is currently experiencing a mining boom: gold extraction increased by more than 180 % between 2004 and 2012 (see Figure 1).⁴ The national government allocates mining permits allowing exploration in a given area. If a company decides to exploit the resource, it has to apply for an extraction permit and environmental license.⁵



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The figure shows the evolution over time of gold production (in kilograms) and total mined area (in square kilometers). Source: Ministerio de Minas y Energia de Colombia. Calculations: Authors.

Mining companies operating in Colombia have to pay royalties to the government; the revenue is distributed among the central, and local governments.⁶

⁴Author calculations based on Government data from Mining Permits and Sistema de Información Minero Colombiano (SIMCO).

⁵In a previous version of this paper we considered the application for mining permits a good proxy for mineral discovery that would lead to extraction of the mineral shortly thereafter, either legally or illegally. Now we use only information for when the title is actually in the extraction phase.

 $^{^{6}}$ The rate for gold mining in our period of study was 4% of production at market prices, except for non-artisan alluvial mining which had a rate of 6%. As of 2012, the central government kept 7.5% of this revenue, 5% went to the state government, while the municipality was allocated 87%. The remaining 0.5% was distributed to municipalities with ports where the gold was exported.

Most of the revenue allocated to the local government must, by law, be used to improve infant mortality, health access, education coverage, clean water access and sanitation indicators.

3.1 Data on mining activity

Since there are no measurements of atmospheric or water-borne mercury levels, we approximate mercury use with gold extraction (by municipality production and by area of the mine).⁷ Mining location and area are obtained from the mining permit database maintained by the nongovernmental organization Tierra Minada based on official government records from the *Catastro Minero Colombiano*.⁸

We combine this information with gold production at the municipality level published by the government agency SIMCO (Sistema de Informacion Minero Colombiano), available since 2001.⁹. However, we focus on mining area, as opposed to production due to several reasons. First, production is only released at the municipality level. We were denied access to production data at the mine level by the Ministry of Mining due to confidentiality issues. Thus, from the production data we are unable to asses proximity from an active mine, or the nearest river from an active mine. Second, there are several inconsistencies in the production data: of the 7,7134 municipality-month observations with positive production, only 56% had at least one active mining permit.¹⁰ There have been reports of collusion between illegal miners and government officials in non-mining municipalities: officials report production as a means to "laundry" illegal gold, which in turn increases royalties revenues for the municipality (El Espectador, 2015b, 2015a). Finally, mining permits are a good proxy for mineral discovery that would lead to extraction of the mineral shortly thereafter, either legally or illegally. Therefore, mining permits are better proxy for overall mining activity than reported production, as the latter might have under or over reporting due to illegal and artisan mining.

The proportion of municipalities with gold permits has increased dramatically, while the increase in municipalities with gold production has been more modest (see Figure 2). Although part of this discrepancy between municipalities with

⁷Almost all (99.7%) of the municipality-month mercury observations for 2006-2012 are missing in the National Health Institute- Information System of Monitoring of Water for Human Consumption-SIVICAP http://www.ins.gov.co/sivicap/Paginas/sivicap.aspx

 $^{^{8}{\}rm The}$ full data set can be downloaded from <code>https://sites.google.com/site/tierraminada/</code>

 $^{^9\}mathrm{From}$ 2001 to 2003 the data was released annually, but since 2004 it has been published on a quarterly basis.

 $^{^{10}\}mathrm{This}$ is an upper bound, as we do not have data on environmental licenses, which are necessary to extract gold legally.

permits and municipalities with production is due to reporting problems, startup costs, and delays in acquiring environmental permits, illegal mining is also a driving force.



Figure 2:

The figures shows the evolution of the proportion of municipalities with some gold production and with some area designated for gold mining. Source: Ministerio de Minas y Energia de Colombia. Calculations: Authors.

Small-scale artisan and illegal mining are widespread in Colombia. According to the 2010 Mining Census, over 63% of mines do not have a permit, and therefore are not in our data. Given that small-scale mining is both an important source of mercury in Colombia (Cordy et al., 2011) and an important source of revenue for poor and marginalized people (World Bank, 2009), our analysis will make an effort to take the legality of mining into account. We classify municipalities as being prone to illegal mining or not depending on whether they had an illegal mine listed in the 2010 Mining Census. In the robustness section we present separate estimations for both types of municipalities.

3.2 Data on newborns

To assess health outcomes in newborns, we use the vital statistics database provided by the government statistics department (DANE). The vital statistics database contains information for all children born in the country. The information include APGAR score¹¹, weight, height, length of the gestation, hospital of birth and municipality where the mother lives. However, since AP-GAR is a subjective measure, we use an indicator for whether the newborn had a score below 7 as is common practice in the literature (Ehrenstein, 2009).¹². We standardize height and weight using information from the World Health Organization (2006). The vital statistics database also include information on the mother such as age, education, marital status, and whether she attended prenatal appointments or not.

We restrict the sample to municipalities close to gold mines.¹³ Summary statistics are presented in Table 1. About 4.5% of newborns have a low APGAR score, and most births are in a medical facility. The average age of the mothers is 25, with a range from 9 to 54 years old. The Low Birth Weight (LBW) rate is low and comparable with more developed nations; however, this is not the national average as this are only the births included in our estimation sample (i.e., in municipalities within 25 km of a mine permit at some point in time and excluding the Orinoco and Amazonia regions).¹⁴

Table 1: Summary statistics for births

	Mean	Median	Std. Dev.	Min	Max	Ν
Low APGAR	4.55	0	20.8	0	100	4019952
In-hospital birth (%)	99.7	100	5.46	0	100	4019952
Weight (gr)	3163.6	3200	461.4	1500	4300	4019952
Low birth weight $(\%)$	6.88	0	25.3	0	100	4019952
Height (cm)	49.6	50	2.35	40	55	4019952
Stunted (%)	6.60	0	24.8	0	100	4019952
Mother's age	24.8	24	6.60	9	54	4019952
Single mother (%)	17.1	0	37.7	0	100	4019952
Mother has post-primary education (%)	67.5	100	46.8	0	100	4019952

Summary statistics for all births from 1999 to 2012 in municipalities within 25 km of a mine permit at some point in time. Low APGAR(=1) indicates whether the baby had an APGAR score below 7 measured 1 minute after birth. In-hospital(=1) indicates whether the birth took place in a medical facility. Weight is the weight (in gr) of the newborn at birth, Low Birth Weght indicates if the newborn had a weight below 2500 gr. Height is the height (in cm) of the newborn at birth. Stunted (=1) if the normalized height (using information from World Health Organization (2006)) is less than -2 standard deviations. Mother's Age is the mother sage in years; Single mother is equal to one if the mother self reports as single; Mother has post primary education indicates if the mother has any secondary or tertiary education. Source: DANE. Calculations: Authors.

 11 The doctor assigns a value from 0 to 2 for each of the following categories: Appearance, Pulse, Grimace, Activity and Respiration. Thus the total possible maximum score is 10 (Montgomery, 2000).

¹²Additionally, the continuous measure is only available since 2008.

 13 Specifically, we consider municipalities with a border within 25 km of a gold mine. Note that the population might live further from the mine if the municipality is big. We exclude the Amazon and Orinoquia regions, and exclude outliers in which more than 15% of the municipalities area is covered by a mining title (i.e, those who are above the 99th percentile for mined area).

 14 The incidence of Low Birth Weight is lower than the national average of 9% because we exclude municipalities far away from the mines especially Bogota where the incidence is 13% and has 20% of the population.

4 Identification strategies

4.1 Spatial exposure to mining

Our identification strategy is a difference-in-differences that compares births near mines with those far from them, before and after mining begins. In order to do this, we must identify births near mines, as well as births downstream from mines. To do the former, we create 5, 10 and 20-kilometer buffers around each mine, and calculate for each municipality the average mined area per capita in a given period (*NearMining_{mt}*).¹⁵

To identify births downstream from mines, we would ideally classify each municipality as being upstream or downstream from a mine. Unfortunately this is not feasible as rivers often enter and exit municipalities several times; therefore, we estimate the exposure to upstream mining in each municipality through various steps. First, using a data set of all rivers in Colombia we identify the closest river to each mine (usually running through the mine¹⁶). For each river segment we calculate the total area from active mines closest to it; and aggregate the total area upstream up to 25 km.¹⁷. In short, the total exposure in river segment j is estimated by:

$$River_Exposure_j = \sum_{i \in U_j} 1_{D(i,j) < 25} Area_i,$$

where U_j is the set of river segments located upstream from segment j, D(i, j) is the distance (following the course of the river) from segment j to segment i in kilometers, $Area_i$ is the total area of active mining titles to which river section i is the closest river to them. The pollution value for segment j therefore depends on how many mines pollute segments upstream, and the size of such mines. We then create 5, 10 and 20-kilometer buffers along the river and calculate the the average area mined upstream per capita in a given period for each municipality $(UpstreamMining_{mt})$.¹⁸. These calculations are done using geographical information systems (GIS) in R.

We use this measure of "upstream mining" to identify the effect of pollution from gold mining on health. However, there is an important underlying assumption in this approach: pollutants that are discharged into the river do not affect the

 $^{^{15}{\}rm More}$ explicitly, for buffer we create a raster with the mined area and multiply it with the population raster of each municipality. We then sum this over each municipality, and calculate the value per capita.

 $^{^{16}}$ A river runs through the entitled area of 48% of the mines. The average distance from the mines to a river is 0.8 km, and the furthest is 5 km (the presence of small creeks is not considered, as they do not appear in our river's database).

 $^{^{17}}$ Bose-O'Reilly et al. (2010) finds that fish more than 25 km downstream from a mine in Tanzania have a low concentration of mercury. The actual concentration of mercury depends on the type of soil, water flow, and other variables that are not available.

¹⁸More explicitly, for buffer we create a raster with the upstream mined area and multiply it with the population raster of each municipality. We then sum this over each municipality, and calculate the value per capita.

population living upstream. A necessary condition for this assumption is that fish eaten by humans are caught locally and do not travel upstream.

The specific regression we estimate is:

$$Y_{imt} = \beta_1 NearMining_{mt} + \beta_2 UpstreamMining_{mt} + X_i \alpha + \gamma_m + \gamma_t + \lambda_{s(m)} \times t + \varepsilon_{imt}, \quad (1)$$

where $NearMining_{mt}$ is a measure of exposure to mines nearby (in all directions) constructed as explained previously. $UpstreamMining_{mt}$ is a measure of exposure to pollution discharged upstream from municipality m at time t constructed as explained above. This variable measures the area (in km^2) mined upstream to which the average inhabitant in municipality m at time t is exposed. Notice that upstream here is any mine that is less than 25 kilometers away from the municipality (along the river) and an individual is exposed if he is within the buffer of the river. γ_m are municipality fixed effects to control for initial differences in mining municipalities (see Ibanez and Laverde (2014)). γ_t are year and week of the year fixed effects and $\lambda_{s(m)} \times t$ are state dummy variables interacted with a time trend to allow for differential time trends for each state. The coefficients of interest are β_1 and β_2 . β_1 captures the net (income and pollution) effect of mining on nearby communities and β_2 allows us to capture the negative externalities (if any) that mining has on downstream communities.

Measurement error is a problem for our measures of mining activity due to illegal mining and differences between the area licensed and the actual area exploited. Additionally, although our spatial calculations try to estimate in the best possible manner exposure to gold mining, they are far from perfect: a) mines can potentially discharge their waste in other rivers; b) we do not have the exact location of each mother's dwelling and must therefore rely on municipality averages. For this reasons our main specification uses dummy variables that indicate whether the municipalities had any exposure (*NearMining_{mt}* > 0 and *UpstreamMining_{mt}* > 0). This is the strategy used in most articles studying the effects of mining.¹⁹

We test whether there is any difference in the trends of newborns before and after mining begins in a municipality. Given that we can not observe newborns before birth, we collapse the data at the municipality-quarter level and estimate the following regression:

$$Y_{mt} = \sum_{j=-6}^{6} \beta_{\tau} \mathbf{1}_{\tau_m+j=t} + \sum_{j=-6}^{6} \alpha_{\pi} \mathbf{1}_{\pi_m+j=t} + \gamma_m + \gamma_t + \lambda_{r(m)} \times t + \varepsilon_{mt}, \quad (2)$$

where τ_m is the quarter in which municipality m has a mine nearby for the first time and π_m is the quarter in which municipality m has a mine upstream for the

¹⁹For example, see von der Goltz and Barnwal (2014) and Santos (2014).

first time. Therefore $1_{\tau_m+j=t}$ and $1_{\pi_m+j=t}$ are indicator variables that are equal to one if year t is j years before/after "near mining" and "upstream mining" begins. Notice that for municipalities that have no exposure these dummies are equal to zero. We plot $\beta_{-6}, ..., \beta_6$ to see how the Y_{mt} changes at the municipality level before and after mining nearby begins. Similarly, we plot $\alpha_{-6}, ..., \alpha_6$ to see how the Y_{mt} changes at the municipality level before and after upstream mining begins.

4.2 Holy Week

Colombia is predominantly a Catholic country, with over 75% of the population declaring themselves as Catholic.²⁰ Holy Week is one of the major Catholic traditions, and both Maundy Thursday and Good Friday are national holidays. Fish consumption increases during Holy Week by 60% (El Colombiano, 2014), and, together with the increase in fish consumption during Lent, this represents an approximate 5% increase in fish consumption during the gestation period of a baby.²¹ We use this exogenous increase in fish consumption to estimate the treatment effect of methyl-mercury exposure on health. An advantage of using Holy Week is that its exact date varies from year to year²² allowing us to partially separate the effect of mercury exposure from seasonal effects. Specifically, we estimate the following equation:

$$Y_{imt} = \beta_1 Gold_{mt} + \beta_2 Holy_week_i + \beta_3 Gold_{mt} \times Holy_week_i + X_i \alpha + \gamma_m + \gamma_t + \lambda_{s(m)} \times t + \varepsilon_{imt}, \quad (3)$$

where $Holy_week_i$ is a dummy variable that indicates whether individual *i*'s gestational period overlaps with Holy Week and γ_m are municipality fixed effects. Note that γ_t includes week fixed effects so we are not capturing seasonal effects. The coefficient of interest is β_3 , which captures the differential effect that eating more fish during gestation has on newborns in areas with gold production or affected by pollution from gold mines, while β_2 measures the effect of the gestational period overlapping with Holy Week (e.g., through additional fish consumption or behavioral change for religious reason) and β_1 captures the net effect of gold mining on newborns' health.

There are however three main problems with this exercise. First, we are only able to partially separate any seasonal effects as Holy Week only varies within a 34-day period. Second, nearly 75% of newborn have a gestational period that overlaps with Holy Week at some point, and the exogenous increase in fish

 $^{^{20}\}mathrm{According}$ to Latinbarometro 2011. The number is closer to 80% according to the Pew Research: Religion & Public Life Project 2012.

 $^{^{21}}$ From a survey of fish vendors in 14 municipalities, we found that prices during Holy Week are the same as the rest of the year for 88% of 171 species-market observations and on average prices increase by 3%. Consequently, we do not expect differentiated effects by income.

 $^{^{22}}$ Since 525 A.D., the last day of Holy Week (Easter) has been established as the Sunday after the first full moon following the March equinox. Therefore, the holiday varies from year to year, but it is always between March 22 and April 25.

consumption only lasts for one week of the entire gestational period. Third, fish is often not eaten where it is caught. On a survey we did in 2014 we found that 59% of species-markets observations come from intermediaries from other unknown municipalities. All these problems make this empirical exercise lowpowered, but we include it since the results suggest that increased consumption of fish from polluted rivers has negative effects on health.

5 Results

5.1 Spatial exposure

The results from estimating the effect of mining on nearby and downstream municipalities (equation 1) are presented in Table 2. Panel A shows that although the net effect of gold mining activity on the APGAR score of newborns in surrounding populations is positive, the effect on downstream populations is negative. We find that the likelihood of having low APGAR births decreases for mothers living within 20 km from a mine by 0.51 percentage points (Panel A, Column 1) (a reduction of 11%), while the likelihood increases for mothers living downstream from a mine by 0.45 percentage points (an increase of 9.8%). These results have several implications: First, the costs and benefits of mining are not uniformly distributed across space; second, the costs of mining for the whole country could potentially be greater than the benefits for the mining municipalities. In particular, in our sample, 69.90% take place downstream from an active mine, while 58.98% take place in the vicinity of a mine²³. Figures 5-6 in Appendix B show a detail distribution of births and municipalities near and downstream from mines across time. Panel B shows that these effects decay with distance (as expected), but are persistent up to 20 kilometers. Living near a mine has no effect on Low Birth Weight or Stunting, while having mining activity upstream seems to increase the likelihood of stunting by 0.29 percentage points. We are not aware of any study relating mercury or mining to stunned birth and the effect does not decay with distance (it seems to increase), therefore we do not place much emphasis on this result and attribute it to sampling variation.

 $^{^{23}56.7\%}$ of births take place simultaneously downstream from a mine and in the vicinity of a mine.

Table 2: Effect of promiting	and mer ponderor	i enposare on siren	outcomes	
Dependent variable:				
	Low APGAR	Low Birth Weight	Stunting	
Panel A: Exposure up to	$20 \ \mathrm{KM}$			
Near mining 20 km > 0	-0.51*	-0.041	0.058	
	(0.27)	(0.081)	(0.12)	
Mining upstream 20 km > 0	0.45^{***}	-0.0026	0.29^{***}	
	(0.15)	(0.080)	(0.10)	
N. of obs.	4019952	4019952	4019952	
Municipalities	642	642	642	
Mean of Dep. Var.	4.55	6.88	6.60	
R^2	0.017	0.0041	0.0049	
Panel B: Exposure by dis	tance			
Near mining $5 \text{ km} > 0$	-0.90**	0.040	-0.10	
	(0.37)	(0.12)	(0.19)	
Near mining 5-10 km > 0	-0.61**	-0.11	0.047	
	(0.28)	(0.11)	(0.17)	
Near mining 10-20 km > 0	-0.42*	-0.0075	0.15	
	(0.25)	(0.085)	(0.13)	
Mining upstream $5 \text{ km} > 0$	0.62**	-0.015	0.33^{*}	
	(0.28)	(0.13)	(0.18)	
Mining upstream 5-10 km > 0	0.59**	-0.15	0.17	
	(0.28)	(0.13)	(0.19)	
Mining upstream 10-20 km $>$	0 0.40**	0.030	0.32^{***}	
	(0.19)	(0.081)	(0.100)	
N. of obs.	4019952	4019952	4019952	
Municipalities	642	642	642	
Mean of Dep. Var.	4.55	6.88	6.60	
R^2	0.017	0.0041	0.0049	

Table 2: Effect of proximity and river pollution exposure on birth outcomes

All regressions include municipality fixed effects, time fixed effects, individual controls and regional trends. Time fixed effects are year and week fixed effects. Individual controls include mother's age, an indicator for single mother and an indicator for whether the mother has any post-primary education. The regional trends allow for a trend for each geographic region (Pacific, Andean and Caribbean). Standard errors, clustered by municipalities, are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

The main threat to identification is that the parallel trends assumption is not met; namely, that municipalities exposed to mining experience a differential trend in the likelihood of Low APGAR in births prior to the exposure compared to other municipalities. Figure 3 shows the result from estimating equation 2. As can be seen, there is a structural change in the likelihood of Low APGAR between three and two years prior to the proximity exposure (matching the results from the previous section). As explained before, this is somewhat expected since prior exploration of the area brings employment and income to the region. However, notice that the effect of river exposure only appears the year that the actual mining title is given. This results matches our prior intuition since rivers should carry pollution only after mining begins.



This left panel shows estimated $\beta_{-6}, ..., \beta_6$ from 2, while the right panel shows the estimated $\alpha_{-6}, ..., \alpha_6$, together with a 95% confidence interval. β_{τ} is equal to 1 if there are τ years until the first proximity exposure, while α_{τ} is equal to 1 if there are τ years until the first river exposure. Notice that β_{-1} is omitted and set to zero. All regressions include municipality fixed effects, time fixed effects, and state trends. Time fixed effects are year and quarter fixed effects. Standard errors, clustered by municipalities, are in parentheses.

5.2 Holy Week

The results of the estimation including Holy Week are presented in Table 3. The first column shows the results defining gestational overlap with Holy Week as equal to one if the newborn gestational period overlap with Holy Week at any point. The second column identifies what trimester, if any, of the gestational period overlaps with Holy Week. Recall that these regressions include week fixed effects to isolate the effect of Holy Week from any seasonal effects.

Holy Week reduces the probability of newborns having a low APGAR score. This might be due to extra fish consumption or to items given up during Lent. The effect is concentrated in babies for which the first weeks of gestation coincide with Holy Week. The coefficient of the interaction between river proximity and Holy Week is positive and statistically significant (Column 1). Since the brain is more susceptible to damage during the first two trimesters and brain development is affected by mercury exposure (see Section 2), we also analyze when (and not only if) does Holy Week overlap with gestation (Column 2). As can be seen the interaction between river exposure and an overlap of Holy Week with the first trimester of gestation increases the likelihood of a Low APGAR birth. Note that the magnitude is large compared to the coefficient of river exposure. We take this as evidence that polluted water is not the problem, but rather contaminated fish consumption.

Table 3: Increased mercury exposure in-utero due to Holy Week				
Dependent variable: Low	APGAR			
	(1)	(2)		
Holy Week	-0.79***			
·	(0.10)			
Near mining 20 km > 0	-0.36	-0.36		
	(0.31)	(0.31)		
Mining upstream 20 km > 0	0.33^{*}	0.33^{*}		
	(0.18)	(0.18)		
Near mining \times Holy Week	-0.15			
	(0.095)			
Upstream mining \times Holy Week	0.20^{*}			
	(0.11)			
Holyweek 1st trimester		-0.30***		
		(0.11)		
Holyweek 2nd trimester		-0.55***		
		(0.13)		
Holyweek 3rd trimester		-1.04***		
		(0.13)		
Near mining \times Holy Week 1st Trim		-0.12		
		(0.11)		
Near mining \times Holy Week 2nd Trim		-0.16		
		(0.11)		
Near mining \times Holy Week 3rd Trim		-0.18		
II. stars and a finite of the la Weals 1 at Their	_	(0.11)		
$Opstream mining \times Holy week 1st 1fm$	1	(0.12)		
Unstroom mining & Halv Wool and Tri	~	(0.13)		
Opstream mining × Hory week 2nd 1rn	.11	(0.22)		
Upstroom mining × Holy Wook and Trin	n	(0.14)		
opstream mining × nory week 5rd 111	11	(0.100)		
N of obs	3567788	3567788		
Mean of Dep Var	4 48	4 48		
R^2	0.017	0.017		

All regressions include municipality fixed effects, time fixed effects, individual controls and state trends. Time fixed effects are year and week of the year fixed effects. Individual controls include mother's age, an indicator for single mother and an indicator for whether the mother has any post-primary education. Standard errors, clustered by municipalities, are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

6 Robustness checks

In this section we check the robustness of our results to using other measures of mining activity; interacting our measures of mining with the price of gold; the effect of gold mining on fiscal measures; possible changes on mother characteristics due to mining; and illegal mining.

6.1 Other measures of mining activity

In order to asses the robustness of our results to the spatial measures we use, we repeat our main regressions using simple measures of mining activity. The measures we use are the proportion of the area of the municipality that is mined, the accumulated production by municipality and indicators of these variables being positive. The results are presented in table 4 on the Appendix. We find that having mining area in the municipality reduces the probability of a baby born with low APGAR by 0.58 percentage points (column 1 Panel B). This is similar in magnitude to the coefficient of 0.51 when using our dummy of "near mining". However for accumulated production the sign is not stable when using the continuous measure or the dummy. This is probably due to the reporting problems mentioned in Section 3.1.

6.2 Price of gold

The income effect of gold mining depends on the price of gold via more income for the same quantity extracted and also because a higher price encourages more extraction. We present the results of interacting the mining variables with the price of gold in Table 5. Column 1 repeats the main results of table 2, while column 2 presents the analogous regressions with the mining variables interacted with the price of gold. This exercise shows, as before, that the net effect of gold mining is positive. In places with any mining (i.e., mining area > 0) an increase of 10 dollars in the price of gold (per troy ounce) is associated with a 0.01 percentage-point improvement in the APGAR scores of newborns.

6.3 Fiscal effect on municipalities

We do not have household level data to analyze assets or consumption of households, but we do have information on the municipality budgets. Table 6 presents the effect of gold production in municipality budget and royalties. There is no significative effect of our mining measure on the fiscal variables of the municipality.

6.4 Birth and mother characteristics

We estimate the analogous of equation 1 using as the dependent variable different municipality and mother characteristics to see if there is any selection in our sample. In particular, at the municipality level we check whether the number of births, the perinatal mortality, or the infant mortality change when exposure to mining changes. At the individual level we check whether the number of prenatal checkups, the likelihood of a premature birth, the likelihood of in-hospital birth, the likelihood that the mother has subsidize health care and the mother's age, marital status and education change when exposure to mining changes.

Table 7 shows that proximity to a gold mine (Column 1) increases the likelihood of in-hospital births and more than four pre-natal checkups and reduces the likelihood of premature birth. These results can be taken as signs of selection into our sample, but also as evidence of the mechanisms behind the "positive" effect of mining on APGAR scores. Specifically, as mining royalties must be partially spend on health and to reduce infant mortality, mining increases the availability of health care (and therefore increases the likelihood of in-hospital births and at least 4 pre-natal checkups) and reduces perinatal and infant mortality, as well as premature births. The results in Column 2 show that river exposure has no impact on the number of births, their characteristics or mother characteristics. The point estimates are consistently close to zero and statistically insignificant. We take this as evidence that there is no sorting due to upstream pollution or proximity to mines, and therefore that our estimates are free of sample bias.

6.5 Illegal mining

Table 8 provides the results of estimating equation 1 separately for municipalities that are prone to illegal mining and those that are not (see section 3.1). The magnitude of the coefficient is considerably higher municipalities prone to illegal mining. This could be because the number of legal mines in our database represents an underestimation of the actual number of mines in those municipalities. The fact that the coefficient of "near mining" is larger could also be to the fact that illegal mines use less capital and therefore employ more people, bringing more income to local households.

6.6 Using only the centroids of the mines

As mentioned one of the advantage of our data is that we know the exact shape and location of the mine, in contrast to previous studies that use a single point. To test the robustness of the results to this assumption, we repeat the regression results of Table 2 but using only the centroid of each mine as the location. The results are presented on Table 12. The coefficients for Panel A are basically unchanged. However, those of Panel B that use the distance gradient vary considerably. This is probably because if the mine is a circle of radius around 5km, when using a single point of location we will be miss-classifying the babies born at a distance between 5-10 km.

7 Conclusions and future work

Mining is an important revenue source for governments and households in some developing countries. However, there is mixed evidence on the overall welfare effect of mining. We contribute to this literature by estimating the net impact of gold mining on the health of newborns in Colombia. In particular, we estimate the effect on the health of newborns by using a difference in differences approach that compares municipalities before and after mining activity started. As the measure of gold activity, we use geographical information systems to estimate population near mines and mining upstream from a river.

We find that mothers living in the vicinity of a mine have a 0.51 percentage points lower probability of having low APGAR score births (from a basis of 4.5%). However, we find that mothers living in municipalities located downstream from a mine experience an increase of 0.45 percentage points in the probability of having low APGAR score births. We provide some suggestive evidence that contaminated-fish consumption is the main mechanisms behind our results by using an exogenous increase in fish consumption caused by the overlap of gestation and Holy Week, a religious holiday that increases fish consumption in the country.

The National Government has already put in place legislation to phase out mercury in mining by 2018. More information on health costs to other population groups and costs of mercury control technologies would be needed to do a full cost-benefit analysis. However, in the meantime mechanisms must be put in place in order to compensate municipalities located downstream from mining areas, as pollution externalities from mining negatively affects them.

The results presented rely on two main assumptions. First, we assume that controlling for time and location fixed effects allows us to estimate the net causal effect of mining on health. Second, we assume that pollution only affects downstream municipalities. These results should encourage future work based on information collected at the household level and actual pollution measurements.

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A Extra Tables

Table I. Other measures of mining detivity on shift outcomes					
	Low APGAR	Low Birth Weight	Stunting (3)		
	(1)	(2)	(0)		
Panel A: Proportion of mined ar	ea				
Mining Area/Municipality Area	-0.0029	0.0024	-0.0012		
	(0.013)	(0.0054)	(0.0066)		
Panel B: Indicator proportion of	mined area				
Mining Area/Municipality Area > 0	-0.58*	0.099	-0.058		
	(0.32)	(0.074)	(0.13)		
Panel C: Accumulated Production	on				
Accumulated Production	-0.0046	-0.010	-0.0048		
	(0.019)	(0.0062)	(0.0047)		
Panel D: Indicator accumulated production					
Production Accumulated > 0	0.10	0.0046	-0.23		
	(0.18)	(0.11)	(0.15)		
N. of obs.	4019952	4019952	4019952		
Municipalities	642	642	642		
Mean of Dep. Var.	4.55	6.88	6.60		
R^2	0.017	0.0041	0.0049		

Table 4: Other measures of mining activity on birth outcomes

All regressions include municipality fixed effects, time fixed effects, individual controls and state trends. Time fixed effects are year and week of the year fixed effects. Individual controls include mother's age, an indicator for single mother and an indicator for whether the mother has any post-primary education. Standard errors, clustered by municipalities, are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Dependent variable: Low	APGAR	
	(1)	(2)
Near mining 20 km > 0	-0.51*	
	(0.27)	
Mining upstream $20 \text{ km} > 0$	0.45^{***}	
	(0.15)	
Near mining 20 km > 0 x Price		-0.0016**
		(0.00081)
Mining upstream $20 \text{ km} > 0 \text{ x}$ Price		0.0011^{**}
		(0.00049)
N. of obs.	4019952	3567788
Municipalities	642	642
Mean of Dep. Var.	4.55	4.48
R^2	0.017	0.017

Table 5: Net effect of mining on APGAR scores for different measures of mining interacted with gold price

All regressions include municipality fixed effects, time fixed effects, individual controls and state trends. Time fixed effects are year and week of the year fixed effects. Individual controls include mother's age, an indicator for single mother and an indicator for whether the mother has any post-primary education. Standard errors, clustered by municipalities, are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 6: Effect of mining on muncipality budget and royaltie's income

Dependent variable:				
	Total budget Royalt			
	(1)	(2)		
Near mining 20 km > 0	-5047.5	147.1		
	(5375.5)	(232.8)		
Mining upstream 20 km > 0	1609.9	-43.5		
	(5227.2)	(213.0)		
N. of obs.	90396	90396		
Municipalities	642	642		
Mean of Dep. Var.				
R^2	0.85	0.66		

All regressions include time fixed effects and state trends. Time fixed effects are quarter and year fixed effects. Standard errors, clustered by municipalities, are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Panel A: Municipality Characteristics				
	(1)	(2)		
IMR	-0.0268	-0.177		
	(0.109)	(0.121)		
PNM	-0.0512	0.233		
	(0.507)	(0.610)		
Births	26.99^{*}	-5.600		
	(13.33)	(22.06)		
Fertility	-0.0000148	-0.00000289		
	(0.0000267)	(0.0000289)		
Panel B: Mother and Birth Charact	eristics			
	(1)	(2)		
Prenatal checkups > 4	0.0166^{*}	-0.0149*		
	(0.00691)	(0.00607)		
Premature	-0.00385	-0.000114		
	(0.00286)	(0.00282)		
In-hospital birth	0.0489	-0.0760		
	(0.0592)	(0.0815)		
Mother's age	-0.0734^{*}	0.0202		
	(0.0368)	(0.0350)		
Single Mother	0.682^{*}	-0.384		
	(0.274)	(0.300)		
At least secondary education (mother)	0.841	0.618		
	(1.025)	(1.054)		

 Table 7: Effect of mining on mother characteristics

 Proximity 20 KM
 River Exposure 20 KM

Each row/column shows the results from a different regression. Column 1 shows the coefficient from a dummy that indicates whether there is any mining title in the municipality. Column 2 and 3 shows the coefficient from a dummy that indicates whether there is proximity or river exposure to mining. Panel A regressions include time and municipality fixed effects and state trends. Time fixed effects are quarter and year fixed effects. Panel B regressions include municipality fixed effects, time fixed effects, and state trends. Time fixed effects, time fixed effects, and state trends. Time fixed effects. Standard errors, clustered by municipalities, are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 8: Effect of mining on birth outcomes by illegal mining					
(1) (2) (3)					
	All	Legal	Illegal		
Panel A: Any mining title					
Near mining 20 km > 0	-0.51*	-0.17	-1.36		
	(0.27)	(0.25)	(0.90)		
Mining upstream 20 km > 0	0.45^{***}	0.25	0.53^{**}		
	(0.15)	(0.20)	(0.21)		
N. of obs.	4019952	2615455	1404497		
Municipalities	642	489	153		
Mean of Dep. Var.	4.55	4.57	4.51		
R^2	0.017	0.014	0.023		

All regressions include municipality fixed effects, time fixed effects, individual controls and state trends. Time fixed effects are year and week of the year fixed effects. Individual controls include mother's age, an indicator for single mother and an indicator for whether the mother has any post-primary education. Standard errors, clustered by municipalities, are in parentheses. * p < 0.10, *** p < 0.05, *** p < 0.01

Table 9: Summary statistics for mines

Table 9. Summary statistics for milles						
	Mean	Median	Std. Dev.	Min	Max	Ν
Prudction(gr.)	12856.4	0	71206.4	0	769456.2	4019952
Mining Area/Municipality Area (Unconditional)	1.09	0	4.53	0	42.7	4019952
Mining Area/Municipality Area > 0	0.23	0	0.42	0	1	4019952
Mining Area/Municipality Area (Conditional)	4.69	0.85	8.45	0.0000011	42.7	934984
Near mining 20 km > 0	0.61	1	0.49	0	1	4019952
Mining upstream 20 km > 0	0.72	1	0.45	0	1	4019952

Source: Catastro Minero Colombiano. Calculations: Authors.

	$\begin{array}{c} \text{APGAR score (0-10)} \\ (1) \end{array}$	Birth Weight (gr) (2)	Height (cm) (3)
Near mining 20 km > 0	0.050**	-0.75	0.022
	(0.020)	(3.99)	(0.025)
Mining upstream 20 km > 0	-0.014	1.68	-0.078***
	(0.024)	(3.81)	(0.022)
N. of obs.	1643226	4019952	4019952
Municipalities	642	642	642
Mean of Dep. Var.			
R^2	0.070	0.026	0.033

Table 10: Effect of proximity and river pollution exposure on birth outcomes: Continuus outcomes

All regressions include municipality fixed effects, time fixed effects, individual controls and state trends. Time fixed effects are year and week of the year fixed effects. Individual controls include mother's age, an indicator for single mother and an indicator for whether the mother has any post-primary education. Standard errors, clustered by municipalities, are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

 Table 11: Effect of proximity and river pollution exposure on birth outcomes:

 Intensive margin

Dependent variable: Low APGAR					
	(1)	(2)	(3)		
Near mining 20 km	-0.010	-0.0059**	-0.010**		
	(0.0064)	(0.0025)	(0.0040)		
Mining upstream 20 km	-0.0026	0.0022^{**}	-0.00094		
	(0.0030)	(0.00100)	(0.0011)		
N. of obs.	4019952	4019952	4019952		
Municipalities	642	642	642		
Mean of Dep. Var.					
R^2	0.017	0.0041	0.0049		

All regressions include municipality fixed effects, time fixed effects, individual controls and state trends. Time fixed effects are year and week of the year fixed effects. Individual controls include mother's age, an indicator for single mother and an indicator for whether the mother has any post-primary education. Standard errors, clustered by municipalities, are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Low APGAR Low Birth Weight Stu Panel A: Exposure up to 20 KM Near mining 20 km > 0 -0.51^* 0.019 0 Mining upstream 20 km > 0 0.43^{***} -0.011 0.50^{-1} 0.0083 00^{-1} Mining upstream 20 km > 0 0.43^{***} -0.011 0.50^{-1} 0.075 00^{-1} N. of obs. 4019952 4019952 4019952 401 Municipalities 642 642 642 66 Mean of Dep. Var. 4.55 6.88 66^{-1} R^2 0.017 0.0041 0.00^{-1} Near mining 5 km > 0 -0.71 0.095^{-1} -0.28^{-1} Near mining 5-10 km > 0 -0.28^{-1} -0.035^{-1} 0.0041^{-1} Near mining 10-20 km > 0 -0.48^{**} 0.045^{-1} 0.009^{-1} 0.009^{-1} Mining upstream 5-10 km > 0 0.44^{*} -0.18^{-1} 0.009^{-1} 0.009^{-1} Mining upstream 10-20 km > 0 0.45^{**} 0.014^{-1} 0.0^{-1} 0.0073^{-1}]	Dependent variable	pendent variable:	
Panel A: Exposure up to 20 KM Near mining 20 km > 0 -0.51^* 0.019 0 Mining upstream 20 km > 0 0.43^{***} -0.011 0.5 Mining upstream 20 km > 0 0.43^{***} -0.011 0.5 Municipalities 642 642 642 Mean of Dep. Var. 4.55 6.88 6 R^2 0.017 0.0041 0.06 Panel B: Exposure by distance (0.43) (0.13) $(0$ Near mining 5 km > 0 -0.71 0.095 -0.66 Near mining 5-10 km > 0 -0.28 -0.035 -0.66 Near mining 10-20 km > 0 -0.48^{**} 0.045 0.56 Mining upstream 5 km > 0 0.39 -0.019 0.666 Mining upstream 5-10 km > 0 0.44^{**} -0.18 0 Mining upstream 10-20 km > 0 0.45^{**} 0.014 0.566 Mining upstream 10-20 km > 0 0.45^{**} 0.014 0.566 Mining upstream 10-20 km > 0 0.45^{**} 0.014 0.566 Mining upstream 10-20 km > 0 </th <th></th> <th>Low APGAR</th> <th>Low Birth Weight</th> <th>Stunting</th>		Low APGAR	Low Birth Weight	Stunting
Near mining 20 km > 0 -0.51^* 0.019 0 Mining upstream 20 km > 0 0.43^{***} -0.011 $0.500000000000000000000000000000000000$	anel A: Exposure up to 2	20 KM		
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Near mining $20 \text{ km} > 0$	-0.51*	0.019	0.13
Mining upstream 20 km > 0 0.43^{***} -0.011 0.5 N. of obs. 4019952 4019952 401 Municipalities 642 642 642 Mean of Dep. Var. 4.55 6.88 6 R^2 0.017 0.0041 0.017 Panel B: Exposure by distance Near mining 5 km > 0 -0.71 0.095 -0.60 Near mining 5-10 km > 0 -0.28 -0.035 -0 Near mining 10-20 km > 0 -0.48^{**} 0.045 0.5 Mining upstream 5 km > 0 0.39 -0.019 0.5 Mining upstream 5-10 km > 0 0.44^* -0.18 0 Mining upstream 10-20 km > 0 0.45^{**} 0.014 0.5 Municipalities 642 642 642 Municipalities 642 642 642 Mean of Dep. Var. 4.55 6.88 6		(0.27)	(0.083)	(0.12)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Mining upstream 20 km > 0	0.43^{***}	-0.011	0.22^{**}
N. of obs. 4019952 4019952 4019952 401 Municipalities 642 642 642 662 Mean of Dep. Var. 4.55 6.88 66 R^2 0.017 0.0041 0.016 Panel B: Exposure by distance 0.017 0.0041 0.066 Near mining 5 km > 0 -0.71 0.095 -0.666 Near mining 5-10 km > 0 -0.28 -0.035 $-0.666666666666666666666666666666666666$		(0.15)	(0.075)	(0.10)
Municipalities 642 642 642 642 642 6688 66 R^2 0.017 0.0041 0.0 Panel B: Exposure by distance 0 -0.71 0.095 -0.66 Near mining 5 km > 0 -0.71 0.095 -0.66 (0.43) (0.13) (000) Near mining 5-10 km > 0 -0.28 -0.035 -0.66 (0.26) (0.11) (000) Near mining 10-20 km > 0 -0.48^{**} 0.045 0.52 (0.24) (0.092) (000) Mining upstream 5 km > 0 0.39 -0.019 0.52 (0.14) (000) Mining upstream 5-10 km > 0 0.44^{**} -0.18 00 (0.26) (0.13) (000) Mining upstream 10-20 km > 0 0.45^{**} 0.014 0.52 (0.18) (0.073) (000) N. of obs. 4019952 4019952 4019952 4019952 4019952 4019952 Municipalities 642 642 <th< td=""><td>. of obs.</td><td>4019952</td><td>4019952</td><td>4019952</td></th<>	. of obs.	4019952	4019952	4019952
Mean of Dep. Var. 4.55 6.88 6 R^2 0.017 0.0041 0.0 Panel B: Exposure by distance (0.43) (0.13) $(0$ Near mining 5 km > 0 -0.71 0.095 -0 Near mining 5-10 km > 0 -0.28 -0.035 -0 Near mining 10-20 km > 0 -0.48^{**} 0.045 0.5 Near mining 10-20 km > 0 -0.48^{**} 0.045 0.5 Mining upstream 5 km > 0 0.39 -0.019 0.6 Mining upstream 5-10 km > 0 0.44^{**} -0.18 0 Mining upstream 10-20 km > 0 0.44^{**} -0.18 0 Mining upstream 10-20 km > 0 0.44^{**} -0.18 0 Mining upstream 10-20 km > 0 0.45^{**} 0.014 0.5 Municipalities 642	Iunicipalities	642	642	642
R^2 0.017 0.0041 0.0 Panel B: Exposure by distance Near mining 5 km > 0 -0.71 0.095 -0 (0.43) (0.13) (0 Near mining 5-10 km > 0 -0.28 -0.035 -0 (0.26) (0.11) (0 Near mining 10-20 km > 0 -0.48** 0.045 0.5 (0.24) (0.092) (0 Mining upstream 5 km > 0 0.39 -0.019 0. (0.28) (0.14) (0 Mining upstream 5-10 km > 0 0.44* -0.18 0 (0.26) (0.13) (0 Mining upstream 10-20 km > 0 0.45** 0.014 0.5 (0.18) (0.073) (0 N. of obs. 4019952 4019952 401 Municipalities 642 642 6 Mean of Dep. Var. 4.55 6.88 6	lean of Dep. Var.	4.55	6.88	6.60
Panel B: Exposure by distance Near mining 5 km > 0 -0.71 0.095 -0 (0.43) (0.13) (0 Near mining 5-10 km > 0 -0.28 -0.035 -0 (0.26) (0.11) (0 Near mining 10-20 km > 0 -0.48** 0.045 0.5 (0.24) (0.092) (0 Mining upstream 5 km > 0 0.39 -0.019 0. (0.28) (0.14) (0 Mining upstream 5-10 km > 0 0.44* -0.18 0 (0.26) (0.13) (0 Mining upstream 10-20 km > 0 0.45** 0.014 0.5 (0.18) (0.073) (0 N. of obs. 4019952 4019952 401 Municipalities 642 642 6 Mean of Dep. Var. 4.55 6.88 6	2	0.017	0.0041	0.0049
Near mining 5 km > 0 -0.71 0.095 -0.095 Near mining 5-10 km > 0 -0.28 -0.035 -0 Near mining 10-20 km > 0 -0.48** 0.045 0.2 Near mining 10-20 km > 0 -0.48** 0.045 0.2 Mining upstream 5 km > 0 0.39 -0.019 0. Mining upstream 5-10 km > 0 0.44* -0.18 0 Mining upstream 10-20 km > 0 0.45** 0.014 0.5 No of obs. 4019952 4019952 4019952 Municipalities 642 642 6 Mean of Dep. Var. 4.55 6.88 6	anel B: Exposure by dist	ance		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Near mining $5 \text{ km} > 0$	-0.71	0.095	-0.11
Near mining 5-10 km > 0 -0.28 -0.035 -0 (0.26) (0.11) (0 Near mining 10-20 km > 0 -0.48^{**} 0.045 0.5 (0.24) (0.092) (0 Mining upstream 5 km > 0 0.39 -0.019 $0.$ Mining upstream 5-10 km > 0 0.44^* -0.18 0 Mining upstream 10-20 km > 0 0.45^{**} 0.014 0.5 Mining upstream 10-20 km > 0 0.45^{**} 0.014 0.5 Mining upstream 10-20 km > 0 0.45^{**} 0.014 0.5 Mining upstream 10-20 km > 0 0.45^{**} 0.014 0.5 Mining upstream 10-20 km > 0 0.45^{**} 0.014 0.5 Mining upstream 10-20 km > 0 0.45^{**} 0.014 0.5 Municipalities 642 642 642 642 Mean of Dep. Var. 4.55 6.88 6		(0.43)	(0.13)	(0.20)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Near mining 5-10 km > 0	-0.28	-0.035	-0.087
Near mining 10-20 km > 0 -0.48^{**} 0.045 0.24 Mining upstream 5 km > 0 0.39 -0.019 0.600 Mining upstream 5 km > 0 0.39 -0.019 0.600 Mining upstream 5-10 km > 0 0.44^{**} -0.18 0.6000 Mining upstream 10-20 km > 0 0.44^{**} -0.18 0.6000 Mining upstream 10-20 km > 0 0.45^{**} 0.014 0.2000 N. of obs. 4019952 4019952 401 Municipalities 642 642 642 Mean of Dep. Var. 4.55 6.88 600000		(0.26)	(0.11)	(0.16)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Near mining 10-20 km > 0	-0.48**	0.045	0.26^{**}
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.24)	(0.092)	(0.12)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Mining upstream 5 km >0	0.39	-0.019	0.33^{*}
$ \begin{array}{cccccc} \mbox{Mining upstream 5-10 km} > 0 & 0.44^{*} & -0.18 & 0 \\ & & & & & & & & & & & & & & & & &$		(0.28)	(0.14)	(0.17)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Mining upstream 5-10 km > 0	0.44^{*}	-0.18	0.19
		(0.26)	(0.13)	(0.17)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Mining upstream 10-20 km >0	0 0.45**	0.014	0.22^{**}
N. of obs. 4019952 4019952 401 Municipalities 642 642 642 Mean of Dep. Var. 4.55 6.88 6 P^2 0.017 0.0041 0.017		(0.18)	(0.073)	(0.10)
Municipalities 642 642 642 662 Mean of Dep. Var. 4.55 6.88 662 P^2 0.017 0.0041 0.017	. of obs.	4019952	4019952	4019952
Mean of Dep. Var. 4.55 6.88 6	Iunicipalities	642	642	642
D^2 0.017 0.0041 0.0	lean of Dep. Var.	4.55	6.88	6.60
R^{-} 0.017 0.0041 0.0	2	0.017	0.0041	0.0049

Table 12: Effect of proximity and river pollution exposure on birth outcomes

All regressions include municipality fixed effects, time fixed effects, individual controls and regional trends. Time fixed effects are year and week fixed effects. Individual controls include mother's age, an indicator for single mother and an indicator for whether the mother has any post-primary education. The regional trends allow for a trend for each geographic region (Pacific, Andean and Caribbean). Standard errors, clustered by municipalities, are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

B Extra Figures





Prevalence of mercury-related health events and gold mining. The solid black line represents the prevalence of mercury poisoning in Colombia per 100,000 individuals. The dotted red line represents gold production in the country. Source: Authors' calculations using Health Ministry data.

B.1 Impacts of different levels of mining

Given that we have the exact shape, size and location of each mine we can estimate the impact of different levels of mining activity, by deciles of the distribution of mining. In other words we estimate the following equation

$$Y_{imt} = \sum_{d=1}^{10} \beta_d q_{mt}^d + X_{imt} \alpha + \gamma_m + \gamma_t + \lambda_{r(m)} \times t + \varepsilon_{imt}, \qquad (4)$$

where q_{mt}^d indicates whether municipality m at time t is at the decile d of proportion of mined area. Notice that $q_{mt}^d = 0, \forall d$ for any municipality m at time t that has no mining titles. Figure 8 shows that the effect is similar for all deciles and we can not reject the null hypothesis that the coefficient β_d are all equal to each other, suggesting that the net effect of mining on newborns' health is positive and the same for all levels of mining. In other words, mining brings benefits, but higher levels of mining do not bring additional benefits.

Figure 5: Proportion of births near and downstream from a mine - 5 KM buffer



This figures shows the number of births and municipalities near/downstream from a mine using a buffer of 5 KM. The left panel has the proportion of births in our data near/downstream from a mine. The right panel has the proportion of municipalities in our data near/downstream from a mine.

Figure 6: Proportion of births near and downstream from a mine - 10 KM buffer



This figures shows the number of births and municipalities near/downstream from a mine using a buffer between 5 and 10 KM. The left panel has the proportion of births in our data near/downstream from a mine. The right panel has the proportion of municipalities in our data near/downstream from a mine.

Figure 7: Proportion of births near and downstream from a mine - 20 KM buffer



This figures shows the number of births and municipalities near/downstream from a mine using a buffer between 10 and 20 KM. The left panel has the proportion of births in our data near/downstream from a mine. The right panel has the proportion of municipalities in our data near/downstream from a mine.



Figure 8: Mined area and APGAR

Impact of different levels of mining activities on the probability of being born with low AP-GAR. The figure plots the coefficients of dummy variables that indicate whether the mining activity (proportion of mined area) is in a given decile. The bars indicate 95% confidence intervals. See equation 4