When Water Runs Red: Gold Mining and Birth Outcomes in the Brazilian Amazon

Luca Moreno-Louzada*

Abstract

A large literature documents that exposure to environmental toxins harms fetal development. This paper studies the Brazilian Amazon, where the expansion of small-scale gold mining releases mercury into river networks that supply predominantly poor, riverine, and Indigenous communities. My identification strategy exploits exogenous time variation stemming from the fluctuation of international gold prices, interacted with the distribution of geological gold deposits across municipalities. I then use the direction of river flows within water basins to identify the potentially treated populations as those that live in locations downstream from gold deposits. The results show a significant increase in birth anomalies and a small decrease in birthweight in treated populations when the price of gold increases, while there is no effect for populations living upstream from these locations.

1 Introduction

The expansion of gold mining is one of the many environmental threats to the Brazilian Amazon. In recent years, there has been a surge in gold extraction activities in the

*Originally an undergraduate thesis in Economics at the University of São Paulo, advised by Naercio Menezes-Filho region, particularly small-scale mining (*garimpo*). Mining inside protected areas increased more than 1000% in the past three decades, with half of this growth occurring between 2010 and 2020 (Mataveli et al. 2022; Siqueira-Gay and Sánchez 2021; MapBiomas 2022). Gold extraction often contaminates river systems supplying predominantly vulnerable populations with mercury, which is deemed one of the main chemicals of major public health concern (WHO 2017).[1] Toxicology evidence links mercury exposure to in-utero neurodevelopmental harm, birth anomalies, low birth weight, and miscarriage (Bjørklund et al. 2019; Dack et al. 2021; Grandjean et al. 1999; Rice et al. 2014).

Despite documented contamination downstream from mining and well-understood biological mechanisms, large-scale causal estimates linking Amazonian mining to birth outcomes remain limited. Most studies are local analyses with small sample sizes, that measure water, soil, or fish characteristics, and evaluate human health and contamination indicators (Crespo-Lopez et al. 2021). There are also reports linking high levels of birth defects and mercury contamination from mining in Indonesia and Suriname, for example, but these are only anecdotal (Paddock 2019; Federl and Nicas 2023). Globally, more than 5% of babies are born with congenital disorders — with over 90% of these births occurring in low and middle income countries —, leading to tens of thousands of deaths each year (WHO 2023). Therefore, though mechanisms for the association between mercury and birth defects are well described, providing large-scale causal evidence remains of great importance.

In this paper, I tackle this issue by estimating the effects of gold mining on health in the Amazon at a larger scale by using health microdata on the universe of births in the region. My identification strategy is similar to a difference-in-differences model, exploiting exogenous time variation stemming from the fluctuation of international gold prices

1. This issue garnered intense media attention in 2020 when reports showed devastating impacts on the Yanomami people, one of the largest tribes that remain relatively isolated in the Amazon Rainforest (Hernandez, Scarr, and Boadle 2020; Garcia et al. 2022). Besides water contamination, which is the focus of this paper, illegal mining is associated with deforestation, which not only leads to environmental degradation but also has social and health consequences for local populations, such as increasing malaria incidence (Castro and Peterka 2023).

interacted with the distribution of geological gold deposits across municipalities. I then use the direction of river flows within water basins to identify the potentially treated populations as those that live in locations downstream from gold deposits. This strategy is inspired by Dias, Rocha, and Soares (2023), who exploited variation in river flows to study the effects of glyphosate usage, and by Pereira and Pucci (2022) that used the geographical distribution of gold deposits to investigate the effects of illegal mining in the Amazon on conflict and homicides.

My results show a significant increase in the rate of birth anomalies in regions downstream from gold deposits in periods where mining activity increases. In terms of magnitude, the estimates imply an increase of about 6 birth anomalies per 10,000 births between 2013 and 2021 in the average municipality exposed to potential mining operations upstream, which represents an increase of 12%. In placebo exercises considering populations living *upstream* from gold deposits, I find null results, which supports the robustness of the identification strategy. These findings are also robust to a battery of robustness and sensitivity tests, such as the inclusion of sociodemographic controls, the addition of higher-level fixed effects to capture regional trends and estimation of count data models. I also find a small decrease in average birthweight and an increase in the rate of preterm births. These findings corroborate the interpretation that mercury contamination may worsen birth outcomes in general for populations downstream from gold extraction operations.

This paper adds to the growing literature in Economics studying the effects of exposure to environmental toxins on birth outcomes, which has focused mostly on air pollution (Chay and Greenstone 2003; Currie and Neidell 2005; Currie and Walker 2011; Hill 2018; Rangel and Vogl 2019) and drinking water (Flynn and Marcus 2021; Hill and Ma 2022). Especially relevant is Dias, Rocha, and Soares (2023) who show that glyphosate usage in Brazil increased infant mortality using a similar method to identify upstream and downstream populations. I add to this literature by exploring results in a novel setting, in which large scale exposure to water pollution from gold mining affects vulnerable populations. More specifically, my results speak to the large literature in toxicology and public health about the negative effects of mercury contamination (Dack et al. 2021; Rice et al. 2014), as well as to the literature on the consequences of gold mining in the Amazon (Pereira and Pucci 2022; Castro and Peterka 2023). My findings are also related to a broader body of research on mining externalities, which explores the trade-offs between negative health effects and positive wealth effects associated with mining (Von der Goltz and Barnwal 2019; Benshaul-Tolonen 2019; Maffioli 2023).

My paper brings important contributions to the literature and has concrete public policy implications. Mining in the Amazon is a pressing issue that has environmental, health, and socioeconomic dimensions, but quantitative research linking different aspects of this phenomenon at a larger level is scarce. To my knowledge, this is the first paper that investigates subclinical effects of mercury contamination in the Amazon at a large scale. Moreover, from a policy point of view, it is crucial to provide causal evidence of the relationship between gold mining and birth defects, and to quantify the magnitude of this effect, which can reinforce calls for stronger environmental legislation and enforcement in the region and help target public health action.

2 Literature Review

2.1 Gold mining in the Amazon

Gold extraction became an important activity in Brazil during the 18th century when large deposits were discovered in the state of Minas Gerais (Furtado 2007). While the importance of gold has waned since then, Brazil consistently ranks among the top 15 gold producers globally. [2] Nowadays, over one third of the gold production in Brazil comes from the Legal Amazon, a large area encompassing nine federal states in the North of the

2. And it has often ranked among the top 10. See World Gold Council (2023)

country which houses the Amazon forest (Manzolli and Rajão 2022).

In Brazil, gold mining can generally be classified into two main categories: industrial mining, which typically involves the use of large machinery for excavation, and small-scale mining, commonly referred to as "garimpo" [3]. *Garimpo* is often conducted using traditional artisanal methods and can take place in open alluvial deposits, exposed mineralized rock formations, or underground tunnels carved into the rock.

Though it is typically carried out by individuals or small groups using limited technology and equipment, several *garimpos* employ heavy machinery for gold extraction (Siqueira-Gay and Sánchez 2021). It is possible to obtain a lease for this kind of activity, but the majority of gold mining conducted in Brazil on an artisanal and small-scale level is considered illegal. This is concerning because when done illegally, miners do not follow minimal sustainability guidelines such as limiting the use of toxic substances and committing to rehabilitating degraded areas (Siqueira-Gay and Sánchez 2021). Over 90% of *garimpo* in Brazil is done in the Amazon region, which has devastating consequences for the biome (MapBiomas 2021).

It is particularly consequential when done illegally within protected areas, such as indigenous reserves. During the past three decades, mining has increased more than 1000% inside indigenous areas, significantly impacting the environment and the health of the local populations (Mataveli et al. 2022). Half of this growth occurred between 2010 and 2020 (MapBiomas 2021). Among the factors driving this expansion are a relaxation of monitoring policies and rising gold prices (Siqueira-Gay and Sánchez 2021).

One of the main consequences of the mining activities in the Amazon is deforestation, as the miners cut down large areas of trees to set up camp (Sonter et al. 2017). This disturbs the local ecosystems, leading to consequences such as increases in the incidence of malaria (Castro and Peterka 2023) and hunger among indigenous populations that rely on the forest to survive (Garcia et al. 2022). There is also evidence that illegal mining leads to

3. I use the terms mining and *garimpo* interchangeably throughout the rest of the text for simplicity, but note that none of my analyses considers industrial mining

increases in violence. Pereira and Pucci (2022) examine the effects of a law passed in 2013 that removed requirements for buyers to ensure the origin of the purchased gold, leading to increases in illegal mining. They show that homicides surged in small municipalities with gold deposits in indigenous lands after this law.

2.2 Mining, mercury exposure and human health

The *garimpeiros* use mercury in extracting gold from the ore because its chemical properties help it separate gold particles from other substances. There are several methods for gold extraction which use mercury in different ways. A common method is adding mercury to material removed from the soil or riverbed, in a process called amalgamation. The amalgam is then burned to separate the gold particles from impurities. Most of the mercury then is volatilized and falls into the atmosphere, where it can travel long distances and have severe consequences for the environment (Pfeiffer et al. 1993). However, a significant amount of mercury reaches water bodies, where it travels downstream and can reach distances of several kilometers (Picado and Bengtsson 2012; Wyatt et al. 2017; Spadini and Charlet 2003).

When in the water, mercury is converted to methyl-mercury by bacteria, which enters the food chain and goes through the process of biomagnification: small animals and fish are preyed on by larger animals and mercury levels increase through successive trophic levels (Pfeiffer et al. 1993; Malm 1998). Local populations who eat contaminated fish are then at risk of contamination. There are several reports of high mercury levels in blood and hair samples from populations living near and downstream from gold mining sites (Meneses et al. 2022; Castilhos et al. 2015; Gibb and O'Leary 2014). Specifically in Amazonian populations, studies find exposure levels that are 2 to 6 times higher than the reference dose, much more than other populations worldwide (Crespo-Lopez et al. 2021).

This is concerning for numerous reasons, as there is a large body of evidence on the detrimental consequences of mercury on human health. It is one of the top ten chemicals of major public health concern according to the World Health Organization, particularly due to its harmful effects on early child development (WHO 2017).

When it enters the body, mercury is highly reactive with sulfur-based proteins, affecting the functioning of enzymes and leading to several cellular and genetic dysfunctions (Dack et al. 2021). Consequently, mercury has several embryo-toxic and teratogenic effects in fish, birds, and mammals — meaning it affects DNA and cell division, causing several mutations (Leonard, Jacquet, and Lauwerys 1983). During pregnancy, it can cross the placenta and accumulate in fetuses in much higher dose ratios than in adults (Bjørklund et al. 2019). This can lead to neurodevelopmental damage in the fetus, resulting not only in birth anomalies such as deformed limbs and mental retardation, but also miscarriages, stillbirths, and higher incidence of low birth weights (Rice et al. 2014).

A significant case highlighting the devastating impact of mercury contamination emerged in Japan in the 1950s (Eto 2000). The incident was centered around Minamata Bay, where residents, primarily from fishing villages, consumed seafood heavily contaminated with mercury compounds. This episode gave rise to a specific set of neurological symptoms stemming from mercury contamination, which are now collectively known as "Minamata disease"[4]. Affected individuals reported numbness in their limbs and lips, auditory and visual impairments, muscular tremors, and severe neurological disturbances. It was later determined that a petrochemical plant, operated by the Chisso Corporation, had discharged dozens of tons of mercury compounds into the bay. Subsequent generations were also impacted, with newborns displaying severe congenital deformities (Harada 1995).

However, there is significant variation in the effects of mercury according to factors such as its chemical form, the nature of contact, and the duration and magnitude of exposure. While specific episodes of environmental disasters provide evidence of the consequences of large-scale exposure, obtaining definitive evidence on the consequences of chronic low-dose exposure is much harder (Dack et al. 2021).

4. The Minamata Convention, an international treaty signed in 2013 to control production and trade of mercury, was also named after this episode.

Many studies focus on the effects of occupational exposure, examining people who are in contact with mercury in their professional activities, such as miners and chemical factory workers. Those exposed to inhalation of mercury vapor in their work environment are at heightened risk of numerous harmful effects on the nervous, cardiovascular, reproductive, digestive, urinary, and immune systems (Gibb and O'Leary 2014).

Moreover, even those who are not directly in contact with mercury may suffer health consequences. Populations who are susceptible to mercury contamination through fish consumption, such as those living near gold mining sites in the Amazon, may face symptoms much like those of Minamata Disease and suffer from neurological impairments. Riverine Amazonian populations have been documented to be at high risk of symptoms such as color vision and visual perimeter deficits, and emotional and motor perturbances, with children being particularly affected (Crespo-Lopez et al. 2021). There is evidence that children born in Amazon regions downstream from gold mining locations have higher rates of mercury blood levels and lower levels of cognitive development (Grandjean et al. 1999).

3 Data and methods

Even though comprehensive data on mercury contamination in the Amazon is not available, I can test the hypothesis that contamination from gold mining affected health outcomes by exploiting variations in the direction of river flows. My identification strategy exploits exogenous time variation stemming from variations in international gold prices, interacted with the distribution of geological gold deposits across municipalities. I then compare birth outcomes in municipalities with and without gold deposits upstream from them.

The approach is justifiable for the following key reasons. First, the main source of contamination for gold mining is mercury. Though there is atmosphere contamination,

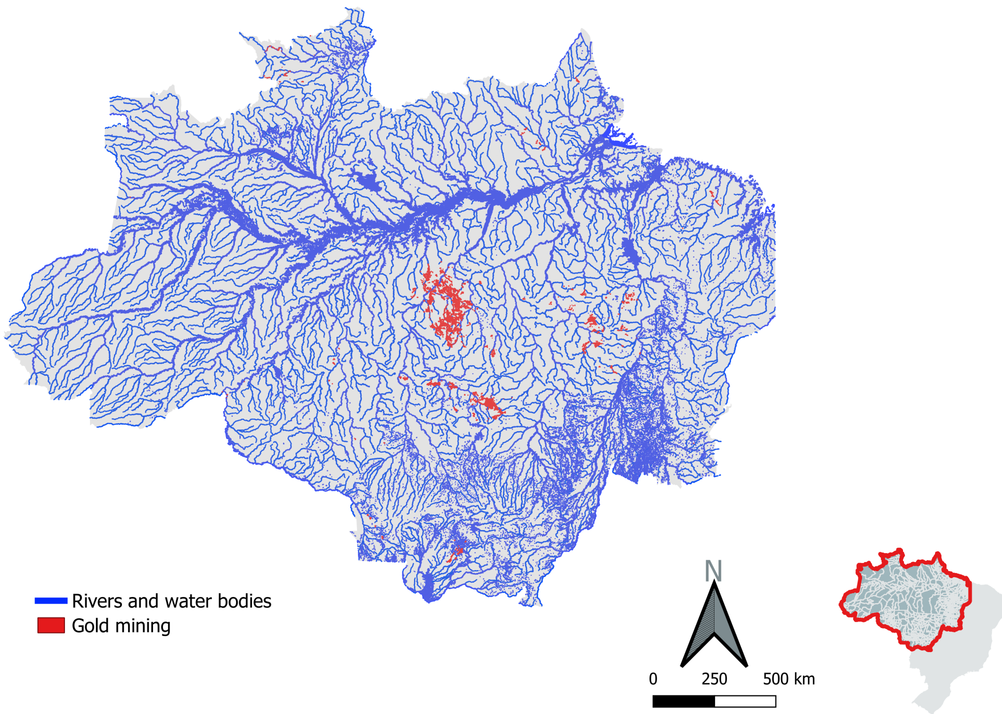


Figure 1: **Rivers and mining in the Brazilian Amazon**. This figure shows the distribution of rivers and water bodies in the Legal Amazon as well as the regions where gold mining was detected in 2021. Own elaboration based on data from different sources (see Data sources).

mercury travels downstream in water, with high levels found near or downstream from mining locations and contamination in upstream areas much less expressive (Spadini and Charlet 2003; Wyatt et al. 2017; Picado and Bengtsson 2012). Second, there is evidence that people living downstream from gold mining have dangerous mercury blood levels (Gibb and O'Leary 2014; Grandjean et al. 1999). Finally, this is particularly consequential because gold mining frequently takes place near water bodies, and the Legal Amazon is home to a vast network of rivers (see Figure 1).

This strategy is inspired by Dias, Rocha, and Soares (2023) that exploited the direction of river flows to study the effects of glyphosate adoption on health outcomes. If mining in a given region affects health outcomes in regions downstream from it, but not in regions upstream, it is reasonable to assume that water contamination drives these effects. I also take advantage of a variation of mining in time by comparing municipalities before and after a significant uptick in gold mining since the early 2010s. Figure 2 and Figure 3 show that this increase was preceded by rising gold prices. The literature suggests that rising global gold prices were a key determinant for the growing mining operations in the Brazilian Amazon (Siqueira-Gay and Sánchez 2021). I use the value in USD, following previous work that employed similar approaches (Swenson et al. 2011; Maffioli 2023).

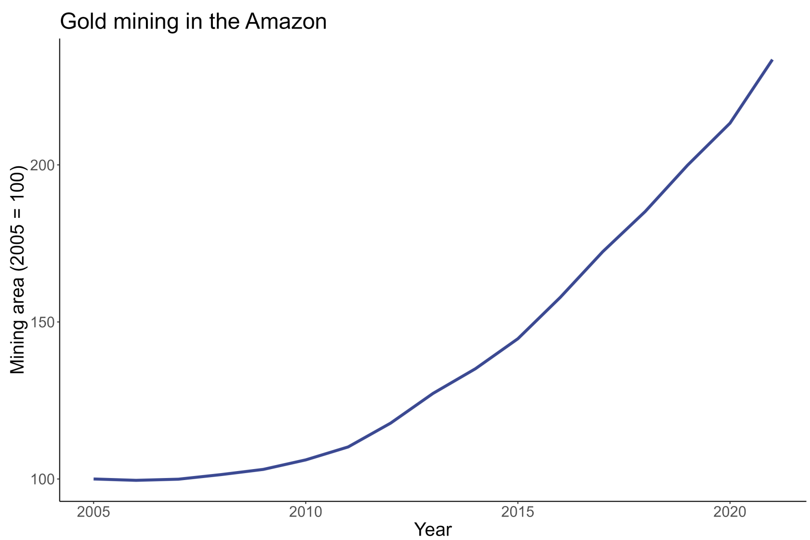


Figure 2: **Evolution of gold mining in the Amazon**. This figure shows the evolution of the total area categorized as gold mining in the Legal Amazon, normalized to the value in 2005. Own elaboration based on data from different sources (see Data sources).

3.1 Measuring gold mining throughout time

Ideally, my identification strategy would require having precise data on mining at a local level, and leverage variation in river direction to estimate causal effects between municipalities in the same water basins as the ones with mining activity upstream. Indeed, recent groundbreaking work using artificial intelligence to interpret satellite data has made available geocoded data on mining locations in the Amazon (Earthrise 2023; MapBiomas 2022). Nevertheless, because this measure is by construction an approximation, there likely is significant measurement error. Moreover, the location of mining activities could be endogenous.

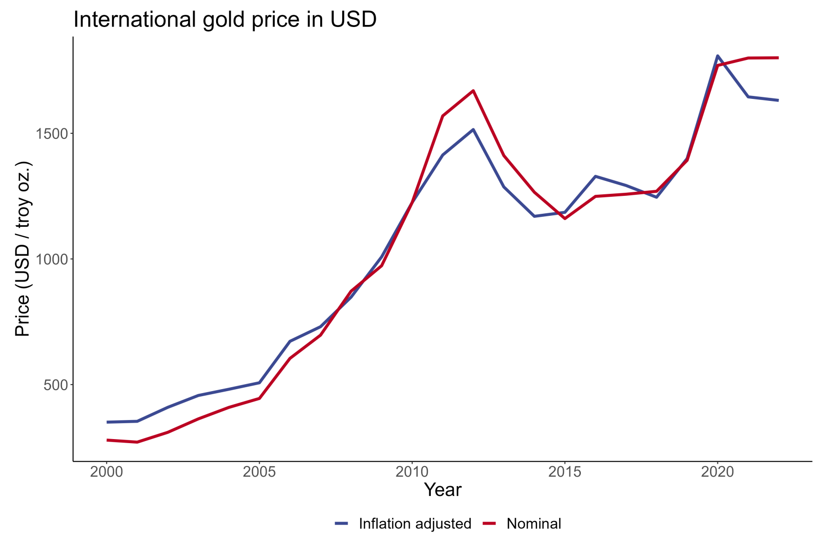


Figure 3: **Evolution of global gold prices**. This figure shows the evolution of the international gold prices (price per troy ounce) in United States Dollars (USD), from 2000 to 2021. The inflation-adjusted lines show values in 2010 USD. One troy ounce is around 31 grams. Own elaboration based on data from different sources (see Data sources).

Therefore, instead of using these data, I follow Pereira and Pucci (2022) and use known geocoded gold deposits as a proxy for gold mining in the region. Since these are geologically determined, and thus have been created millions of years ago, they also help to deal with possible endogeneity of mining location. Figure 4 shows the distribution of gold deposits in the Amazon. Note the clear correlation with gold mining locations in Figure 1, which uses the satellite data from MapBiomas.

My strategy requires combining the exogenous spatial variation arising from geocoded gold deposits with time variation in gold mining activities, which should also be exogenous to local municipalities. I argue that exogeneity of the international prices of gold holds for two main reasons. First, Brazil is not a price maker in the gold market, detaining less than 3% of annual production (World Gold Council 2023). Second, gold prices are much less affected by supply than other commodities, as price changes are usually driven by financial factors such as the dollar index and the federal funds rate (Qian, Ralescu, and Zhang 2019).

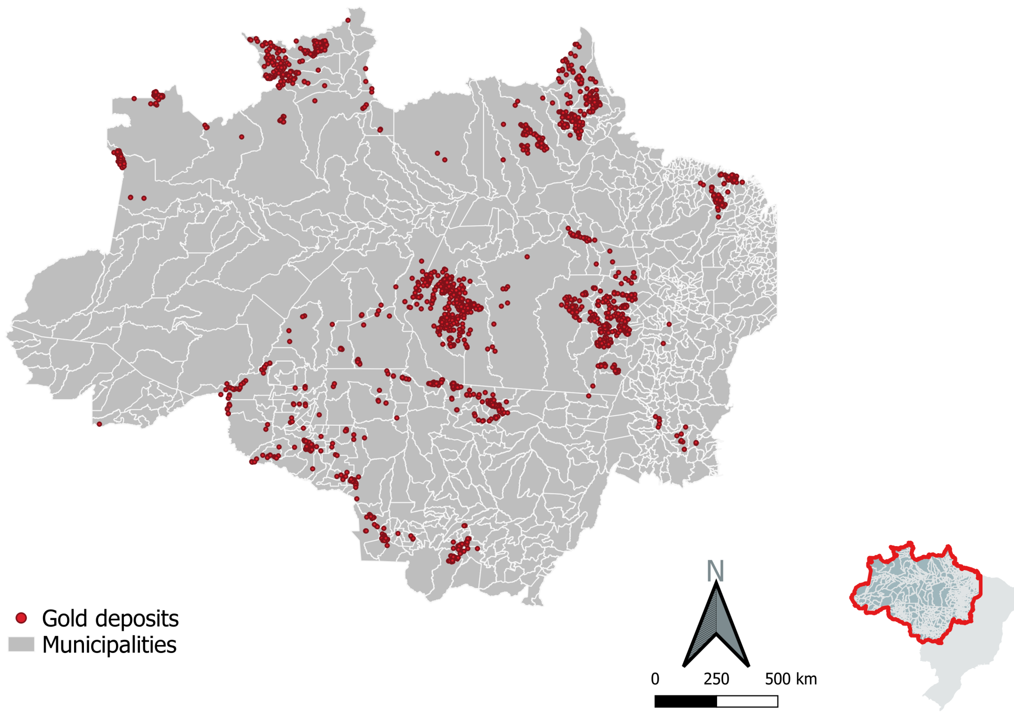


Figure 4: **Gold deposits in the Brazilian Amazon**. This figure shows the distribution of known gold deposits in the Legal Amazon. Own elaboration based on data from different sources (see Data sources).

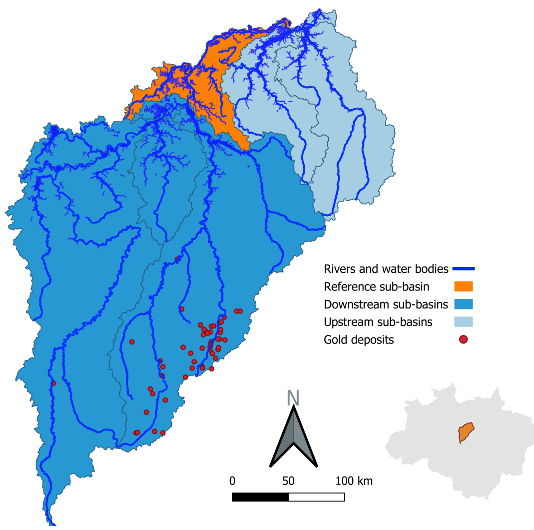
3.2 Identifying the direction of water flows

Having defined the treatment variable, which is the interaction of the upstream-deposits indicator with the global price of gold, the final step in my estimation strategy requires identifying the upstream-deposits variable. I follow the strategy used by Dias, Rocha, and Soares (2023), which is based on the concept of drainage basin, defined as a region where all the water that falls within it ultimately flows into a particular body of water. These water basins — called ottobasins[5] in Brazil— are categorized in different levels, starting from level 1, which encompasses the whole continent, and continuing to local basins that are subdivisions of the higher levels. Following their method, I focus my analysis on levels 3 and 4, as level 2 basins are excessively large, and a municipality can include dozens

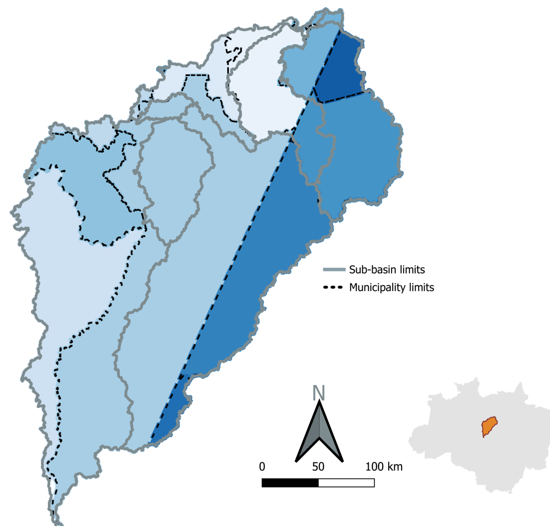
5. Named after the classification method for water bodies developed by Otto Pfafstetter (Pfafstetter 1989)

of level 5 basins. For simplicity, hereafter I will refer to level 3 ottobasins as basins, and level 4 ottobasins as sub-basins.

Within each basin, sub-basins are numbered according to the direction of water flows. I then identify which sub-basins are upstream and downstream from each other, and can know whether each sub-basin has gold deposits upstream from it (see Figure 5a).



(a) **Illustration of identification strategy**. This figure shows an example water basin with sub-basins within it. The orange sub-basin would be categorized as not treated, as the gold deposits are present in sub-basins downstream from it, but not upstream.



(b) **Example of municipality and water basins limits**. Sub-basin limits (gray lines) and municipality limits within an example water basin (dashed lines and colors).

Figure 5: **Illustration of basins and municipalities**. Own elaboration based on data from different sources (see Data sources).

However, a municipality may contain more than one sub-basin, and may even be divided among different basins. Therefore, I consider each intersection between municipalities and sub-basins as a separate unit of analysis (see Figure 5b). I then identify gold deposits upstream and downstream from each sub-basin-municipality, and aggregate at the level of municipalities. Since the main analysis considers only a dummy of whether a municipality has gold deposits upstream, if any sub-basins that intersect a given municipality have gold deposits upstream from it in its basin, this municipality is considered as treated.

The full sample comprises 768 municipalities [6]. However, as detailed in the next section, I exclude municipalities with gold deposits inside their territory to ensure my specifications capture the effect of mining *upstream* from municipalities. The main sample therefore includes 616 municipalities, with 212 in the treatment group and 404 in the control group. The table below displays the number of units in each group.

Table 1: **Sample size by availability of gold deposits**

Gold deposits	Upstream gold deposits	Number of municipalities
No	No	404
No	Yes	212
Yes	No	10
Yes	Yes	142

3.3 Empirical specification

With the data in hand, I use the estimation strategy outlined above to estimate the causal effects of mining on birth anomalies, exploiting geographical variation from the location of gold reserves and time variation from exogenous changes in international gold prices. [7] Traditionally, DiD models have a binary treatment variable, which varies in a cross-section (units are either in the control group or in the treated group), and a dummy variable for the post-treatment period, which varies across time.

Hence, to incorporate gold prices in the model, the classical DiD approach would require defining a threshold for gold prices (i.e. the time variation would be a dummy indicating the moment in which the price of gold rises above a certain value). As choosing this threshold would be an arbitrary decision, I instead directly use gold prices as the

6. The official count for municipalities in the Legal Amazon is 772. I exclude three border municipalities in Maranhão — Paço do Lumiar, Raposa, and São José de Ribamar — because they lie in water basins mostly outside the Legal Amazon. Additionally, I combine the municipalities of Mojuí dos Campos and Santarém in Pará, which separated in 2012.

7. The main regressions consider only municipalities without gold deposits, N = 616, from 2007 to 2021. Most regressions, therefore, have $616 \times 15 = 9,240$ observations

time-series variable: time variation stems from a continuous variable instead of a post-treatment dummy. This approach has been used in studies of commodity shocks, particularly those involving illegal activities for which precise production data is not available (Dube and Vargas 2013; Vásquez-Cortés 2021; Sviatschi 2022). The timing of the variation in the international gold prices is the same for all municipalities in a given year. Identification thus relies on the assumption that in the absence of the increase in mining, birth outcomes would have evolved similarly in municipalities with and without gold deposits upstream. Because the occurrence of gold deposits was determined millions of years before the beginning of the analysis, this assumption is likely to hold.

However, it is likely that municipalities with mining themselves, as opposed to mining upstream from them, have several socioeconomic confounding effects. For example, gold mining has been shown to locally increase wealth, while also having detrimental health effects due to pollution among workers and their immediate families (Von der Goltz and Barnwal 2019). Therefore, I exclude municipalities that have gold deposits from my sample. This ensures my estimates capture the effect of upstream mining, which would arguably only affect birth outcomes through water contamination. [8].

Given these assumptions, my main specification estimates the following regression:

$$Y_{it} = \alpha_i + \delta_t + \beta(P_t \times GoldUp_i) + \lambda_t X_i' + \varepsilon_{it} \tag{1}$$

where Y_{it} is the health outcome in municipality i in year t, α_i controls for fixed unobserved municipality-specific characteristics, δ_t are year fixed effects, P_t is the log of the average international price of gold in year t, $GoldUp_i$ is a dummy variable indicating whether there are gold deposits upstream of municipality i in the same water basin (note that it does not vary across time), X_i' is a vector of socioeconomic controls, which are

8. I also conduct robustness tests with the full sample, controlling for the availability of gold deposits in the municipalities (also interacted with the time variables) in a similar fashion as done by Dias, Rocha, and Soares (2023)

measured at baseline and interacted with year dummies, and ε_{it} is a random error. The socioeconomic controls are municipal income, share of municipal income from industrial activities (including mining), and share of the population covered by primary care health programs. Following Pereira and Pucci (2022), instead of adding these controls measured in current values, I add them by interacting their fixed level in 2007 (first year the health variable is available) with year-fixed effects. This avoids bias arising from the outcome and covariates being simultaneously determined. The regressions are weighted by the mean number of births across the entire sample period, and standard errors are clustered at the water basin level.

I also estimate placebo regressions using gold deposits *downstream* from municipalities, as well as deposits for other minerals, which would not lead to mercury contamination.

3.4 Data sources

All data come from publicly available sources: DATASUS[9] (birth microdata from SINASC), Agência Nacional de Águas[10] (hydrographic basins and flow direction), Serviço Geológico do Brasil[11] (mineral deposit locations), IBGE[12] (municipal income, industry share, and population), World Bank[13] (international gold prices), Secretaria de Atenção Primária à Saúde[14] (primary health coverage data), and MapBiomas[15] (AI-based satellite mining data, not used in the main analysis).

3.5 Descriptive statistics

Table 2 below shows summary statistics of the main variables.

9. https://datasus.saude.gov.br/
10. https://metadados.snirh.gov.br/geonetwork/srv/api/records/b228d007-6d68-46e5-b30d-a1e191b2b21f
11. https://geoportal.cprm.gov.br/geosgb/
12. https://www.ibge.gov.br/estatisticas/economicas/contas-nacionais.html
13. https://www.worldbank.org/en/research/commodity-markets
14. https://egestorab.saude.gov.br/paginas/acessoPublico/relatorios/relHistoricoCoberturaAB.xhtml
15. https://mapbiomas.org/en/download-dos-atbds?cama_set_language=en

Table 2: **Summary statistics of main variables in 2013**

Variable	Mean	S.D	Max	Min	N
$GoldUp_i$	0.34	0.48	1.00	0.00	616
Number of births	1081.15	4003.35	76222.00	16.00	616
Anomalies per 1k births	4.92	7.42	52.63	0.00	616
Mean birth-weight	3238.60	80.09	3537.02	2970.91	616
Preterm (%)	0.12	0.04	0.32	0.00	616
SF Coverage	84.93	24.21	100.00	0.00	616
Industrial GDP (%)	0.08	0.10	0.79	0.01	616
GDP per capita	13598.74	15015.98	152438.63	3504.06	616

Note: This table shows summary statistics, measured across municipalities in 2013, for the main variables considered in the analysis. "SF" coverage refers to the percentage of the population covered by the primary care health program "Saúde da Família".

One aspect worth noting from these statistics is the high variance of the anomaly rate variable. Indeed, birth anomalies are not only relatively rare but may also be under-reported. Out of over 11,000 municipality-year observations in the sample, almost 5,000 are zero. This could cause problems with the use of OLS regression, and therefore I also estimate alternative specifications using count data models. These are discussed in more detail in section 4.

However, the high number of zeros does not mean that birth anomalies are not relevant in terms of public health policy. In 2021 alone, for example, there were a total of 5,326 birth anomalies in my sample of 768 municipalities in the Amazon, corresponding to 60.5 per 10,000 births (or about 0.6%). As this prevalence is remarkably lower than the global estimate of between 2 and 3% of births, the Brazilian Ministry of Health notes that the country experiences severe under-reporting of birth anomalies, which is likely even worse in less urbanized areas such as the Amazon [16].

To further explore the distribution of congenital birth anomalies, the most common

16. The rate of birth anomalies in 2021 in the whole country was close to 0.85%. See the Boletim da situação epidemiológica das anomalias congênitas no Brasil (Ministério da Saúde, 2023) for more details.

anomalies in the sample of municipalities are displayed in Table 3.

Table 3: **Birth anomalies per 10,000 births by type — Brazilian Amazon**

Congenital Anomaly	2005	2013	2021
Malformations of feet	8.65	7.89	7.47
Polydactyly	5.03	5.34	6.56
Hydrocephaly	3.21	2.93	2.52
Cleft lip	1.98	1.97	1.66
Musculoskeletal malformations	1.66	2.86	3.38
Down syndrome	1.64	1.59	2.20
Anencephaly	1.45	1.80	1.54
Malformations of ear	1.16	2.08	3.07
Malformations of mouth, tongue, and pharynx	1.12	1.15	4.23
Spina bifida	1.04	1.41	1.86
Microcephaly	0.45	0.44	0.75
Other	18.66	18.41	25.24

Note: This table shows the total rate of birth anomalies per 10,000 births in the 768 municipalities in the sample, categorized according to ICD-10 codes.

4 Results

4.1 Birth anomalies and gold mining

A first look at the data in Figure 6 shows that in the mid-to-late 2010s there was an uptick in the rate of birth anomalies in municipalities in the Amazon, particularly among municipalities with gold deposits upstream from them. Though this coincides with the period that saw a large increase in gold mining in the region, drawing causal inference requires a more careful analysis. Therefore, the main results from the empirical strategy are displayed in Table 4, which show coefficients based on differences-in-differences models as in Equation 1. Importantly, the regressions exclude municipalities that have gold deposits, such that they capture the effect of gold availability upstream, and not in the immediate municipality areas.

Each column shows results from a regression based on Equation 1. The dependent

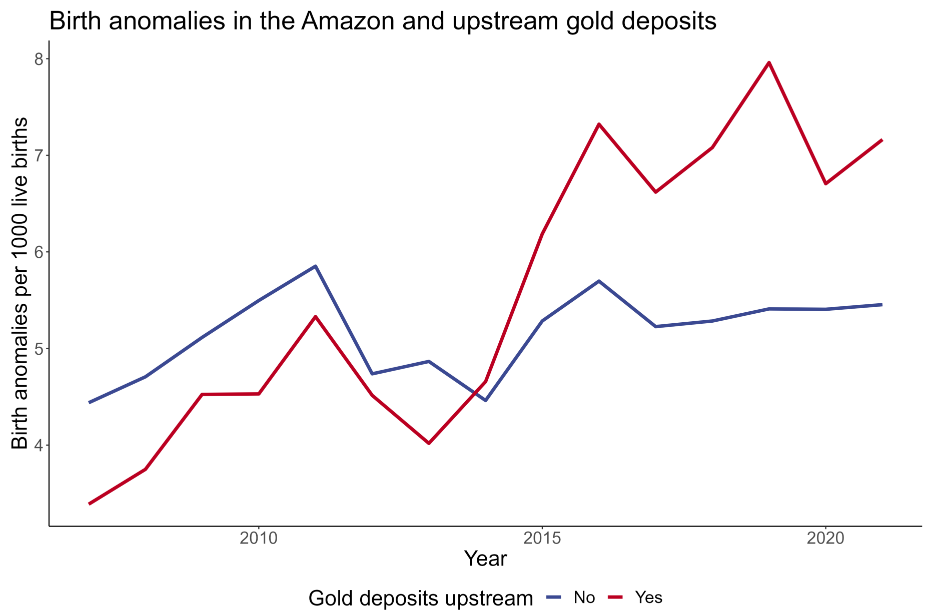


Figure 6: **Birth anomalies in the Amazon.** This figure shows the evolution of the average rate of birth anomalies in municipalities by the availability of gold deposits upstream (excluding municipalities with gold deposits). Averages are calculated as the mean across municipalities for each year, weighted by the number of births in each municipality and year.

variable is the number of birth anomalies per 1,000 live births, and $Gold_{Up} \times P_{Gold}$ is the interaction of the dummy variable indicating the existence of upstream gold deposits and the international price of gold in logs. In Column (1), there are no controls, only municipality and year fixed effects. Columns (2) and (3), on the other hand, include controls for socioeconomic variables. The interpretation of the results is that there was a relative increase of around 0.022 anomalies per 1,000 births for each percentage increase in the price of gold. For example, gold prices went up by about 27% between 2013 and 2021, suggesting treated municipalities saw a relative increase of around 0.6 birth anomalies per 1,000 on average during this period.

As a placebo exercise, Panel A in Table 5 replicates Table 4, but replacing the upstream treatment variables with their downstream counterparts. Supporting the main results, these point estimates are smaller in magnitude and not statistically distinguishable from zero, as expected. These regressions also exclude municipalities with deposits themselves.

Table 4: **Results: Effect of Gold Mining on Birth Anomalies**

	Dependent variable:		
	Birth anomalies per 1000		
	(1)	(2)	(3)
$Gold_{Up} \times P_{Gold}$	2.283^{*}	2.263^{**}	2.239^{**}
	(1.159)	(1.012)	(0.970)
Income controls		Y	Y
Health controls			Y
Observations	9,240	9,240	9,240
R^2	0.254	0.267	0.269

Note: This table shows results from regressions estimating the effects of exposure to upstream gold deposits in the Legal Amazon on the birth anomaly rate (birth anomalies per 1,000 live births), between 2007 and 2021. Regressions are similar to difference-in-differences models, based in Equation 1, where the treatment variable is a dummy equal to 1 if there are gold deposits upstream of the municipality and 0 otherwise, interacted with the log of the international gold price. All regressions exclude municipalities that have gold deposits, include municipality and year fixed effects, and are weighted by the mean number of births across the entire sample period. The socioeconomic controls are added as the interaction of year dummies with their fixed value in 2007, and are as follows: log GDP per capita and share of GDP from industrial activities (income), and share of the population covered by the primary health program Saúde da Família (health). Standard errors shown in parentheses are clustered at the water basin level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

A second placebo exercise is shown in Panel B, which replaces the gold deposit indicator with other minerals such as iron, diamonds, copper, clay, and tin. Though their extraction may cause other kinds of pollution, the mining of these substances does not use mercury — and should be somewhat independent from gold prices. Therefore, this test helps rule out the possibility that another factor related to geological deposits is driving the results. Again, coefficients are smaller in magnitude and not statistically significant, and point estimates have the opposite sign than their counterparts in Table 4.

Table 5: **Placebo regressions**

	Birth anomalies per 1000		
Panel A: Gold deposits downstream	(1)	(2)	(3)
$Gold_{Down} \times P_{Gold}$	0.965	0.808	0.906
	(1.048)	(0.736)	(0.815)
Income controls		Y	Y
Health controls			Y
Observations	9,240	9,240	9,240
R^2	0.252	0.265	0.267
Panel B: Other deposits upstream			
	Birth anomalies per 1000		
	(1)	(2)	(3)
$Others_{Up} \times P_{Gold}$	−1.032	−0.817	−1.038
	(0.757)	(0.640)	(0.658)
Income controls		Y	Y
Health controls			Y
Observations	9,240	9,240	9,240
R^2	0.252	0.265	0.267

Note: Panels report placebo versions of the regressions in Table 4. Panel A replaces upstream gold with a dummy for gold downstream. Panel B replaces upstream gold with a dummy for other minerals upstream. Standard errors shown in parentheses are clustered at the water basin level. *p<0.1; **p<0.05; ***p<0.01

4.2 Robustness tests and additional results

Even though the results hold with the inclusion of controls and the placebo regressions help rule out the hypothesis that the results are spurious, I conduct further sensitivity tests to support the validity of the results. Table 6 shows the results from these tests, considering alternative specifications of the main model. Column (1) replicates the preferred specification in Column (3) of Table 4. In, Column (2), I replace the year fixed effects with year-state dummies interactions to capture regional trends (there are 10 states in the sample), while in Column (3), I use a slightly smaller regional unit — mesoregions (31 in the sample). In Column (4), the gold price in USD is adjusted for inflation. In Column (5), I include municipalities with gold deposits within them and instead control for this local gold availability by adding a dummy interacted with the price of gold. In all columns, the coefficients remain positive and significant at 5%.

Column (6) replaces the current gold price with the price in the previous year, as one might expect that there are effects of changes in the price of gold on births happening one year later. It is reassuring that the results remain positive and significant when considering the lagged price of gold. This is further discussed in Section 4.3, where I also show robustness to other lags and leads (placebos).

Table 6: **Robustness tests: alternative specifications**

	Birth anomalies per 1000					
	(1)	(2)	(3)	(4)	(5)	(6)
$Gold_{Up} \times P_{Gold}$	2.239**	1.079**	1.279**	2.963**	1.148**	2.044**
	(0.970)	(0.485)	(0.489)	(1.265)	(0.481)	(0.901)
Income controls	Y	Y	Y	Y	Y	Y
Health controls	Y	Y	Y	Y	Y	Y
State dummies		Y				
Mesoregion dummies			Y			
Adj. for inflation				Y		
Full sample					Y	
Lagged price						Y
Observations	9,240	9,240	9,240	9,240	11,520	8,624
R^2	0.269	0.384	0.427	0.270	0.376	0.272

Note: This table shows results from alternative specifications of the regression in Column (3) of Table 4. Standard errors shown in parentheses are clustered at the water basin level. *p<0.1; **p<0.05; ***p<0.01

A further test is needed due to the nature of the response variable. As birth anomalies are relatively rare events, with usually less than 10 anomalies per 1,000 live births recorded, there are many observations with values of 0, meaning municipalities that had 0 anomalies in a given year. Typical fixed effect linear models thus may be biased, such that it might be preferable to use Poisson or Negative Binomial regressions instead. This is because birth anomalies likely characterize non-normally distributed and over-dispersed count data — meaning values are often zero and are never negative — and therefore it is better to choose functional forms that ensure these properties (see Chapter 18 in Wooldridge (2010)).

Table 7: **Robustness tests: count data models**

	Dependent variable:			
	Birth anomalies			
	Negative Binomial		Poisson	
	(1)	(2)	(3)	(4)
$Gold_{Up} \times P_{Gold}$	0.649^{*}	0.692^{*}	0.629^{**}	0.562^{**}
	(0.359)	(0.393)	(0.288)	(0.268)
Income controls		Y		Y
Health controls		Y		Y
Observations	9,240	9,240	9,240	9,240

Note: This table shows results from regressions similar to that in Table 4, but using count data models instead. Columns(1)-(2) show results from Negative Binomial Generalized Linear Models, while columns (3)-(4) use Poisson Quasi–Maximum Likelihood estimators. The dependent variable is the number of birth anomalies, and the number of births is added as a control. Other variables, controls, fixed effects, and weighting schemes are the same as the regressions in Columns (1) and (3) of Table 4. Standard errors shown in parentheses are clustered at the water basin level. *p<0.1; **p<0.05; ***p<0.01

Table 7 shows results using these alternative estimators. The coefficients are all positive, suggesting that the results from the linear models are not driven by random patterns stemming from the large number of null observations in the data. Regarding magnitude, these coefficients should be interpreted in terms of log-counts of birth anomalies. For example, the coefficient in column (4) would suggest that when the price of gold in USD goes up by 27% (which was the approximate change between 2013 and 2021), those municipalities that have gold reserves upstream see an increase of $0.56 \times 0.27 = 0.151$ in the expected log count of anomalies, which translates to about 15%. Recall that the analogous calculation using linear models from Table 4 yielded about 0.6 birth anomalies per 1,000. This means the value of 15% is not too different from the OLS results, as the mean anomaly rate in 2013 was about 4.9 anomalies per 1,000 births (Table 2).

An additional analysis considers the effect of gold availability on other birth outcomes. Panel A of Table 8 shows the results for other outcomes that could be expected to also be affected by mercury contamination. Column (1) shows a slight negative effect on birthweight though it does not translate into a higher share of low-birthweight births (below 2,500g) nor of very-low-birthweight births (below 1,500g). There is also a significant, though small, increase in the preterm rate. In terms of magnitude, these coefficients suggest a decrease of around 3g in the mean birthweight between 2013 and 2021 in the average municipality, and an increase of 0.4 percentage points in the share of preterm births. Though small when compared to the baseline values of these variables (around 3200g and 12% preterm rate), these changes corroborate the interpretation that mercury contamination from gold extraction operation is indeed worsening birth outcomes generally.

The regressions in panel B explore some demographic characteristics of the births, showing there was no significant change in the birth rate, mean mother age, and shares of male and white births. This is reassuring, as it suggests there is no underlying change in the pattern of births or mothers that may be driving the results I find for congenital anomalies.

4.3 Mechanisms and effect timing

The results obtained with Equation 1 yield estimates of the intention to treat effect (ITT), meaning the effect of *potential* exposure to upstream mining operations. However, I do not know whether mining was in fact occurring in these locations.

As discussed previously, satellite data from MapBiomas (2022) provides approximate information on mining location, obtained through machine learning algorithms that identify deforested land. Though this data is not precise enough for us to differentiate data at the sub-basin level, I can use it to estimate the first stage of the effect of the variables on the actual area that is mined.

As a suggestive test for the mechanism, Table 9 below displays coefficients from re-

Table 8: **Additional results**

Panel A: Additional health outcomes				
	(1)	(2)	(3)	(4)
	Birthweight	LBW rate	VLBW rate	Preterm rate
$Gold_{Up} \times P_{Gold}$	-11.297^{***}	0.00000	0.00004	0.015^{***}
	(3.515)	(0.001)	(0.0005)	(0.003)
Observations	9,240	9,240	9,240	9,240
R^2	0.694	0.493	0.360	0.637
Panel B: Additional demographic outcomes				
	(5)	(6)	(7)	(8)
	Birth rate	Male births (%)	Mother age	White births (%)
$Gold_{Up} \times P_{Gold}$	-0.0001	0.0002	-0.005	-0.002
	(0.0004)	(0.002)	(0.036)	(0.006)
Observations	9,240	9,240	9,240	9,240
R^2	0.845	0.976	0.914	0.755

Note: This table shows results from regressions similar to that in Column (3) of Table 4, but considering different dependent variables. Standard errors shown in parentheses are clustered at the water basin level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

gressions similar to those in Table 4, but analyzing the effect of the interaction between the availability of gold deposits and gold prices on increases in the actual mined area. Here, I consider gold deposits and mining in the municipality itself (instead of upstream or downstream from it), such that the sample includes both municipalities with and without gold deposits.

The interpretation of these results is that municipalities that have gold deposits saw an increase of around $4/100km^2$ in gold mining for each percentage point increase in gold prices. For example, considering the 27% increase between 2013 and 2021, the average municipality would see an increase of about $4 \times 0.27 = 1.08$ square kilometers in the area identified as gold mining [17]. This is reassuring for my main identification strategy,

17. To give a sense of scale, aggregate data from MapBiomas (2021) indicates that the total area of *garimpo*

Table 9: **Mechanism: increases in gold mining**

	Dependent variable:			
	Mining			
	(1)	(2)	(3)	(4)
$Gold_{Up} \times P_{Gold}$	4.574**	4.402**	4.969**	6.207**
	(2.289)	(2.096)	(2.368)	(2.960)
Income controls		Y	Y	Y
State dummies			Y	Y
Adj. for inflation				Y
Observations	11,520	11,520	11,520	11,520
R^2	0.842	0.842	0.844	0.844

Note: This table shows results from regressions of the area identified as gold mining on the interaction between a dummy indicating gold availability and the price of gold. Regressions are at the municipality level and include municipality fixed effects, and year or state-year interactions. Standard errors shown in parentheses are clustered at the municipality level.
*p<0.1; **p<0.05; ***p<0.01

as it indicates that indeed the treatment variable captures increases in mining activity following gold price hikes.

Another concern with understanding the mechanism behind the findings for birth outcomes is an issue with the timing of the effects. The data is annual, and estimates from the baseline specification yield concurrent reduced form estimates — meaning they estimate what happens with birth outcomes in a given year when the price of gold rises in that same year. However, it must be considered that this causal channel works in several steps. Given that miners might take time to respond to price fluctuations, this process is not immediate. More importantly, the mechanism requires mining to be carried out, mercury to enter the water network and go up trophic levels, and then there are nine months before this contamination is reflected in birth outcomes. It is thus reasonable to expect that these results are not concurrent, but happen in a lagged fashion instead. Although the continuous nature of the treatment timing indicator does not allow us to

gold mining in Brazil increased by around 520 km^2 in this period.

plot typical event-studies, this can be tested by running regressions with lags and leads of the price of gold. Figure 7 displays coefficients from this exercise.

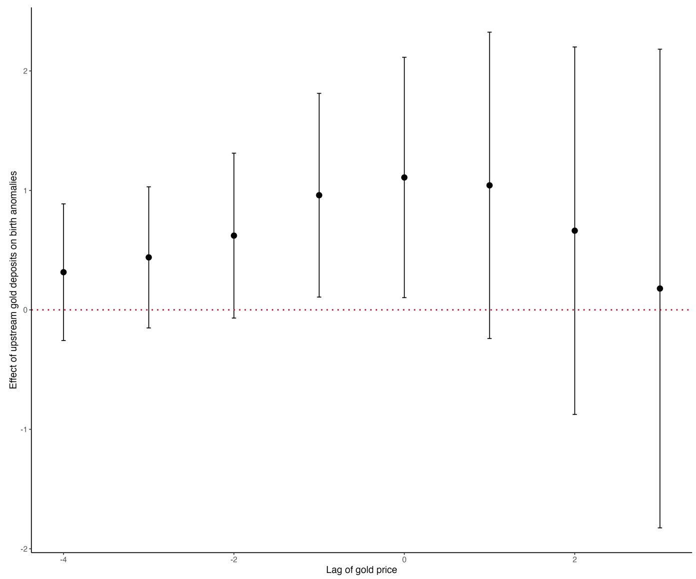


Figure 7: **Timing of the effect of gold mining on birth anomalies**. This figure shows coefficients and 95% confidence intervals of regressions similar to those in column (4) of Table 6, but considering lags and leads of gold prices.

The coefficient on time 0 is the regression from the main specification. It includes controls and state-year interactions, such that this coefficient is equivalent to that in column (4) of Table 6. The coefficient labeled -1, on the other hand, shows the effect of changes in the price of gold on births happening one year later. It has similar magnitude than the main coefficient at time 0, confirming the hypothesis that the analysis is capturing lagged effects. Interestingly, though statistically equal to zero, the point estimates suggest there also seem to be some effects with lags further back. This is again unsurprising, considering that it might take many months to set up mining operations after the change in incentives to mine and these can go on for years. Finally, it is reassuring that the effects approach zero when considering leading prices, meaning that there is no effect of future prices on past births.

5 Discussion

In this work, I investigated the impacts of gold mining in the Brazilian Amazon on the birth outcomes of populations living downstream from mining operations. The methodological strategy compares municipalities with and without gold deposits upstream, and results point to an uptick in the rate of congenital anomalies in treated municipalities during periods of rising global gold prices and increased mining incidence.

These results seem relatively robust, as they survive several sensitivity tests. Placebo tests, particularly those assessing *downstream* exposure to gold deposits, also support the identification strategy. The idea of using river flows to analyze the effect of water contamination relies on the assumption that gold mining in a given location increases contamination in locations downstream from that, but not in those that are upstream. I find null results in this placebo test, meaning there is no effect of gold deposits if they lie further down the river instead of further up. This is reassuring, as one concern is that I could be capturing the effect of the proximity to gold mining instead of water contamination. Mining may impact health outcomes in other ways — both by affecting different variables locally such as wealth, inequality, and crime, and by causing other kinds of environmental degradation such as deforestation and air pollution.

Despite excluding municipalities with gold deposits to mitigate this concern, it cannot be definitively confirmed that the study captures the effects of water contamination *per se*. The control group ideally should consist of municipalities close to gold mines but randomly located upstream. However, the current specification does not distinguish between those immediately upstream and those farther away, resulting in a control group that includes municipalities distant from gold deposits. The definition of upstream and downstream using level 3 ottobasins — following Dias, Rocha, and Soares (2023) — helps capture some of this, as places too far away from each other are not categorized in the same basin. Still, further analysis should take into account distances from gold deposits to better handle this issue and identify intensity effects.

Another concern with asserting causality with certainty is that I do not have precise data on gold mining. My findings therefore represent intention to treat estimates. While regressions with a first stage suggest mechanisms, they do not confirm that gold mining, let alone mercury contamination, is the definitive driver of results. Further analysis could also incorporate more detailed data on mining operations, as well as local data with mercury concentration indicators, to gain more insights into the causal channel at play. It would also be possible to extend the timing analysis by considering monthly price and birth data instead of annual data. This analysis could then incorporate factors such as birth seasonality and seasonal variations in climate which impact river dynamics.

I also find results on birthweight and preterm births, which suggests there are other negative effects on birth health beyond a higher incidence of birth anomalies. These findings dialogue well with the public health and toxicology research on mercury contamination and the effects of mining in the Amazon. As discussed, one of the main consequences of mercury in physiological terms is how it hinders *in utero* neurodevelopment leading to congenital anomalies (Rice et al. 2014). While some literature reviews have found mixed results, much due to limited sample sizes (Dack et al. 2021), it is reassuring to see that I found results on variables that the medical literature suggests are the most affected by mercury, while not finding results on other demographic characteristics such as number of births and mean age of mothers. This supports the argument for causality, as it means that it is not some external factor affecting birth patterns that is driving the results.

In sum, while it's not easy to assert causality, these results highlight the existence of negative health effects. This has immense support in health literature and calls for stronger enforcement of environmental policies in the Amazon. Still, it must be considered that there are also social aspects related to *garimpo* activities. While operations are often carried out by organized groups with international funding, many miners are low-educated members of riverine populations that turn to gold extraction as they lack alternative sources of income (Herraiz and Silva 2015). They endure poor working conditions without institutional labor rights support. This means that besides environmental regulation, there must also be specific measures that alleviate poverty in these regions and tackle the social aspect of mining.

6 Concluding remarks

This paper provides evidence that gold mining in the Brazilian Amazon is associated with increases in birth anomalies in locations downstream from mining operations. The pattern does not appear upstream or when using other minerals, and it is robust to alternative specifications and placebo tests. These are reduced-form, intention-to-treat estimates, but their sign and timing align with established pathways of methylmercury exposure.

The results complement existing research on mining's impact on issues like deforestation, hunger, and violence, underscoring the critical need for multifaceted policy interventions. Stronger enforcement in protected areas and along river corridors, routine monitoring of mercury in water, fish, and maternal health, and basic supply-chain traceability to raise the cost of laundering illicit gold are potential policy solutions. Because garimpo also reflects scarce income opportunities, actions that expand legal employment and improve local services can reduce the incentives that pull workers into mining, recognizing the importance of local context.

Further work should measure the channel more directly by linking deposit upstream status to observed mining locations to measure a first stage relationship, collecting or assembling mercury concentration data, modeling downstream exposure at varying distances, and exploiting higher-frequency price and birth data to refine timing. Together, these steps would clarify mechanisms and support the design of targeted health and environmental policy.

References

Benshaul-Tolonen, Anja. 2019. "Local industrial shocks and infant mortality." *The Economic Journal* 129 (620): 1561–1592.

Bjørklund, Geir, Salvatore Chirumbolo, Maryam Dadar, Lyudmila Pivina, Ulf Lindh, Monica Butnariu, and Jan Aaseth. 2019. "Mercury exposure and its effects on fertility and pregnancy outcome." *Basic & Clinical Pharmacology & Toxicology* 125 (4): 317–327.

Castilhos, Zuleica, Saulo Rodrigues-Filho, Ricardo Cesar, Ana Paula Rodrigues, Roberto Villas-Bôas, Iracina de Jesus, Marcelo Lima, Kleber Faial, Antônio Miranda, Edilson Brabo, et al. 2015. "Human exposure and risk assessment associated with mercury contamination in artisanal gold mining areas in the Brazilian Amazon." *Environmental Science and Pollution Research* 22:11255–11264.

Castro, Marcia C, and Cassio Peterka. 2023. "Malaria is increasing in Indigenous and artisanal mining areas in the Brazilian Amazon." *Nature Medicine,* 1–3.

Chay, Kenneth Y, and Michael Greenstone. 2003. "The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession." *The Quarterly Journal of Economics* 118 (3): 1121–1167.

Crespo-Lopez, Maria Elena, Marcus Augusto-Oliveira, Amanda Lopes-Araújo, Leticia Santos-Sacramento, Priscila Yuki Takeda, Barbarella de Matos Macchi, José Luiz Martins do Nascimento, Cristiane SF Maia, Rafael R Lima, and Gabriela P Arrifano. 2021. "Mercury: What can we learn from the Amazon?" *Environment International* 146:106223.

Currie, Janet, and Matthew Neidell. 2005. "Air pollution and infant health: what can we learn from California's recent experience?" *The Quarterly Journal of Economics* 120 (3): 1003–1030.

Currie, Janet, and Reed Walker. 2011. "Traffic congestion and infant health: Evidence from E-ZPass." *American Economic Journal: Applied Economics* 3 (1): 65–90.

Dack, Kyle, Matthew Fell, Caroline M Taylor, Alexandra Havdahl, and Sarah J Lewis. 2021. "Mercury and prenatal growth: a systematic review." *International Journal of Environmental Research and Public Health* 18 (13): 7140.

Dias, Mateus, Rudi Rocha, and Rodrigo R Soares. 2023. "Down the River: Glyphosate Use in Agriculture and Birth Outcomes of Surrounding Populations." *Review of Economic Studies* 90 (6): 2943–2981.

Dube, Oeindrila, and Juan F Vargas. 2013. "Commodity price shocks and civil conflict: Evidence from Colombia." *Review of Economic Studies* 80 (4): 1384–1421.

Earthrise. 2023. *Amazon Mining Watch.* Available at: https://github.com/earthrise-media/mining-detector#methodology.

Eto, Komyo. 2000. "Minamata disease." *Neuropathology* 20:14–19.

Federl, Fabian, and Jack Nicas. 2023. "Gold's Deadly Truth: Much Is Mined With Mercury." *The New York Times,* https://www.nytimes.com/2023/09/22/world/americas/gold-mercury-mining-poison.html.

Flynn, Patrick, and Michelle M Marcus. 2021. "A watershed moment: The Clean Water Act and infant health."

Furtado, Celso. 2007. *Formação econômica do Brasil.* 1st ed. São Paulo: Companhia das Letras.

Garcia, Hévilla Maria, Germano de Garcia Alves Feitosa, Hildson Leandro de Menezes, Thânia Maria Rodrigues Figueiredo, Ruan Neto Pereira Alves, Nádia Nara Rolim Lima, Alberto Olavo Advincula Reis, Jaime Emanuel Brito Araújo, Sionara Melo Figueiredo de Carvalho, Sávio Samuel Feitosa Machado, et al. 2022. "Pandemic of hunger: The severe nutritional deficiency that kills Yanomami ethnic children." *Journal of Pediatric Nursing* 65:e1–e2.

Gibb, Herman, and Keri Grace O'Leary. 2014. "Mercury exposure and health impacts among individuals in the artisanal and small-scale gold mining community: a comprehensive review." *Environmental Health Perspectives* 122 (7): 667–672.

Grandjean, Philippe, Roberta F White, Anne Nielsen, David Cleary, and Elisabeth C de Oliveira Santos. 1999. "Methylmercury neurotoxicity in Amazonian children downstream from gold mining." *Environmental Health Perspectives* 107 (7): 587–591.

Harada, Masazumi. 1995. "Minamata disease: methylmercury poisoning in Japan caused by environmental pollution." *Critical Reviews in Toxicology* 25 (1): 1–24.

Herraiz, Aurelio Diaz, and Maria de Nazaré Souza da Silva. 2015. "Diagnóstico socioambiental do extrativismo mineral familiar (garimpo) na calha do Rio Madeira, em Humaitá, Amazonas." *PEGADA-A Revista da Geografia do Trabalho* 16 (2).

Hill, Elaine L. 2018. "Shale gas development and infant health: evidence from Pennsylvania." *Journal of Health Economics* 61:134–150.

Hill, Elaine L, and Lala Ma. 2022. "Drinking water, fracking, and infant health." *Journal of Health Economics* 82:102595.

Leonard, A, P Jacquet, and RR Lauwerys. 1983. "Mutagenicity and teratogenicity of mercury compounds." *Mutation Research/Reviews in Genetic Toxicology* 114 (1): 1–18.

Maffioli, Elisa M. 2023. "The local health impacts of natural resource booms." *Health Economics* 32 (2): 462–500.

Malm, Olaf. 1998. "Gold mining as a source of mercury exposure in the Brazilian Amazon." *Environmental Research* 77 (2): 73–78.

Manzolli, Bruno, and Raoni Rajão. 2022. *Boletim do Ouro 2021-2022.* Centro de Sensoriamento Remoto da Universidade Federal de Minas Gerais (CSR - UFMG). Available at: https://csr.ufmg.br/csr/wp-content/uploads/2022/09/boletim-ouro_.pdf.

MapBiomas. 2021. *A expansão da mineração e do garimpo no Brasil nos últimos 36 anos.* Available at: https://mapbiomas-br-site.s3.amazonaws.com/Fact_Sheet_1.pdf.

———. 2022. *Collection 7.1 of the Annual Series of Land Use and Land Cover Maps of Brazil.* Available at: https://mapbiomas.org/en/download-dos-atbds?cama_set_language=en.

Mataveli, Guilherme, Michel Chaves, João Guerrero, Elton Vicente Escobar-Silva, Katyanne Conceição, and Gabriel de Oliveira. 2022. "Mining Is a Growing Threat within Indigenous Lands of the Brazilian Amazon." *Remote Sensing* 14 (16): 4092.

Meneses, Heloisa do Nascimento de Moura, Marcelo Oliveira-da-Costa, Paulo Cesar Basta, Cristiano Gonçalves Morais, Romulo Jorge Batista Pereira, Suelen Maria Santos de Souza, and Sandra de Souza Hacon. 2022. "Mercury contamination: A growing threat to riverine and urban communities in the Brazilian Amazon." *International Journal of Environmental Research and Public Health* 19 (5): 2816.

Paddock, Richard C. 2019. "The Hidden Cost of Gold: Birth Defects and Brain Damage." *The New York Times* (September 11, 2019). https://www.nytimes.com/2019/11/09/world/asia/indonesia-mercury-pollution-gold-mining.html.

Pereira, Leila, and Rafael Pucci. 2022. *A Tale of Gold and Blood: The Consequences of Market Deregulation on Local Violence.* Insper Working Paper. Available at: https://www.insper.edu.br/wp-content/uploads/2022/11/Pereira_Pucci_Oct2022_ATaleOfGoldBlood_WP_Insper.pdf.

Pfafstetter, Otto. 1989. "Classificação de bacias hidrográficas: metodologia de codificação." *Rio de Janeiro, RJ: Departamento Nacional de Obras de Saneamento (DNOS)* 19.

Pfeiffer, WC, LD Lacerda, W Salomons, and O Malm. 1993. "Environmental fate of mercury from gold mining in the Brazilian Amazon." *Environmental Reviews* 1 (1): 26–37.

Picado, Francisco, and Göran Bengtsson. 2012. "Temporal and spatial distribution of waterborne mercury in a gold miner's river." *Journal of Environmental Monitoring* 14 (10): 2746–2754.

Qian, Yao, Dan A Ralescu, and Bo Zhang. 2019. "The analysis of factors affecting global gold price." *Resources Policy* 64:101478.

Rangel, Marcos A, and Tom S Vogl. 2019. "Agricultural fires and health at birth." *Review of Economics and Statistics* 101 (4): 616–630.

Rice, Kevin M, Ernest M Walker Jr, Miaozong Wu, Chris Gillette, and Eric R Blough. 2014. "Environmental mercury and its toxic effects." *Journal of Preventive Medicine and Public Health* 47 (2): 74.

Siqueira-Gay, Juliana, and Luis E Sánchez. 2021. "The outbreak of illegal gold mining in the Brazilian Amazon boosts deforestation." *Regional Environmental Change* 21:1–5.

Sonter, Laura J, Diego Herrera, Damian J Barrett, Gillian L Galford, Chris J Moran, and Britaldo S Soares-Filho. 2017. "Mining drives extensive deforestation in the Brazilian Amazon." *Nature Communications* 8 (1): 1013.

Spadini, L, and L Charlet. 2003. "Distribution of anthropogenic mercury in French Guyana river sediments downstream from gold mining sites." In *Journal de Physique IV (Proceedings),* 107:1263–1266. EDP sciences.

Sviatschi, Maria Micaela. 2022. "Making a narco: Childhood exposure to illegal labor markets and criminal life paths." *Econometrica* 90 (4): 1835–1878.

Swenson, Jennifer J, Catherine E Carter, Jean-Christophe Domec, and Cesar I Delgado. 2011. "Gold mining in the Peruvian Amazon: global prices, deforestation, and mercury imports." *PLOS ONE* 6 (4): e18875.

Vásquez-Cortés, Mateo. 2021. *Peer Effects and Recidivism: Wartime Connections and Criminality among Colombian Ex-combatants.* Working Paper. Available at: https://www.mateovasquezcortes.com/wp-content/uploads/2022/01/Network_crime.pdf.

Von der Goltz, Jan, and Prabhat Barnwal. 2019. "Mines: The local wealth and health effects of mineral mining in developing countries." *Journal of Development Economics* 139:1–16.

WHO. 2017. *World Health Organization — Mercury and health factsheet.* Available at: https://www.who.int/news-room/fact-sheets/detail/mercury-and-health.

———. 2023. *World Health Organization — Congenital disorders factsheet.* Available at: https://www.who.int/news-room/fact-sheets/detail/birth-defects.

Wooldridge, Jeffrey M. 2010. *Econometric analysis of cross section and panel data.* 2nd ed. Cambridge: MIT press.

World Gold Council. 2023. *Gold Producion by Country.* Available at: https://www.gold.org/goldhub/data/gold-production-by-country.

Wyatt, Lauren, Ernesto J Ortiz, Beth Feingold, Axel Berky, Sarah Diringer, Ana Maria Morales, Elvis Rojas Jurado, Heileen Hsu-Kim, and William Pan. 2017. "Spatial, temporal, and dietary variables associated with elevated mercury exposure in Peruvian riverine communities upstream and downstream of artisanal and small-scale gold mining." *International Journal of Environmental Research and Public Health* 14 (12): 1582.