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

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Abstract

This paper aims to investigate the effects of gold mining, which contaminates water mainly through mercury, on the birth health of local populations in the Amazon. Our identification strategy uses a differences-in-differences approach, exploiting exogenous variation stemming from changes in the regulatory framework, fluctuation of international gold prices, and local geographical characteristics — namely, the direction of river flows and distribution of geological gold deposits. Our results show a significant increase in birth anomalies, and a subtle decrease in birthweight, for populations downstream from potential gold extraction operations, while there is no effect for populations living upstream from these locations.

1 Introduction

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

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ities in the 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). 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 et al., 2020; Garcia et al., 2022).

Such an increase is concerning for several reasons. 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). Moreover, the use of mercury during the gold extraction process contaminates water courses, and there is ample evidence about the negative effects of mercury on human health (Bjørklund et al., 2019; Dack et al., 2021; Grandjean et al., 1999). Specifically, toxicology research shows that the way mercury interacts with proteins in the body is particularly damaging for intra-uterine development, leading to neurodevelopmental consequences such as birth anomalies, miscarriages, and low birth weight (Rice et al., 2014).

However, even though there is compelling evidence that gold mining in the Amazon leads to mercury contamination, especially downstream from mining locations, and that mercury contamination is associated with several negative health consequences, evidence linking these two phenomena directly is lacking. 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).

In this study, we aim to 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. We apply a combination of instrumental variables and differences-in-differences approach, leveraging exogenous variation stemming from changes in international gold prices and local geographical characteristics, such as the direction of river flows and distribution of geological gold deposits. This strategy is largely inspired by Dias et al. (2023), who exploited variation in river flows to study the effects of glyphosate usage, and by Pereira and Pucci (2022), who used the geographical distribution of gold deposits to investigate the effects of illegal mining in the Amazon on conflict and homicides.

Our results show a significant increase in the rate of birth anomalies in regions downstream from gold deposits in periods where mining activity increases. In placebo exercises considering populations living *upstream* from gold deposits, we 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, alternative choices of the time-series variation in the differences-in-differences estimator, and others.

These results add to the large literature on 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). Our findings also contribute to a broader literature on the externalities of mining and other primary activities. In this sense, the paper dialogues with Dias et al. (2023) who show that glyphosate usage in Brazil increased infant mortality, and also with other literature that 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).

With this, the 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 our knowledge, this is the first time that subclinical effects of mercury contamination in the Amazon are investigated at a large scale. The confirmation of a relationship between gold mining and birth anomalies can be helpful for policies aiming to alleviate health consequences for local populations as well as provides direct evidence of the harmful effects of mining, which can be used to reinforce calls for stronger environmental legislation and enforcement in the region.

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 [1]. 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 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" [2]. *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,

[1] And it has often ranked among the top 10. See World Gold Council (2022).

[2] We use the terms mining and *garimpo* interchangeably throughout the rest of the text for simplicity, but note that none of our analysis considers industrial mining

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). Moreover, a law passed in 2013 deregulating the market for gold led to increases in illegal mining, as it removed requirements for buyers to ensure the origin of the purchased gold (Pereira and Pucci, 2022).

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 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 increases in violence. In one of the only studies that apply econometric methods to the issue of mining in the Amazon, Pereira and Pucci (2022) show that after the law passed in 2013 increased incentives for illegal mining, homicides surged in small municipalities with gold reserves in indigenous lands.

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 reveal that the levels of exposure are more than 2 to 6 times the internationally recognized reference doses, much higher 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 et al., 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"[3]. 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).

Many studies focus on the effects of occupational exposure — 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

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

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, we can test the hypothesis that contamination from gold mining affected health outcomes by exploiting variations in the direction of river flows. We do so by employing a difference-in-differences estimator, comparing municipalities that have gold deposits upstream with those that do not.

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, 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 below).

This strategy is inspired by Dias et al. (2023), who 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. We also take advantage of a variation of mining in time by comparing municipalities before and after a significant uptake in gold mining since the early 2010s. Figure 2 shows this increase — especially in protected areas —, which was driven by rising gold prices and a 2013 law that deregulated the raw gold market, in practice inciting illegal gold mining (Siqueira-Gay and

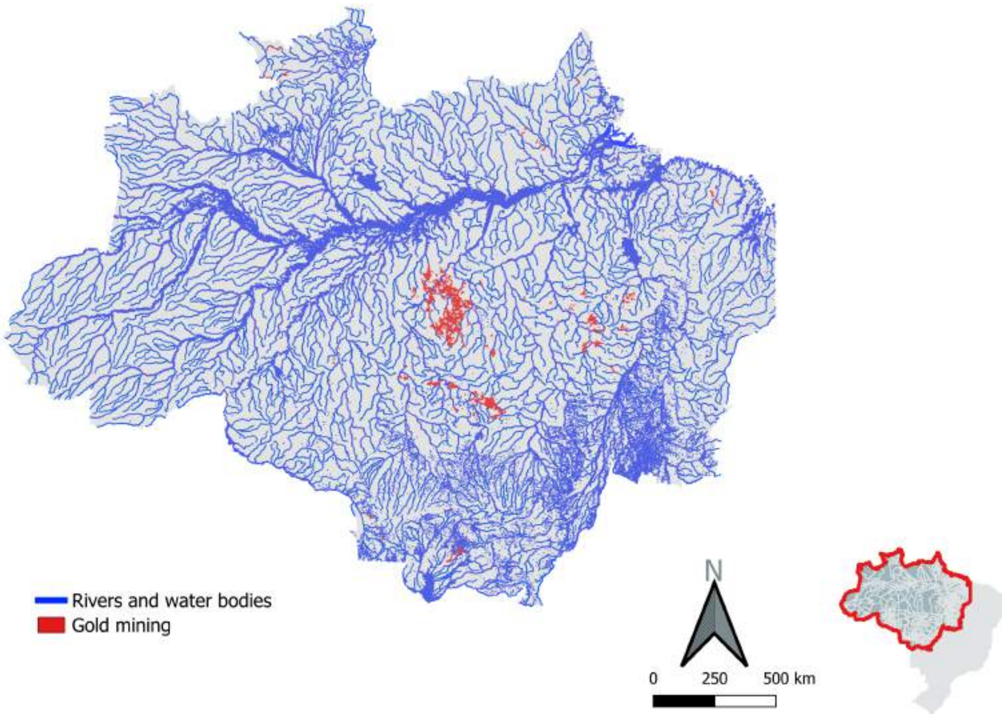

Figure 1: **Rivers and mining in the Brazilian Amazon**. This figure shows the distribution of rivers and water bodies in the Legal Amazon as well as the regions where gold mining was detected in 2021. Own elaboration based on data from different sources (see Data sources).

Sánchez, 2021; Pereira and Pucci, 2022).

3.1 Measuring gold mining throughout time

Ideally, our 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 in which there is 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 (ear, 2023; MapBiomas, 2022). Nevertheless, because this

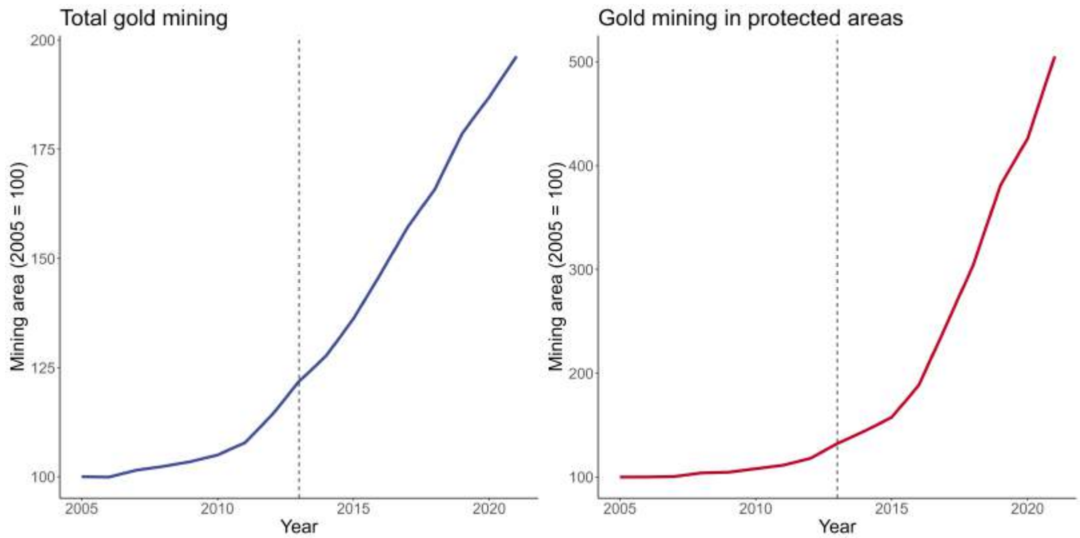

Figure 2: **Evolution of gold mining in the Amazon**. This figure shows the evolution of the total area categorized as gold mining in the Legal Amazon, normalized to the value in 2005. The red line shows mining in protected areas (Indigenous Territories and Conservation Areas). The dashed line marks the deregulation of the raw gold market in 2013. Own elaboration based on data from different sources (see Data sources).

measure is by construction an approximation, there likely is significant measurement error. There may also be endogeneity in the location of mining activities.

Therefore, instead of using these data, we 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 3 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.

The strategy requires combining this exogenous spatial variation with time variation in gold mining activities, which should also be exogenous to local municipalities. For that, we employ two different strategies. First, directly following Pereira and Pucci (2022), we consider the year 2013, when the law deregulating the raw gold markets was introduced. However, differently from Pereira and

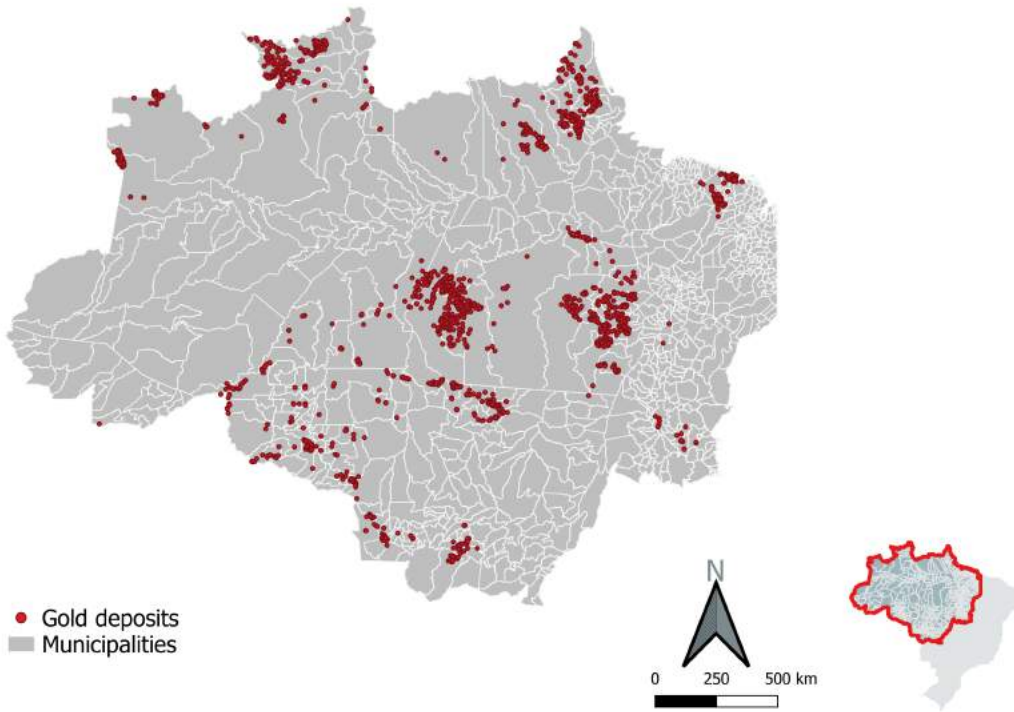

Figure 3: **Gold deposits in the Brazilian Amazon**. This figure shows the distribution of known gold deposits in the Legal Amazon. Own elaboration based on data from different sources (see Data sources).

Pucci (2022), we do not need a strategy that contrasts legal and illegal mining. Therefore, a second strategy involves interacting the gold deposit variable with international gold prices, which are also arguably exogenous to gold extraction in Brazil and have been deemed a crucial driver of the increases in gold mining in the Amazon (Siqueira-Gay and Sánchez, 2021).

Figure 4 below displays the evolution of international gold prices, showing there was a large increase also during the 2010 decade. In terms of Brazilian Reais, the greatest increase was after 2015, mostly due to currency depreciation.

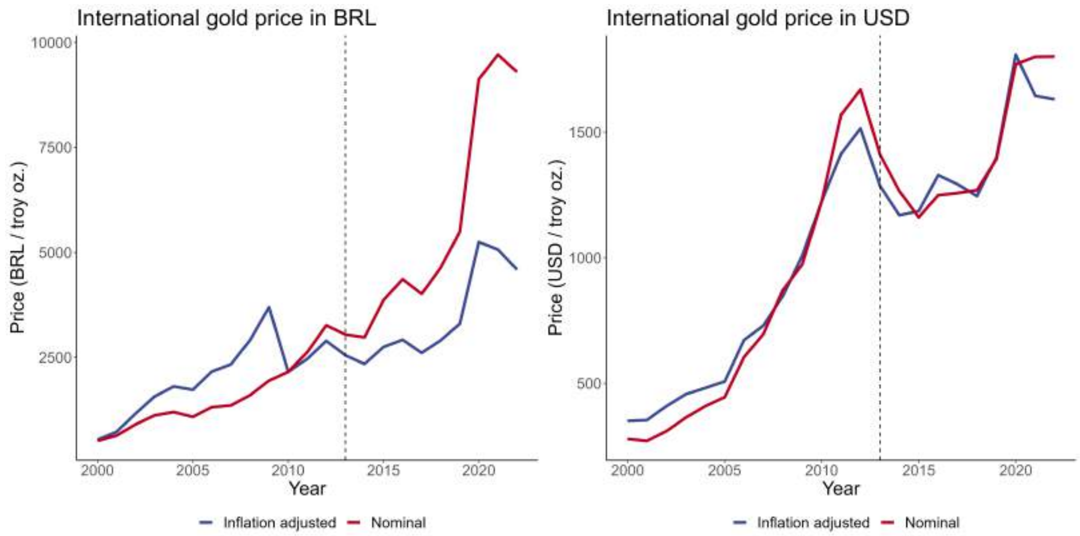

Figure 4: **Evolution of global gold prices**. This figure shows the evolution of the international gold prices (price per troy ounce), in both Brazilian Reais (BRL) and United States Dollars (USD), from 2005 to 2021. The inflation-adjusted lines show values in 2010 USD and BRl. One troy ounce is around 31 grams. The dashed line marks the deregulation of the raw gold market in 2013. 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 time variable — either a post-2013 indicator or the global price of gold —, it is then needed to determine how to identify the upstream-deposits variable. Using the geocoded information, it is possible to determine whether a given municipality has gold deposits. However, deciding which municipalities lie upstream or downstream from each other is trickier.

The strategy used by Dias et al. (2023) 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 [4] in Brazil— are categorized in different levels, starting from level 1 which encom-

[4]Named after the classification method for water bodies developed by Otto Pfafstetter (Pfafstetter, 1989)

passes the whole continent, and continuing to local basins that are subdivisions of the higher levels. Following their method, we focus our analysis on levels 3 and 4, as level 2 basins are excessively large, and a municipality can include dozens of level 5 basins. For simplicity, hereafter we 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. We 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 5).

However, a municipality may contain more than one sub-basin, and may even be divided among different basins. Therefore, we consider each intersection between municipalities and sub-basins as a separate unit of analysis (see Figure 6). We 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 [5]. However, as detailed in the next section, we exclude municipalities with gold deposits inside their territory to ensure our 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.

[5]The official count for municipalities in the Legal Amazon is 772. We 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, we combine the municipalities of Mojuí dos Campos and Santarém in Pará, which separated in 2012.

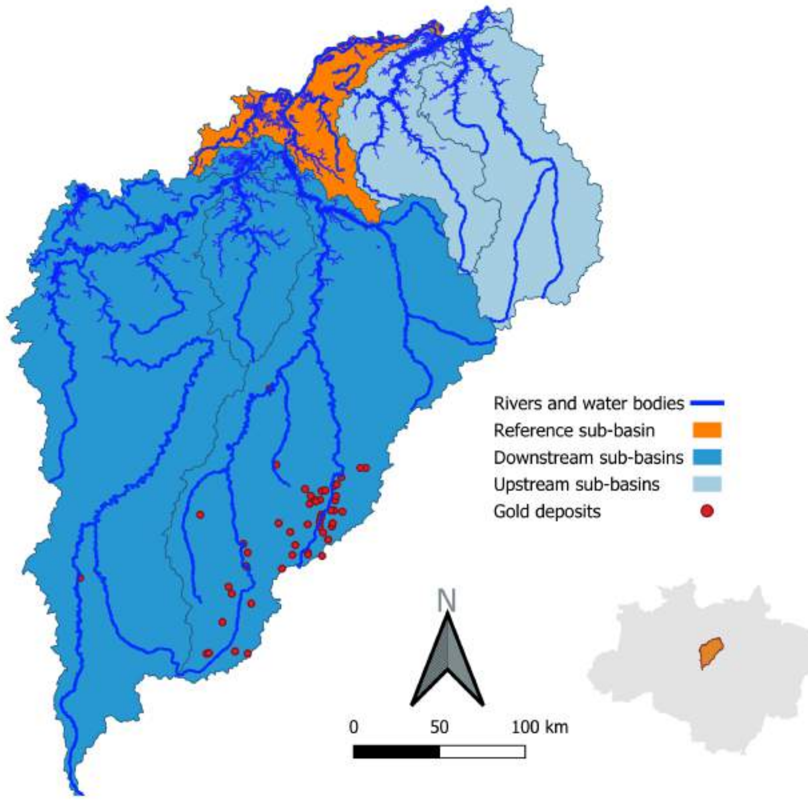

Figure 5: **Illustration of identification strategy**. This figure shows an example water basin with sub-basins within it. In this example, the orange sub-basin would be categorized as not treated, as the gold deposits are present in sub-basins downstream from it, but not upstream. Own elaboration based on data from different sources (see Data sources).

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

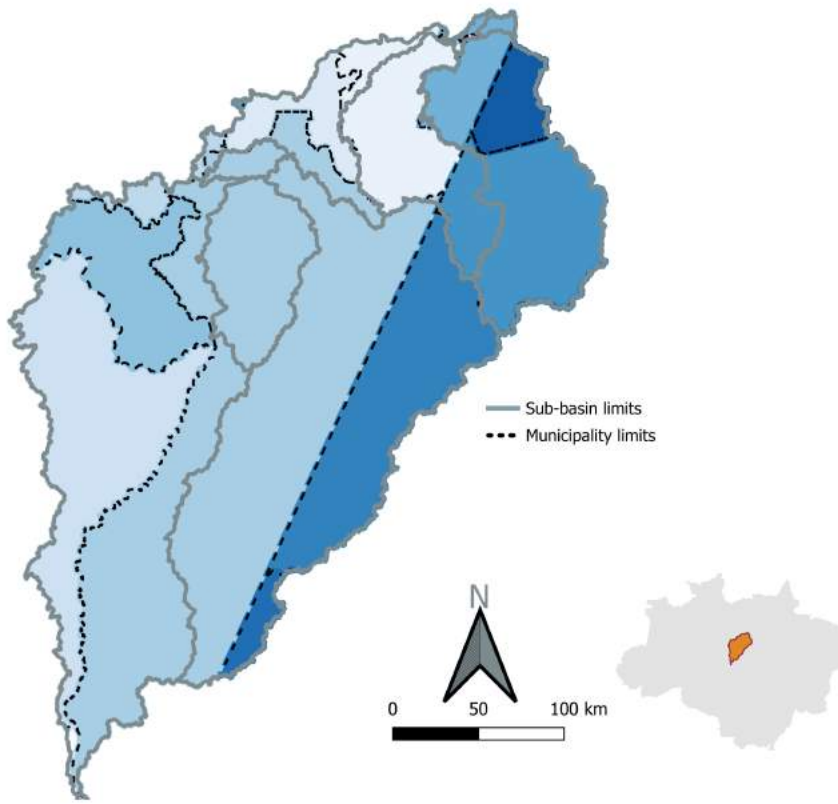

Figure 6: **Example of municipality and water basins limits**. This figure displays sub-basin limits (gray lines) and municipality limits within an example water basin (dashed lines and colors). Own elaboration based on data from different sources (see Data sources).

3.3 Empirical specification

With data in hand, we use a panel [6] of municipalities and a difference-in-differences (DiD) approach 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. 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. This is the case when considering the 2013 law that deregulated the raw gold markets as the beginning of treatment, as done by Pereira and Pucci (2022). However, introducing a continuous variable to measure time variation is preferable as it allows me to explore within-year variations, instead of simply comparing municipalities before and after 2013. Since the literature suggests that regulatory frameworks and international gold prices both contributed to the rise in gold mining in the Amazon, exploring both approaches seems reasonable.

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). Because choosing this threshold would be an arbitrary decision, we instead directly use gold prices as the 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 such as cocaine (Dube and Vargas, 2013; Vásquez-Cortés, 2021; Sviatschi, 2022).

The timing — whether a post-2013 dummy or 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

[6] The main regressions consider only municipalities without gold deposits, N = 616, from 2005 to 2021. Moreover, two municipalities had no births in 2005. Most regressions therefore have $616 \times 17 - 2 = 10,470$ observations

upstream. Because the occurrence of gold deposits was given millions of years before the beginning of the analysis, this assumption is likely to hold.

However, it may be the case that mining in the municipalities themselves, as opposed to mining upstream from them, has several socioeconomic 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, we exclude municipalities that have gold deposits from our sample. This ensures our estimates capture the effect of upstream mining, which would arguably only affect birth outcomes through water contamination. [7].

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

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

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 (note that it does not vary across municipalities), $GoldUp_i$ 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), and ε_{it} is a random error. 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.

We estimate specifications using the global price in both Brazilian Reais (BRL) and United States Dollars (USD). Moreover, following the specification used by Pereira and Pucci (2022), we present results using a simpler model where the price variable is replaced by a dummy equal to 1 after 2013, to capture the effect of the deregulation of the raw gold market. Importantly, besides these alternative spec-

[7]We 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 et al. (2023)

ifications, we estimate placebo regressions using gold deposits *downstream* from municipalities, as well as deposits for other minerals, which would not lead to mercury contamination. In additional robustness tests, we add a vector of controls such as municipal income, share of municipal income from industrial activities, 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, we add them by interacting their fixed level in 2007 with year-fixed effects. This avoids bias arising from the outcome and covariates being simultaneously determined. However, because the health data are not available before 2007, such that this requires excluding some years from the sample, we omit these controls in the main specification.

3.4 Data sources

All data used are obtained from publicly available sources, listed below:

- **DATASUS[8]:** This is a system managed by the Ministry of Health, from which microdata for births (SINASC — Sistema de Informações Sobre Nascidos Vivos) was extracted. We then calculate yearly averages by municipality from 2005 up to 2021 of different variables, used as dependent variables in the regression analyses. Namely: rate of birth anomalies per 1,000 live births, mean birth weight, rate of newborns with low birth weight (below 2,500g), pre-term birth rate (gestation length below 37 weeks), share of newborns with low Apgar1[9] score, total number of births, as well as other demographic characteristics such as share of male and white births and mean mother age.

- **Agência Nacional de Águas[10]:** The National Water Agency provides geocoded

[8] https://datasus.saude.gov.br/

[9] The Appearance, Pulse, Grimace, Activity, Respiration (Apgar) score is a test performed on newborn infants shortly after birth. Apgar1 refers to the score 1 minute after birth.

[10] https://metadados.snirh.gov.br/geonetwork/srv/api/records/b228d007-6d68-46e5-b30d-a1e191b2b21f

data on all water bodies in Brazil, including direction of water flows and limits of each ottobasin. We use these data to identify which municipalities are upstream and downstream of each other in the same ottobasin.

- **Serviço Geológico do Brasil[11]:** This dataset contains geocoded data on all known mineral deposits in Brazil. We use it to identify gold deposits in each municipality and water basin.
- **IBGE[12]:** From the Brazilian Institute of Geography and Statistics (IBGE), we obtain the municipal level variables by year: municipal income, share of municipal income from industrial activities, and population.
- **World Bank[13]:** From the World Bank's Commodity Price Data databank, we obtain yearly averages of the international gold price.
- **FUNAI[14] and Ministério do Meio Ambiente[15]**: From the Brazilian Ministry of Environment and the National Indigenous People Foundation (FUNAI), we obtain shapefiles with limits of protected areas where mining is not allowed: Indigenous Territories (Terras Indígenas Homologadas) and Conservation Areas (Unidades de Conservação de Proteção Integral and Reservas Extrativistas).
- **Secretaria de Atenção Primária à Saúde[16]:** From the Brazilian Ministry of Health, we obtain data on the share of the population, by municipality and year, covered by primary health care (Saúde da Família).
- **MapBiomas[17]:** This source provides datasets with geocoded mining loca-

[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://www.gov.br/funai/pt-br/atuacao/terras-indigenas/geoprocessamento-e-mapas

[15] http://mapas.mma.gov.br/i3geo/datadownload.htm

[16] https://egestorab.saude.gov.br/paginas/acessoPublico/relatorios/relHistoricoCoberturaAB.xhtml

[17] https://mapbiomas.org/en/download-dos-atbds?cama_set_language=en

tions derived from artificial intelligence analyses of satellite data. Note that these are not used in the main analysis.

3.5 Descriptive statistics

Table 2 below shows summary statistics of the main variables.

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 13,000 municipality-year observations in the sample, over 5,000 are zero. This could cause problems with the use of OLS regression, and therefore we 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 was a total of 5,326 birth anomalies in our 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 underreporting of birth anomalies, which is likely even worse in less urbanized areas such as the Amazon [18].

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

[18] 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.

4 Results

4.1 Birth anomalies and gold mining

A first look at the data in Figure 7 shows that in the mid-to-late 2010s there was an uptake 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.

Column (1) shows the upstream gold deposit variable interacted with the post-2013 dummy, capturing the effect of the law that deregulated raw gold markets. The interpretation is that, after 2013, municipalities that have gold reserves upstream had a relative increase of 2.1 anomalies per 1,000 live births. Columns (2) and (3), on the other hand, use the international price of gold in logs. The interpretation in this case is a relative increase of 0.018—0.021 anomalies per 1,000 births for each percentage increase in the price of gold. In USD, 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. Meanwhile, in BRL, gold prices nearly tripled in the period, suggesting a relative increase of more than 3 anomalies per 1,000 births. Therefore, though the magnitudes of the coefficients seem similar at first glance, the model with USD provides more conservative estimates. As using USD prices is also the employed approach in previous similar work, we choose this as our preferred specification (Swenson et al., 2011; Maffioli, 2023).

As a placebo exercise, Table 5 replicates Table 4, but replacing the upstream treatment variables with their downstream counterparts. Supporting the main

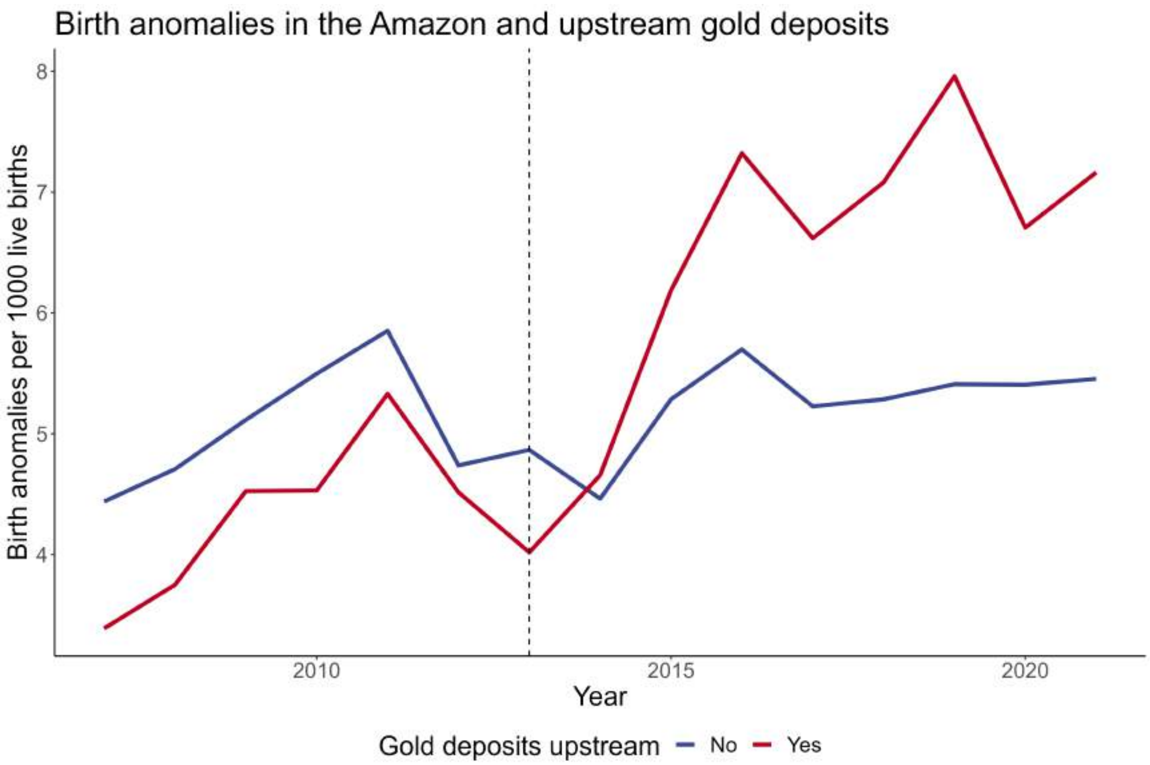

Figure 7: **Birth anomalies in the Amazon**. This figure shows the evolution of the average rate of birth anomalies in municipalities by the availability of gold deposits upstream (excluding municipalities with gold deposits). Averages are calculated as the mean across municipalities for each year, weighted by the number of births in each municipality and year. The dashed line marks the deregulation of the raw gold market in 2013.

results, these point estimates are smaller in magnitude and not statically distinguishable from zero, as expected. These regressions also exclude municipalities with deposits themselves.

A second placebo exercise is shown in Table 6, 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 rules out the possibility that another factor related to geological deposits is driving the results. Again, coefficients are smaller

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

	Dependent variable:		
	Birth anomalies per 1000		
	(1)	(2)	(3)
$Gold_{Up} \times \mathbf{1}\{t \geq 2013\}$	2.082^{**}		
	(0.974)		
$Gold_{Up} \times P_{BRL}$		1.795^{**}	
		(0.834)	
$Gold_{Up} \times P_{USD}$			2.056^{**}
			(0.859)
N	10,470	10,470	year-fixed R^2
0.253	0.255	0.248	

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 2005 and 2021. Regressions are difference-in-difference 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. In Column (1), it is interacted with a dummy equal to 1 after 2013, while in Columns (2) and (3) it is interacted with the log of the international gold price in USD and BRL. 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. Standard errors shown in parentheses are clustered at the water basin level. *p$<$0.1; **p$<$0.05; ***p$<$0.01

in magnitude and not statistically significant (except for the coefficient in column (3), which is significant at 5%, but has the opposite sign and is almost half the size of its counterpart in Table 4).

Table 5: **Placebo: Gold deposits downstream**

	Dependent variable:		
	Birth anomalies per 1000		
	(1)	(2)	(3)
$Gold_{Down} \times \mathbf{1}\{t \geq 2013\}$	1.148		
	(0.987)		
$Gold_{Down} \times P_{BRL}$		0.943	
		(0.817)	
$Gold_{Down} \times P_{USD}$			0.627
			(0.930)
N	10,470	10,470	10,470
R^2	0.246	0.246	0.243

Note: This table shows results from placebo regressions versions of the regressions in Table 4. Instead of using a dummy for the existence of gold upstream, these models use a dummy for gold downstream. Standard errors shown in parentheses are clustered at the water basin level. *p<0.1; **p<0.05; ***p<0.01

Table 6: **Placebo: Other deposits upstream**

	Dependent variable:		
	Birth anomalies per 1000		
	(1)	(2)	(3)
$Others_{Up} \times \mathbf{1}\{t \geq 2013\}$	-1.070		
	(0.789)		
$Others_{Up} \times P_{BRL}$		-0.904	
		(0.593)	
$Others_{Up} \times P_{USD}$			-1.314^{**}
			(0.633)
N	10,470	10,470	10,470
R^2	0.244	0.244	0.244

Note: This table shows results from placebo regressions versions of the regressions in Table 4. Instead of using a dummy for the existence of gold upstream, these models use 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 across the three different models and the placebo regressions help rule out the hypothesis that the results are spurious, we conduct further sensitivity tests to support the validity of the results. Table 7 shows the results from these tests, considering alternative specifications of the USD model. Column (1) presents a specification without covariates, analogous to that in Column (3) of Table 4, but considering only 2007 to 2021. The next columns control for municipal covariates added as interactions of year dummies with baseline measures of different socioeconomic variables. Column (2) controls for municipal income and the share of municipal GDP from industrial activities (including mining). Column (3) controls for the share of the population covered by a major primary care health program (Programa Saúde da Família). In, Column (4), we replace the year fixed effects with year-state dummies interactions. In Column (5), the gold price in USD is adjusted for inflation, while in Column (6), we consider only gold deposits that lie within protected areas, and are therefore surely illegal mining. Finally, in Column (7), we 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 are mostly still significant at 5%.

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 8 shows results using these alternative estimators. The coefficients are all positive and significant, suggesting that the results from the linear models are

Table 7: **Robustness tests: alternative specifications**

	Birth anomalies per 1000						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Gold_{Up} \times P_{USD}$	2.283*	2.263**	2.239**	1.079**	1.261**	0.954*	1.148**
	(1.159)	(1.012)	(0.970)	(0.485)	(0.622)	(0.554)	(0.481)
Income controls		Y	Y	Y	Y	Y	Y
Health controls			Y	Y	Y	Y	Y
State dummies				Y	Y	Y	Y
Adj. for inflation					Y		
Protected areas only						Y	
Full sample							Y
Observations	9,240	9,240	9,240	9,240	9,240	9,240	11,520
R^2	0.254	0.267	0.269	0.384	0.384	0.383	0.376

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

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 (3) 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 $0.58 \times 0.27 = 0.156$ in the expected log count of anomalies, which translates to about 16%. 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 16% 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 9 shows the results for other birth outcomes that could be expected to also be affected by mercury contamination. Columns (1) and (2) show a slight negative effect on birthweight, both in terms of the average birthweight and in terms of the share of low-birthweight births (below 2,500g).

Table 8: **Robustness tests: count data models**

	Birth anomalies					
	Negative Binomial			Poisson		
	(1)	(2)	(3)	(4)	(5)	(6)
$Gold_{Up} \times \mathbf{1}\{t \geq 2013\}$	0.532***			0.866***		
	(0.202)			(0.270)		
$Gold_{Up} \times P_{BRL}$		0.485***			0.793***	
		(0.166)			(0.169)	
$Gold_{Up} \times P_{USD}$			0.580***			0.733***
			(0.225)			(0.276)
N	10,470	10,470	10,470	10,470	10,470	10,470

Note: This table shows results from regressions similar to that in Table 4, but using count data models instead. Columns(1)-(3) show results from Negative Binomial Generalized Linear Models, while columns (4)-(6) 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 regressions in Table 4. Standard errors shown in parentheses are clustered at the water basin level. *p<0.1; **p<0.05; ***p<0.01

There is no significant effect in the preterm rate nor in the rate of low APGAR1 score. 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.

Table 9: **Additional results**

Panel A: Additional health outcomes				
	(1)	(2)	(3)	(4)
	Birthweight	LBW rate	Preterm rate	Low APGAR1 rate
$Gold_{Up} \times P_{USD}$	-14.674^{*}	0.003^{**}	0.012	0.001
	(7.522)	(0.001)	(0.008)	(0.008)
N	10,470	10,470	10,470	10,470
R^2	0.670	0.488	0.619	0.544
Panel B: Additional demographic outcomes				
	(5)	(6)	(7)	(8)
	Birth rate	Male births (%)	Mother age	White births (%)
$Gold_{Up} \times P_{USD}$	0.0004	-0.001	0.068	-0.016
	(0.001)	(0.002)	(0.109)	(0.030)
N	10,472	10,470	10,470	10,470
R^2	0.822	0.972	0.894	0.730

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

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, we 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 me to differentiate data at the sub-basin level, we 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 10 below displays coefficients from regressions 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, we 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.

Table 10: **Mechanism: increases in gold mining**

	Dependent variable:		
	Gold mining area (km^2)		
	(1)	(2)	(3)
$Gold \times P_{USD}$	3.187**	2.841**	4.493*
	(1.615)	(1.438)	(2.320)
State dummies		Y	Y
Adj. for inflation			Y
N	13,056	13,056	13,056
R^2	0.825	0.826	0.827

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

The interpretation of these results is that municipalities that have gold deposits saw an increase of around $3/100km^2$ 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 $3 \times 0.27 = 0.81$ squared kilometers in the area identified as gold mining [19]. This is reassuring for our main identification strategy, 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 and that setting up operations requires some time, 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 of gestation for this contamination to be reflected in birth outcomes. It is thus reasonable to expect that these results are not concurrent, but happen in a lagged fashion instead. This can be tested by running regressions with the lagged price of gold. Figure 8 displays coefficients from this exercise.

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 7. 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 is slightly larger than the main coefficient at time 0, confirming the hypothesis that the analysis is actually 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 go to zero when

[19]To give a sense of scale, aggregate data from MapBiomas (2021) indicates that the total area of *garimpo* gold mining in Brazil increased by around 520 km^2 in this period.

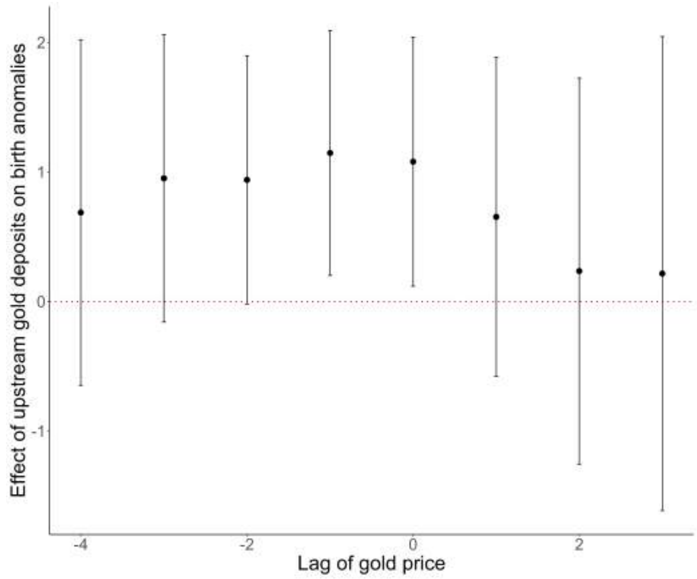

Figure 8: **Timing of the effect of gold mining on birth anomalies**. This figure shows coefficients and 95% confidence intervals of regressions similar to those in column (4) of Table 7, but considering lagged prices of gold instead.

considering leading prices, meaning that there is no effect of future prices on past births.

5 Discussion

In this work, we 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 uptake 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. We 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 we 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 et al. (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 for sure 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.

We also find results on birthweight, 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 we 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 da 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. Though it is hard to assert causality, this relationship is robust to many sensitivity and placebo tests and has its underlying physiological mechanisms founded in solid health literature.

In complementing existing research on mining's impact on issues like deforestation, hunger, and violence, this study underscores the critical need for multifaceted policy interventions. The implications are far-reaching, demanding immediate action on several fronts. Implementing robust environmental laws, establishing effective monitoring systems, and addressing social concerns through targeted alleviation efforts are imperative. Simultaneously, tracking the gold supply chain is crucial to curb illegal sales and prevent the laundering of illicitly obtained gold.

Recognizing the importance of local context, interventions should be tailored to address specific social aspects. This entails exploring alternative sources of income for communities affected by mining activities. To ensure a comprehensive and sustainable approach, collaborative efforts are required across governmental, environmental, and social sectors. Further research should investigate this topic further to assert definitively the mechanisms at play and aid the design of effective policies across health, environmental, and social domains.

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