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ORIGINAL PAPER

Lithium-ion batteries and fertility in Africa

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Abstract
This study investigates how the global adoption of modern electrical batteries influenced women's fertility choices in the Democratic Republic of the Congo, a country rich in cobalt, an essential component of lithium-ion batteries. The findings reveal that women living in cobalt-rich villages experience higher fertility rates and a greater desire for children relative to those in non-cobalt-rich communities. I attribute this phenomenon to the use of children in cobalt mines, as opposed to other mineral mining activities, which leads to a short-term increase in household wealth and motivates parents to have more children. These results provide novel insights into our understanding of the complex relationship between economic development, natural resources, and fertility decisions in developing economies.

Keywords Lithium-ion batteries · Child labor · Fertility · Cobalt mining

JEL Classification O13 · I25 · J13

1 Introduction

Research on women's fertility holds significant importance for economists and social scientists, particularly in African countries where fertility plays a crucial role in long-term socio-economic development (Galor 2022; Becker 1960).

However, limited attention has been given to contexts of low socio-economic development, where the extraction of natural resources often involves the use of children amid weak government enforcement of regulations regarding child labor. When children are employed in these resource extraction activities, the opportunity cost of having a child decreases, providing incentives for parents in such areas to increase the size of their families (Hazan and Berdugo 2002; Doepke and Zilibotti 2005).

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This study investigates the effects of the surge in global demand for lithium-ion batteries on the fertility decisions of women living in cobalt-rich communities of the Democratic Republic of the Congo (DRC). Cobalt, an essential component of modern electric batteries extensively used in wireless devices such as PCs, smartphones, and electric vehicles, is primarily found in the DRC. The DRC, renowned for its rich reserves of crucial minerals, serves as a plausible example where stringent child labor regulations are lacking (Carlson 2006; Maystadt et al. 2014) and where evidence of child labor in cobalt mines is prevalent (Nkulu et al. 2018; Unicef 2017).

Using survey data on the birth history of women living in the DRC, I employ a difference-in-differences approach, exploiting two sources of variation: the geographic variations in cobalt deposits within the DRC (Figs. 1 and 2), and the temporal variation stemming from the sharp increase in cobalt production driven by the global adoption of lithium-ion batteries that has occurred since 2007 (Fig. 3).

The baseline model compares fertility rates of women living in cobalt-rich villages before and after the cobalt mining boom with those living outside cobalt deposits, who serve as the comparison group. The study reveals that, following the boom in cobalt mining production, women in cobalt-rich communities exhibited higher fertility rates and a desire to have children compared to those living in non-cobalt-rich villages.

I discuss different channels explaining the association between fertility and cobalt mining. First, I present suggestive evidence that children living in cobalt mining villages achieve lower education and are more likely to be employed outside their family

Fig. 1 World map of major cobalt deposits. *Notes:* Figure retrieved from the US Geological Survey (2019). Based on USGS Global 30 arc-second elevation data (1996) and from Natural Earth (2014)

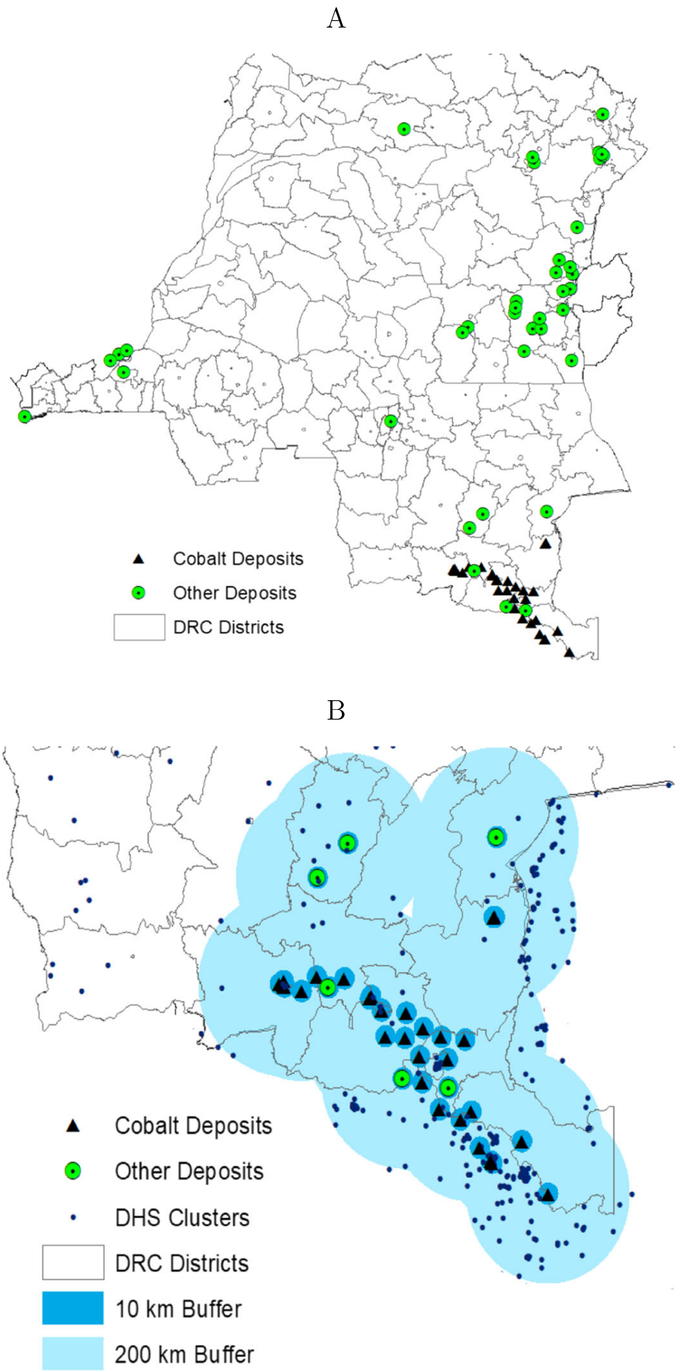


Fig. 2 Map of mineral deposits in the DRC and villages of residence of surveyed women

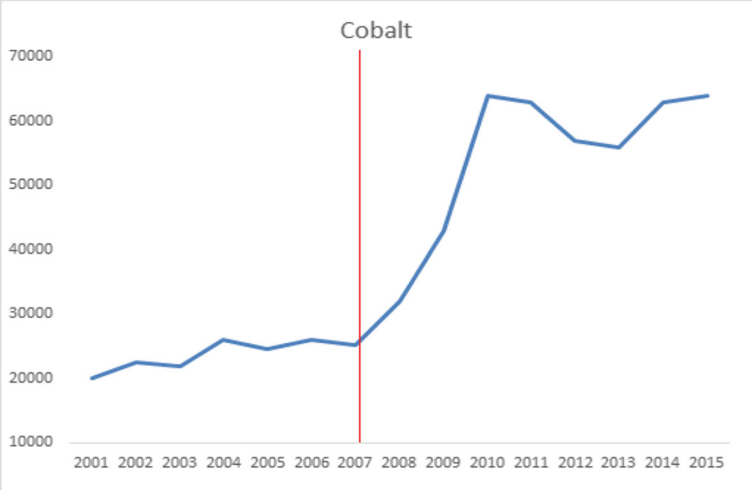


Fig. 3 Cobalt production in the DRC (tons). *Notes:* The figure is obtained from data provided by the British Geological Survey (2018) and the US Geological Survey (2019). Data on cobalt production in the DRC consider large-scale registered cobalt deposits only. Official data on cobalt production from artisanal-small scale cobalt mines are not available

environment than their peers living in non-cobalt-rich communities (Malpede 2022). As a result, household wealth among families with at least one child increased following the cobalt mining boom. Similarly, I also show that the use of contraceptive methods in cobalt-rich villages following the cobalt-mining boom declined, demonstrating a greater willingness of families surrounding cobalt deposits to have children. These results align with the arguments presented by Doepke and Zilibotti (2005), suggesting that families opt for child labor rather than investing in their children's education in the absence of effective child labor regulations.

The baseline model incorporates various individual and household controls, such as the woman's education level, residency status, and birth year. To ensure the validity of the results, I also assess the influence of endogenous migratory flows to and from cobalt-rich communities on the coefficient estimates, which remain robust even after excluding women who have migrated from the sample. Furthermore, I compare women living in cobalt-mining villages with those living in other mineral-rich areas of the DRC, confirming the evidence of increased fertility in cobalt-rich communities after 2007 as opposed to other mineral-rich communities.

The findings of this study contribute to three strands of economic literature. First, Galor and Weil (1999) and Galor and Moav (2002) suggest that during the demographic transition, parents substitute quality for quantity in response to the increase in the return to human capital, as confirmed empirically (Bleakley and Lange 2009; Becker et al. 2010). The results of this paper validate the quantity-quality trade-off in the specific context of the African continent.

Focusing on historical Christian missionary activities, which were essential in promoting human capital in colonial Africa, Okoye and Pongou (2023) found that the restrictions of missions in some areas of Nigeria have led to lower levels of education and higher fertility today, inducing a slower pace of the demographic transition. Likewise, I find that the use of child labor in mining activities has effects similar to the restriction of missionary activity. Both hinder the development of human capital and lead to lower education levels, which, in turn, results in higher fertility rates and lower per-capita incomes in the long term.

Second, the results of this paper strongly support the theory of Galor and Mountford (2008) on the differential effect of trade on the demand for human capital across developed and developing countries. Specifically, the theory predicts that in countries that are far from the technological frontier, such as the DRC, a significant portion of the gains from international trade (defined as the trade between high and low-income countries) is directed towards population growth (or increased fertility).

Third, the present article expands the literature on the economic effects of mineral abundance in surrounding areas. Recent studies have demonstrated the positive impacts of mineral extraction on women's empowerment, infant health, and household wealth in developing countries in Latin America and sub-Saharan Africa (Baum and Benshaul-Tolonen 2021; Benshaul-Tolonen 2018; Aragón and Rud 2013). Moreover, Wanamaker (2012) showed that the extractive industry was a determinant for the decline in fertility rates in the US in the late 1800s.

In contrast, using the recent cobalt mining boom, this study reveals that in the context of poor child labor regulations, fertility rates have significantly increased in surrounding communities, potentially delaying the fertility transition of cobalt-rich regions in sub-Saharan Africa.

The remainder of the paper proceeds as follows: Section 2 provides an overview of the institutional background and discusses the theoretical factors underlying the effects of child labor on fertility. Section 3 describes the data sources and outlines the empirical strategy. Section 4 presents the main results, demonstrating the effects of cobalt mining on women's fertility rates in the DRC. In Section 5, the study provides evidence of the mechanisms behind the increased fertility in cobalt-rich villages. Section 6 discusses the potential threats to the validity of the estimates, and finally, Section 7 concludes the paper.

2 Background and institutional context

The fertility rate in Africa, although declining, remains the highest in the world. According to the United Nations World Population Prospect (UNFPA, 2022), each woman had an average of 4.21 children, down from 5.24 children in 2000.[1]

The long-term determinants of fertility in Africa are of significant interest to social scientists as well as economists. According to the unified economic growth theory, technological advancement leads to greater demand for education, triggering a fertility decline and resulting in higher incomes (Galor and Moav 2002; Okoye and Pongou 2023).

[1] The Population Data Portal of the United Nations Population Fund (UNFPA) is freely accessible at the following link: https://pdp.unfpa.org/

However, there are significant regional and national differences. Ezeh et al. (2009) show that fertility decline has stalled in some sub-Saharan African countries. The main reasons for this stall can be attributed to declines in contraceptive use, increases in unmet need for family planning, increasing preferences for larger families, and increases in adolescent fertility. Women in the Democratic Republic of the Congo, Niger, and Somalia have more than six children per woman, which is almost double the average of North African women who have around three children. Rural areas have higher fertility rates than urban areas.

Regarding the specific example of the DRC, the sub-Saharan African country is going through a demographic transition characterized by a decline in both mortality and fertility rates over time. This fertility decline started during the 1960s and is still ongoing. According to UNFPA, the crude death rate has decreased from 19.6 deaths per 1000 people in 1960 to 9.2 deaths per 1000 people in 2020, while the total fertility rate has decreased from 6.98 children per woman in 1960 to 5.96 children per woman in 2020. Shapiro and Hinde (2017) argue that the decline can be attributed to several factors, including lower mortality after the civil war ended in 2003, low availability and accessibility of modern contraceptive methods, and an increase in primary education enrollment rate, which rose from 58% in 2004 to 71% in 2017 (UNFPA).

However, the decline in fertility rate in the DRC is still incomplete and, most importantly, uneven across regions, as shown by the wide variation in provincial fertility rates. According to the latest available data from the 2014 Demographic and Health Survey (DHS), the provincial fertility rates in the DRC ranged from 4.3 children per woman in Kinshasa, the capital city and largest urban area, to 8.5 children per woman in Nord-Ubangi, a rural province in the north-western part of the country. Shapiro and Tambashe (2003) provide a comprehensive overview of the relationship between education, employment, and fertility, as well as the differences between urban areas such that of Kinshasha and rural ones, with the latter characterized by higher fertility rates than the former.

This is consistent with the general pattern observed in many developing countries, where urbanization is associated with lower fertility due to factors such as higher education, better health care, more employment opportunities, and greater exposure to mass media and modern values.

Another reason associated with women's fertility decisions is the availability of natural resources. Access to natural resources was found to have a significant impact on household wealth (Aragón and Rud 2013) and, in turn, on women's fertility rates (Benshaul-Tolonen et al. 2019) and family structure (Black et al. 2003). Natural resources, such as minerals, play a crucial role in the well-being and development of communities by providing food and income. However, the management of those resources can have significant impacts on women's fertility and reproductive health. For example, low-income families who depend on natural resources for their livelihoods and send their children to work exhibit higher fertility rates (Hazan and Berdugo 2002; Doepke and Zilibotti 2005; Shanan 2021).

The Democratic Republic of Congo (DRC) is naturally abundant in crucial minerals, including cobalt, a key component of lithium-ion batteries, which have become the most popular technology in the battery sector, with over 70% of electrical batteries being lithium-ion-based in 2017 (Cobalt Institute 2019). Lithium-ion batteries are commonly used in electronic devices such as PCs, tablets, smartphones, and electric vehicles.

The Co-Cu sediments, which provide the type of cobalt used in electric batteries, are primarily located in two provinces in southern DRC, namely Haut-Katanga and Lualaba (Fig. 1).[2] According to the latest report by the Multiple Indicator Cluster Surveys (MICS) elaborated by Unicef in 2018, the provinces of Haut-Katanga and Lualaba, where the majority of cobalt extraction occurs, have high fertility rates of 7.8 and 7.5 children per woman, respectively. These figures are comparable to the DHS statistics in 2013, which reported a fertility rate of 7.6 children per woman. However, these numbers are considerably higher than the 2007 statistics, when the fertility rate was 6.0. Figure A.1 shows the spatial distribution of the provincial fertility rates in the DRC based on the DHS data.[3]

Numerous reports, including those by Amnesty International (2016, 2017) and Unicef (2017), estimate that over 40,000 boys and girls work in cobalt deposits across the Haut-Katanga province. This is more than double the number of children working in other DRC provinces. In a recent survey conducted in 150 cobalt-mining communities, Faber et al. (2017) showed that 11% of individuals aged between 3 and 17 years who live in these communities work outside their homes. Of these, 23% (equivalent to 4714 children) work in the cobalt mining sector, primarily as sorters, surface workers, and cleaners. Such jobs require small hands and are mostly performed on the surface. This makes them less dangerous compared to gold, diamond, or zinc mining, which is done underground. Because of this perception, parents may be more willing to allow their children to work in cobalt mines (Unicef 2017).

One of the key economic questions is how children's involvement in the labor force affects the decisions parents make about having more children. In the first theoretical model proposed by Basu and Van (1998), families decide on the size of their family based on the opportunity cost of their children's education. If child labor regulations are lacking, more jobs become available for children, increasing the cost of their education. As a result, families in areas without effective child labor regulations may choose to send their children to work instead of investing in their education, leading to higher fertility rates. This is known as the quantity-quality (Q-Q) fertility trade-off.

The study of Hazan and Berdugo (2002) is the first paper to analyze the role of public policy in shaping the relationship between child labor and fertility in the short and the long run. Doepke (2004) provided a quantitative analysis of this relationship, showing how policy differences between Korea and Brazil put the two countries, which had similar and very high fertility in 1960, on a very different path. Doepke and Zilibotti (2005) extended the analysis in Hazan and Berdugo (2002) by adding heterogeneity between households and making the political decision to ban child labor endogenous. These studies show that when child labor is legal or unregulated, families have increased fertility, and children are more likely to work. Conversely, illegal child labor causes families to invest in their children's education and reduce fertility.

[2] The four biggest cobalt deposits in Haut-Katanga and Lualaba account for about 80% of the total cobalt reserves in the country.

[3] Summary statistics at the subnational level for the Democratic Republic of the Congo, obtained from the DHS and the MICS, can be found at the following webpage: https://apps.who.int/gho/data/node.searo.NODESUBREGfertility-COD?lang=en.

Empirical studies on the relationship between child labor and fertility decisions have mainly focused on the United States. For example, Acemoglu and Angrist (2000) used state-by-state variation in child labor regulations across the US during the early twentieth century to study the positive effects of binding child labor regulations on individual education achievements. High education achievements, in turn, resulted in declining fertility rates of families living in states with more stringent child labor regulations. More recently, Shanan (2021) used census data and child labor regulation variations across the US during the early twentieth century to show that parents have fewer children in response to the constraints imposed on the labor supply of their potential children.

The above papers are the closest to this study; however, several significant differences exist between these papers and the present article. First, the literature has mostly addressed the relationship between child labor and fertility with theoretical models (Hazan and Berdugo 2002; Doepke and Zilibotti 2005). This paper, on the other hand, assesses this meaningful relationship empirically.

Second, while previous papers remain relatively agnostic on the underlying mechanisms, this study goes further to investigate how cobalt mining has increased child labor in surrounding communities, leading to an overall increase in wealth standards of households with at least one child, which in turn resulted in higher fertility rates and desire for more children.

Ultimately, this paper sheds light on the unique effects of unregulated cobalt mining on women's fertility, which cannot be attributed to any other mineral deposit, which might harm the long-term economic development of countries reliant on mineral resources.

3 Data and empirical procedure

3.1 Data

This paper uses two data sources to assess the effects of cobalt mining on women's fertility rates. The first dataset, which includes the geographical locations of all known mineral deposits in the DRC, has been retrieved from the US Geological Survey (2019).[4] This dataset is then matched with the GPS data of all Congolese women during their fertile ages (i.e., between 15 and 49) surveyed in two waves of the DHS (which occurred in 2007 and 2014). I then compute the distance between each woman and the nearest cobalt deposit.

Cobalt deposits in the DRC shown in Fig. 1 were all known before the demand for cobalt sharply increased since 2007. Additionally, I consider known deposits of all other minerals in the country (Fig. 2). This aims to validate the results concerning the effects of cobalt-mining exposure on fertility against a second control group, which comprises all women living in villages near other mineral deposits. As opposed to

[4] I consider the cobalt deposits instead of cobalt mines since their existence is plausibly exogenous to families' fertility decisions.

cobalt and copper deposits, other minerals are primarily located in the far eastern part of the country, close to the border with Uganda, Rwanda, and Burundi (Fig. 2).[5]

The geographical variation in cobalt-mining deposits in the DRC, combined with the georeferenced data of women surveyed in the two rounds of the DHS, allows the treatment and control groups to be constructed.

Concerning the birth history of each Congolese woman, I use the two available rounds of the DHS. Specifically, two rounds of surveys are currently available. The first round was conducted in 2006, and the results were published in 2007. The second round was conducted between 2013 and 2014, and the results were published in 2014. The analysis considers all women during their fertile period (i.e., aged between 15 and 49). Each interviewed woman voluntarily reports the number of children ever born and their respective birth years. Since this study aims to assess the relationship between cobalt-mining exposure and fertility, I also include the number of stillbirths.[6]

I consider three fertility measures for each woman: the 5-, 3-, and 1-year fertility rates. The first measure considers the number of children ever born for each woman in the last 5 years preceding the interview, that is, for all women surveyed in 2007, the number of children born in the period between 2002 and 2007, while for all women surveyed in 2014, the number of children ever born during the period 2009–2014. The second measure of fertility considers the number of children born by each woman during the last 3 years before the interview. Finally, the third measure of fertility considers the number of births from each woman the year before the interview. In addition to the number of births per woman, I consider their desire to have children. The DHS also provides this information. In these surveys, each woman is asked if she is willing to have children.

I construct a cross-sectional database of 28,822 women during their fertile period (i.e., aged between 15 and 49), among which 1291 women reported living within 200 km of a cobalt deposit at the time of the survey.[7] Of the 322 women who lived within 10 km of a cobalt deposit, 119 were surveyed in 2007 and 203 in 2014. Similarly, of the 969 women who lived between 10 and 200 km, 372 were surveyed in 2007 and 597 in 2014. Additionally, the analysis considers 738 women who lived in towns or villages surrounding other mining sites, 256 surveyed in 2007 and 482 in 2014.

Household wealth is another variable that is used to discuss the channel behind the increased fertility of women exposed to cobalt mining. Sending a child to work as a cobalt miner might provide a positive income shock for those families, as shown by Aragón and Rud (2013). I specifically check for this mechanism. I use two measures of household wealth. The first one is the wealth index provided by the DHS to measure household wealth. This wealth index divides households into five wealth quintiles. The indicator ranges from one (bottom quintile), where the poorest 20% of the households surveyed lie, to five (top quintile), representing the wealthiest 20% of

[5] Other major minerals located in the DRC did not share the same production trends of cobalt (Fig. A.2).

[6] Restricting the sample to the number of stillbirths will evaluate the impacts of cobalt mining on infant health. However, the health effects of cobalt mining go beyond the scope of this paper. The reason is that while the mechanism driving fertility in cobalt-mining communities is the boost in the wealth of households with at least one child, different mechanisms drive infant health beyond child labor (Benshaul-Tolonen 2018).

[7] I specifically restrict women aged between 15 and 49, given the age distribution of Congolese mothers shown in Fig. A.3.

the surveyed households. In addition, I compute a second index of "Living Standard" which approximates the living conditions of each household. This variable considers the probability of having specific assets such as electricity, clean water, radio, television, and refrigerator. All these variables are available in both waves of the DHS, allowing me to perform a pre- and post-analysis. The "Living Standard" variable takes values from zero to five depending on the number of assets owned by the household. So, for instance, it takes a value of five if the household owns all five assets mentioned above. Otherwise, if the household owns only three out of five assets, the variable will take a value of three.

Table 1 reports summary statistics of relevant variables pre- and post-2007 for villages within 10 km, between 10 and 200 km from the closest cobalt deposit, and within 10 km away of any other mineral deposit in the DRC. On average, each woman living within 10 km of a cobalt deposit had approximately 0.77 children born in the last 5 years preceding the first round of interviews, 0.45 over the previous 3 years,

Table 1 Extensive descriptive statistics—women between ages 15 and 49

	Pre < 10 km Mean	Pre > 10 km Mean	Pre other Dept. Mean	Post < 10 km Mean	Post > 10 km Mean	Post other Dept. Mean
Fertility						
Births in the last 5 years	0.77	0.97	0.98	0.99	1.08	0.89
Births in the last 3 years	0.45	0.64	0.59	0.68	0.65	0.58
Births in the past year	0.14	0.24	0.23	0.26	0.25	0.22
Average annual births per woman	0.16	0.19	0.19	0.21	0.22	0.19
Desire to have children (%)	0.53	0.52	0.66	0.71	0.63	0.68
Use of contraceptives (%)	0.22	0.14	0.14	0.13	0.14	0.12
Labor market						
Work outside household (%)	0.06	0.05	0.04	0.16	0.06	0.09
Household wealth						
Wealth index	4.68	4.42	4.16	4.61	4.29	4.35
Wealth index (with children)	4.61	4.60	3.93	4.80	4.34	4.05
Living standard index	2.36	1.49	0.89	2.76	1.64	0.71
Additional variables						
Age	25.39	25.67	27.38	24.27	25.23	27.67
Education (years)	3.70	3.43	3.60	3.23	3.54	3.09
Usual resident	0.99	0.99	0.97	0.98	0.98	0.99
Ever migrated	0.22	0.25	0.24	0.23	0.25	0.25
Urban residence (%)	0.98	0.84	0.82	0.93	0.78	0.86
Household members	6.49	6.59	7.19	7.74	7.12	4.83
Observations	119	372	256	203	597	482

Notes: This table reports the women's sample average characteristics. Observations include all women aged between 15 and 49 surveyed in the DHS 2007 and 2014 waves, and living within 200 km from a cobalt deposit and 0.14 in the last year. These statistics compare to an average of 0.99 children born within the previous 5 years preceding the interview to women living within 10 km of a cobalt deposit surveyed in 2014; 0.68 children were born on average to each woman during the last 3 years, and 0.26 during the previous year.

In relative terms, between 2007 and 2014, the 5-year fertility rate of women living in cobalt-mining communities increased by 28% compared to an increase of 11% exhibited by women living over 10 km from a cobalt deposit. Similarly, the 3-year fertility rate of women living within 10 km of a cobalt deposit increased by approximately 50% between 2007 and 2014. Conversely, that for women living over 10 km of a cobalt deposit grew by 2%.[8]

3.2 Model

Given that the dependent variables consist of count data, the baseline model follows a difference-in-differences strategy estimated with fixed effect Poisson regressions, exploiting the geographical variation of cobalt deposits in the DRC and the temporal variation provided by the boom in cobalt mining production. Under the hypothesis that the adoption of lithium-ion batteries increased women's fertility, we expect to find a significant increase in women's births in villages surrounding a cobalt deposit.

The empirical strategy is presented as follows:

$$y_{i,c,d} = \exp\{\alpha + \beta\ (Post)_t \times (\text{Cobalt Dep.})_i + \gamma\ \mathbf{X}_i^{'} + \sigma_{dt}\} + \epsilon_{i,c,d} \quad (1)$$

where the outcome variable $y_{i,c,d}$ represents the measures of fertility rates of woman i, living in village c, in the sub-regional district d. I consider three measures of fertility: (i) the number of births per woman during the 5 years before the survey, (ii) the number of births per woman in the 3 years before the interview date, (iii) the total number of births per woman in the last year before the interview date.

The indicator variable $(Post)_t$ takes a value equal to zero if the year is 2007 and a value of one if the year is 2014. $(\text{Cobalt Dep.})_i$ represents the measure of distance between the village c and the nearest cobalt deposit. In the baseline specification, it takes a value of zero if the woman lives beyond 10 km and within 200 km from the nearest cobalt deposit and a value of one if the woman lives within 10 km from a cobalt deposit. Equation 1 also includes $(Post)_t$ and $(\text{Cobalt Dep.})_i$ as individual variables, as is standard in all DiD specifications.

The choice of the 10 km treatment distance is based on the previous literature focusing on the impact of mining activities on local communities (Aragón and Rud 2013, 2015; Benshaul-Tolonen 2018) and commuting behavior in Africa (Shaver et al. 2016; Kung et al. 2014) which find mine treatment effects to be concentrated to people living within 5–20 km from the mine. However, I further consider the possibility that children only cover a limited distance. For this reason, in Section 6, I check the heterogeneous effects by distance to a cobalt deposit by employing a spatial lag model.

[8] In addition to Table 1, Fig. A.4 reports the balance plots of the key control variables for the control and the treatment group.

The interaction between the $(Post)_t$ and the $(\text{Cobalt Dep.})_i$ variables defines the control and the treatment groups. The control group comprises all births given by women aged 15–49 within 200 km from a cobalt deposit before 2007. On the other hand, all births that occurred after 2007 given by women aged 15–49 within 10 km from a cobalt deposit compose the treatment group.

It is worth emphasizing that the empirical procedure considers the cobalt deposits in the DRC rather than the actual mining sites. For this reason, I do not observe the year in which a cobalt-mining deposit became operational. Therefore, the methodology estimates the intention-to-treat effect rather than the actual treatment. The underlying assumption is that all women exposed to cobalt-mining activities after 2007 (i.e., those living in cobalt-rich villages) have been equally exposed to the same treatment. Considering the actual mining sites would enable the estimation of the actual treatment effect. However, since opening a mine and its everyday operations require specific policies, investments, and governmental institutions, the treatment would be endogenous.

Given that data on women's fertility present many zero counts (Fig. A.5), throughout the paper, I estimate a Poisson model, which is more suited than the standard log-linear ordinary squares (OLS) since the former makes use of zero counts and is consistent in the presence of heteroskedasticity (Silva and Tenreyro 2006).

The regressions control for a vector of individual-specific characteristics $\mathbf{X}_i^{'}$, which may influence the decision of a woman to give birth. The regressions also control if the woman reported having migrated from her place of birth, along with the number of years she has lived in the village where she was surveyed. The inclusion of this control alleviates concerns about migratory flows in and out of cobalt-rich villages.[9]

Another factor directly linked to fertility is the education level. Women who achieved fewer years of education typically show higher fertility rates than those who completed more years of education. Therefore, I include a control for each surveyed woman's completed years of schooling. Additionally, I control for the woman's birth year since we expect young women to have fewer pregnancies than older ones.

Moreover, by including district-by-year fixed effects, σ_{dt}, the identification relies on comparing the number of births per woman occurring before and after 2007 within the same district. This approach removes potential confounding from time-invariant structural differences between villages, which is a prime concern. Moreover, including district-by-time fixed effects removes potential confounding from time-variant differences between districts of the DRC, such as different business environments, policies, corruption, and education expenses.[10]

Our coefficient of interest is β, representing the difference-in-differences estimate of the cobalt boom on women's fertility rates. Standard errors are clustered at the village level.

[9] For instance, if a woman gave birth to a child while living in a non-cobalt village and later moved to a cobalt-rich one, the inclusion of this control allows us to take this into account.

[10] Since we only have 2 years (i.e., 2007 and 2014) and include district-by-year fixed effects, the regressions do not include a post-treatment dummy variable since it would be collinear with σ_{dt}.

4 Results

Table 2 reports the link between proximity to a cobalt deposit and the number of births per woman before and after 2007 using a standard Poisson model with fixed effects. For all regressions, the sample includes all women aged 15–49 surveyed in the two waves of the DHS, and the standard errors are clustered at the village level.

In panels A, B, and C, the dependent variables are the number of births per woman during the 5, 3, and 1 year preceding the interview, respectively. The reported coefficients correspond to the interaction between Post_t, an indicator variable equal to one if the birth occurred after 2007, and $(\text{Cobalt Dep.})_i$, an indicator variable equal to one if the woman lives within 10 km from the nearest cobalt deposit.

Column 1, in panels A, B, and C, presents the results from a specification without individual controls or fixed effects. The results suggest that living within 10 km of a cobalt deposit increased the number of births per woman during the 5 years between 2008 and 2013 by 20 percentage points. The number of births per woman from 2010 to 2013 increased by 19%, and the number of births from 2012 to 2013 increased by 12%.

Table 2 Cobalt mining exposure and fertility

	(1)	(2)	(3)
Panel A: 5-year fertility			
Post × cobalt deposit	0.203*	0.261**	0.200**
	(0.121)	(0.108)	(0.118)
Panel B: 3-year fertility			
Post × cobalt deposit	0.193**	0.215***	0.164**
	(0.083)	(0.077)	(0.081)
Panel C: 1-year fertility			
Post × cobalt deposit	0.119**	0.125**	0.111**
	(0.048)	(0.049)	(0.051)
Individual controls	No	Yes	Yes
District × year FE	No	No	Yes
Observations	1291	1291	1291
(Pseudo) R^2	0.245	0.249	0.249

Notes: This table reports estimates of the relationship between distance to a cobalt deposit and women's fertility in the DRC. For all regressions, the sample includes all women aged 15–49 surveyed in the two waves of the DHS. In panels A, B, and C the dependent variables are respectively the number of births during the 5 years, 3 years, and 1 year preceding the interview. The reported coefficients correspond to the interaction between Post_t, and indicator variable equal to one if the birth occurred after 2007, and $(\text{Cobalt Dep.})_i$, and indicator variable equal to one if the woman lives within 10 km from the nearest cobalt deposit. Column 1 presents the results from a specification without individual controls, or fixed effects. Column 2 adds individual controls, which include the number of completed years of education, type of residence, year of birth, and household size. Column 3 adds district-by-time fixed effects. Standard errors, in parentheses, are clustered at the village level. Significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Column 2 adds individual controls, which include the number of completed years of education, residence status (i.e., usual resident of a visitor), and year of birth. I find that women living within 10 km of a cobalt deposit show an increase of 26% in the number of births during the 5 years, 21% during the 3 years, and 13% during the year before the interview.

Finally, column 3 adds district-by-time fixed effects. This is the preferred specification. The coefficient estimates resemble those shown in the previous columns and corroborate the validity of the relationship between exposure to cobalt-mining activities and fertility. I find that women living within 10 km of a cobalt deposit show an increase of 20% in the number of births during the 5 years, 16% during the 3 years, and 11% during the year before the interview.

Besides the effects on fertility decisions, I also estimate the relationship between exposure to cobalt mining and the woman's desire to have children. Table A.1 in the Appendix shows that women living in communities surrounding a cobalt deposit were 22% more willing to have children in the 2014 round of surveys relative to those living outside cobalt-rich areas. These results further confirm the validity of the relationship between cobalt mining and women's fertility decisions.

4.1 Heterogeneous effects by age

To determine whether cobalt mining has affected women's fertility decisions differently depending on their age, I estimated a similar specification as presented in Eq. 1 separately for each age group. The first group is composed of young women aged between 15 and 24, the second group is composed of women aged between 25 and 34, and the third group is composed of women aged between 35 and 49. The specification includes the complete set of fixed effects and individual controls as in Eq. 1.

Table 3 reports the relationship between the distance to a cobalt deposit and the number of births per woman before and after 2007 using the Poisson model with fixed effects. This time, column 1 shows the beta coefficients of the link between the distance to a cobalt deposit and the number of births of young women aged between 15 and 24. Column 2 shows the estimates for women aged 25–34. Column 3 shows the coefficient estimates for women aged 35–49. For all regressions, I include the complete set of individual controls for education, type of residence, and year of birth.

Table 3 Cobalt mining exposure and fertility: heterogenous effects by age groups

	Age group 15–24 (1)	Age group 25–34 (2)	Age group 35–49 (3)
Panel A: 5-year fertility			
Post × cobalt deposit	0.110	0.456**	0.056
	(0.156)	(0.205)	(0.235)
Panel B: 3-year fertility			
Post × cobalt deposit	0.207**	0.268**	0.119
	(0.103)	(0.133)	(0.158)

Table 3 continued

	Age group 15–24 (1)	Age group 25–34 (2)	Age group 35–49 (3)
Panel C: 1-year fertility			
Post × cobalt deposit	0.073	0.101	0.159*
	(0.069)	(0.089)	(0.091)
Individual controls	Yes	Yes	Yes
District × year FE	Yes	Yes	Yes
Observations	581	407	303

Notes: This table reports estimates of the relationship between distance to a cobalt deposit and women's fertility in the DRC. Columns 1–3 show the results from a model estimated using a Poisson specification. All regressions include the complete set of individual controls, which include the number of completed years of education, year of birth, household size, and fixed effects. In panels A, B, and C, the dependent variables are respectively the number of births during the 5 years, 3 years, and 1 year preceding the interview. The reported coefficients correspond to the interaction between Post_t, and indicator variable equal to one if the birth occurred after 2007, and $(\text{Cobalt Dep.})_i$, and indicator variable equal to one if the woman lives within 10 km from the nearest cobalt deposit. Standard errors, in parentheses, are clustered at the village level. Significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Once again, in panels A, B, and C, the dependent variables are the number of births per woman during 5, 3, and 1 year, respectively, preceding the interview. The reported coefficients correspond to the interaction between Post_t, an indicator variable equal to one if the birth occurred after 2007, and $(\text{Cobalt Dep.})_i$, an indicator variable equal to one if the woman lives within 10 km from the nearest cobalt deposit. These estimates give us insights into the most and least affected groups of women. In particular, they suggest that exposure to cobalt mining increased the fertility of women aged between 25 and 34, while no effect is found for women aged 35 and above.

5 Unpacking the mechanism: cobalt, wealth, and fertility

In Section 2, I have summarized the economic literature focusing on the mechanisms through which child labor affects parental fertility decisions. In this section, I first present suggestive evidence of the use of children in cobalt mines in the DRC. Second, I empirically assess the wealth channel through which exposure to cobalt mining affects women's fertility. For this purpose, I first establish the relationship between cobalt mining and household wealth. Subsequently, I test whether household wealth explains the shift in women's fertility using the method proposed by Acharya et al. (2016), which estimates the unbiased average controlled effect of a treatment.

5.1 Child labor in cobalt mines

The increased number of jobs in artisanal cobalt mines explicitly targeting children might be a valid explanation for the higher fertility rates exhibited by women living in cobalt-mining villages. Before the cobalt mining boom, children residing in cobalt-rich areas of the DRC typically engaged in agricultural pursuits, such as farming or tending to animals. Families commonly undertook these endeavors to supplement their income and ensure sustenance for their households (International Labor Organization 2013).

However, a study by Malpede (2022) reveals that individuals exposed to cobalt mining during their childhood attained lower levels of education compared to those living in villages surrounding other varieties of mineral deposits in the DRC. Additionally, the study reveals that children residing in villages where cobalt mining takes place were more prone to be employed outside their households and exhibited lower cognitive as well as physical development.

In this section, I provide suggestive evidence of the participation of children during school age (6–14 years old) in jobs outside their homes. To do so, I use DHS data provided in the first wave in 2007 and in the second wave in 2014. In each survey, the parents are asked if their child works, and if they do, if they work within or outside the family environment.[11] Exploiting this information allows me to compute the percentage of children who reported working outside their families.[12]

Panel A of Fig. 4 shows how children's participation in the workforce outside the family environment declined in all DRC between 2007 and 2014. However, this is not true for districts closer to cobalt deposits. I find that, on average, the proportion of children aged 6–14 working declined by 15% from 2007 to 2014 for most of the southern DRC districts except for the districts of Mutshatsha, Kambove, and Lubumbashi (where most of the cobalt deposits are located) where the proportion of children working increase up to 10% since 2007.

Panel B of Fig. 4 complements results in panel A by showing how children aged between 6 and 14 living in villages surrounding a cobalt deposit achieve lower education than their peers (computed as the number of completed schooling years). Specifically, I find that children living in the cobalt-rich districts achieved up to 0.2 years of education lower than their peers (or 6% lower education in absolute terms, considering that the average number of years of schooling in the DRC is 3.5).

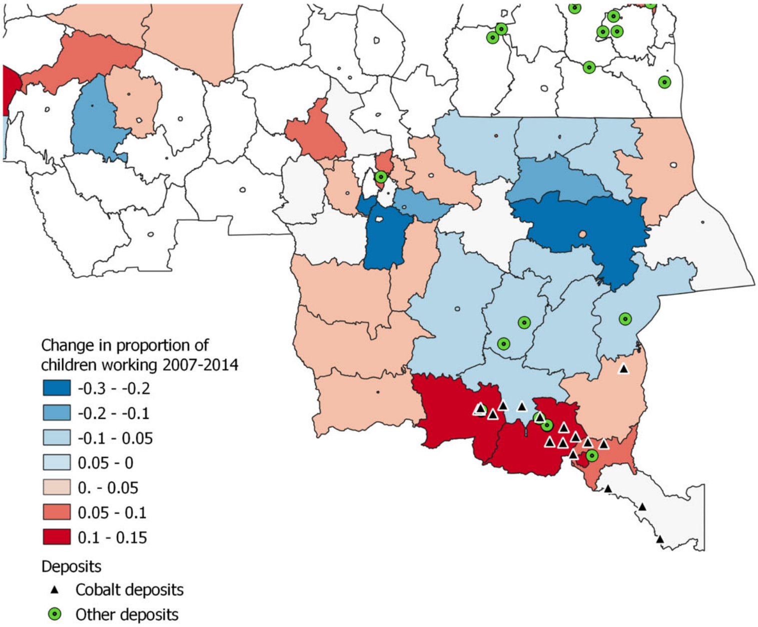
In addition to what is presented above, two existing studies provide further evidence of the use of children in the workforce in cobalt mining villages of the DRC. Nkulu et al. (2018) presented additional empirical support for the use of children in regions engaged in cobalt extraction. Through the implementation of a localized investigation conducted within the confines of Kolwezi town, the researchers posit that children residing within a community that had undergone a conversion into a cobalt-mining enclave exhibited significantly elevated levels of cobalt in their urine and bloodstream, surpassing those found among individuals inhabiting a proximate control zone, with discrepancies reaching up to a factor of 12.

Finally, Faber et al. (2017) conducted large-scale surveys among more than 2500 households living in 150 mining communities of the copper-cobalt belt of the DRC. The authors show that 11% of children between the ages of 3 and 17 in the mining communities of the copper-cobalt belt work outside the household. Among them, 23% (or an estimated 4714 children in the entire population of the 426 communities)

[11] Descriptive statistics of these variables are provided in Tables A.2 and A.3 in the Appendix.

[12] We do not know if those children are actually employed in cobalt mines or other dangerous activities. No official statistics exist on the number of children engaged in cobalt mines since this is illegal.

A



B

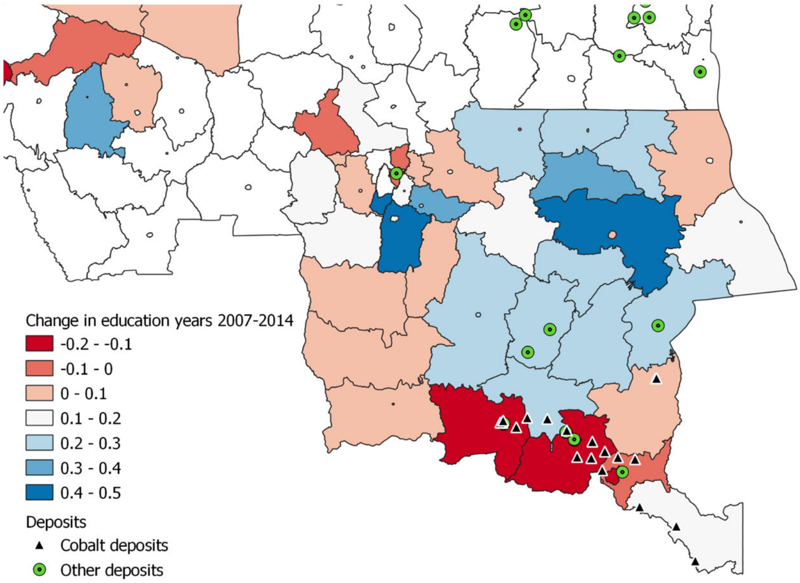


Fig. 4 Change in proportion of children working and completed years of education. *Notes:* **A** The change in the proportion of working children aged 6–14 from 2007 to 2014. **B** The change in the average completed years of education from 2007 to 2014 per district. All data use the information provided in the two rounds of DHS (2007 and 2014)

work in the cobalt mining sector. Moreover, they find that children living in the mining communities of the copper-cobalt belt who work in artisanal mining are mainly sorters (26%), surface workers (23%), and cleaners (17%). In addition, households that report mining child labor in the mining communities of the copper-cobalt belt have 7.8 household members on average compared to 5.7 in other households living in non-cobalt mining villages.

Taken together, this information provides suggestive evidence of the use of children in cobalt mines. In the next section, I investigate how cobalt mining has affected the wealth of families in surrounding communities.

5.2 Wealth and fertility

To understand the relationship between the presence of a cobalt deposit and household wealth, I estimate model (2) in which I regress household wealth on the presence of a cobalt deposit, using the following ordered probit model:

$$W_{h,c,d,t} = \alpha + \beta\ (Post)_t \times (\text{Cobalt Dep.})_h + \gamma\ \mathbf{X}_h^{'} + \sigma_{dt} + \epsilon_{h,c,d,t} \tag{2}$$

Here, the dependent variable is represented by one of the two measures of household wealth, i.e., the wealth index and the living standards measure for household h, living in village c, in district d and surveyed in year t to have migrated from her place of birth. The indicator variable $(\text{Cobalt Dep.})_i$ indicates the presence of a cobalt deposit within 10 km from the village where the household h lives. The model includes the usual household-specific controls. Sub-regional district time trends are also included. Standard errors are clustered at the village level.

The results of model (2) are presented in Table 4 and show the positive effects of proximity to a cobalt deposit on household wealth.

Having established the effects of a cobalt deposit within 10 km on the two measures of household wealth, I now address whether those constitute the mechanism through which a cobalt deposit influences women's fertility decisions. For this purpose, I first estimate the following Poisson model (3), in which I regress the fertility measures of woman i, from household h, living in cluster c, and surveyed in year t $(y_{i,h,c,d,t})$ on household wealth and living standards. Again, the model controls for a vector of individual-specific characteristics $\mathbf{X}_i^{'}$, which may influence the decision of a woman to give birth.

$$y_{i,h,c,d,t} = \exp\{\alpha + \beta\ (Wealth_h) + \gamma\ \mathbf{X}_i^{'} + \sigma_{dt}\} + \epsilon_{i,c,d,t} \tag{3}$$

Panel A of Table 5 reports the results of model (3) above. Overall, the results in the table indicate a positive relationship between the two measures of household wealth after 2007 and the number of births of women in surrounding villages.

The results from Tables 4 and 5 suggest that the presence of a cobalt deposit within 10 km has a positive effect on household wealth, which translates into higher fertility in the short term. While this analysis is a first step in analyzing the underlying mechanism, it does not demonstrate the mediating role of wealth.

Table 4 Cobalt mining exposure and household wealth

	Dep. variable: wealth			Dep. variable: living standards		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × cobalt deposit	0.229***	0.192***	0.196***	0.364***	0.292	0.372***
	(0.005)	(0.001)	(0.002)	(0.207)	(0.184)	(0.119)
Cobalt Dep. within 10 km	−0.048	−0.191	−0.205***	−0.774	−0.808	−0.829***
	(0.225)	(0.289)	(0.006)	(0.558)	(0.339)	(0.249)
Household controls	No	Yes	Yes	No	Yes	Yes
District × year FE	No	No	Yes	No	No	Yes
Mean of dependent var.	4.49	4.49	4.49	1.71	1.71	1.71
Observations	742	742	742	539	539	539
R^2	0.639	0.654	0.786	0.532	0.564	0.607

Notes: This table presents results of the relationship between distance to a cobalt mine deposit and two measures of household wealth estimated using the ordered probit model presented in Eq. 2. The sample includes households surveyed in 2007 and 2014. Households living within 10 km from a cobalt deposit constitute the treatment group. The control group is composed of households living between 10 and 200 km from the nearest cobalt deposit. Columns 1 and 4 present the results with no control. Columns 2 and 5 add controls for household characteristics. Columns 3 and 6 add district-by-year fixed effects. Standard errors are clustered at the village level. Significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5 Wealth and fertility

	Dependent variable:		
	5-year fertility	3-year fertility	1-year fertility
	(1)	(2)	(3)
Panel A. Reduced form			
Wealth	0.041	0.052*	0.092***
	(0.026)	(0.030)	(0.031)
Living standards	0.013**	0.026**	0.034**
	(0.006)	(0.011)	(0.016)
Individual controls	Yes	Yes	Yes
District × year FE	Yes	Yes	Yes
Panel B. Mediation analysis			
Direct controlled effect of	0.096*	0.175**	0.137
cobalt mining (wealth)	(0.052)	(0.083)	(0.092)
Direct controlled effect of	0.084	0.112	0.175
cobalt mining (Liv. standards)	(0.068)	(0.094)	(0.125)
Individual controls	Yes	Yes	Yes
District × year FE	Yes	Yes	Yes

Notes: Panel A reports estimates of the relationship between household wealth and women's fertility in the DRC. In columns 1–3, the dependent variables are respectively the number of births during the 5 years, 3 years, and 1 year preceding the interview. Panel B reports the estimated coefficients of the ACDE of cobalt mining on women's fertility after controlling for the two measures of household wealth and living standards in the first stage. All regressions consider the complete set of individual controls and fixed effects. Standard errors, in parentheses, are clustered at the village level following Acharya et al. (2016). Significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

For this reason, I follow Acharya et al. (2016) who provide a method to estimate the unbiased average controlled direct effect (ACDE) of a treatment; this is, the causal effect of a treatment (which in our case is the presence of a cobalt deposit within 10 km from the village of residence) when the effect of the mediator (wealth) is already taken into account.

The approach of Acharya et al. (2016) is helpful in our setting for two reasons: First, it allows us to analyze whether the boost in household wealth is one mechanism through which the presence of a cobalt deposit influences women's decision to give birth and whether other mechanisms contribute to explaining this relationship. Second, it provides a more rigorous way to assess the mechanisms to the standard method of testing for mechanisms, where one simultaneously controls for the treatment and mediating variables, but that often leads to biased and inconsistent estimates.[13]

The ACDE is estimated through the following two-stage regression: In the first stage, the dependent variable (women's fertility) is transformed by removing the effect of the mediator variable. In the second stage, the demediated dependent variable is regressed on the treatment (i.e., a cobalt deposit within 10 km).

If the relationship between distance to a cobalt deposit and the demediated women's fertility is significant, we can conclude that the treatment influences the variable of interest through other pathways in addition to the proposed mechanism. By contrast, if the treatment has no effect on our dependent variable, once the mechanism is accounted for, we can conclude that higher returns of child labor in cobalt-rich communities caused an increase in household wealth and, in turn, in their fertility decision.

I run the following two-stage model to estimate the ACDE of the presence of a cobalt deposit and test whether its influence on women's fertility runs exclusively through the boost in household wealth:

$$\begin{aligned} y_{i,h,c,d} &= \exp\{\alpha + \beta_1 \ (Post)_t \times (\text{Cobalt Dep.})_i + \beta_2 \text{Wealth}_{h,c,d} + \gamma \ \mathbf{X}_i^{'} + \sigma_{dt}\} \\ &\quad + \epsilon_{i,c,d} \qquad (4) \\ \tilde{y}_{i,h,c,d} &= \exp\{\alpha + \tilde{\beta}_1 \ (Post)_t \times (\text{Cobalt Dep.})_i + \gamma \ \mathbf{X}_i^{'} + \sigma_{dt}\} + \mu_{i,h,c,d} \end{aligned}$$

where $\tilde{y}_{i,h,c,d} = y_{i,h,c,d} - \hat{\beta}_2 Wealth_{h,c,d}$ represents the demediated measures of women's fertility, and $\mu_{i,h,c,d}$ is the associated error term the consistent error term estimated through bootstrapping.[14]

$\text{Wealth}_{h,c,d}$ represents one of the two measures of household wealth (i.e., the wealth index and the measure of standard of living) of household h, living in village c, in district d. The indicator variable $(Post)_t$ takes a value equal to zero if the year is 2007 and a value of one if the year is 2014. $(\text{Cobalt Dep.})_i$ represents the measure of distance between the village c and the nearest cobalt deposit. In the baseline specification, it

13 See Acharya et al. (2016) for a detailed discussion on how simultaneously controlling for the treatment and the proposed mechanism leads to either M-bias or post-treatment bias.

14 In Acharya et al. (2016), the standard errors are biased in the second stage estimation since they do not consider the first-stage estimation of $\hat{\beta}_2$. Unbiased and consistent standard errors can be obtained by deriving a consistent estimator for the variance of $\tilde{\beta}_1$ for linear models or through bootstrapping. Here, I employ the bootstrapping.

takes a value of zero if the woman lives beyond 10 km and within 200 km from the nearest cobalt deposit and a value of one if the woman lives within 10 km from a cobalt deposit. The interaction between the $(Post)_t$ and the $(\text{Cobalt Dep.})_i$ variables defines the treatment. As in the previous models, this specification includes individual-specific controls such as type of residence, if the woman reported having migrated from her place of birth, the number of years she has lived in the village where she was surveyed, her level of education, and year of birth. Sub-regional district time trends are also included.

Once again, the model controls for a vector of individual-specific characteristics $\mathbf{X}_i^{'}$, which may influence the decision of a woman to give birth.[15]

Panel B of Table 5 reports the estimated ACDE of the proximity to a cobalt deposit after 2007 on the number of births per woman in the DRC. In columns 1–3, the dependent variables are, respectively, the number of births during the 5, 3, and 1 year preceding the interview. The results indicate that the coefficients for the ACDE of cobalt exposure are much smaller than those presented in Table 2 and lose significance. This means that once we account for the effect of household wealth, the presence of a cobalt deposit within 10 km only has marginal effects on women's fertility. In other words, the impact of a cobalt deposit on women's fertility is explained by the boost in wealth, as hypothesized at the beginning of this study.

The analysis carried out in this section contributes to the literature in different ways. First, it provides first-time evidence of the consequences of a cobalt deposit on family fertility decisions.

Second, it demonstrates that the boost in the wealth of households exposed to cobalt mining is the primary mechanism that explains the relationship between cobalt mining and fertility decisions. This has yet to be analyzed by previous studies in the literature on the consequences of cobalt mining.

6 Threats to identification

In this section, I address potential concerns about the baseline specification. First, I check for the validity of the parallel trend assumption. Second, I show that exposure to cobalt mining only affects women living within 10 km. In comparison, no relationship is found for women living at any distance between 10 and 200 km away from a cobalt deposit. Third, I address the endogenous migration flows from and to the treatment groups, which could have affected the estimates. Fourth, I compare women living in cobalt-surrounding communities with women living in other mineral-rich villages of the DRC. Fifth, I consider the possible caveats arising from the perturbation in the

[15] As discussed in Acharya et al. (2016), this method provides an unbiased estimate of the ADCE under two conditions: sequential unconfoundedness and no intermediate interactions. The first condition entails two related assumptions: First, there is no omitted variable bias for the effect of the treatment (presence of a cobalt deposit within 10 km) on the outcome (women's fertility), conditional on pretreatment confounders. Second, there is no omitted variable bias for the effect of the mediator (wealth) on the outcome, conditional on the treatment, and pretreatment and intermediate confounders.

GPS of the individuals surveyed in the DHS. Finally, I employ a spatial randomization test to show that the baseline results are not spurious because of a misspecification of the model.

6.1 Parallel trends

The difference-in-differences strategy presented above relies on the parallel trends assumption. We expect that the individuals in the control and treatment groups would have shared the same pattern in fertility rates in the absence of the cobalt mining boom. Therefore, verifying the validity of the parallel trends assumption aims to exclude any other event that occurred before the cobalt boom affected parental fertility decisions in the control or treatment group.

To guarantee the existence of the parallel trends, I regress the average annual number of births per woman for each village on the distance to the nearest cobalt deposit using the same individual-specific controls and fixed effects defined in the baseline Eq. 1 for each year from 1999 to 2013. I obtain the average number of births per woman for each village by dividing the total number of births in a specific year by the number of women surveyed in each village.

The results of this exercise are shown in Fig. 5 and indicate that the relationship between exposure to a cobalt deposit and the annual number of births per woman is not statistically different from zero before the cobalt mining boom, and only become positive and significant after 2010.

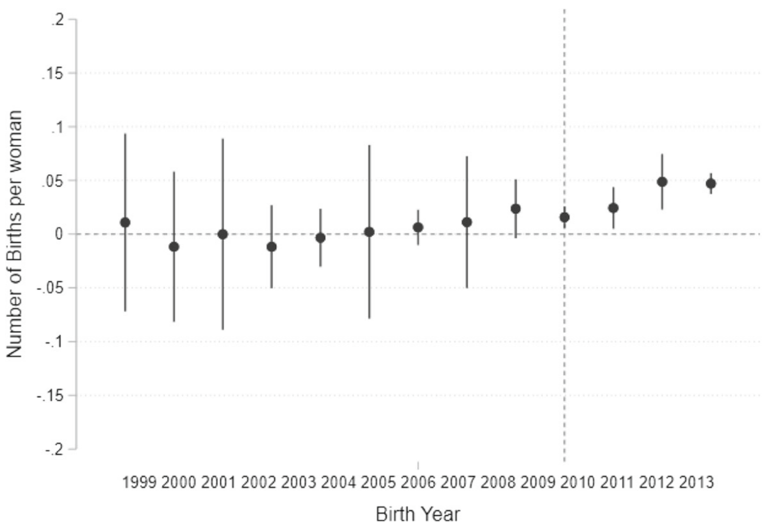


Fig. 5 Estimates of the relationship between average annual number of births per woman and distance to a cobalt deposit from 1999 to 2013. *Notes:* The sample includes all women between 15 and 49 surveyed in the two available waves of the DHS (i.e., 2007 and 2014). The regression includes the complete set of individual-specific controls and district fixed effects

Those results provide suggestive evidence of the parallel trend assumption, that is, the control and treatment groups exhibited similar trends before the cobalt-mining boom and that the control group was not affected by the latter.[16]

6.2 Heterogeneous effects by distance

A possible concern stems from the choice of the 10 km cut-off distance defining the treated and controlled individuals. The choice of distances is crucial for rightly estimating the effects of exposure to cobalt mining on women's fertility. The 10 km distance is chosen following similar papers focusing on the impact of mining exposure (Benshaul-Tolonen 2018; Aragón and Rud 2013) and is based on the average commuting distance reported by individuals surveyed in the DHS.

However, since it is plausible that children do not cover such a distance daily, in this section, I use a second model to assess the heterogeneous treatment effects by distance from a cobalt deposit. In this model, I consider a finer treatment distance of 5 km. We expect the highest impact of cobalt to be concentrated in women living within 5 km of the nearest cobalt deposit and slightly declining for women up to 10 km. No effect should be seen for women living beyond 10 km from a cobalt deposit.

Equation 5 alleviates concerns about the chosen treatment distance:

$$y_{i,c,d,t} = \exp\{\alpha + \sum_b \beta_b (\text{Post})_t \times \text{I}(\text{distance} \in \text{b}) + \gamma\ \mathbf{X}_i^{'} + \sigma_{2,dt}\} + \epsilon_{i,c,d,t} \quad (5)$$

for $b \in \{0-5, 5-10, ..., 50-70, 70-100\}$.

Each woman is recorded to a defined distance bin: 0–5 km, 5–10 km, 10–20 km, 30–50 km, 50–70 km, and 70–100 km, and compared with the reference category 100–200 km away from the nearest cobalt deposit.

As opposed to Eq. 1, in Eq. 5, the treatment is given by the interaction between $(\text{Post})_t$ and I(distance $\in$ b). Variable $(\text{Post})_t$ is an indicator variable that takes a value of zero if the birth occurred before 2007 and a value of one if the birth occurred after 2007. Variable I(distance $\in$ b) consists of a series of indicator variables that take a value equal to zero if the woman lives in the reference category bin and a value equal to one if the woman lives in one of the defined distance bins. This specification controls for the usual fixed effects and individual level controls as in Eq. 1.

The results of the estimation of Eq. 5 are reported in Fig. 6 and confirm that the effects of cobalt exposure on fertility rates are concentrated among women living within 10 km of a cobalt deposit, with the largest effects exhibited by women within 5 km of a deposit.[17]

[16] In addition to this test, I employ a further check in which I estimate the correlation between living within 10 km of a cobalt deposit and women's fertility rates, restricting the sample to only those surveyed in 2007 (i.e., before the cobalt boom) and then restricting the sample to only those surveyed in 2014 (i.e., after the cobalt boom). The results of this exercise are shown in Fig. A.2 in the Appendix. The absence of a statistical relationship between distance to a cobalt deposit and fertility rates before the cobalt boom allows us to exclude any difference between the control and the treatment group.

[17] Table A.5 in the Appendix complements the results shown in Fig. 6. On average, women living within 5 km of a cobalt deposit exhibited a 30% increase in fertility rates after 2007 compared to those living in non-cobalt-rich communities.

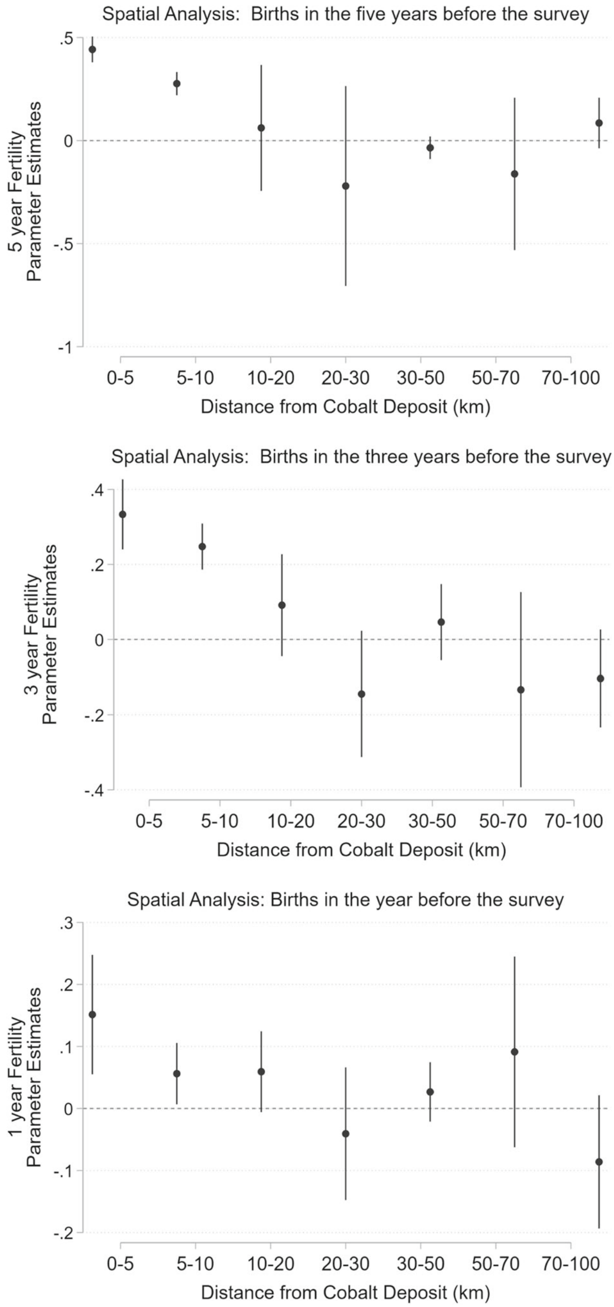


Fig. 6 Heterogeneous effects by distance from cobalt deposit: 5 km cut-off. *Notes:* This figure shows the results from a model allowing for heterogeneous treatment effects by distance with 5 km distance bins using the baseline set of control variables and 95% confidence intervals. The sample is all women, who at the time of the DHS interview were between 15 and 49, pooling DHS datasets of 2007 and 2014. Regressions also included all women specific controls, survey year, and sub-regional district-by-time fixed effects

6.3 Endogenous migration

A factor that might bias the results is endogenous migration. Households might have migrated towards cobalt-rich villages attracted by the presence of the crucial mineral and the consequent boost in wealth. In response, those families might have pushed up their fertility rates in cobalt-surrounding villages. I assess the role of migration in explaining the impact of cobalt mining on women's fertility in two ways.

First, I use the individual information provided by the DHS in which women are asked whether their residence corresponds to their place of birth. Additionally, they specify how many years they had been living in the place of residence at the time of the interview.[18]

To understand if women responded to the presence of a cobalt deposit by migrating, I estimate model (6) in which I regress the probability to migrate from the place of birth on the presence of a cobalt deposit, using the following linear probability model:

$$Pr(Migrate_{i,c,d,t} = 1) = \alpha + \beta\ (Post)_t \times (\text{Cobalt Dep.})_i + \gamma\ \mathbf{X}_i^{'} + \sigma_{dt} + \epsilon_{i,c,d,t} \tag{6}$$

Here, the dependent variable is represented by the probability of woman i, living in village c, in district d, and surveyed in year t to have migrated from her place of birth. The indicator variable $(\text{Cobalt Dep.})_i$ indicates the presence of a cobalt deposit within 10 km from the village where woman i lives. As before, the model includes the usual individual-specific controls. Sub-regional district time trends are also included. Standard errors are clustered at the village level.

The results of model (6) are presented in Table 6 and show no statistical relationship between proximity to a cobalt deposit and probability of migration from the place of birth.

Furthermore, I estimate the baseline Eq. 1 restricting the sample to women who have never migrated. This exercise is helpful because if the coefficient estimates obtained from the sample restriction to women who have never migrated are similar in magnitude to those obtained considering the whole sample, then this would imply that endogenous migration does not undermine the results of the empirical procedure. Results are shown in Table A.6. The exclusion of women who have migrated reinforces the positive effect of the presence of cobalt deposits on women's fertility.

In addition, I perform a further check in which I consider two possible scenarios. First, suppose that only the poorest and least educated women migrated from the control to the treatment group. Second, suppose that the wealthiest and most educated women migrated in the opposite direction (i.e., from the treatment group to the control group after 2007). Results of these two scenarios are reported in Table A.7 in the Appendix. Once again, the coefficient estimates do not differ in magnitude and significance from those reported in Table 2.

Taken together, the tests performed in this section alleviate concerns of alteration of the estimates due to endogenous migratory flows in and out of cobalt-rich villages.

[18] Out of 1291 women living within 200 km of a cobalt deposit, 1029 reported having never migrated from their place of birth. This translates into 16% of women having migrated at least once.

Table 6 Cobalt mining and probability to migrate

	(1)	(2)	(3)
Cobalt Dep. within 10 km	−0.080	−0.054	0.147
	(0.104)	(0.106)	(0.141)
Individual controls	No	Yes	Yes
District × year FE	No	No	Yes
Mean of dependent var.	0.224	0.224	0.224
Observations	1291	1291	1291
R^2	0.153	0.103	0.062

Notes: This table presents results of the relationship between distance to a cobalt deposit and the probability to migrate to the place where the interview was conducted. The sample includes women aged 15–49 surveyed in 2007 and 2014. Women living within 10 km from a cobalt deposit constitute the treatment group. The control group is composed of women living between 10 and 200 km from the nearest cobalt deposit. Column 1 presents the results with no control. Column 2 adds controls for individual characteristics. Column 3 adds district-by-year fixed effects. Standard errors are clustered at the village level. Significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

6.4 Cobalt deposits vs. other mineral deposits

To confirm that the effects on fertility are a direct consequence of cobalt-mining exposure and that they are unrelated to other types of mineral deposits, I run the same model defined in Eq. 1 in which the control group is represented by women aged 15–49 living within 10 km of *any other* mineral deposit in the DRC rather than women living between 10 and 200 km from a cobalt deposit. This exercise was possible since the DRC is notably rich in other minerals such as diamonds, zinc, copper, silver, and gold.

Gold, in particular, is one such mineral that is abundant in the DRC. It is typically found underground, and mining is a dangerous job primarily involving adult males. Unlike cobalt, gold mining does not require children's labor, and parents are more likely to send their children to work in cobalt mines because it is perceived as less risky (Unicef 2017).[19]

I estimate the baseline regression presented in Eq. 1, controlling for the same individual-specific characteristics and fixed effects. This time variable $(\text{Cobalt Dep.})_i$ takes a value of zero if woman i lives in a mining village and a value of one if woman i lives in a cobalt-mining village.

Results of this robustness check are reported in Table 7. Panels A, B, and C present results on the 5-, 3-, and 1-year fertility rates, respectively. Column 3 shows the results of the preferred specification in which I include the complete set of woman-specific controls and sub-regional district-by-time fixed effects.

[19] Gold mining is an excellent example of a non-child labor-intensive mining operation. Two recent studies conducted by Benshaul-Tolonen et al. (2019); Benshaul-Tolonen (2022) established a causal relationship between gold mining booms, infant health, and women's empowerment. The author also finds that maternal fertility declines in the vicinity of gold mining sites. These findings are in stark contrast to the effects of cobalt mining and provide a valuable point of reference for understanding the unique impacts of cobalt mining.

Table 7 Cobalt mining exposure and fertility: cobalt deposits vs. other mineral deposits

	(1)	(2)	(3)
Panel A: 5-year fertility			
Post × cobalt deposit	0.144	0.204***	0.176**
	(0.089)	(0.078)	(0.082)
Panel B: 3-year fertility			
Post × cobalt deposit	0.191**	0.249***	0.212***
	(0.091)	(0.081)	(0.091)
Panel C: 1-year fertility			
Post × cobalt deposit	0.296*	0.351**	0.286*
	(0.157)	(0.155)	(0.164)
Individual controls	No	Yes	Yes
District × year FE	No	No	Yes
Observations	1060	1060	1060
(Pseudo) R^2	0.232	0.239	0.241

Notes: This table reports estimates of the relationship between distance to a cobalt deposit and women's fertility in the DRC. For all regressions, the sample includes all women aged 15–49 surveyed in the two waves of the DHS living within 10 km from any mineral deposit in the DRC. In panels A, B, and C, the dependent variables are, respectively, the number of births during the 5 years, 3 years, and 1 year preceding the interview. The reported coefficients correspond to the interaction between Post_t, and indicator variable equal to one if the birth occurred after 2007, and $(\text{Cobalt Dep.})_i$, and indicator variable equal to one if the woman lives within 10 km from the nearest cobalt deposit. Column 1 presents the results from a specification without individual controls, or fixed effects. Column 2 adds individual controls, which include the number of completed years of education, type of residence, year of birth, and household size. Column 3 adds district-by-time fixed effects. Standard errors, in parentheses, are clustered at the village level. Significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Once again, those results confirm the positive effects of exposure to cobalt deposits on the number of births per woman. Living within 10 km of a cobalt deposit increases 5-year, 3-year, and 1-year fertility rates by 17%, 21%, and 28%, respectively, compared to women living within 10 km of any other mineral deposit in the DRC.

Finally, I run a falsification test where women in villages within 10 km of non-cobalt deposits are compared to women in villages between 10 and 200 km of non-cobalt deposits. Results of this robustness check are reported in Table A.8 in the Appendix, which shows a non-statistically significant relationship between exposure to non-cobalt mining and maternal fertility.

6.5 Perturbation of GPS

A further potential caveat is due to the perturbation in the GPS of the individuals surveyed in the DHS. In the DHS, the location of each individual is reported with an error ranging from 0 to 2 km for individuals living in urban areas and between 5 and 10 km for individuals residing in rural areas. These errors are randomly assigned to individuals to protect their privacy. This systematic difference in the GPS between urban and rural areas constitutes the most relevant issue.

To alleviate possible alterations of the empirical estimates due to GPS perturbations, I consider a "donut" specification. In this specification, the treatment group comprises women living within 10 km of a cobalt deposit, while the control group comprises women living beyond 15 km. This implies a "donut hole" of women living between 10 and 15 km from a cobalt deposit who were excluded from the sample.

The results from this specification are reported in Table A.9 in the Appendix and do not differ in magnitude from those obtained in the baseline Eq. 1. This last result alleviates concerns about the alteration of estimates due to perturbation of the GPS.

6.6 Spatial randomization test

Finally, to show that the main results are spurious due to a misspecified model, I follow Benshaul-Tolonen (2018) and use a spatial randomization test. In this test, the true locations of all cobalt deposits are simultaneously offset between 0 and 50 km in any direction. The exercise shows that the results attenuate towards zero when doing so.

Figure A.7 shows the distribution of treatment effects (i.e., the interaction between the variables $Post_t$ and $Cobalt\ Dep._i$ for 5-, 3-, and 1-year fertility) when the location of each cobalt deposit was randomized 1000 times. The dashed line shows the initial treatment effect using the baseline model. The exact p-value is presented in the figure and shows that it is unlikely that a misspecification of the model presented in Eq. 1 is driving the results for women's fertility.

7 Conclusion

The widespread diffusion of modern high-tech wireless devices and the associated boom in cobalt production from mining in the Democratic Republic of the Congo has led to a significant increase in the number of children engaged in cobalt mining activities (Unicef 2017; Amnesty International 2017; Faber et al. 2017).

Children living in cobalt-mining communities of the DRC are more likely to be employed in the workforce and achieve lower education relative to their peers living in non-cobalt mining communities (Malpede 2022). By leveraging this unique context, this article investigates whether cobalt mining influenced parental decisions regarding fertility. The results provide evidence that cobalt mining increased fertility rates among Congolese women living in cobalt-rich communities of the DRC.

I show that the primary driver behind the fertility increase is the immediate boost in wealth experienced by households with at least one minor child, compared to that of childless families. To further explore the relationship between fertility and mining activities, I compare women living in cobalt-rich areas and those residing in other mineral-rich areas of the DRC. The results indicate that fertility rates in other mineral-rich surroundings did not exhibit the same increase observed in cobalt-rich communities. This finding highlights the unique impact of cobalt mining on fertility dynamics in sub-Saharan Africa.

This study represents a first step towards understanding how the global demand for cobalt-powered electrical devices has affected parental fertility decisions in the context of mineral abundance but without stringent child labor regulations. It highlights the need for effective child labor regulations and responsible resource extraction practices to ensure the welfare of populations and foster inclusive and sustainable development in mineral-rich regions.

Moreover, by raising awareness of the complex interplay between mineral extraction, child labor, and fertility rates, this study contributes to the ongoing discussions surrounding sustainable mineral extraction and protecting children's rights in resource-rich regions (Sovacool et al. 2020).

Future research could delve deeper into the long-term socio-economic impacts of child labor in cobalt-rich communities and explore additional factors influencing fertility decisions. This would provide a more comprehensive understanding of the complex dynamics at play and inform the development of targeted interventions to promote sustainable development and protect children in mineral-rich communities.

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Data Availability The datasets analyzed during the current study are publicly available in the Demographic Health Surveys repository at the following link: https://dhsprogram.com/data/available-datasets.cfm and in the United States Geological Surveys at the following link: https://mrdata.usgs.gov/major-deposits/map-us.html.

Declarations

Conflict of interest The author declares no competing interests.

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