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# THE DARK SIDE OF BATTERIES: CHILD LABOR AND COBALT MINING IN THE DEMOCRATIC REPUBLIC OF CONGO

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# The Dark Side of Batteries: Child Labor and Cobalt Mining in the Democratic Republic of the Congo

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**Abstract**

This paper provides evidence that the rapid increase in the demand for lithium-ion batteries has reduced the education rates of individuals living in cobalt-rich regions of the Democratic Republic of the Congo (DRC). In contrast with other minerals, I find that children in cobalt-mining villages are more likely to work outside their domestic environment and less likely to be in school. I also show that children exposed to cobalt mining are associated with lower cognitive and physical development. These results were obtained by exploiting the exogenous geographic variation of cobalt deposits before the sharp increase in the worldwide demand for cobalt-based electric batteries and using individual education attainment data. These findings suggest that the lower educational achievement of children living in cobalt-rich communities of the DRC is caused not only by a lack of solid child labor regulations (CLRs) but also by a mining industry that generates pollution.

*Key words*: Lithium-ion Batteries, Cobalt Mining, Child Labour

*JEL Classification*: I25, J13, O13

## 1 Introduction

Child labor and its associated reduction in educational attainment are crucial issues for the socioeconomic development of low and middle-income countries.[1] While activities

[1]Child labor is reported to be a significant determinant of low socio-economic development of Sub-Saharan African countries (Hilson, 2010; International Labor Organization, 2015). It subtracts children from school, negatively affecting human capital in the long run (Hazan and Berdugo, 2002; Bau et al., 2020).

such as farming and family business management are generally associated with the use of child labor in developing countries, far less is known about the short and long-term effects of harmful (or hazardous) child labor activities, such as illegal mining.[2] Children as young as five employed outside their family business in the paid job market tend to work considerably more hours than their peers working within their families.[3] As a consequence, those children might abandon their education earlier.

This paper focuses on the effects that the boom in worldwide demand for modern lithium-ion batteries has had on completed education attainment and child labor outcomes in the Democratic Republic of the Congo (DRC). It does so by exploiting the effects of the plausibly exogenous cobalt boom that occurred in the DRC as a consequence of the diffusion of high-tech devices such as smartphones, PCs, wireless headphones, and electric vehicles. Unlike other types of mineral deposits, cobalt is primarily mined on the surface and relies on small hands to be washed out from the dust (Amnesty International, 2017; Unicef, 2017). In section 2, I provide evidence supporting the specific use of children in cobalt deposits and the differences compared with other types of mines.

To examine the impacts of the cobalt mining boom, I combine three sources of variation: i) geographic variations in human exposure to cobalt mining, ii) time variation in the production of cobalt induced by the worldwide adoption of lithium-ion batteries, and iii) age-specific exposure of individuals to cobalt deposits. The geographical variation comes from the presence of a cobalt deposit in the DRC and is retrieved from the US Geological Survey (2019). Sub-Saharan Africa is naturally abundant in crucial minerals, and the presence of cobalt is plausibly exogenous to the educational achievements of individuals. The boom of cobalt production from mining that occurred in the DRC in 2007 constitutes the source of time variation. Data sources on Congolese individuals, including their village of residence, education attainment, and individual characteristics, are obtained from the Demographic and

[2]The International Labour Organization (ILO) defines hazardous child labor activities as follows: "Hazardous child labor is defined by article 3, comma d, of the ILO Convention concerning the Prohibition and Immediate Action for the Elimination of the Worst Forms of Child Labour, 1999 (No. 182) as work which, by its nature or the circumstances in which it is carried out, is likely to harm the health, safety or morals of children".

[3]Edmonds and Pavcnik (2005) report that children between 4 and 16 years of age working in domestic work or helping with their relatives typically allocate 16 hours per week against an estimated 31 hours per week worked by children outside their family.

Health Surveys (DHS).

This study assumes that individuals who were between six and 14 at the time of the cobalt-mining boom and lived in villages or towns surrounding cobalt-mining deposits were less likely to complete their education relative to those living in non-cobalt villages.

The empirical strategy compares birth-year cohorts based on the proximity to a cobalt deposit in their village of residence, interacted with a post-2007 indicator variable. This method identifies an intention-to-treat effect under the assumption that trends in outcomes would have been similar in areas close to a cobalt deposit in the absence of the sudden boom of cobalt production from mining in the DRC. I provide evidence supporting the plausibility of this assumption. Moreover, the production of other minerals was not affected by the discovery of modern lithium-ion batteries in 2007.[4] This allows to rule out any confounding factors related to other types of mines.

I first show that individuals who, during their childhood, were exposed to cobalt mining achieved about 0.5 fewer years of education relative to their peers who were exposed to other types of mineral deposits. Second, I show that children aged 6-14 living in towns and villages surrounding cobalt-mining deposits are more likely to be employed outside their family businesses and less likely to be in school. Third, I find that children living in cobalt-rich communities have lower cognitive and physical abilities.

The comparison of individuals living in cobalt-mining villages with those in other mineral-rich towns suggests that the lower educational attainment is not only driven by working in the mining industry but working in an unregulated mining industry that generates pollution, such as that of cobalt. I report this set of results suggesting that cobalt-mining exposure during childhood drives the loss in education attainment in cobalt-mining communities of the DRC.

The analysis controls for district changes and trends within the DRC between 2007 and 2014. A set of relevant individual-specific controls is included in the empirical strategy such as gender, mother's level of education, whether the parents are alive, type of residence, wealth index, year of birth, and the year in which the DHS survey was conducted. In addition, to account for spatial autocorrelation of cobalt deposits,

[4] Figure 2 shows the production of major minerals in the DRC (i.e., cobalt, gold, diamonds, zinc, copper, and petroleum).

I use the method proposed by Conley (1999).

Furthermore, the abundance of a crucial mineral might increase violence in the surrounding areas. As a result, the outbreak of conflicts might lead to lower schooling and a higher probability of children working, independently of the child labor channel. For instance, some households might out-migrate to avoid conflicts or feel unsafe to send their children to school. To account for this possibility, I include controls for the individual exposure to violent events using the Armed Conflict Location and Event Data (ACLED).

One potential concern is that educational attainment for those exposed to cobalt mining during their childhood might reflect preexisting trends. I check for the existence of pre-treatment trends by employing a birth-year cohort analysis considering all individuals born from 1960 to 2000. Results of the cohort analysis show significant adverse effects on education attainment only for those post-cohorts born within 20 kilometers of a cobalt deposit.

A second concern is that some other change might have caused the education attainment of individuals in the control group to increase after 2007. If no other shock occurred after 2007, we would expect the impact of the cobalt-mining boom to be only limited to those living in the proximity of a cobalt deposit, while no effect should be noted for those living far away. To check for this, I compute the heterogeneous effects of cobalt exposure by distance of a cobalt deposit. This also serves as a test for the validity of the 20 km cutoff distance. Consistent with previous literature on the impacts of mining, the implementation of a spatial-lag model confirms the effects of cobalt mining on education attainment to be concentrated within 20 km of a cobalt deposit (Benshaul-Tolonen, 2018).

An additional concern is that the area surrounding a cobalt deposit might change as a result of the mining activities. This may create other channels explaining the decline in educational attainment and the increase in child labor outcomes in cobalt-mining villages. For instance, there might be fewer schools in cobalt-mining villages compared with the rest of the country. For this reason, I use the most comprehensible available dataset reporting the number and location of all registered primary schools in the DRC.[5] Migration might also constitute another potential driver of children's

[5]Data on the number and location of schools in the DRC are provided by the UNESCO Associated Schools Network (ASPnet).

outcomes in cobalt-rich areas. Thus, I assess whether education changes have resulted from endogenous migration flows in and out of the treatment group.

Furthermore, to check if the effects of the cobalt-mining boom on the education attainment are due to cobalt mining or are a direct consequence of any mining activity, I first employ a set of placebo tests on individuals who, at the time of the cobalt-mining boom, were between six and 14 and lived in any other mining village in the DRC. Second, I show that cobalt mining negatively affects primary education only, whereas no effects are shown on secondary education. Third, I use the location of cobalt deposits in nearby Zambia as a placebo test.

By showing the relationship between cobalt mining and child labor, the main contribution of this paper is to raise awareness for more effective child labor regulations in mineral-rich areas in a context of low socioeconomic development as that represented by the DRC.

This paper is connected to several previous studies documenting the relationship between economic booms and human capital formation. Carrillo (2019) focuses on both short and long-run effects of coffee booms in education achievements and future wealth conditions of young adults in Colombia. A similar paper by Atkin (2016) documents how the arrival of formal jobs during years of expansions in export manufacturing industries in Mexico led to reduced school attendance and lower educational attainment.

Another paper similar in theme to this study is Charles et al. (2018), which investigates the relationship between college attendance of young adults in the United States and the housing booms. Using the housing boom that occurred in the United States during the 2000s, Charles et al. (2018) conclude that young adults were more likely to leave college since the housing boom represented an additional source of available jobs. However, whereas Charles et al. (2018) focus on college attendance, this paper emphasizes primary education.

Recently, using variations in profits from cocaine, Sviatschi (2019) has addressed the use of child labor in coca-suitable areas in Peru. Children exposed to increases in return for cocaine are more likely to be incarcerated for violent and drug-related crimes as adults. Interestingly, Sviatschi (2019) also finds no long-term effect of those individuals who, during their childhood, worked in coca plants going to the legal sector. Moreover, previous literature on child labor in the mining industry has mainly focused on the effects of gold mining on children's health (Benshaul-Tolonen, 2018; Benshaul-Tolonen et al., 2019) and education (Ahlerup et al., 2020) and on the economic effects in the surrounding communities (Bazillier and Girard, 2020).

This study differs from the previous literature on child labor in numerous ways. First, Carrillo (2019) studies a form of not-harmful child labor, represented by household farming, which is likely to have smaller impacts on primary education and therefore different long-term implications compared with harmful child labor practices. Second, previous papers have limited their scope to middle-income countries such as Mexico and Colombia. In contrast, this paper targets individuals living in contexts of low socioeconomic conditions and without effective child labor regulations, such as the DRC.

The remainder of the paper is organized as follows. Section 2 provides background information about the global demand for electric batteries and cobalt production in the DRC. Section 3 outlines the conceptual framework. Section 4 describes the data. Section 5 discusses the empirical strategy for examining the effects of cobalt mining on education attainment. In section 6, I examine the contemporaneous effects on children's outcomes. Section 7 presents the results of the analysis and investigates potential mechanisms. Finally, section 8 concludes.

## 2 Background and Institutional Context

In this section, I provide information on the geographical and institutional context relevant to the present study. I start with data regarding the worldwide adoption of modern cobalt-based lithium-ion batteries and the gradual substitution of the old nickel-based electric batteries. I then proceed with the geographical distribution of cobalt deposits in the world and its historical country-specific production.

Currently, the most popular technology of the battery sector is the lithium-ion battery. This modern type of electrical battery has gradually substituted the old-fashioned nickel-based battery types used extensively in the past. Compared with the latter, lithium-ion batteries have superior energy, power density, and cycling ability (Cobalt Institute, 2019). These significant advantages make lithium-ion batteries the first choice for the manufacture of new electronic vehicles.

Figure A.1 in the appendix highlights the global demand breakdown of modern lithium-ion batteries by type, showing how cobalt-based batteries dominate worldwide demand of lithium-ion batteries, with lithium-cobalt-oxide (LCO), lithium-nickel-cobalt-aluminum-oxide (NCA), and lithium-nickel-manganese-cobalt-oxide (NMC) technology supplying almost 70% of the global market.

The possible applications of modern lithium-ion batteries are manifold and depend on the minerals used. Specifically, the most popular lithium-ion technology is the LCO battery, the main feature of which is the high-energy density translating into an extended run time. This characteristic makes the LCO particularly suitable for portable devices such as cell phones, tablets, laptops, wireless headphones, and cameras (Cobalt Institute, 2019). LCO batteries contain approximately 60% cobalt, which accounts for 50% of the total weight of the cathode. The second most popular lithium-ion battery type is NMC, which contains about 20% of cobalt. Finally, NCA shares similar qualities with NMC batteries in that it also has high specific energy, specific power, and a long life span.

The common denominator among the vast majority of lithium-ion batteries is cobalt. The common denominator among the vast majority of lithium-ion batteries is cobalt.

Since the worldwide adoption of more efficient batteries, which started in 2007 with the diffusion of modern smartphones and wireless electrical devices, global demand for cobalt has surged. The US Geological Survey (2019) shows that in 2015, the global demand increased to 90 Mt from about 50 Mt registered before 2007. Moreover, the global demand for cobalt will further accelerate in the next few years, reaching 155 Mt in 2025 (Alves Dias et al., 2018). Figure 1 shows that cobalt deposits are primarily located in the Central African copper-cobalt belt in DRC (Kinshasa) and Zambia (Selley et al., 2005; Slack et al., 2017). In addition, Figure A.2 in the appendix illustrates that approximately 9,000 Mt of cobalt (which account for about 90% of total worldwide current reserves) are deposited in the DRC, making Sub-Saharan Africa the largest world supplier of the mineral (SP Global Market Intelligence, 2018). In 2017, a large portion of the country's cobalt-mine production came from cobalt ores mined by industrial or mechanized methods. A small portion (about 20%) was gathered by tens of thousands of artisanal miners by handpicking cobalt-rich ores.[6]

Spencer (2016) has estimated that artisanal mines in the DRC produced approximately 10,500 tons of cobalt in 2015, and China represents the leading destination for DRC cobalt exports (US Geological Survey, 2019). This highlights the importance of the DRC as a supplier of such a critical mineral for the modern era.[7]

# 3 Conceptual Framework

In this section, I provide a brief conceptual framework guided by recent reports such as those by Amnesty International (2016, 2017) and Unicef (2017) and surveys such as that by Faber et al. (2017) providing evidence of children's participation in cobalt mines in the DRC. These reports are used to generate predictions for the empirical analysis.

The DRC is naturally rich in this critical mineral, with roughly 65% of the world's cobalt production coming from its southeastern province of Lualaba, near the border with Zambia (Figure 2). The DRC only supplies cobalt from mining and does not refine it because it lacks the basic technology needed to do so.[8]

The boom in cobalt mining has occurred very fast and came overwhelmingly from outside the DRC. Starting in 2007 with the sharp increase in modern lithium-ion batteries, China entered the cobalt market by importing supplies of the mineral directly from the DRC. The production of the African country increased remarkably, tripling in just three years to around 60 Mt per year in 2010. A cobalt production peak was reached in 2011 when the DRC mine production amounted to more than 60 Mt (Figure 2). These levels remained constant until 2016, when the increasing pressure for modern electric vehicles (EVs) started a second cobalt boom, which is not over yet.[9]

[6] 2017 is the latest year for which public data is available.

[7] A report by Center for International Forestry Research (2013) provides detailed information on how Artisanal and Small-scale Mining (ASM) works. Artisanal miners work either legally, in concessions earmarked for ASM by the DRC government. These zones are known as Zones d'exploitation artisanale (artisanal exploitation zones). They are created by the National Minister of Mines. However, a large portion of artisanal miners works illegally. They use shovels, pickaxes, and other rudimentary tools to excavate copper and cobalt ores.

[8] Olivetti et al. (2017) show that only 0.4% of the total production of cobalt from mining is refined in the DRC. In contrast, the vast majority of the entire production is sold to Chinese-owned companies, which refine the raw product in China.

[9] Data accuracy of cobalt mining statistics of the DRC is an important issue. There exist different

However, the vast mineral wealth has failed to increase the overall standard of living of the Katanga province in the specific case and that of the country as a whole. Various reasons for this have been proposed. Cuvelier (2017), for instance, points to the unskilled migration waves that have occurred in the Katanga province since the late 2000s. Such unskilled labor has contributed to lowering wages in cobalt-rich regions.

In addition, assessing the long-term effects of child labor has been a crucial task for social scientists as well as clinical researchers. Nevertheless, what distinguish children working on cobalt mining sites from other forms of child labor such as farming and housework activities is that while the latter constitute not-harmful practices for children and are often compatible with school attendance, mining activities are believed to be harmful practices for children (International Labor Organization, 2015; Demographic and Health Surveys, 2014) and take them out from school. Indeed, children working in mines typically start their day early in the morning and stop working in the afternoon, making the continuation of their education incompatible with such a job.[10]

Moreover, in a recent article, the Financial Times (2019) has shown consistent evidence that Chinese-owned cobalt mines hire informal miners. In particular, the report estimates there are around 200,000 informal cobalt miners in the DRC who in large part work in Chinese and DRC-owned mines. In addition, Unicef (2017) estimated that in 2014 approximately 40,000 boys and girls aged between six and 14 worked in cobalt mines across the whole of Katanga province.[11] Amnesty International

sources of cobalt production from mining in the DRC, each showing slightly different numbers. For instance, the DRC Chamber of Mines reported a cobalt production of 69,328 tons for 2015, whereas Cobalt Institute (2019) indicated a production of 66,120 tons. The US Geological Survey (2019) instead reported a total cobalt production of 63,000 tons. However, those figures do not consider artisanal-produced cobalt, which accounts for 15-20% of the total production of cobalt in the DRC. Cobalt Institute (2019) estimated that artisanal cobalt production in 2015 amounted to 10,500 tons. For this reason, the DRC Ministry of Mines reported a cobalt production of 84,400 tons, also considering artisanal-based production.

[10]Faber et al. (2017) conducted a set of large-scale representative surveys in artisanal mining communities of cobalt-rich areas of the (DRC). They estimate that 11% of children in these communities work outside of the home, of which 23% (or an estimated 4,714 children in the entire population of the 426 communities) work in the cobalt mining sector.

[11]Additional reports by the CNN news, Sky News, and the Financial Times make also use of CCTV cameras and show that although companies are not allowed to buy cobalt from unknown sources, since the unethical use of child labor cannot be excluded, the vast majority of them keeps this practice.

(2017) also suggests the cobalt diggers include an unknown number of children.[12] This is more than double the number of children reported working in the rest of the DRC provinces.

Finally, Nkulu et al. (2018) have provided further evidence of the use of children in cobalt-mining areas. Using a case study performed in the town of Kolwezi, the authors argue children living in a neighborhood that had been transformed into a cobalt-mining village had as much as 12 times the levels of cobalt in their urine and blood than people living in a nearby control area. This produces the conceptual framework's first testable hypothesis:

PREDICTION 1: *Individuals who, at the time of the boom of cobalt production, were 6-14 years old and lived in villages surrounding cobalt deposits achieved lower education rates relative to individuals growing up in non-cobalt-mining communities.*

What makes cobalt mining a good example of such illegal child labor forms is that it is possible for children to work since it is mainly mined on the earth's surface rather than underground like the rest of the minerals mined in the DRC (e.g., gold, diamond, silver, zinc, and copper).[13] Moreover, the typical job assigned to children consists of washing the tiny cobalt matters from the dust. They typically do this operation in large groups in swamps and small lakes.

Faber et al. (2017) conducted a set of large-scale representative surveys in mining communities of the copper-cobalt belt of the DRC. They were administered in 150 mining communities among 2,635 households (15,023 household members). The surveys show that 11% of individuals aged between three and 17 living in these communities reported they worked outside of their home, of which 23% (corresponding to 4,714 children) reported working in the cobalt-mining sector. The surveys also provide helpful insights into the specific types of jobs conducted by children living in the cobalt-mining communities. This produces the conceptual framework's second

[12] Amnesty International (2017) interviews different children working in cobalt mines. Remarkable is the example of the 11 year old Lukasa, who supports his family by digging small quantities of cobalt by hand

[13] According to the most recent report by Amnesty International (2017) all children interviewed in locations close to cobalt deposits, namely Kasulo, Kolwezi, Malo Lake, Kambove and Kapata report working above ground

testable prediction:

PREDICTION 2: *Children aged 6-14 living in cobalt-mining villages exhibit a higher probability to work outside their domestic environment and lower probability to be enrolled in a school relative to children living in non-cobalt-mining villages.*

Although the health effects of child labor in cobalt mines are well known (Nkulu et al., 2018), assessing the economic consequences of this phenomenon has proven to be a difficult task. For example, Basu and Van (1998) have found that child labor decreases adult wages, making child labor necessary and more persistent over time. The effect of being rich in critical minerals on child labor and child cognitive development is an empirical question. It depends not only on the intensity to which the minerals are extracted but also on the general wealth of households surrounding the mining sites and the effectiveness of institutions and policies to prevent the children from being sent to the mines, thus subtracting time and energies from school.

As opposed to other kinds of minerals, Faber et al. (2017) have argued that children working in cobalt mines are mainly sorters (26%), surface workers (23%), and cleaners (17%). These jobs are performed primarily on the surface rather than underground and specifically require small hands (Potter and Lupilya, 2016). Parents perceive this as a relatively safer labor practice than digging underground, making them more willing to send their children to work in cobalt mines compared with other dug-mineral mines. Evidence of this parental belief is presented in the Unicef (2017) report and in Faber et al. (2017).[14] This produces the conceptual framework's third testable prediction.

PREDICTION 3: *The effects of cobalt mining on education rates are concentrated among villagers around cobalt deposits only, while no effect is shown on individuals living in other dug mining-villages.*

[14] Unicef (2017) reports children either collecting the mineral from the mountains of tailings or working in streams and lakes close to the concessions where they washed and sorted the stones to earn between one and two dollars a day.

# 4 Data

This paper uses two sources of data to assess the effects of cobalt mining on education and child labor outcomes. The first dataset, which includes the geographical location of all known mineral deposits in the DRC, is retrieved from the US Geological Survey (2019). This dataset is then matched with GPS data of all Congolese individuals surveyed in the DHS to compute the distance between each individual and the nearest cobalt deposit. The DHS provides data on each individual's completed level of education, children's outcomes, and the additional controls.

## 4.1 Mineral Deposits in DRC

The geographical location of all known cobalt deposits in the world is obtained from the US Geological Survey (2019).

Figure 3 shows the distribution of all cobalt deposits in the DRC, which were all known before the sharp increase in the demand for cobalt in 2007. Most cobalt deposits are located in the southeastern part of the DRC near the border with Zambia. The four biggest cobalt deposits account for about 80% of the total cobalt mined in the country and are located in the provinces of Katanga and Lualaba.

In addition, I consider known deposits of all other minerals in the country. This is done to validate the results of the effects of cobalt mining exposure on fertility against a second control group composed of all individuals living in villages surrounding other mining sites. As opposed to the deposits of cobalt and copper, the rest of the mineral deposits are located in the far eastern part of the country, close to Uganda, Rwanda, and Burundi.

The geographical variation of cobalt mining deposits in the DRC, combined with the geo-referenced data on individuals surveyed, allows computing to define the treatment and control groups. Sub Saharan African regions and particularly the DRC, are naturally abundant in crucial minerals, and since the geographical presence of cobalt deposits were known before the worldwide diffusion of lithium-ion batteries, they are plausibly exogenous with respect to the outcome variable of the study over the period of analysis.

## 4.2 Education and Child Labor Data

I examine whether the exposure to cobalt mining during childhood leads to early school dropout, and consequently, lower education attainment using survey data from the Demographic and Health Surveys. The DHS provides data on completed education level, cognitive skills of all children, as well as specific questions asked to parents about their children. Parents report whether their children are employed within or outside their domestic environment (e.g., household activities or helping in managing family businesses). Moreover, parents are also asked to report whether their children are enrolled in a school.

I use the two available rounds of DHS conducted in the DRC: the first in 2007, and the second in 2014, which and represents the post-cobalt extraction boom. Both surveys were conducted with the use of a GPS device. This constitutes confidential data, and therefore, to protect the privacy of the participants, they come with a randomly assigned error ranging from zero to two kilometers for individuals living in urban areas and between five and ten kilometers for individuals residing in rural areas to protect their privacy. For this reason, the DHS does not recommend researchers to restrict their studies to less than five kilometers of distance. The systematic difference in the GPS between urban and rural areas constitutes the most relevant issue. However, the inclusion of the control variable precisely controlling for different types of residence (i.e., urban or rural) alleviates this concern.[15]

To identify which cohorts have been exposed to the cobalt mining shock, I match data on birth year, completed years of education, and children's outcomes with each individual's place of residence. This allows computing the distance to the nearest cobalt deposit.

As a measure of wealth, I use the wealth index provided by the DHS which divides households into five wealth quintiles. The indicator ranges from 1 (bottom quintile), where the poorest 20% of the households surveyed lies, to 5 (top quintile), which represents the wealthiest 20% of the surveyed households.

As an additional control, I use the Armed Conflict Location & Event Data Project

[15]The DHS do not provide information on places where individuals moved during his life. In other words, each individual is asked about the village of residence and whether they ever moved from that village. Therefore, if an individual reports to have moved in the past, it is unknown which village was coming from.

(ACLED) which includes all violent events along with their date and location of occurrence.[16] Events include civilian targeting such as violence against civilians and explosions/remote violence events in which civilians were directly targeted, and political violence events, such as battles, violence against civilians, and explosions/remote violence event types, as well as the mob violence sub-event type (e.g., riots).

I constructed a database of a total of 43,385 individuals in the DRC who were born between 1960 and 1999. From this sample, people who live within 200 kilometers from the nearest cobalt deposit were kept. Individuals who were born from 1993 onward (who at the time of the boom of cobalt were at most 14) and lived within 20 kilometers of a cobalt deposit constitute the treatment group, while those born until 1992 (i.e., they were already 15 years old in 2007, therefore not fitting in the child labor definition of the International Labor Organization) are part of the control group.

The distance is computed using a GIS software and GPS coordinates of individuals recorded during the surveys and the exact position of the mineral deposit. The definition of treatment group closely follows relevant economic and medical literature focusing on the economic and medical effects of mining activities, respectively. For instance Cust (2015) examines the labor market effects of various industrial mines in Indonesia. He finds that the impacts of mining activities propagate to approximately 10 kilometers within each mine. Aragón and Rud (2015) find that the effects of pollution due to mining are felt up to 20 kilometers with a mineral mine.

In contrast, Benshaul-Tolonen (2018) finds that gold mines within 10 kilometers have positive effects on infant health due to better local development.

Therefore, we expect that by increasing the distance from the individual to the nearest cobalt deposit, the effect of cobalt mining on the variable of interest would decrease. I limit the individuals living in villages within 200 kilometers of a cobalt deposit and control for sub-regional changes over time to exclude confounding factors and any other change that occurred in 2007 besides the boom in cobalt mining.

Tables 1 and 2 report summary statistics of relevant variables pre and post 2007 for villagers and children living within 20 kilometers from the nearest cobalt deposit and those between 20 and 200 kilometers.

The average number of years of education completed by young adults in the DRC

[16] ACLED data are retrievable at the following link: https://acleddata.com/data-export-tool/

is less than four. The DHS data reveals that six years of education represent the highest education level for adults in the DRC. This level is reached by about 18% of the total adult population.[17] DHS data also show that almost 95% of those individuals typically achieve their primary education level before turning 15.

These statistics compare to an average of 3.75 years of education completed by individuals living in cobalt-mining communities in 2007, as opposed to 3.23 years and 3.57 years among individuals in non-cobalt-mining villages or close to other mining sites, respectively.

In relative terms, between 2007 and 2014, the average completed years of education of individuals in cobalt-mining communities declined by 9% as opposed to an increase of 8% exhibited by individuals living beyond 20 km of a cobalt deposit, and a slight decline by 4% by individuals living around other mineral-mining sites. Similarly, the proportion of children aged 6-14 enrolled in school and living in cobalt-mining villages declined from 86% to 73%, while that of children living beyond 20 km or nearby other mining sites stayed around 80% over the period of the analysis. Finally, the proportion of children reportedly working outside their family more than doubled for those living in cobalt-mining communities. At the same time, it remained approximately 10-12% for those living in villages surrounding any other type of mining site.

The final sample contains 2,192 individuals across 44 villages or towns, among which 704 lived within 20 km of a cobalt deposit across 22 villages, and 1,488 lived between 20 and 200 km also across 22 villages; and a final sample of a total of 1,141 children for which we have information on whether they are employed and 1941 children for which we know whether they are in school. I collapse these to the birth-year cohort and DHS cluster of birth (i.e., village or town). Figure 3 shows the GPS (blue dots) of the individuals interviewed in the DHS. The data described in this section is used in to estimate the effects of the exposure of cobalt mining on the educational attainment described in the following section.

[17]DHS show that 761 out of 9,452 adult individuals complete six years of schooling in their life.

# 5 Empirical Strategy

In this section, I test the first prediction from the conceptual framework: that the educational attainment of individuals who during their childhood were exposed to the cobalt-mining shock will be lower than that of the individuals in non-cobalt-mining villages.

The baseline specification follows a difference-in-difference strategy and exploits the geographical variation of cobalt deposits in the DRC together with the temporal variation provided by the exposure of individuals who, at the time of the shock, were between 6 and 14 (i.e., born after 1992) and lived within 20 km of a cobalt deposit.[18]

The empirical strategy is presented as follows:

$$\begin{aligned} \text{Education}_{i,j,c,d,t} = \alpha + \beta_1 \ (Post)_j \times (\text{Cobalt Deposit})_c + \beta_2 \ (\text{Cobalt Deposit})_c + \\ + \gamma \ \mathbf{X}_i^{'} + \delta_j + \sigma_{1,c} + \sigma_{2,dt} + \epsilon_{i,j,c,d,t} \end{aligned} \tag{1}$$

where the outcome variable $Education_{i,j,c,d,t}$ represents the number of completed school years of individual $i$, born in year $j$, living in village $c$, in district $d$, surveyed in year t. $(Post)_j$ indicates whether the individual $i$ was born after 1992 (i.e., aged at most 14 in 2007 and therefore exposed to cobalt mining shock) or earlier than 1992 (i.e., aged 15 or more at the time of the boom). Variable $(Post)_j$ is interacted with $(\text{Cobalt Deposit})_c$, which represents the measure of the distance between the cluster of residence $c$ of individual $i$ and the nearest cobalt deposit. Individuals born after 1992 and living within 20 km of a cobalt deposit define the treatment group. On the other hand, individuals living beyond 20 km and within 200 km of a cobalt deposit define the control group.

The choice of the 20 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

[18] In the baseline model, I consider all individuals regardless if they have moved from their place of birth, or if they commute to go to work. In Section 7.3, I restrict the sample to usual residents who report having never migrated. Comparing the estimates of the unrestricted sample with those obtained restricting the sample to individuals who have never migrated allows us to understand the effects of the endogenous migratory flows.

people living within 5–20 kilometers from the nearest mine. However, I consider the possibility that children only cover a limited distance. For this reason, in Section 7.4 I relax this assumption and test for heterogeneous effects by distance of a cobalt deposit considering a finer treatment distance of 10 km.

$\mathbf{X}_i'$ is a vector of individual and household-specific characteristics composed of a set of indicator variables for the gender of the individual, the type of residence, the number of household members, the household wealth index, and finally, the number of violent events to which the individual was exposed. $\delta_j$ represents birth-year fixed effects, and $\sigma_{1,c}$ are cluster fixed effects. Moreover, different factors such as business environment, policies, corruption, education expenses might vary at the district level and over time. For this reason the specification 1 also controls for district by survey year fixed effects, $\sigma_{2,dt}$.[19]

Given that we have only two survey years conducted respectively before and after the cobalt mining boom and include district by year fixed effects, the regressions do not include a post treatment dummy variable since it would be collinear with $\sigma_{2,dt}$. Finally, $\epsilon_{i,j,c,d,t}$ are random error terms clustered at the village/town level, which I allow to be correlated within districts over time. In addition, I estimate a regression using the method proposed by Conley (1999) to account for arbitrary spatial and serial correlation.[20]

The coefficient of interest is $\beta$, representing the difference-in-difference estimate of the exposure of cobalt mining on educational achievements.

## 5.1 Cohort Analysis

The difference in difference strategy presented above relies on the parallel trends assumption. In other words, in the case of no occurrence of the cobalt mining boom, we would expect that individuals in the control and treatment group would have shared the same pattern of education achievements.

To exclude the existence of pre-treatment trends in education between Congolese individuals living more or less close to cobalt deposits, I implement a cohort-specific

[19]There are eleven regions in the DRC, identifies with the code "admn1". Twenty-one sub-regional districts are instead represented as "admn2" and correspond to provinces.

[20]This approach computes a variance-covariance matrix that is spatially weighted, with weights starting at one and declining to zero until a given cutoff, which in this case is set at 50 km.

relationship between the pre-cobalt boom and individuals' educational achievements. The cohort-specific relationship allows for a visual and precise representation of the effects of cobalt booming.

The cohort-specific relationship is presented as follows:

$$\text{Education}_{i,k,c,d} = \alpha + \sum_{k} \beta_k \times (\text{Cobalt Deposit})_c + \gamma\, \mathbf{X}_i^{'} + \sigma_{1,c} + \sigma_{2,dt} + \epsilon_{i,k,c,d} \quad (2)$$

As in the baseline specification 1 the outcome variable $Education_{i,j,c,d,t}$ represents the number of completed school years of individual $i$, belonging to the birth-year cohort $k$, living in village $c$ and district $d$. $(\text{Cobalt Deposit})_c$ represents the measure of the distance between the cluster of residence $c$ of individual $i$ and the nearest cobalt deposit.

In this specification, the parameters of interest are $\beta_k$ which give the results of the cohort-specific relationships between the measure of the distance of each individual surveyed and the nearest cobalt deposit and either education attainment or cognitive skills.

Let us suppose the sharp increase in the cobalt production from mining effectively subtracted children from school. In that case, a break from the preexisting trend of $\beta_k$ should start only from individuals born after 1993 and living in cobalt-mining communities. In other words, the analysis must not yield any statistically significant relationship between distance of a cobalt deposit and education attainment of all individuals born before 1992. To have robust estimates, I group birth cohorts into three-year groups. For instance, I group individuals born in 1960, 1961, and 1962 in one cohort and so on until individuals born in 1999. This is done to ensure enough observations for each cohort.

Figure 4 plots the coefficients of the relationship between distance to a cobalt deposit and education rate of individuals for each birth-year cohort along with the respective 95 percent confidence intervals. No statistical relationship between proximity to a cobalt deposit and schooling attainments among cohorts between 1960 and 1992 is shown.

The absence of a relationship for all individuals born until 1992 provides reassuring evidence that there were no preexisting differential trends in schooling achievements across individuals in communities within and beyond 20 kilometers from a deposit of cobalt. On the other hand, a negative and statistically significant relationship between proximity to a cobalt deposit and education emerges for cohorts of individuals born since 1993. This result corroborates the evidence of reduced schooling rates among individuals in cobalt-mining communities.[21]

## 6 Contemporaneous Effects on Children's Outcomes

In this section, I test the second prediction from the conceptual framework: that the children exposed to cobalt mining show a higher probability of working outside their families and lower probability of being in school than children living in non-cobalt-mining villages.

To estimate the contemporaneous impact of cobalt mining on children's employment and school attainment, I consider all children aged 6-14 in the two rounds of the surveys. Descriptive statistics are presented in Table 2. I match each child in the sample with their distance to the nearest cobalt deposit and estimate its impact on the probability to i. be employed outside their family's related business or household activities, ii. be enrolled in school.[22]

$$\begin{aligned}\Pr(\text{Outcome} = 1)_{i,j,c,d,t} &= \alpha + \beta_1 \, (Post)_t \times (\text{Cobalt Deposit})_c + \beta_2 \, (\text{Cobalt Deposit})_c + \\ &+ \gamma \, \mathbf{X}_i^{'} + \delta_j + \sigma_{1,c} + \sigma_{2,dt} + \epsilon_{i,j,c,d,t}\end{aligned} \tag{3}$$

where $\text{Outcome} = 1_{i,j,c,d,t}$ is the outcome of child i at age j residing in village c, in district d, surveyed in year t; $(Post)_t$ indicates whether the child $i$ was surveyed in 2007 or in 2014. As for the baseline model in equation 1, variable $(Post)_t$ is interacted with $(\text{Cobalt Deposit})_c$, which represents the measure of the distance between the cluster of residence $c$ of child $i$ and the nearest cobalt deposit. This time the treatment group

[21] I further check the validity of the parallel trend assumption by running the main specification provided in Equation 1, limiting the sample of children aged between 6 and 14 surveyed in 2007 only (pre-boom cohorts) and in the 2014 wave only. The results of this exercise are presented in the Appendix and further, validate the effects of proximity to a cobalt deposit on the educational attainment of children aged between 6 and 14.

[22] Employment is based on reporting of having worked in the 12 months preceding the interview.

is composed of all children living in communities within 20 km of a cobalt deposit and interviewed in 2014. In contrast, the control group comprises all children living beyond 20 km and within 200 km of a cobalt deposit.

$\mathbf{X}_i'$ is a vector of individual and household-specific characteristics composed of a set of indicator variables for the gender of the child, the type of residence, the number of household members, whether the father and/or the mother are alive; the household wealth index, and finally the number of violent events to which the child was exposed. $\delta_j$ are age fixed effects; $\sigma_{1,c}$ are cluster fixed effects, $\sigma_{2,dt}$ are district by survey year fixed effects, and $\epsilon_{i,j,c,d,t}$ are random error terms, which I allow to be correlated within districts over time.

One limitation of this and any other analysis that attempts to measure changes in child school enrollment and child labor using survey data is that employment may be under-reported. This should not bias the estimate as long as the measurement error in employment is uncorrelated with the independent variable. Nevertheless, if such correlation exists, it is most likely positive since parents likely misreport their children's employment when they are not permitted to work. This will lead to a downward bias of the estimate and is not a primary concern for the analysis.

That said, the beta coefficient resulting from this specification compares the outcomes of children who live in cobalt-mining villages with those residing in non-mining villages before and after the cobalt boom.

# 7 Results

## 7.1 Completed Years of Education

I begin by examining the results of the baseline Equation 1. Table 3 reports beta coefficients resulting from this specification which compare the educational attainment of individuals who grew up in cobalt mining areas with individuals who lived in communities far of a cobalt deposit before and after the cobalt-mining boom.

Column 1 presents results from a specification considering only fixed effects for the year of birth for each individual. In this first specification, I find a significant impact of cobalt mining on schooling achievements later in life, with a coefficient of -0.666 (and a standard error of 0.144). Columns 2-3 add other controls and fixed effects sequentially. The addition of individual and household-specific controls such as gender, type of residence, household wealth index, and exposure to violent events, along with the inclusion of cluster fixed effects in column 2, has negligible effects on the estimated coefficient, which is now -0.478 (and a standard error of 0.220). Finally, the specification in column 3 includes district by survey year fixed effects. Results confirm what is shown in columns 1-2, with a coefficient of -0.488 (and a standard error of 0.210).

All columns report standard errors accounting for arbitrary spatial and serial correlation using the method proposed by Conley (1999). I find that the coefficient estimates are essentially unchanged across different assumptions about the covariance-variance matrix, suggesting spatial correlation is not a potentially significant issue in my setting.

Overall, I observe that cobalt mining activities reduce educational attainment in cobalt deposit areas. The estimates imply that the boom of cobalt led to a decline in completed schooling of approximately 0.5 years of those individuals born since 1993 (post-boom cohorts) and growing up in areas surrounding a cobalt deposit, compared with those individuals who were born until 1992 (pre-boom cohorts).[23]

To understand these coefficients, we compare them to the mean of the dependent variables. The average completed education of Congolese individuals is around 3.5 years. Therefore, the estimate in column 3 implies that people in cobalt-mining communities showed a decline in their education by 14% compared with individuals living outside cobalt-mining communities after 2007.

In the following sections, I address additional potential mechanisms such as endogenous migratory flows in and out of the treatment group and the number of primary schools in cobalt-mining villages compared with the rest of the country. Furthermore, I will compare the educational attainment of individuals living in cobalt-mining communities with those surrounding other types of mineral deposits. Finally, I perform a series of placebo tests. First, I consider the childhood exposure to cobalt of individuals in Zambia. Zambia constitutes a valid control since it is a neighbor country of the

[23]Individuals who were born in 1992 were 15 years old in 2007 when the cobalt mining boom occurred. Therefore, people born *until* 1992 were considered as pre-boom cohort. Individuals born *from* 1993 were at most 14 years old in 2007 when the cobalt mining boom occurred. These are considered as post-boom birth years cohorts.

DRC, and its cobalt production did not increase over the time of the analysis. Second, I check that cobalt mining exposure did not affect secondary education. The reason behind this further check is that cobalt mining mainly involves children between six and 14 mainly enrolled in primary schools. Results of the placebo test on secondary education are reported in Table A.1 in the Appendix.

## 7.2 Children's Outcomes

The results of the estimation of the contemporaneous impact of exposure to cobalt mining activities on children's employment and school attainment are presented in Table 4 and suggest that cobalt mining is associated with a higher probability of children being employed outside their homes and a lower probability of being in school.

Specifically, columns 1 and 4 present results from a specification including the year of birth fixed effects only, without individual and household-specific controls or additional fixed effects. In this first specification, I find a positive and significant impact of cobalt mining on the probability of a child to be employed, with a coefficient of 0.224 (and a standard error of 0.072), and a negative impact on being in school with a coefficient of -0.209 (and a standard error of 0.067).

Columns 2 and 5 add controls and fixed effects sequentially. The addition of individual and household-specific controls has minor effects on the estimated coefficients, which are now 0.219 (and a standard error of 0.075) on the probability to be employed, and -0.168 (and a standard error of 0.067) of being in school. Finally, the specifications in columns 3 and 6 add district by survey year fixed effect. Results confirm what is shown in columns 1-2 and 4-5, with a coefficient of 0.210 (and a standard error of 0.079) on the probability to be employed, and -0.169 (and a standard error of 0.064) of being in school.

Concerning the effects on completed education, all columns report standard errors that account for arbitrary spatial and serial correlation using the method proposed by Conley (1999).

Taken together, the results described in Table 4 suggest that the presence of a cobalt deposit within 20 km of the place of residence significantly increases (by 21 percentage points) the probability that a child aged 6-14 will be employed and decreases (by 17 percentage points) the likelihood that they will be in school.

#### 7.2.1 Gender Heterogeneity

Unicef (2017) and Amnesty International (2017) showed how the proportion of boys and girls working in cobalt mines was strikingly similar. However, boys were slightly more present than girls. The reason behind this similar pattern between genders is argued in Faber et al. (2017) and lies in the main tasks performed by children in cobalt mines. Children working in cobalt mines are mainly sorters, surface workers, and cleaners. Indeed, children's duties especially involve washing the tiny cobalt matters from the dust due to their small hands regardless of their gender. This work is generally performed on the surface and is perceived as safer by parents relative to other mines dug minerals.

If this is the case, one would expect boys and girls to be similarly affected by the exposure to cobalt mining. Confirming this prediction is a test that indicates the cobalt-mining shock affected schooling primarily through changes in the opportunity cost of education. Table A.2 shows estimates of the effect of exposure to cobalt mining on child labor separately for females and males using the model in equation 3.

Specifically, columns 1 and 5 present results from a specification including only the year of birth fixed effects for boys and girls, respectively. In this first specification, I find a positive and significant impact of cobalt mining on the probability of both girls and boys on being employed, with a coefficient of 0.143 (and a standard error of 0.075) for girls and 0.304 (and a standard error of 0.095) for boys. Columns 2 and 6 add individual controls and fixed effects sequentially. The estimated coefficients are now 0.121 (and a standard error of 0.081) for girls and 0.304 (and a standard error of 0.095) for boys. Finally, in the specifications in columns 4 and 8, there is a negative and significant impact on the probability of both girls and boys of being in school, with a coefficient of -0.144 (and a standard error of 0.069) for girls, and a coefficient of -0.200 (and a standard error of 0.058) for boys.

All columns report standard errors that account for arbitrary spatial and serial correlation using the method proposed by Conley (1999).

Taken together, the results described in Table A.2 suggest that the presence of a cobalt deposit within 20 km of the place of residence significantly affects the probability of both boys and girls being in school, with boys being slightly more affected than girls.

### 7.2.2 Children's Health

Another reason children in cobalt-mining villages of the DRC leave school early is that working in a cobalt mine that generates pollution might cause adverse effects on their health (Nkulu et al., 2018; Faber et al., 2017). Working in an artisanal cobalt mine with no effective child labor regulation might worsen their physical and cognitive development.

I exploit this possible mechanism by estimating the same linear probability model as in equation 3. Here, I match each child on the sample with their distance to the nearest cobalt deposit and estimate its impact on the probability of: i. being mentally affected; ii. showing difficulties in speech; iii. having hearing difficulties; and iv. showing difficulties in walking.[24] As in equation 3, I consider all children aged 6-14 in the two waves of the DHS.

Results in Table 5 provide evidence that working in a polluting industry such as cobalt mining affects children's health.

These additional findings indicate that the lower number of completed years of education undertaken by children living in cobalt mining communities of the DRC is not only driven by working in the mining industry and therefore being subtracted from school but also as a result of worse health due to the exposure to cobalt pollution. This also finds support from the recent medical study analyzing the amount of cobalt in the urine of children living around a cobalt mine (Nkulu et al., 2018).

## 7.3 Other Potential Mechanisms

There is a non-negligible possibility that the cobalt deposit area changes in response to the mining activity. This can potentially create other channels whereby cobalt mining might indirectly affect children's education and propensity to work outside their domestic environment. One of the potential changes is the increasing violence due to the presence of a valuable mineral such as cobalt. In the baseline model, I have addressed this possibility by including an individual-specific control on the exposure

[24]These variables result from the interviewer's assessment and therefore depend on the interviewer's subjective feeling. On the other hand, these assessments constitute the best data on children's cognitive and physical development available at the individual level for the DRC.

to the number of violent events before and after the cobalt-mining boom.[25]

In addition to violence, I address two other potential channels: i. endogenous migration flows, and ii. the number of primary schools in cobalt mining villages compared with the rest of the country.

*Endogenous Migration*

Endogenous in and out-migration flows represent a possible channel through which cobalt mining might indirectly affect individual education attainments. In the DHS, each individual is asked whether their village of residence is the same as their birth. Moreover, individuals provide information on how many years they have been living in the village of residence at the time of the interview.

I use this information first to understand the number of individuals who have migrated from their native village. In particular, of the total sample of 2,362 individuals living within 200 km of a cobalt deposit, 2,102 reported having never migrated from their place of birth. This translates into 11% of individuals who have migrated at least once in their life.[26]

To understand if migration affects the results, I first estimate equation 1 restricting the sample to individuals who have never migrated. This exercise is useful because if the coefficient estimates obtained from the sample restriction to individuals who have never migrated are similar to those obtained considering the whole sample, this will imply that endogenous migration does not undermine the results of the empirical procedure. Table 6 indeed presents similar results to Table 3. Therefore, we can reasonably rule out possible concerns of alteration of the estimates due to migration.

Furthermore, I consider that only individuals with specific characteristics migrated from the control to the treatment group. Here we consider the following two cases: First is the extreme case in which only the poorest and least educated individuals migrated from the control to the treatment group. This scenario is plausible since

[25]In addition to the number of violent events, Figure A.4 in the Appendix shows the location of all armed groups in the DRC and the Congolese army (FARDC) provided by the International Peace Information Service (IPIS) "the webmap of armed groups of DRC". A total of 1,758 armed groups are reported on the map. Among which 1257 belong to the FARDC.

[26]Table A.3 in the Appendix shows no relationship between distance to a cobalt deposit and the probability of people to migrate from one village to another.

individuals without a job might see a mine opening as an opportunity to work. If this is the case, then poor and uneducated individuals are often associated with high fertility rates, which might result in higher fertility rates in the treatment group and, at the same time, in lower fertility in the control group. Consequently, this would overestimate the positive impact of cobalt mining on fertility.

Second, we consider the opposite direction of migration. Here, only the wealthiest and most educated individuals migrated from the treatment group to the control group after 2007. Wealthy and well educated individuals are associated with lower fertility rates. If this is the case, then the fertility of those who stayed in the treatment group would increase, while those in the control group would now exhibit reduced fertility.

Combining the two cases, we obtain the worst scenario in terms of selective migration from and to the treatment group. I address this potential scenario by excluding from the sample the poorest 20% of individuals who migrated *to* the treatment from the control group after the cobalt mining boom occurred in 2007, and only the wealthiest 20% (i.e., with a wealth index equal to 5) of those individuals who migrated *from* the treatment group to the control group after 2007.[27]

Results are shown in Table 7 and corroborate the negative effects of cobalt-mining exposure on completed education.[28]

*Presence of Primary Schools*

To address the education channel, I use the most comprehensive available dataset reporting the location of all registered primary and secondary schools in the DRC. This dataset is provided by the UNESCO Associated Schools Network (ASPnet).[29]

[27] The wealth index computed by the DHS Program has values ranging from 1 (representing the poorest quintile of the population) to 5 (the highest quintile of the population). Excluding the poorest 20% of the individuals who migrated means that I exclude those individuals with a wealth index equal to 1 out of 5.

[28] I also run a specification in which I exclude from the sample the poorest 40% (i.e., with wealth index $\leq 2$) of people who migrated *to* the treatment group from the control group after 2007 and only the wealthiest 40% ((i.e., with wealth index $\geq 4$)) of those individuals who migrated *from* the treatment group to the control group after 2007. Results confirm the similar patterns observed in the baseline specification.

[29] The UNESCO Associated Schools Network provides information on about 11,500 primary and secondary schools across 182 countries. The list for all schools is available at the following url: https://aspnet.unesco.org/

Although this dataset does not provide information on the opening time of each school nor the number of children enrolled per each year, I use the exact location of each school to check for possible differences in the number of schools per inhabitant in cobalt mining areas against the rest of the DRC (Figure A.5). If we suppose, for instance, that the number of schools in the cobalt mining communities is significantly lower than in the rest of the country, this would imply that the effects on education rates in cobalt mining areas might have been, at least in part, the result of disruptions in primary schools in those areas.

ASPnet data shows that among the 182 registered primary and secondary schools in the DRC, 17 are located in Lualaba and Haut-Katanga. In contrast, 165 are located in the rest of the country (mainly on the eastern side, see Figure A.5). Considering a total population of about 89.6 million people, of which 6.2 million live in the Lualaba and Haut-Katanga districts, this implies there are 3.7 schools per 100,000 inhabitants in cobalt mining districts, and 2.1 in the rest of the DRC. Hence, we conclude there is no significant difference in the number of schools.

Although this finding does not provide robust statistical evidence that the creation or destruction of schools has affected fertility rates, it offers valuable insights that in cobalt mining communities, there are not fewer schools compared with the rest of the country.

## 7.4 Addressing Potential Concerns

In this section, I present additional potential concerns and describe how I address them. I start by addressing the possibility that some other change might have caused the education attainment of individuals in the control group to increase. For this, I use a model that allows for heterogeneous effects by distance of a cobalt deposit. Furthermore, I compare the education attainment levels of individuals living in cobalt mining areas with those of individuals living in other mineral-rich areas in the DRC. Finally, I perform a series of placebo tests on completed years of secondary education and on cobalt deposits in nearby Zambia.

### 7.4.1 Heterogeneous Effects by Distance

Here I test the third prediction from the conceptual framework: that the effects of cobalt mining on individuals' education rates are concentrated in villages nearby a cobalt deposit only. In other words, we expect the exposure to cobalt mining to affect individuals living within 20 km of a cobalt deposit. At the same time, no relationship should be found for people living at *any* distance beyond 20 kilometers of a cobalt deposit.

To do this, I use a spatial lag model that allows for non-linear effects on education attainment with distance from the cobalt deposit (Benshaul-Tolonen, 2018).

Hence, the following Equation is estimated:

$$\begin{aligned}\text{Education}_{i,c,d,t} = \alpha + \sum_b \beta_b (\text{Post})_t \times (\text{Cobalt Deposit})_c + \sum_b \beta_b \times (\text{Cobalt Deposit})_c + \\ + \gamma\, \mathbf{X}_i' + \delta_t + \sigma_{1,d} + \sigma_{2,dtrend} + \epsilon_{i,c,d,t}\end{aligned} \tag{4}$$

for $b \in \{0-10, 10-20, ..., 40-60, 60-80, 80-100\}$.

This spatial lag model allows for non-linear effects with distance from the nearest cobalt deposit. Each individual is recorded to a distance bin: 0–10 kilometers, 10–20 kilometers, and so forth, and compared with the reference category 100–200 kilometers away. This time, I consider a finer treatment distance of 10 km. The specification controls for the same fixed effects, trends, and individual controls included in the baseline specification. The results from this alternative model are presented in Figure 5 and corroborate the estimates obtained in the baseline specification.

Moreover, this model indicates that the relationship between cobalt mining and education is significant within 20 km of a cobalt deposit, with individuals living within 10 km of a cobalt deposit being slightly more affected than those living between 10 and 20 km. No relationship arises for individuals living at any distance beyond 20 kilometers away of a cobalt deposit.

#### 7.4.2 Cohort Analysis in a Spatial Lag Model

Here, I consider a further cohort-specific relationship between pre-cobalt boom and children's educational attainment in a spatial lag model. This additional specification test allows for a better understanding of both temporal and geographic distribution of the effects on educational attainment. Unlike the spatial lag model presented in Equation 4, this time each individual is recorded to a distance bin of 0-10 kilometers, 10-30 kilometers, 30-50 kilometers, and 50-100 kilometers and compared with the reference category 100-200 kilometers away. I consider 20 km distance bins to allow for a more significant number of individuals to compare across birth years. The specification controls for the same fixed effects, trends, and individual controls included in the baseline specification.

The regression is specified as follows:

$$\begin{aligned} \text{Education}_{i,c,d,k} = \alpha + \sum_{b} \sum_{k} \beta_{b,k} \times (\text{Cobalt Deposit})_{c} + \gamma \, \mathbf{X}_{i}^{'} + \\ + \sigma_{1,d} + \sigma_{2,dtrend} + \epsilon_{i,c,d,k} \end{aligned} \tag{5}$$

for $b \in \{0-10, 10-30, 30-50, 50-100\}$.

The results from this alternative model are presented in Figure 6 and are very similar to those shown in Figures 4 and 5.

#### 7.4.3 Cobalt Mining vs. Other Dug-Mineral Mining

In this section, I test that the effects of cobalt mining on child labor and education rates are concentrated within cobalt-mining villagers and do not extend to individuals living in other mineral-mining villages.

*Effects on Completed Years of Education*

To confirm that the negative effects on child education are entirely due to cobalt-mining exposure and not a consequence of any other type of mine, I estimate a slightly different version of the baseline specification presented in equation 1 in which I identify a second set of the control group, which is constituted by children being far of a cobalt deposit but within 20 kilometers to *any other* deposit in the DRC.

This time individuals born after 1992 and living within 20 km of a cobalt deposit define the treatment group. Individuals living within 20 km of any other mineral deposit represent the control group.

Table 8 reports beta coefficients resulting from this specification which compares the educational attainment of individuals who grew up in cobalt mining areas with individuals who lived in communities surrounding mineral deposits before and after the cobalt-mining boom.

Column 1 presents results from a specification considering only fixed effects for the year of birth for each individual. In this first specification, I find a significant impact of cobalt mining on schooling achievements later in life, with a coefficient of -0.427 (and a standard error of 0.115). Columns 2 and 3 sequentially add other controls and fixed effects. The addition of individual and household-specific controls such as gender, type of residence, household wealth index, and exposure to violent events, along with the inclusion of cluster fixed effects in column 2, has negligible effects on the estimated coefficient, which is now -0.313 (and a standard error of 0.122). Finally, the specification in column 3 includes district by survey year fixed effects. Results confirm what is shown in columns 1 and 2, with a coefficient of -0.323 (and a standard error of 0.081).

Overall, I observe that cobalt mining has reduced educational attainment by approximately 0.3 years in cobalt areas compared with other mineral-mining communities.

*Effects on Children's Outcomes*

Regarding the estimation on the completed years of education, here I estimate a slightly modified version of the linear probability model presented in equation 3. This time the treatment group consists of all children living in communities within 20 km of a cobalt deposit and interviewed in 2014. The control group comprises all children living within 20 km of any other mineral deposit of the Sub-Saharan country.

The results of the estimation of the contemporaneous impact of exposure to cobalt mining activities on children's employment and school attainment are presented in

Table 9 and suggest that cobalt mining is associated with a higher probability of children being employed outside their homes and a lower probability of being in school compared with children living in villages surrounding other mineral deposits.

Specifically, columns 1 and 4 present results from a specification including fixed effects for the year of birth, without individual and household specific controls or additional fixed effects. In this first specification, I find a positive and significant impact of cobalt mining on the probability of a child of being employed, with a coefficient of 0.160 (and a standard error of 0.068), and a negative impact on being in school with a coefficient of -0.183 (and a standard error of 0.051).

Columns 2 and 5 add controls and fixed effects sequentially. The addition of individual and household specific controls has minor effects on the estimated coefficients, which are now 0.149 (and a standard error of 0.068) on the probability of being employed, and -0.116 (and a standard error of 0.037) of being in school. Finally, the specifications in columns 3 and 6 add district by survey year fixed effect. Results confirm what is shown in columns 1-2 and 4-5, with a coefficient of 0.150 (and a standard error of 0.068) on the probability of being employed, and -0.117 (and a standard error of 0.037) of being in school. In regard to the effects on completed education, all columns report standard errors that account for arbitrary spatial and serial correlation using the method proposed by Conley (1999).

Comparing individuals within 20 kilometers of a cobalt deposit with those living in communities within 20 kilometers from any other mineral deposit leads to similar results to those outlined in Tables 3 and 4. These findings further corroborate the evidence that the boom in cobalt production from mining that occurred since 2007 has caused children in areas surrounding cobalt deposits to achieve lower education rates than children living in non-cobalt-mining villages in the DRC.

# 8 Conclusion

This paper provided evidence that childhood exposure to cobalt mining in a context of low enforcement of child labor regulations leads to lower educational attainment later in life. I contributed to the literature by showing that the natural geographic presence of deposits of cobalt along with the labor tasks specifically requiring the use of children to be performed is associated with a higher probability of those children being employed outside their domestic environment and a lower probability of being in school.

In a cobalt mine, children are not sent underground to search for the mineral. Instead, they are mainly sorters, surface workers, and cleaners. Children are chosen to perform these relatively not dangerous tasks because of their small hands, which are required to wash the tiny cobalt matters from the dust. However, more effective child labor regulations can prevent parents from sending their children to work in cobalt mines.

Moreover, I found that children living in cobalt-rich communities are associated with lower cognitive and physical abilities compared with their peers living in other mineral-rich villages of the DRC.

In the second half of the paper, I show that although the illegal use of children in cobalt mines affects all children between 6 and 14, it slightly impacts more boys than girls. I then address additional mechanisms potentially explaining the decline in education in cobalt-mining communities, such as increasing violence due to the presence of a valuable mineral or migration flows into and out of cobalt-mining villages, along with the presence of schools.

The final part of the paper focused on the effects that cobalt mining had on child labor and the education rates of individuals living in nearby villages relative to individuals in villages or towns surrounding other mineral deposits in the DRC. This is relevant because cobalt is considered an essential mineral for the technological development of the next decade, and since its production is predicted to double by 2025, regulating artisanal small-scale cobalt mines in the DRC is instrumental in alleviating negative long term socio-economic impacts on cobalt-rich locations.[30]

Overall, this paper provides a first step at understanding how hazardous child labor practices significantly affect the educational attainment of children living in surrounding areas, motivating the use of strict child labor controls in cobalt-rich areas.

[30] See reports by the US Geological Survey (2019) and the Cobalt Institute (2019).

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# 9 Figures and Tables

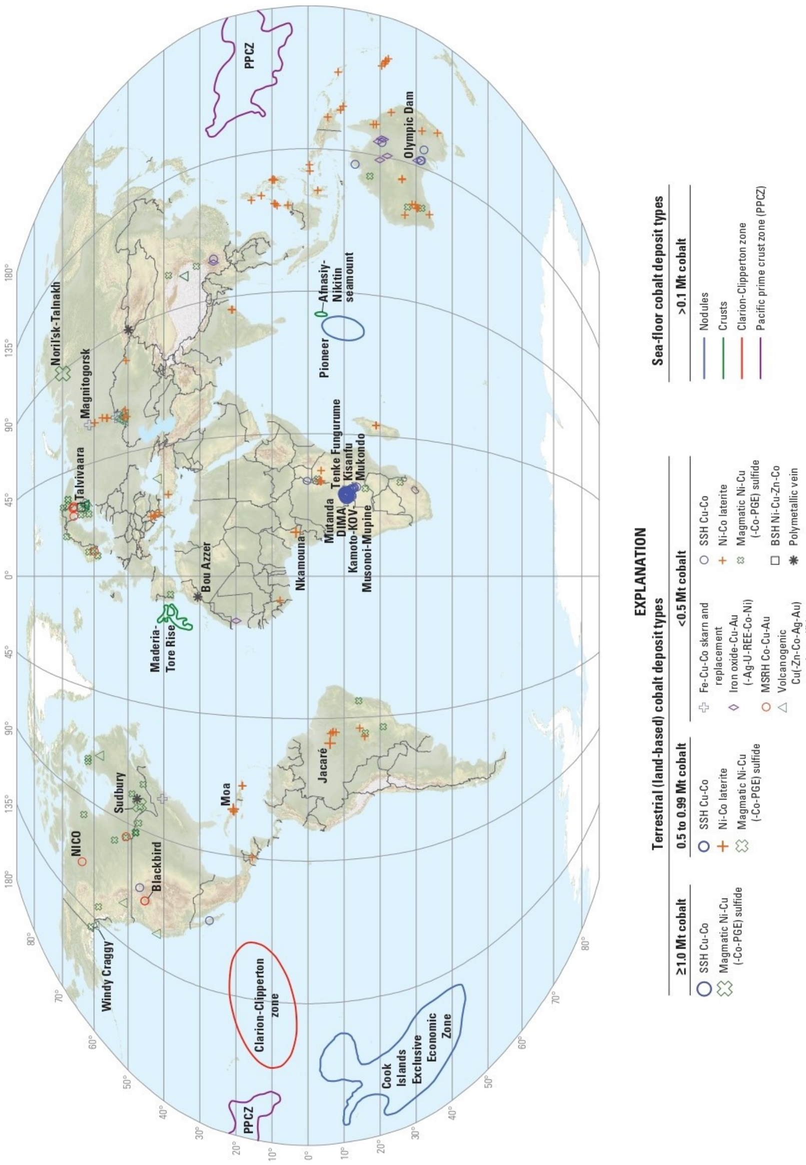



Figure 1: World map showing the global distribution of major cobalt-bearing mineral deposits (those containing equal to or more than 500,000 metric tons of cobalt) and selected smaller deposits that represent minor types. The sizes of the symbols for terrestrial (land-based) deposits reflect the amounts of contained cobalt. Additional data on these and other deposits are found in the USGS report documentation (US Geological Survey, 2019).

*Notes:* Figure retrieved from the U.S. Geological Survey (2019). Based on USGS Global 30 arc-second elevation data (1996) and from Natural Earth (2014).

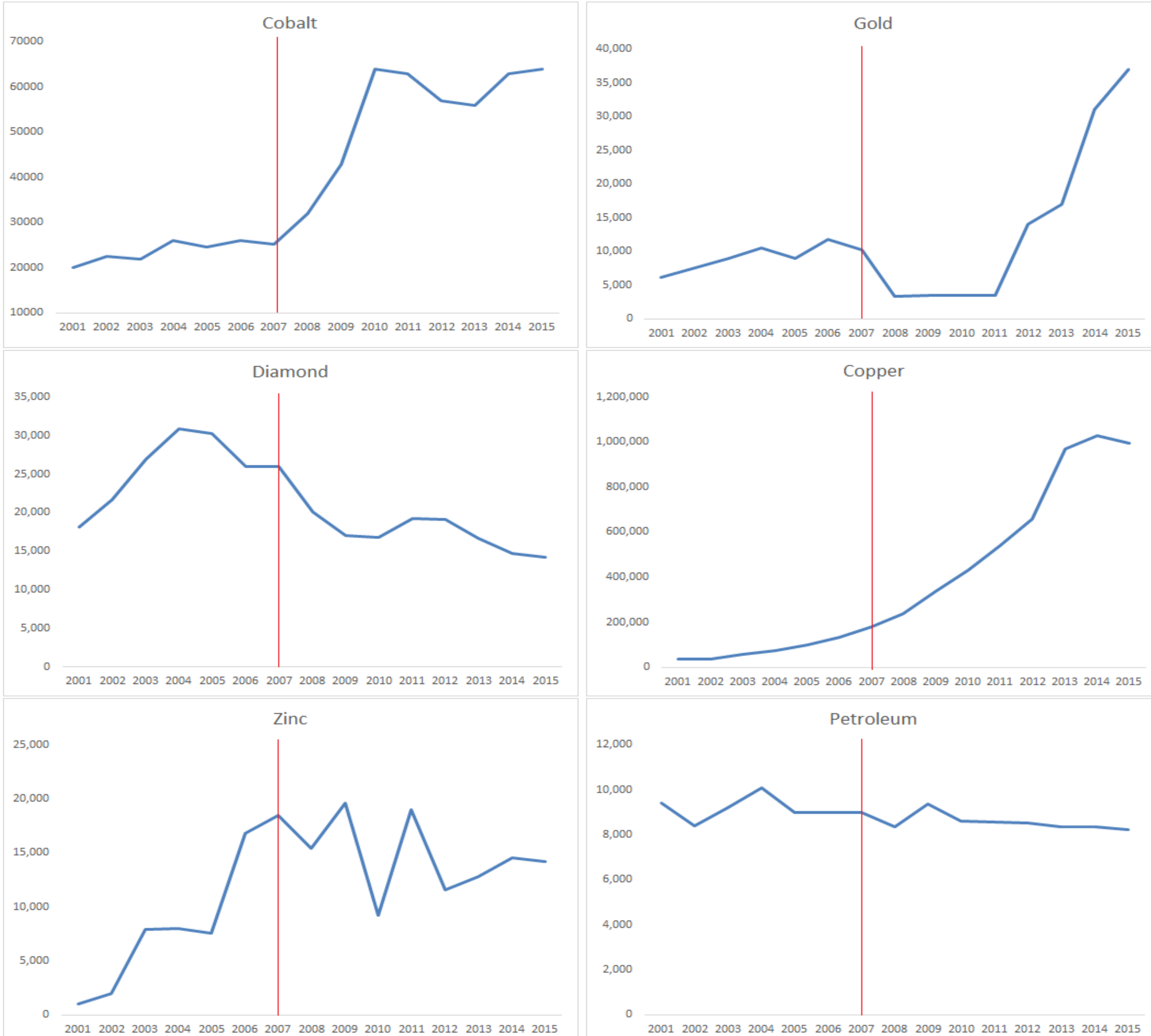
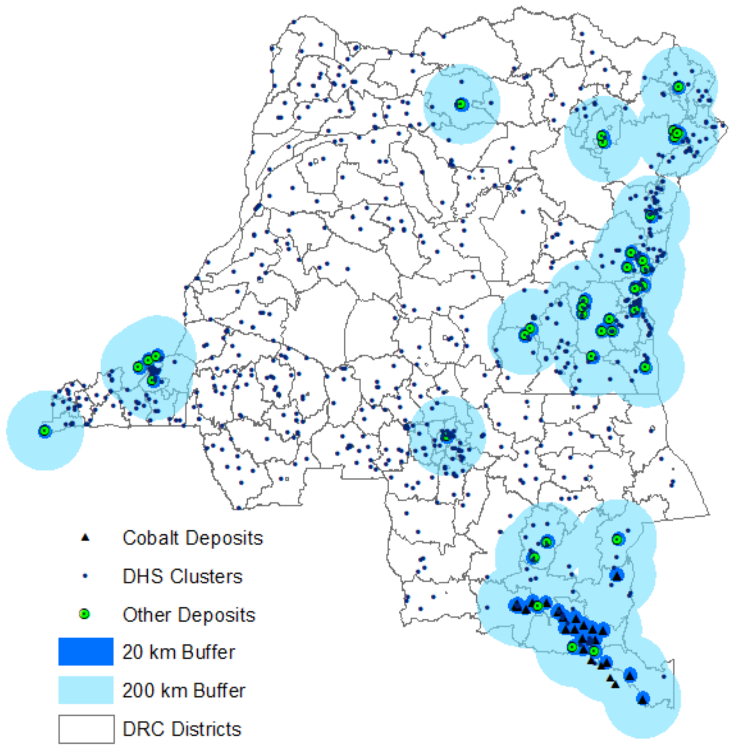



Figure 2: Total Production of major minerals in the DRC.

*Notes:* The data in this figure is retrieved from the US Geological Survey (2019) and is expressed in Metric Tons.

Panel A




Panel B

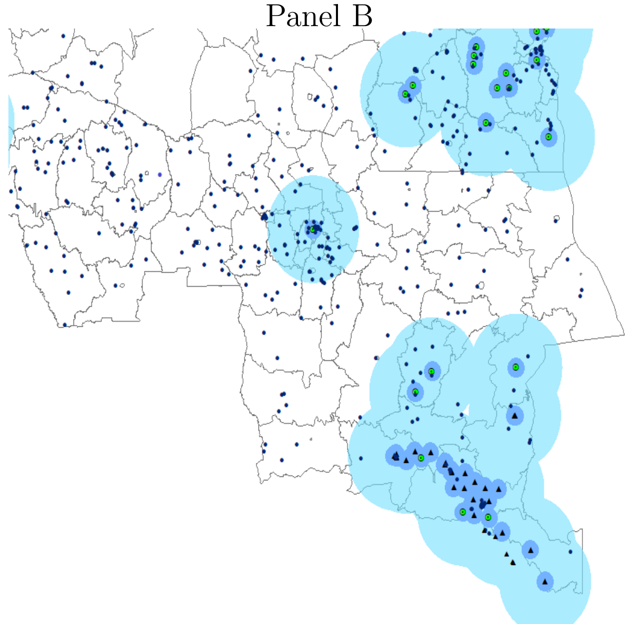


Figure 3: Location of all Mining Deposits in the DRC and gps of all Individuals Surveyed in the 2007 and 2014 DHS waves.

*Notes:* The data in this figure is a combination of author's calculations, using a GIS software and the US Geological Survey (2019) and Demographic and Health Surveys (2014).

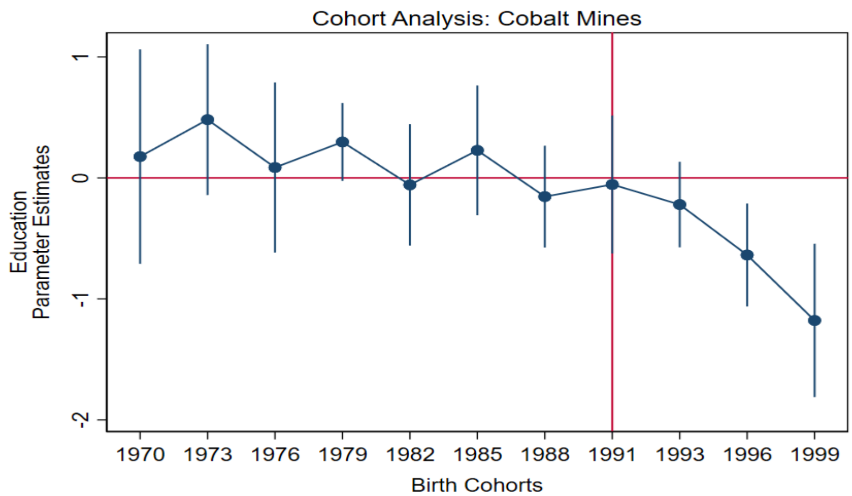



Figure 4: Pre-Cobalt Boom and Completed Years of Education; Three-Year Cohort-Specific relationships for all Individuals Born between 1960 and 1999

*Notes:* This figure reports estimated birth year (birth cohort) fixed effects in completed years of education for all individuals born between 1960 and 1999 using the baseline set of control variables and 95% confidence intervals. The sample is all individual born between 1960 and 1999, pooling DHS datasets of 2007 and 2014. Individuals living beyond 20 km of a cobalt deposit compose the reference group. Regressions also included all individual specific controls, survey year and sub-regional district by time fixed effects. To focus on individuals of relevant ages ($<$ 14 y.o. at the time of the cobalt mining boom), the last four birth cohorts are two years long.

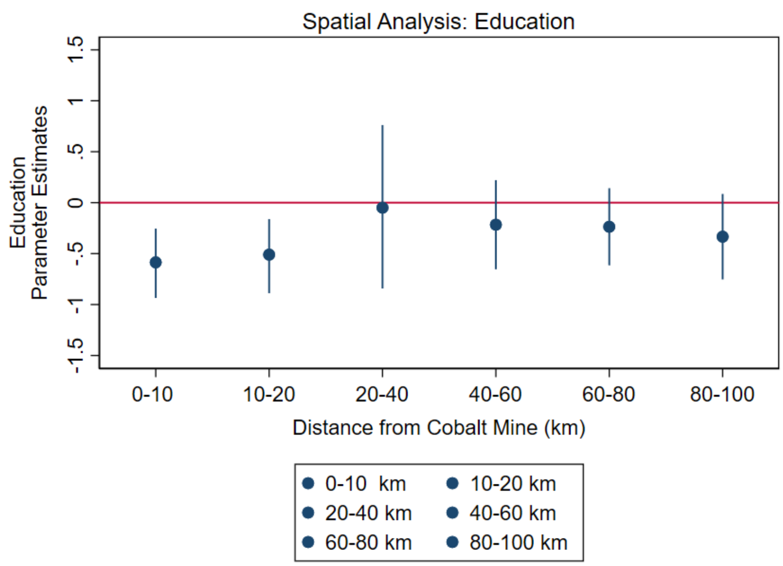



Figure 5: Heterogeneous effects by distance of a cobalt deposit

*Notes:* This Figure shows the results from a spatial lag model with 10 kilometers distance bins using the baseline set of control variables and 95% confidence intervals. The sample is all individual born between 1960 and 1999, pooling DHS datasets of 2007 and 2014. Individuals living beyond 20 km of a cobalt deposit compose the reference group. Regressions also included all individual specific controls, survey year and sub-regional district by time fixed effects

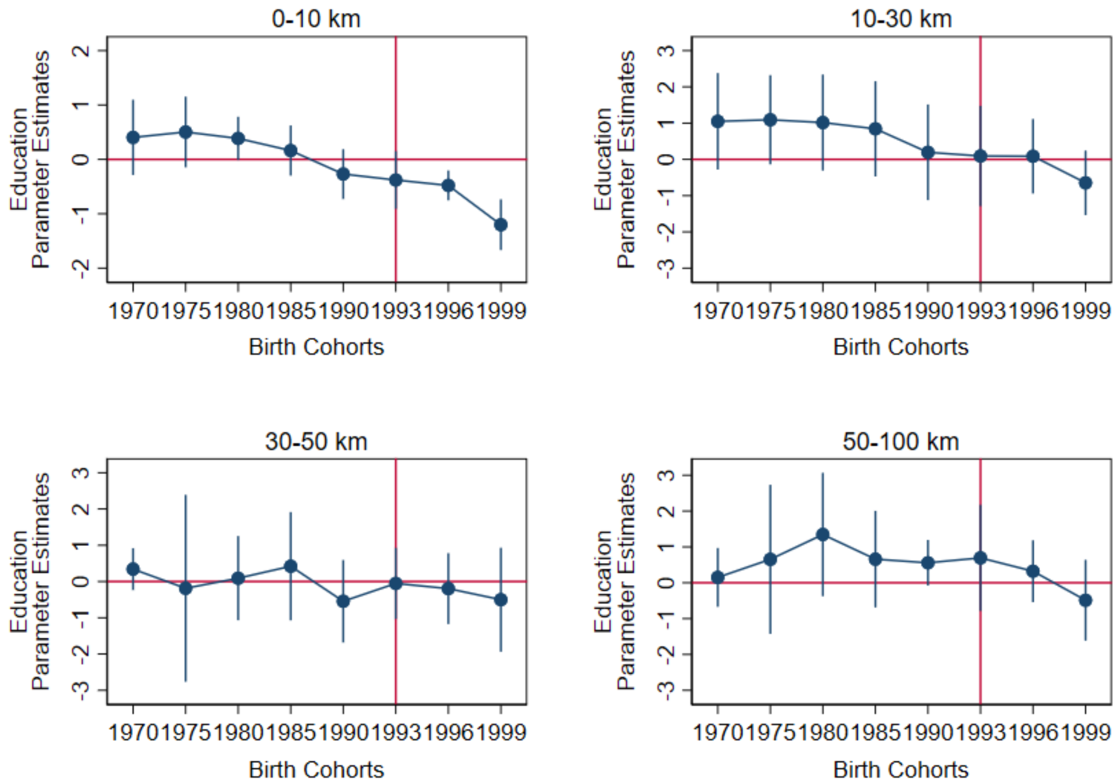



Figure 6: Birth Cohorts in a Spatial Lag Model. Five-Year cohort-specific relationships for individuals born between 1960 and 1999

*Notes:* This figure reports estimated birth year (birth cohort) fixed effects in completed years of education for all individuals born between 1960 and 1999 using a spatial lag model with 20 kilometers distance bins using the baseline set of control variables and 95% confidence intervals. The sample is all individual born between 1960 and 1998 pooling DHS datasets of 2007 and 2014. Individuals living beyond 20 km of a cobalt deposit compose the reference group. Regressions also included all individual specific controls, survey year and sub-regional district by time fixed effects. To focus on individuals of relevant ages (< 14 y.o. at the time of the cobalt boom), the last four birth cohorts are three years long.

Table 1: Extensive Descriptive Statistics - All Individuals

| | Pre < 20 km Mean | Pre > 20 km Mean | Pre any dept. Mean | Post < 20 km Mean | Post > 20 km Mean | Post any dept. Mean |
|---|---|---|---|---|---|---|
| ***Education*** | | | | | | |
| Completed edu. years | 3.759 | 3.228 | 3.569 | 3.454 | 3.510 | 3.417 |
| | (0.085) | (0.100) | (0.048) | (0.0672) | (0.068) | (0.042) |
| ***Controls*** | | | | | | |
| Gender | 1.488 | 1.48 | 1.49 | 1.495 | 1.485 | 1.489 |
| | (0.023) | (0.031) | ( 0.01) | (0.0175) | (0.019) | (0.011) |
| Age | 23.98 | 23.972 | 23.57 | 22.48 | 22.47 | 22.30 |
| | (0.274) | (0.390) | (0.159) | (0.2172) | (0.247) | (0.142) |
| Type of residence | 1.011 | 1.836 | 1.373 | 1.088 | 1.60 | 1.285 |
| | (0.01) | (0.023) | (0.013) | (0.0100) | (0.018) | (0.010) |
| Household members | 6.819 | 6.084 | 6.841 | 7.740 | 6.752 | 6.967 |
| | (0.175) | (0.170) | (0.096) | (0.1324) | (0.091) | (0.076) |
| Wealth index | 4.786 | 2.08 | 3.806 | 4.669 | 3.477 | 4.280 |
| | (0.019) | (0.074) | (0.033) | (0.0290) | (0.046) | (0.024) |
| Violent events | 12.88 | 8.168 | 30.7 | 50.801 | 9.210 | 100.5 |
| | ( 0.17) | (0.771) | (9.975) | (1.404) | (0.524) | (4.19) |
| Observations | 454 | 810 | 902 | 250 | 678 | 1,660 |

*Notes:* This table reports the individuals' sample average characteristics. Observations include all individuals born from 1960 to 1999 surveyed in the two rounds of the Demographic and Health Surveys (i.e., 2007 and 2014), living within 200 kilometers of a cobalt deposit.

Table 2: Extensive Descriptive Statistics - Children aged 6-14

| | Pre<br>< 20 km<br>Mean | Pre<br>> 20 km<br>Mean | Pre<br>any dept.<br>Mean | Post<br>< 20 km<br>Mean | Post<br>> 20 km<br>Mean | Post<br>any dept.<br>Mean |
|---|---|---|---|---|---|---|
| ***Education*** | | | | | | |
| Attending School | 0.8617 | 0.794 | 0.797 | 0.7275 | 0.8013 | 0.824 |
| | (0.020) | (0.027) | (0.012) | (0.020) | (0.02) | (0.014) |
| ***Child Labor*** | | | | | | |
| Works outside family | 0.0886 | 0.1714 | 0.1262 | 0.184 | 0.0445 | 0.118 |
| | (0.02) | (0.029) | (0.063) | (0.024) | (0.012) | (0.094) |
| ***Controls*** | | | | | | |
| Gender | 1.471 | 1.495 | 1.489 | 1.485 | 1.506 | 1.52 |
| | (0.029) | (0.028) | (0.013) | (0.031) | (0.029) | (0.019) |
| Age | 9.641 | 9.990 | 9.734 | 9.843 | 10.05 | 9.82 |
| | (0.157) | (0.152) | (0.073) | (0.166) | (0.155) | (0.100) |
| Type of residence | 1.121 | 1.87 | 1.45 | 1.136 | 1.613 | 1.37 |
| | (0.019) | (0.018) | (0.013) | (0.021) | (0.02) | (0.018) |
| Household members | 8.187 | 7.133 | 7.953 | 8.518 | 8.243 | 7.6 |
| | (0.204) | (0.120) | (0.084) | (0.181) | (0.176) | (0.102) |
| Father alive | 0.9468 | 0.9142 | 0.9127 | 0.8955 | 0.9212 | 0.914 |
| | (0.013) | (0.01) | (0.007) | (0.019) | (0.01) | (0.010) |
| Mother alive | 0.9751 | 0.9809 | 0.9696 | 0.9638 | 0.9589 | 0.961 |
| | (0.009) | (0.00) | (0.004) | (0.011) | (0.01) | (0.007) |
| Wealth index | 4.72 | 1.914 | 3.600 | 4.497 | 3.335 | 4.0 |
| | (0.026) | (0.064) | (0.035) | (0.068) | (0.073) | (0.046) |
| Violent events | 12.06 | 10.92 | 37.86 | 42.61 | 12.27 | 120. |
| | (0.276) | (0.859) | (1.10) | (2.55) | (0.999) | (8.19) |
| Observations | 284 | 315 | 1,001 | 249 | 293 | 419 |

*Notes:* This table reports the children' sample average characteristics. Observations include all children aged 6-14 surveyed in the two rounds of the Demographic and Health Surveys (i.e., 2007 and 2014), living within 200 kilometers of a cobalt deposit.

Table 3: Cobalt Mining Exposure and Educational Attainment

| | Dep. Variable: Years of Education | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post x Cobalt Deposit | -0.666*** | -0.478** | -0.488** |
| | (0.144) | (0.220) | (0.210) |
| Cobalt Deposit within 20 km | 0.420*** | 0.147 | 0.196*** |
| | (0.105) | (0.146) | (0.018) |
| Individual Controls | No | Yes | Yes |
| Cluster FE | No | Yes | Yes |
| District X Year FE | No | No | Yes |
| Mean of dependent var. | 3.507 | 3.507 | 3.507 |
| Observations | 2362 | 2192 | 2192 |
| $R^2$ | 0.093 | 0.102 | 0.104 |

Notes: This table presents results of the relationship between distance to a cobalt deposit and the reported completed years of education of all individuals surveyed in two rounds of the Demographic and Health Surveys (i.e., in 2007 and 2014). Individuals who, during their childhood lived within 20km from a cobalt deposit constitute the treatment group. The control group is composed of all individuals living between 20km and 200km from the nearest cobalt deposit. Column (1) presents the results from a specification with age fixed effects only. Column (2) adds cluster fixed effect and individual-specific controls such as gender, type of residence, year of birth, wealth index and the number of violent events in the area. Column (3) includes the district by year fixed effects. All columns correct for spatial autocorrelation of the error terms (Conley, 1999). Standard errors are clustered at the DHS cluster (i.e., village/town) level. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

Table 4: Cobalt Mining Exposure and Child Labor outcomes

| Dep. Variable: | Employed | | | In school | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post x Cobalt Deposit | 0.224*** | 0.219*** | 0.210*** | -0.209*** | -0.168** | -0.169*** |
| | (0.072) | (0.075) | (0.079) | (0.029) | (0.067) | (0.064) |
| Cobalt Deposit within 20 km | -0.095*** | 0.049 | 0.045 | 0.287*** | 0.143*** | 0.142*** |
| | (0.030) | (0.058) | (0.060) | (0.024) | (0.055) | (0.055) |
| Individual Controls | No | Yes | Yes | No | Yes | Yes |
| Cluster FE | No | Yes | Yes | No | Yes | Yes |
| District X Year FE | No | No | Yes | No | No | Yes |
| Mean of dependent var. | 0.110 | 0.110 | 0.110 | 0.793 | 0.793 | 0.793 |
| Observations | 1272 | 1141 | 1141 | 2072 | 1941 | 1941 |
| $R^2$ | 0.102 | 0.128 | 0.131 | 0.131 | 0.162 | 0.163 |

Notes: This table presents results of the relationship between distance to a cobalt deposit and the probability of being employed and attending the primary school for children aged 6-14 surveyed in the Demographic and Health Surveys (i.e., in 2007 and 2014). Children within 20km from a cobalt deposit constitute the treatment group. The control group is composed of children living between 20km and 200km from the nearest cobalt deposit. Columns (1) and (4) present the results from a specification with age fixed effects only. Columns (2) and (5) add cluster fixed effect and individual-specific controls such as gender, type of residence, year of birth, wealth index , if the mother and/or the father are alive, their level of education, and the number of violent events in the area. Columns (3) and (6) include the district by year fixed effects. All columns correct for spatial autocorrelation of the error terms (Conley, 1999). Standard errors are clustered at the DHS cluster (i.e., village/town) level. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

Table 5: Cobalt Mining Exposure and Child Health outcomes

| | Mentally backward (1) | Walking difficulty (2) | Hearing difficulty (3) | Concentration difficulty (4) |
|---|---|---|---|---|
| Post x Cobalt Deposit | 0.281*** | 0.184*** | 0.003 | 0.180*** |
| | (0.004) | (0.008) | (0.003) | (0.012) |
| Individual Controls | Yes | Yes | Yes | Yes |
| Cluster FE | Yes | Yes | Yes | Yes |
| District X Year FE | Yes | Yes | Yes | Yes |
| Mean of dependent var. | 0.031 | 0.021 | 0.008 | 0.115 |
| Observations | 428 | 428 | 427 | 425 |
| $R^2$ | 0.135 | 0.041 | 0.037 | 0.126 |

Notes: This table presents results of the relationship between distance to a cobalt deposit and the probability of being employed and attending the primary school for children aged 6-14 surveyed in the Demographic and Health Surveys (i.e., in 2007 and 2014). Children within 20km from a cobalt deposit constitute the treatment group. The control group is composed of children living within 20km from any other deposit. All Columns present the results controlling for gender differences, place of residence, if the child's mother or father are alive, year of birth fixed effects and subregional district fixed effects. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

Table 6: Childhood Cobalt Mining Exposure and Educational Attainment: People who have never migrated

| | Dep. Variable: Years of Education | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post x Cobalt Deposit | -0.640*** | -0.571*** | -0.574*** |
| | (0.092) | (0.167) | (0.169) |
| Cobalt Deposit within 20 km | 0.921*** | 0.701*** | 0.745*** |
| | (0.159) | (0.193) | (0.155) |
| Individual Controls | No | Yes | Yes |
| Cluster FE | No | Yes | Yes |
| District X Year FE | No | No | Yes |
| Mean of dependent var. | 3.458 | 3.458 | 3.458 |
| Observations | 2102 | 1939 | 1939 |
| $R^2$ | 0.121 | 0.129 | 0.133 |

Notes: This table presents results of the relationship between distance to a cobalt deposit and the reported completed years of education of all individuals surveyed in two rounds of the Demographic and Health Surveys (i.e., in 2007 and 2014) who have never migrated from their place of birth. Individuals who live within 20km from a cobalt deposit constitute the treatment group. The control group is composed of all individuals living between 20km and 200km from the nearest cobalt deposit. Column (1) presents the results from a specification with age fixed effects only. Column (2) adds cluster fixed effect and individual-specific controls such as gender, type of residence, year of birth, wealth index and the number of violent events in the area. Column (3) includes the district by year fixed effects. All columns correct for spatial autocorrelation of the error terms (Conley, 1999). Standard errors are clustered at the DHS cluster (i.e., village/town) level. Significant at ***$p< 0.01$, **$p< 0.05$, *$p< 0.1$.

Table 7: Cobalt Mining Exposure and Educational Attainment: Selective Migration Flows

| | Dep. Variable: Years of Education | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post x Cobalt Deposit | -0.642*** | -0.599*** | -0.603*** |
| | (0.129) | (0.157) | (0.132) |
| Cobalt Deposit within 20 km | 0.479*** | 0.473*** | 0.501 |
| | (0.116) | (0.135) | (0.391) |
| Individual Controls | No | Yes | Yes |
| Cluster FE | No | Yes | Yes |
| District X Year FE | No | No | Yes |
| Mean of dependent var. | 3.646 | 3.646 | 3.646 |
| Observations | 2262 | 2094 | 2094 |
| $R^2$ | 0.169 | 0.184 | 0.184 |

Notes: This table presents results of the relationship between distance to a cobalt deposit and the reported completed years of education of all individuals surveyed in two rounds of the Demographic and Health Surveys (i.e., in 2007 and 2014). Wealthiest individuals who have migrated from the treatment to the control group, and the least wealthy individuals who have migrated from the control to the treatment group are excluded from the sample. Column (1) presents the results from a specification with age fixed effects only. Column (2) adds cluster fixed effect and individual-specific controls such as gender, type of residence, year of birth, wealth index and the number of violent events in the area. Column (3) includes the district by year fixed effects. All columns correct for spatial autocorrelation of the error terms (Conley, 1999). Standard errors are clustered at the DHS cluster (i.e., village/town) level. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

Table 8: Cobalt Mining Exposure and Educational Attainment: Cobalt Deposits vs Other Dug-Mineral Deposits

| | Dep. Variable: Years of Education | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post x Cobalt Deposit | -0.427*** | -0.313** | -0.323*** |
| | (0.115) | (0.122) | (0.081) |
| Cobalt Deposit within 20 km | 0.236** | 0.227* | 0.224* |
| | (0.095) | (0.130) | (0.118) |
| Individual Controls | No | Yes | Yes |
| Cluster FE | No | Yes | Yes |
| District X Year FE | No | No | Yes |
| Mean of dependent var. | 3.494 | 3.494 | 3.494 |
| Observations | 3625 | 3266 | 3266 |
| $R^2$ | 0.083 | 0.096 | 0.097 |

Notes: This table presents results of the relationship between distance to a cobalt deposit and the reported completed years of education of all individuals surveyed in two rounds of the Demographic and Health Surveys (i.e., in 2007 and 2014). Individuals who, during their childhood lived within 20km from a cobalt deposit constitute the treatment group. The control group is composed of all individuals living within 20km from the nearest mining deposit. Column (1) presents the results from a specification with age fixed effects only. Column (2) adds cluster fixed effect and individual-specific controls such as gender, type of residence, year of birth, wealth index and the number of violent events in the area. Column (3) includes the district by year fixed effects. All columns correct for spatial autocorrelation of the error terms (Conley, 1999). Standard errors are clustered at the DHS cluster (i.e., village/town) level. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

Table 9: Cobalt Mining Exposure and Children's Outcomes: Cobalt Deposits vs Other Dug-Mineral Deposits

| Dep. Variable: | Employed | | | In school | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post x Cobalt Deposit | 0.160** | 0.149** | 0.150** | -0.183*** | -0.116*** | -0.117*** |
| | (0.068) | (0.068) | (0.068) | (0.051) | (0.037) | (0.037) |
| Cobalt Deposit within 20 km | -0.060 | 0.053 | 0.053 | 0.244*** | 0.108*** | 0.108*** |
| | (0.045) | (0.035) | (0.035) | (0.023) | (0.029) | (0.029) |
| Individual Controls | No | Yes | Yes | No | Yes | Yes |
| Cluster FE | No | Yes | Yes | No | Yes | Yes |
| District X Year FE | No | No | Yes | No | No | Yes |
| Mean of dependent var. | 0.116 | 0.116 | 0.116 | 0.751 | 0.751 | 0.751 |
| Observations | 2180 | 1962 | 1962 | 3466 | 3095 | 3095 |
| $R^2$ | 0.089 | 0.116 | 0.116 | 0.132 | 0.156 | 0.156 |

Notes: This table presents results of the relationship between distance to a cobalt deposit and the probability of being employed and attending the primary school for children aged 6-14 surveyed in the Demographic and Health Surveys (i.e., in 2007 and 2014). Children within 20km from a cobalt deposit constitute the treatment group. The control group is composed of children living between 20km and 200km from the nearest mineral deposit. Columns (1) and (4) present the results from a specification with age fixed effects only. Columns (2) and (5) add cluster fixed effect and individual-specific controls such as gender, type of residence, year of birth, wealth index , if the mother and/or the father are alive, their level of education, and the number of violent events in the area. Columns (3) and (6) include the district by year fixed effects. All columns correct for spatial autocorrelation of the error terms (Conley, 1999). Standard errors are clustered at the DHS cluster (i.e., village/town) level. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

# Appendix for Online Publication

## A.1 Additional Information on Lithium-ion Batteries

The LCO batteries are not particularly suitable for large and heavy devices since their principal disadvantage consists in having a low life span and relatively low safety performance at hot and cold temperatures. However, Cobalt Institute (2019) reckons that the majority of research which nowadays focuses on electric batteries is mainly focusing on the LCO, and constant improvements are being made in terms of greater durability and safety.

Although the NMC battery has a lower capacity than that of the LCO, they have a high cycling rate which, combined with a high capacity, high power, and the particularly long-life, makes the latter ideally suited to be used in the new generation of electric cars and buses. NMC also suits its use for power tools, modern e-bikes, and electric motor vehicles. An additional feature of the NMC battery is that it has the lowest self-heating rate out of the different types of lithium-ion batteries. Hence, it is also particularly safe.[31]

The downsides to the technology of NCA are that it is expensive and has poor safety. For these reasons, NCA batteries are mainly used in industry, medical devices, and electric power trains.

[31]Considering no breakthrough invention in battery technology, Cobalt Institute (2019) forecasts that each electric-vehicle battery will need about 18 pounds of cobalt. This is over 1,000 times as much as the current quantity of cobalt required in a battery of a smartphone (i.e., approximately 7 grams). A recent report by Euractiv (2019) states that Volkswagen, for example, expects it will need to build six giant battery factories within a decade to supply its electric-car plants.

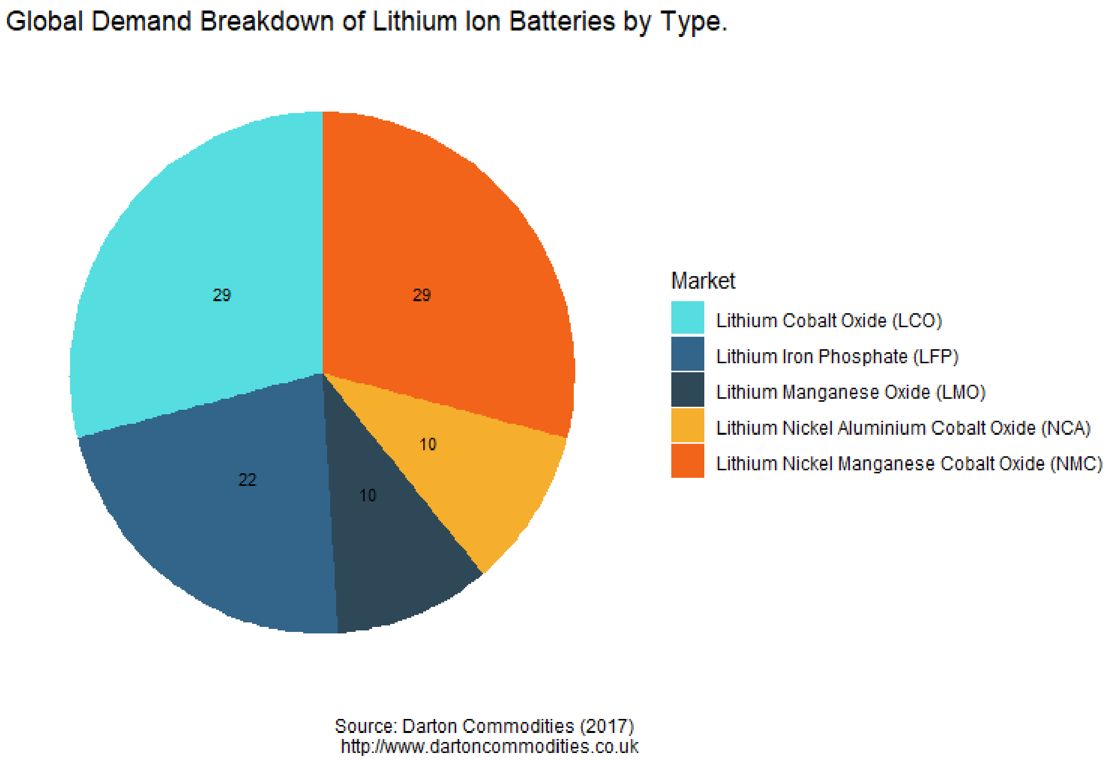



Figure A.1: Global Demand Breakdown of Lithium-ion Batteries by Type

*Notes:* The data in this figure is retrieved from Darton Commodities (2017).

## A.2 Additional Results and Statistics

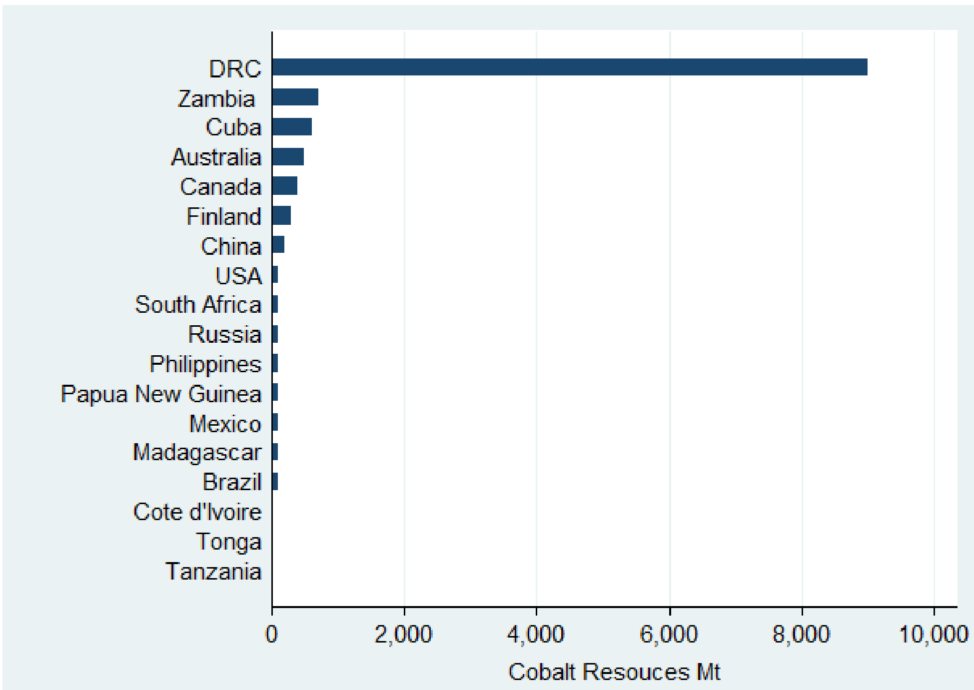
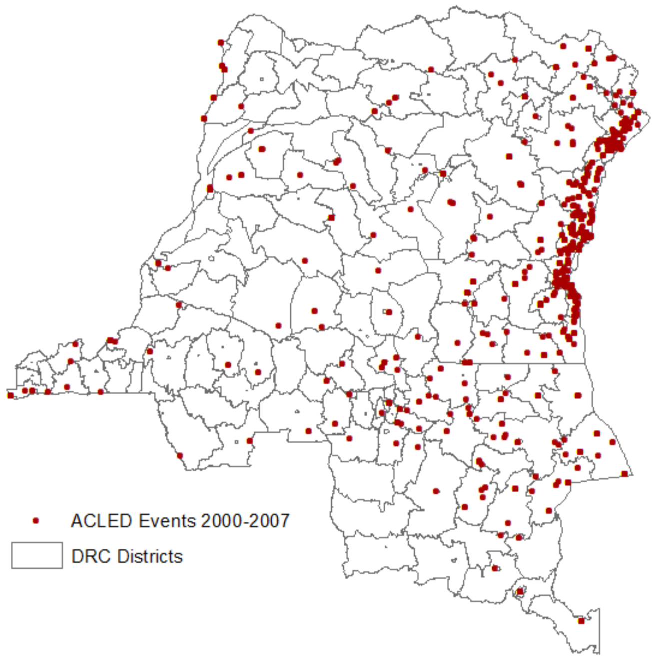



Figure A.2: Estimated Cobalt Reserves by Country in 2018. Million Tons

*Notes:* The data in this figure is retrieved from Alves Dias et al. (2018) and SP Global Market Intelligence (2018).

Panel A




Panel B

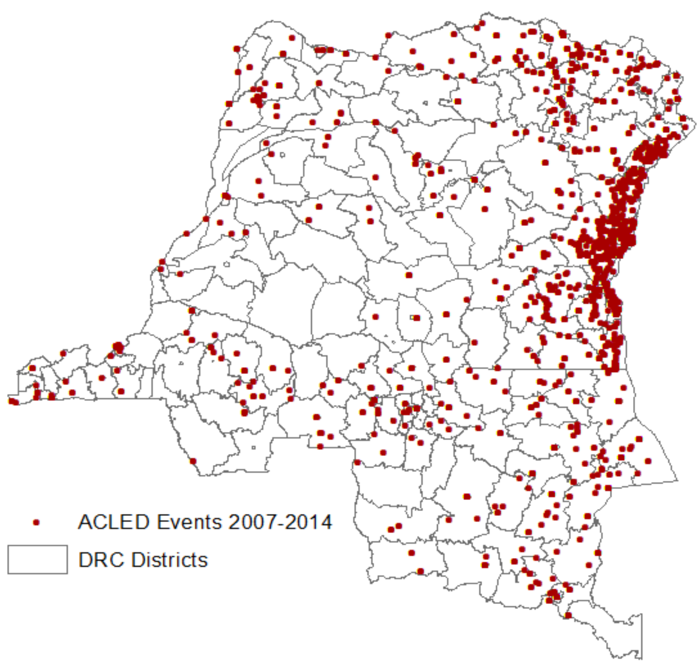



Figure A.3: ACLED Events in DRC

*Notes:* The data in this figure is retrieved from the ACLED database on political violence in DRC.

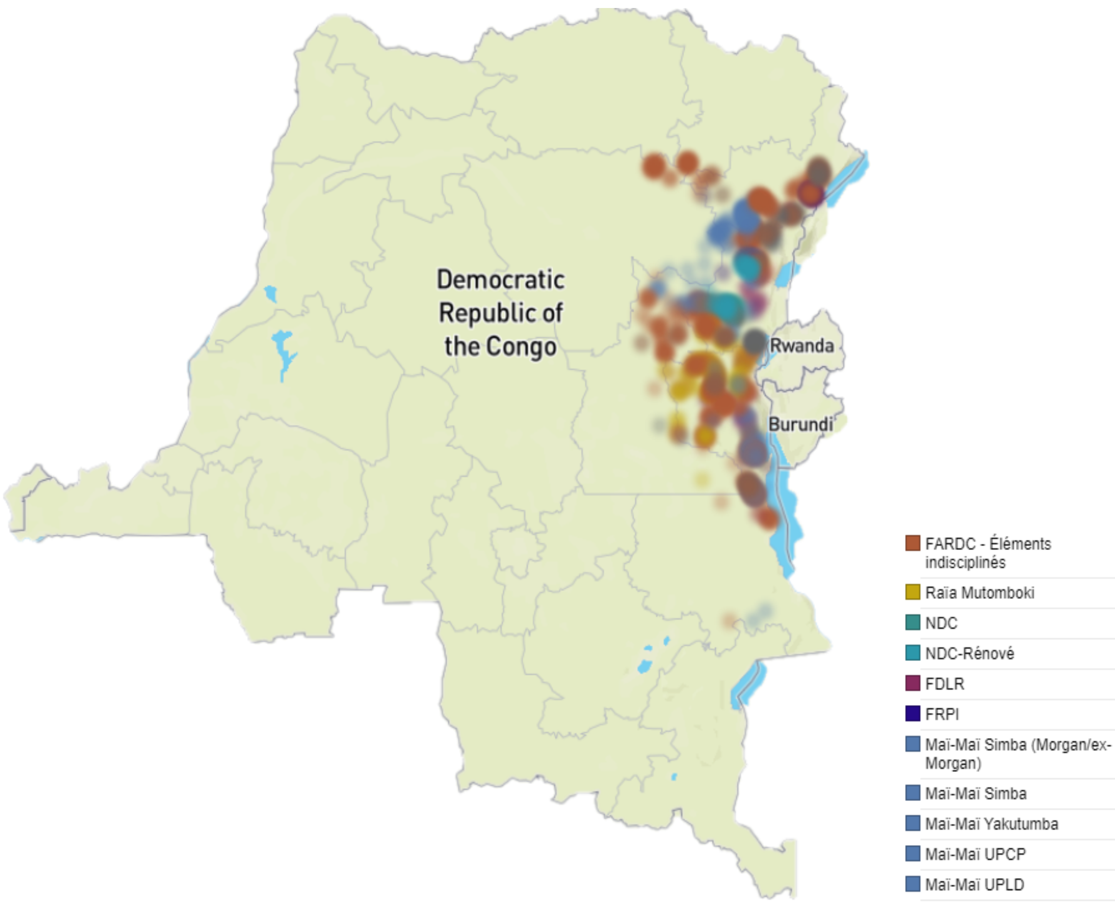



Figure A.4: Presence of Armed Groups in the DRC

*Notes:* The data in this figure is retrieved from the webmap of armed groups of DRC (IPIS).

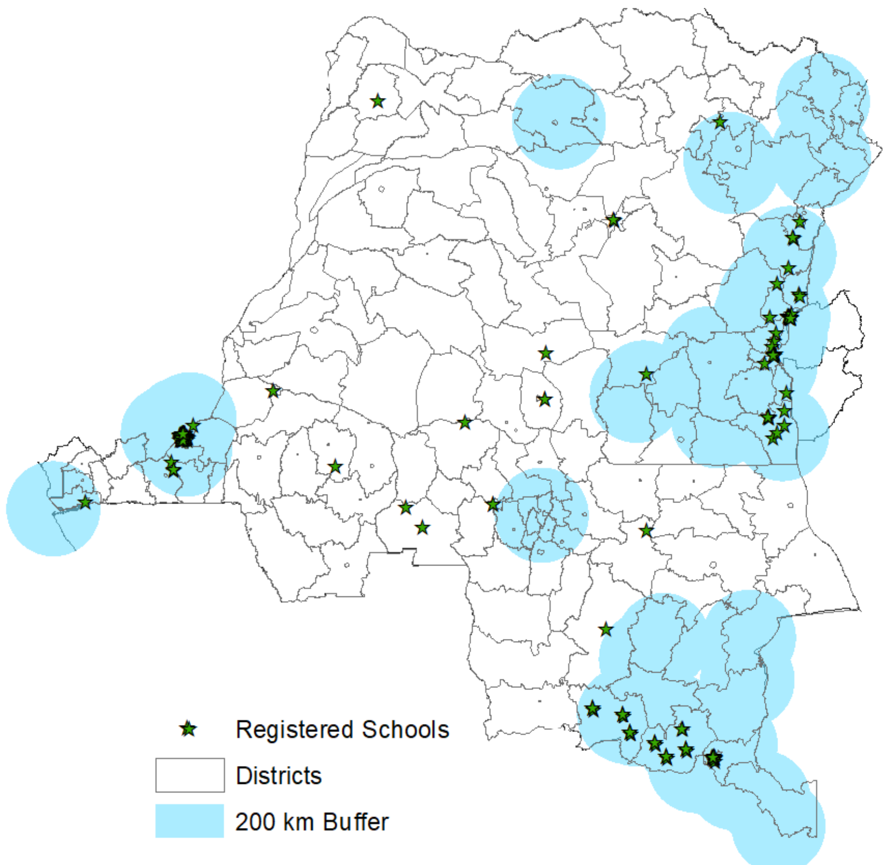



Figure A.5: Location of registered primary and secondary schools in the DRC

*Notes:* The data in this figure is retrieved from the UNESCO Associated Schools Network (ASPnet).

### A.2.1 Effects on Secondary Education

Table A.1: Childhood Cobalt Mining Exposure and Secondary Education: Placebo Test

| | Sec. Education (1) | Sec. Education (2) | Sec. Education (3) |
|---|---|---|---|
| Post x Cobalt Deposit | 0.028 | 0.138 | 0.141 |
| | (0.129) | (0.108) | (0.092) |
| Cobalt Deposit within 20 km | 0.104*** | -0.118*** | -0.133*** |
| | (0.030) | (0.032) | (0.026) |
| Individual Controls | No | Yes | Yes |
| Cluster FE | No | Yes | Yes |
| District X Year FE | No | No | Yes |
| Observations | 2500 | 2323 | 2323 |

Notes: This table presents results of a placebo test on the effects of childhood exposure to cobalt mining production on completed years of *secondary* school. The baseline specification is presented in Equation (1). Column (1) presents the results controlling for individual's year of birth fixed effects. Column (2) adds controls for gender differences, place of childhood residence, if the individual is a migrant and if the individual is currently attending primary school. Column (3) adds survey year fixed effects and subregional district fixed effects. Columns (4)-(6) show the effects of cobalt mining exposure during childhood on wealth later in life. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

### A.2.2 Heterogeneous Effects on Gender

Table A.2: Cobalt Mining Exposure and Child Labor outcomes

| | Females | | | | Males | | | |
|---|---|---|---|---|---|---|---|---|
| | Employed | Employed | School | School | Employed | Employed | School | School |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Post x Cobalt Deposit | 0.143* | 0.121 | -0.143** | -0.144** | 0.304*** | 0.304*** | -0.199*** | -0.200*** |
| | (0.075) | (0.081) | (0.072) | (0.069) | (0.095) | (0.095) | (0.062) | (0.058) |
| Cobalt Deposit within 20 km | 0.042 | 0.033 | 0.128** | 0.127** | 0.064 | 0.064 | 0.158*** | 0.157*** |
| | (0.030) | (0.035) | (0.065) | (0.064) | (0.096) | (0.098) | (0.044) | (0.045) |
| Individual Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| Cluster FE | No | Yes | No | Yes | No | Yes | No | Yes |
| District X Year FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 581 | 581 | 979 | 979 | 560 | 560 | 962 | 962 |

Notes: This table presents results of the relationship between distance to a cobalt mine deposit and the probability of being employed and attending the primary school for children aged 6-14 surveyed in the Demographic and Health Surveys (i.e., in 2007 and 2014). Children within 20km from a cobalt deposit constitute the treatment group. The control group is composed of children living between 20km and 200km from the nearest mineral deposit. Columns (1) and (4) present the results from a specification with age fixed effects only. Columns (2) and (5) add cluster fixed effect and individual-specific controls such as gender, type of residence, year of birth, wealth index , if the mother and/or the father are alive, their level of education, and the number of violent events in the area. Columns (3) and (6) include the district by year fixed effects and correct for spatial autocorrelation of the error terms (Conley, 1999). Standard errors are clustered at the DHS cluster (i.e., village/town) level. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

Table A.3: Childhood Cobalt Mining Exposure and Migration

| | Migration (1) | Migration (2) | Migration (3) |
|---|---|---|---|
| Post x Cobalt Deposit | -0.006 | -0.010 | -0.007 |
| | (0.009) | (0.012) | (0.011) |
| Cobalt Deposit within 20 km | 0.007 | 0.014 | 0.016 |
| | (0.009) | (0.016) | (0.017) |
| Individual Controls | No | Yes | Yes |
| Cluster FE | No | Yes | Yes |
| District X Year FE | No | No | Yes |
| Observations | 260 | 249 | 249 |

Notes: This table presents results of the relationship between distance to a cobalt deposit during childhood and probability to migrate of individuals interviewed in the DHS data. Column (1) presents the results controlling for individual's year of birth. Column (2) adds controls for gender differences, place of residence, wealth index. Column (3) adds survey year fixed effects and district by year fixed effects. Standard errors are clustered at the DHS cluster (i.e., village/town) level. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

### A.2.3 Spatial Analysis: Cobalt Mining on Children (6-14 y.o.)

Here, I use a spatial lag model in order to capture spatial variations of the exposure to cobalt mining activities on current children in the DRC. As for the long term analysis, if no other shock other than the cobalt mining boom affected children's education, then we would expect the impact of cobalt mining to be only limited to those living within 10 kilometers of a cobalt deposit, while no effect for those people living beyond 10 kilometers. Hence, the following Equation is estimated:

$$\begin{aligned} \text{Education}_{i,c,d,t} = \sum_b \beta_b (\text{Post})_t \times (\text{Cobalt Dep.})_c + \sum_b \beta_b \ (\text{Cobalt Dep.})_c + \\ + \gamma \ \mathbf{X}'_{i,c} + \delta_k + \sigma_{1,d} + \sigma_{2,dtrend} + \epsilon_{i,c,d,t} \end{aligned} \tag{6}$$

for $b \in \{0-10, 10-30, ..., 50-70\}$ .

This spatial lag model allows for non-linear effects with distance from the nearest cobalt mine. Each children is recorded to a distance bin: 0–10 kilometers, 10–30 kilometers, etc. and compared with the reference category 70–100 kilometers away. The specification controls for the same fixed effects, trends and individual level controls as the baseline specification. The results from this alternative model can be seen in Figure A.6.

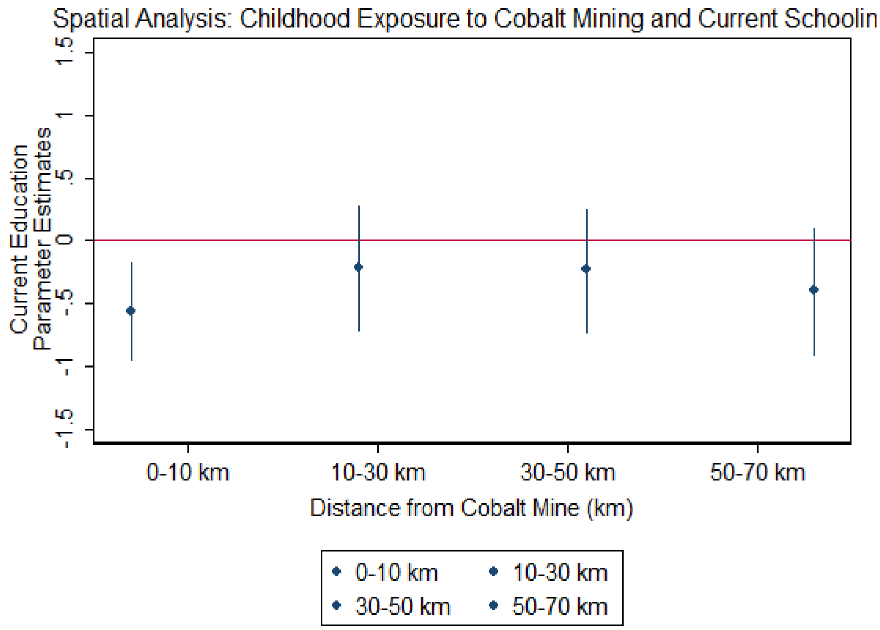



Figure A.6: Current Year of Education for all Children between 6 and 14 years old

*Notes:* This Figure shows the results from a spatial lag model with 20 kilometers distance bins using the baseline set of control variables and 95% confidence intervals. The sample is all individual born between under the age of 14 , pooling DHS datasets of 2007 and 2014. Regressions also included all individual specific controls, survey year and sub-regional district by time fixed effects

### A.2.4 Artisanal Cobalt Mines

Unregulated labor conditions are strictly dependent on the supervision, which is made into place by the company that owns the mine. As mentioned in section 2, about 20% of the total production of cobalt in the DRC comes from artisan-based mines, which are not owned by any company and therefore constitute the biggest threat of child labor. Artisan-based mines were born due to the sudden boom in demand for cobalt. 70% of the total production of cobalt in the DRC is owned by Chinese companies, where active actions and controls to prevent child labor are officially stated. However, no data is provided by those companies. Finally, the rest 10% of the total cobalt mined in the DRC comes from mines owned by European, Canadian and Australian companies.

The methodology considers the ownership of each mine by interacting the distance of a cobalt mine with the country owning the mine. This is because DRC-owned and artisan-based cobalt mines might be less compelling with the law and might incentivize illegal child labor activities.

Once again, results suggest that education attainments decreased more in areas surrounding artisan-based and DRC-owned mines compared with cobalt mines owned by countries outside Africa.

Table A.4 reports beta coefficients of the effect of the boom of cobalt on an individual's education attainment based on Equation 1. Column 1 presents results of the impact of living within 10 kilometers away from *any* cobalt deposit on the outcome variable of interest from a specification including a set of fixed effects, i.e., survey year, sub-regional district by time fixed effect, individual-specific fixed effects such as woman's level of education, age, birth cohort, an indicator variable showing if the individual has ever migrated and type of residence. On the other hand, Column 2 presents results of the effects of living within 10 kilometers away from *an artisanal or DRC owned* cobalt deposit on the outcome variable of interest from the same specification used in Column 1, including all controls and fixed effects.

In these specifications, I find negative and significant effects of cobalt mining on the individual's educational attainment, with a coefficient of 0.496 (and a standard error of 0.185) and a coefficient of 0.502 (and a standard error of 0.176) for artisanal cobalt mining effect.

Taken together, these results imply that artisanal cobalt mining has greater effects on education attainment compared with large-scale non-artisanal cobalt mining. In other words, the results from this sample restriction further confirm that, although the unethical child labor uses are practices diffused in all cobalt mines, those which are entirely unsupervised (such as the artisanal-based ones) are associated with lower education attainments compared with high-scale cobalt mines.

Table A.4: Childhood Cobalt Mining Exposure and Education Attainment: Artisanal Mining

| | Education<br>Coef./SE | Education<br>Coef./SE | Education<br>Coef./SE |
|---|---|---|---|
| Post x Art. Cobalt Deposit | -1.104*** | -1.207*** | -1.185*** |
| | (0.095) | (0.199) | (0.221) |
| Cobalt Deposit within 20km | 1.674*** | 2.868*** | 12.075 |
| | (0.208) | (0.644) | (158.378) |
| Individual Controls | No | Yes | Yes |
| Cluster FE | No | Yes | Yes |
| District X Year FE | No | No | Yes |
| Observations | 606 | 606 | 527 |

Notes: This table presents results of the effects of childhood exposure to artisanal cobalt mining production on education attainment compared to not-artisanal cobalt mining. The baseline specification is presented in Equation (1). Column (1) shows the effects of not-artisanal cobalt mining exposure on completed years of primary education and considers all controls. Column (2) considers the distance to an artisanal cobalt mine and considers all control variables. Columns (3) and (4) show the effects of cobalt mining exposure during childhood on wealth later in life. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

### A.2.5 Parallel Trend: Current Education Year

Here I run the main specification provided in Equation 1, limiting the sample of children aged between 6 and 14 surveyed in 2007 only (pre-boom cohorts) and in the 2014 wave only. I use the same control variables, sub-regional district time trends, and fixed effects defined in the baseline Equation 1. The regressions estimated are presented as follows:

$$\text{Education}_{i,c,d,t} = \alpha + \beta\ (\text{Cobalt Deposit})_c + \gamma\ \mathbf{X}'_{i,c} + \delta_t + \sigma_{1,d} + \epsilon_{i,c,d,t} \qquad (7)$$

Here the indicator variable $(\text{Cobalt Deposit})_c$ indicates the presence of a cobalt deposit within 10 kilometers from the village where individual $i$ is living. If nothing occurred in cobalt-mining areas before 2007, then we would expect the coefficient $\beta$ to be not significantly different from zero when limiting the sample to individuals surveyed in 2007 only, while to be significantly different from zero when considering only individuals interviewed in 2014. Figure A.7 shows the effects of proximity to a cobalt deposit on the current educational attainment of children aged between 6 and 14.

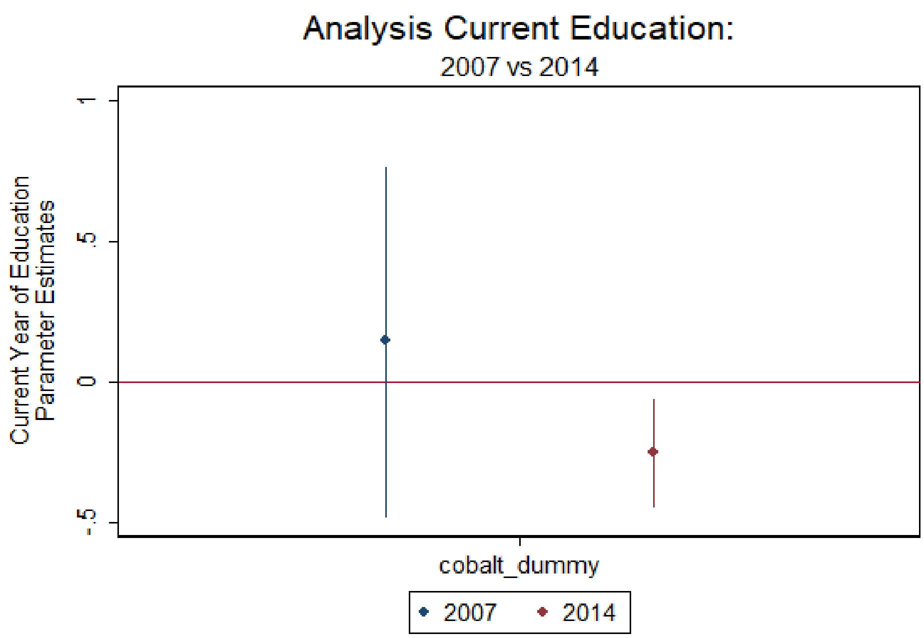



Figure A.7: Pre-Cobalt Boom and Children's Education Attainment

*Notes:* This Figure shows the relationship between living within 10 km of a cobalt deposit and children's current year of education, for all individuals surveyed pre cobalt boom, in 2007 (left) and for all individuals surveyed post cobalt boom, in 2014 (right) using the baseline set of control variables and 95% confidence intervals. The sample is all individuals who at time of the DHS surveys were between 6 and 14. Regressions also included all individual specific controls, birth year and sub-regional district fixed effects

### A.2.6 Cobalt Mining in Zambia

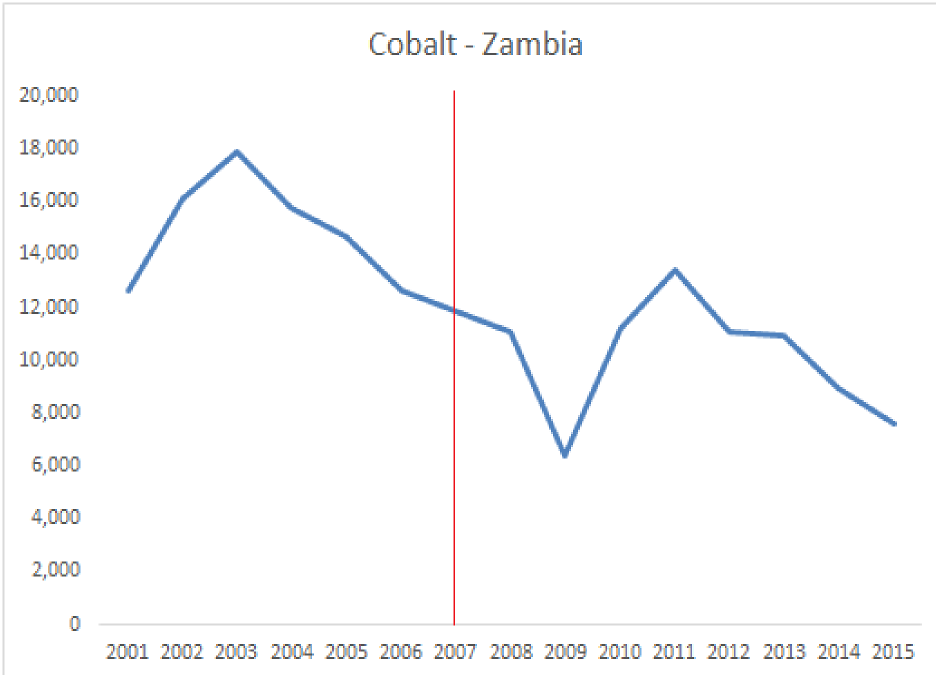
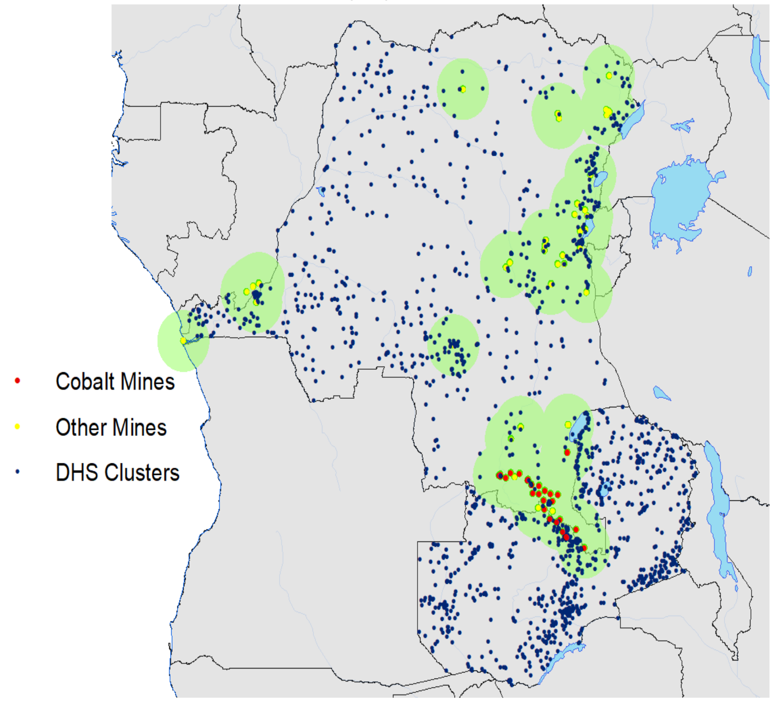



Figure A.8: Total Cobalt Production from Mining in Zambia. Metric Tons

*Notes:* The data in this figure is retrieved from the US Geological Survey (2019).

Panel A




Panel B

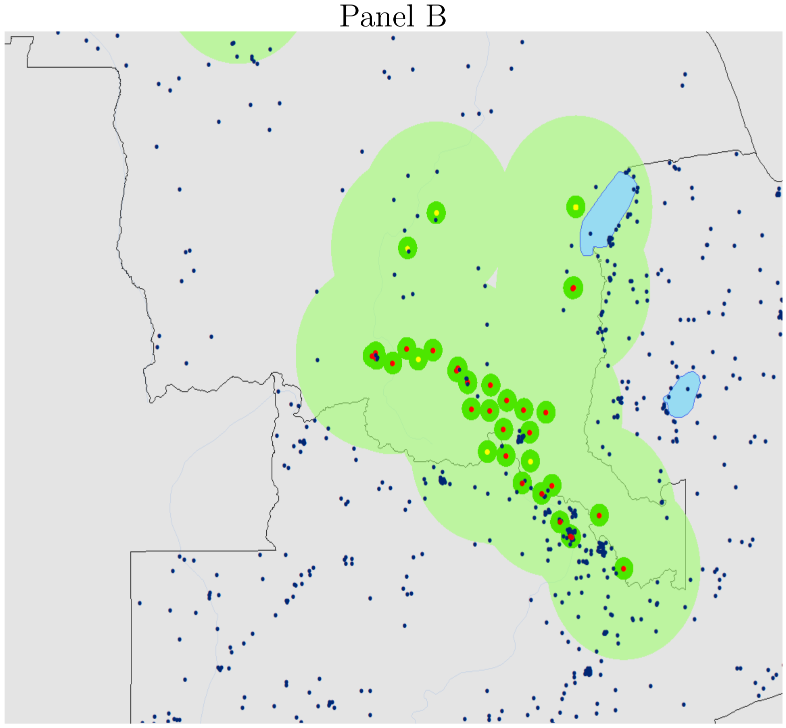


Figure A.9: Location of Cobalt Mines in DRC and Zambia

*Notes:* The data in this figure is retrieved from the US Geological Survey (2019).

Table A.5: Childhood Cobalt Mining Exposure and Education Attainment: Placebo Test on Zambia

| | Education Coef./SE | Education Coef./SE | Education Coef./SE | Wealth Coef./SE | Wealth Coef./SE | Wealth Coef./SE |
|---|---|---|---|---|---|---|
| Post x Cobalt Deposit | 0.024 | 0.079 | 0.074 | 0.089 | -0.008 | 0.003 |
| | (0.182) | (0.175) | (0.175) | (0.182) | (0.123) | (0.117) |
| Cobalt Deposit within 20 km | 0.148 | 0.223** | 0.180* | 0.619*** | 0.014 | -0.057 |
| | (0.106) | (0.104) | (0.103) | (0.171) | (0.125) | (0.127) |
| Female | No | Yes | Yes | No | Yes | Yes |
| Urban | No | Yes | Yes | No | Yes | Yes |
| Ever migrated | No | Yes | Yes | No | Yes | Yes |
| Current Student | No | Yes | Yes | No | Yes | Yes |
| Survey Year FE | No | No | Yes | No | No | Yes |
| District x Time FE | No | No | Yes | No | No | Yes |
| Year of Birth FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4515 | 4451 | 4451 | 4663 | 4598 | 4598 |

Notes: This table presents results of a placebo test on the effects of childhood exposure to cobalt mining on completed years of primary school in Zambia. In this specification Zambia is used as a control group since its cobalt production from mining was constant over the time of the analysis. Column (1) presents the results controlling for individual's year of birth fixed effects. Column (2) adds controls for gender differences, place of childhood residence, if the individual is a migrant and if the individual is currently attending primary school . Column (3) adds survey year fixed effects and subregional district fixed effects. Columns (4)-(6) show the effects of cobalt mining exposure during childhood on wealth later in life. Significant at ***$p< 0.01$, **$p< 0.05$, *$p< 0.1$.

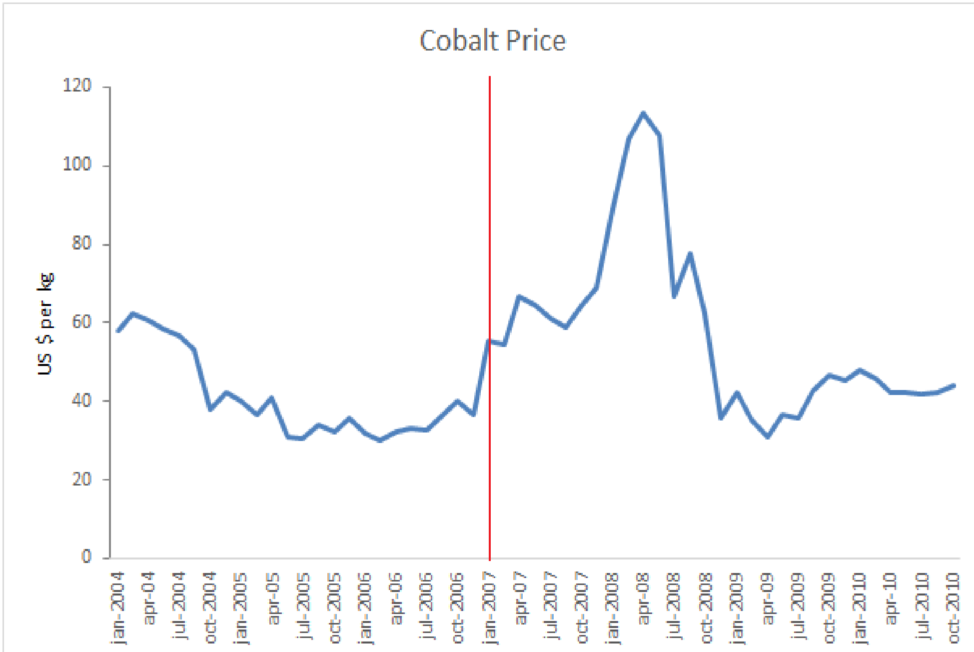



Figure A.10: Cobalt Price Trends. US dollars per kilogram.

*Notes:* The data in this figure is retrieved from British Geological Survey (2018) and Mineral Bulletin (2010).

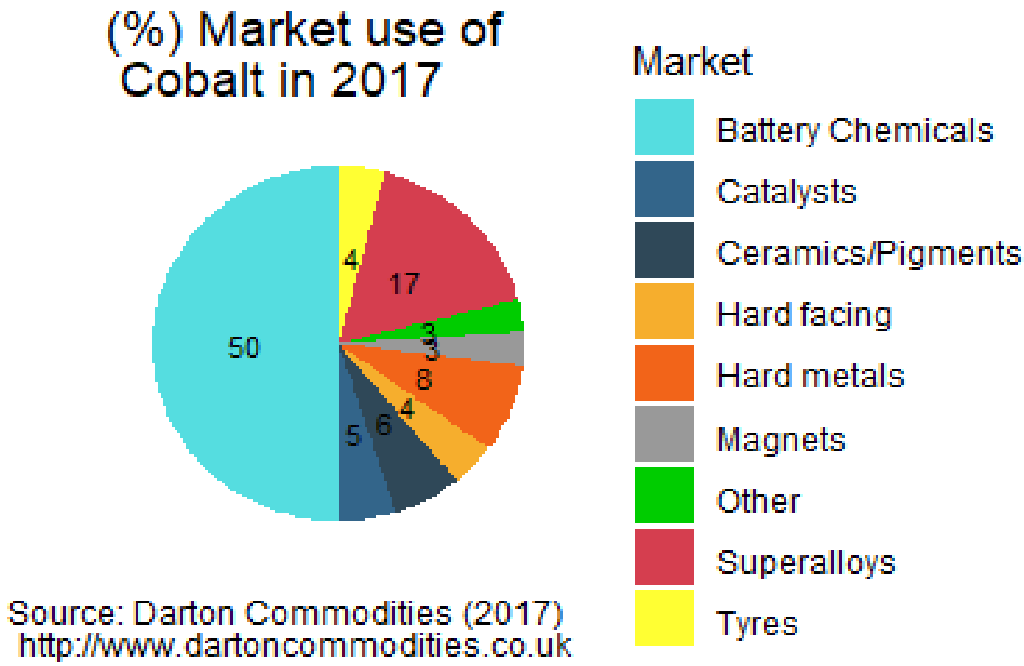



Figure A.11: Market Use of Cobalt in Percentage

*Notes:* The data in this figure is retrieved from Darton Commodities (2017) and Alves Dias et al. (2018).

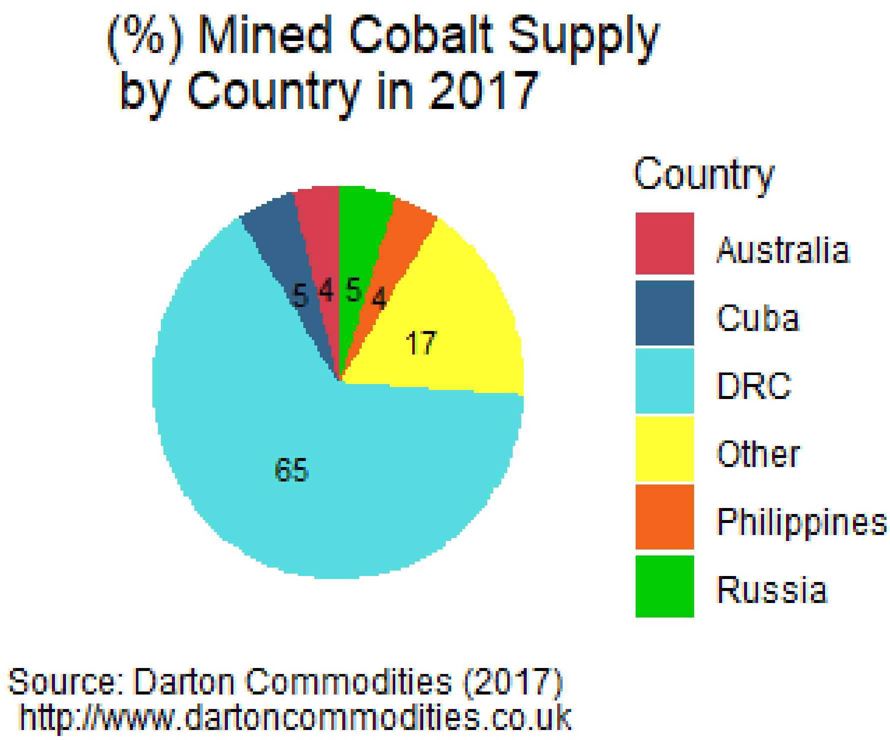



Figure A.12: Mined Cobalt Supply by Country in Percentage

*Notes:* The data in this figure is retrieved from Darton Commodities (2017) and Alves Dias et al. (2018).

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