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# THE DARK SIDE OF BATTERIES: EDUCATION, FERTILITY AND COBALT MINING IN THE DEMOCRATIC REPUBLIC OF CONGO

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# The Dark Side of Batteries: Education, Fertility and Cobalt Mining in the Democratic Republic of Congo

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**Abstract**

Being rich of crucial minerals might be a leading determinant of local economic development. On the other hand, intensive extraction might prove to negatively affect the health and wealth of people living close to mineral deposits and the surrounding environment. I examine the effects that local cobalt mining had on child labor and subsequently on fertility rates in the DRC by exploiting geographic variation of cobalt deposits prior to the boom of modern electric batteries and using both education attainment and fertility data. I find that the boom in cobalt mining led to a reduction in educational achievements of individuals who were between 6 and 14 at the time of the boom, and it was accompanied by higher fertility rates. Moreover, the analysis shows an initial improvement in wealth of households exposed to cobalt mining which however, disappears after seven years. The results are robust to spatial spillover effects and selective migration.

JEL Classification: I25, J13, O13

## 1 Introduction

Child labor and its associated reduction in education attainment are crucial issues for the socio-economic development of low and middle-income countries.[1] While not-harmful labor

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[1]Child labor is reported to be a major determinant of low development of Sub-Saharan African countries (Unicef, 2017; International Labor Organization, 2015). It subtracts children from school negatively affecting human capital in the long run (Hazan and Berdugo, 2002).

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

This paper focuses on the effects that cobalt mining had on completed education attainment and fertility rates by exploiting the effects of the plausibly exogenous cobalt boom occurred in the Democratic Republic of Congo in 2007, which was generated by the sharp increase in worldwide demand of modern lithium-ion batteries contained in high-tech devices such as smartphones, PCs, wireless headphones and electric vehicles. More than 70% of the world reserves of cobalt is contained in the DRC (US Geological Survey, 2019) making the sub-saharan country the largest world supplier of such a crucial mineral (see Figure 1).
By providing a robust quantitative assessment, this paper aims at addressing the following questions: have individuals, who during their childhood have been exposed to cobalt mining achieved a lower level of education? Consequently, since child labor is a family decision, has the boom in the production of cobalt from mining resulted in higher fertility rates in cobalt mining areas since 2007?

To examine the impacts of the cobalt mining boom, I combine three sources of variation: i. geographic variations in the exposure to cobalt mining activities in the DRC, ii. time variation in the production of cobalt induced by the world-wide adoption of lithium-ion batteries, and iii. age specific exposure to cobalt deposits. The geographical variation comes from the presence of a cobalt deposit in the DRC. Sub Saharan Africa is naturally abundant of crucial minerals and the presence of cobalt is plausibly exogenous with respect to the education achievements of individuals and fertility of women in the DRC.[3] The boom of cobalt mining occurred in the DRC in 2007 constitutes the source of time variation. The assumption of this study is that individuals who were aged between 6 and 14 at the time of cobalt mining boom[4] and lived in cobalt mining villages or towns were more likely to work as cobalt miners and abandon their education as a result. These individuals constitute the treatment group. On the other hand, those individuals living in areas beyond 10 kilometers from a cobalt mine

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

[3]Some parts of the country are naturally "more suitable" for the extraction of the critical mineral, while others are not. Notably the eastern part of the DRC is rich of gold, diamonds, zinc and silver while the western side of the country is rich of petroleum and cement. See Figure 3 for a visual representation of the location of mineral deposits in the Democratic Republic of Congo.

[4]The ILO defines child labor as whoever between 6 and 14 years of age is working

deposit serve as a first comparison group. In addition, the production of other minerals was not affected by the discovery of modern lithium-ion batteries in 2007.[5]. Therefore, I can rule out any confounding factors related to other types of mine.

The empirical strategy therefore compares birth-year cohorts based on the proximity to a cobalt mine deposit in their childhood place of residence, interacted with a post 2007 indicator variable. This strategy identifies an intention-to-treat effect under the assumption that trends in outcomes would have been similar in areas close to a cobalt mine 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. Data sources include geocoded cobalt deposit locations, place of residence during childhood of individuals surveyed, their education attainment and wealth index.

I first show that education attainment of individuals, who grew up in cobalt-mining areas was negatively affected by the exposure to cobalt mining activities. In particular, individuals who at the time of the cobalt mining boom aged between 6 and 14 and lived in cobalt mining areas, achieved about 0.5 years of education less compared to their peers, who were not exposed to cobalt mining, with the largest effects on primary education completion.[6]

A second focus of the present study is to understand if families living close to a cobalt mining deposit are more prone to have children. The rationale behind this question is that children as young as six might be sent to work as cobalt miners. As a result, families face a lower opportunity cost of having a child. This might increase the fertility rates of families in cobalt mining areas.[7] The methodology addresses this question by comparing fertility rates of women aged between 15 and 39 living in villages more or less close to a cobalt deposit.

Results from the comparison of fertility rates of women before and after 2007 reveal that after the cobalt mining boom women living close to a cobalt deposit had 0.3 more children during the five years preceding the date of the interview. This translates in an increase of 0.06 children per year per woman.

I report the aforementioned set of results suggesting that the loss in education attainment in cobalt mining areas of the Democratic Republic of Congo is mainly driven by the exposure to illegal cobalt mining during childhood. In addition, I show that the mechanism behind the increase in fertility rates in cobalt mining areas lies in the initial wealth gains due to children

[5]Figure 14 shows the production of other minerals in the DRC (i.e. gold, diamonds, zinc, copper and petroleum)

[6]As a placebo test, I find no effect on individuals aged 14-18 during the boom in cobalt mining. Suggesting that those individuals were already enrolled in secondary education.

[7]Doepke and Zilibotti (2005) develop a model of Child Labor Regulations (CLR) in which parents are induced to choose between higher families and smaller ones. Working children provide a large fraction of their family income. In a context of a unregulated child labor market such as the Democratic Republic of Congo, the availability of jobs specifically targeting children (because of their small hands along with a lower salary compared to adults) might induce parents to increase their fertility rate.

working rather than going to school.

The analysis controls for subregional changes and trends within the DRC between 2007 and 2014.[8] A set of relevant individual-specific controls is included in the empirical strategy such as gender, mother level of education, type of job performed by the father, if the parents are alive, if the village of residence is in a rural or urban area and year of birth. In addition, the model also controls for the year of which the DHS survey was conducted[9].

One potential concern is that education attainment for those exposed to the cobalt mining boom during their childhood might reflect preexisting trends. In other words, if the exposure to the cobalt mining boom during childhood had a negative treatment effect on education attainment, and no other event interfered to it, we would expect to see the negative impact of the proximity to a cobalt mine deposit only for post-cobalt boom cohorts relative to pre-boom cohorts. Those concerns are alleviated by the implementation of a cohort analysis which shows significant negative effects in education attainment for those post-cohorts born within 10 kilometres from a cobalt mine deposit.

An additional concern is that some other change might have caused the education attainment of individuals in the control group (i.e. children living between 10 and 100 km from a cobalt deposit) to increase after 2007.[10] If no other shock occurred after 2007 then we would expect the impact of cobalt mining boom to be only limited to those living within 10 kilometres from the nearest cobalt mine deposit, while no effect should be for those people living beyond 10 kilometres. To check for this, I use a spatial lag model that allows for non-linear effects with distance from the cobalt mine. Consistent with previous literature on the effects of mining (Benshaul-Tolonen, 2018) the implementation of a spatial-lag model confirms the effects of cobalt mining on education attainment to be concentrated within 10 km from a cobalt deposit.[11]

Another potential concern arises from various reports (Amnesty International, 2017; International Labor Organization, 2015) which show how illegal child labor practices consistently occur in artisanal small-scale and state-owned cobalt mines. On the other hand, European and American owned cobalt mines are believed to implement more severe measure to contrast child labor practices.[12] Results show that the negative impact of cobalt mining on completed

[8]DRC subregions are defined at the administrative level 2 as reported by the DRC government.

[9]Two waves of DHS surveys were used in the analysis. The first wave was conducted in 2007, and is regarded as the pre cobalt boom survey and the second wave was conducted in 2014, and is considered as the post boom survey.

[10]For example, the number of schools in the control group might have increased after 2007, driving the education achievements upwards as a result.

[11]As a further check I implement a birth-year cohort analysis in a spatial lag model. This is done to check if cobalt mining affected only post-boom cohorts within 10 km from a cobalt deposit.

[12]Nevertheless, there are reports and video footage raising concerns on illegal child employment in those mines too.

education is in large part due to artisanal and state-owned cobalt mines rather than European and American based companies.[13] Furthermore, to check if the effects of the cobalt mining boom on the education attainment are really due to cobalt mining or are a direct consequence of any mining activities, I employ a set of placebo tests on individuals who at the time of cobalt mining boom were between 6 and 14 and lived within 10 kilometres from *any other mine* in the DRC. Further tests reveal cobalt mining to negatively affect primary education only, while no effects are shown on secondary education. Moreover, I perform a placebo test on cobalt mine deposits in Zambia.[14]

Finally, the results are robust to alternative strategies which control for endogenous selective migration and restricting the sample to those individuals who never migrated.[15]

This study has several policy implications. First, by showing the relationship between cobalt mining and child labor, the paper documents a possible channel of future worse wealth conditions of those individuals who during their childhood were exposed to cobalt mining activities. This result helps to understand what policies can prevent the diffusion of illegal child labor practices in a context of low socio-economic development as that represented by the Democratic Republic of Congo. Second, by providing novel evidence on the close relationship between child labor and fertility decisions, this paper suggests that the initial positive wealth shock due to dropping out from school to work entirely disappear in adulthood.

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. The study concludes that individuals, who during their childhood, faced higher returns to coffee related work completed fewer years of education and had negative effects on their future wealth. A similar paper is Atkin (2016) who documents that the arrival of formal jobs during years of substantial expansions in export-manufacturing industries in Mexico led to reduced school attendance and lower educational attainment, although it had no overall impacts on subsequent labor market income. This paper differentiates from Atkin (2016) and Carrillo (2019) in different ways. First, it focuses and provides also evidence on the relationship between child labor and fertility decisions of families. Second, Carrillo (2019) focuses on 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. Moreover while Atkin (2016) and Carrillo (2019) focus on middle income countries such

[13]However, the analysis also shows a small but significant negative relationship between high-scale European and American cobalt mines and children education.

[14]The production of cobalt from mining in Zambia did not increase after 2007. More on the reasons are found in the background section of this paper.

[15]As what concerns fertility rates, the methodology also shows that the increase in fertility rates is mainly driven by the increase in the likelihood of having the first child.

as Mexico and Colombia, this paper focuses on individuals living in contexts of low socio-economic growth such as the Democratic Republic of Congo. Therefore, the relationship between reduction in education attainment and wealth later in life is not trivial and deserves a deeper understanding. As a result, this study shows no effects of fewer years of schooling on future wealth conditions in the DRC, in line with theoretical models (Eckstein and Wolpin, 1999). Finally, Atkin (2016) focuses on large formal firms, which provide valuable on-the-job-training opportunities and skill accumulation that may offset income losses from reduced formal schooling.

Another paper, similar in spirit of this study, is Charles et al. (2018) which investigate the relationship between college attendance of young adults in the US and the housing booms. Using the housing boom occurred in the US during the 2000s, Charles et al. (2018) conclude that young adults were more likely to drop from college, since the housing boom represented an additional source of available jobs. Although, in the years following the housing boom young adults appear to re-attend college, the trend was not completely reversed. Thus, providing evidence that these shocks may have permanently affected college education in the United States. However, while Charles et al. (2018) focuses on college attendance, this paper focuses on primary education. As a results, children who drop their primary education in order to work might lack basic knowledge and cognitive skills to perform well in more complicated labor tasks during their adulthood. Consequently, the long-term effects might be very different.

These results are also confirmed by Sviatschi (2019) which uses variations in return to cocaine, to address the use of child labor in coca suitable areas in Peru. Children who have been exposed to increases in return of cocaine are more likely to be incarcerated for violent and drug-related crimes as adults. Interestingly, Sviatschi (2019) also finds no long-term effects of those individuals, who during their childhood, worked in coca plants going to the legal sector.[16]

There exists also an important literature which investigates the effects of general mining activities on health of individuals living in nearby areas both in the short and in the long-term. De Putter et al. (2011); Banza et al. (2009) provide evidence about the adverse effects of the pollution due to general mining activities on the health of surrounding population. Xia and Deininger (2019) show that children living in tobacco farms have higher likelihood of suffering from illnesses related to green tobacco sickness. A recent study (Nkulu et al., 2018)

[16]Beegle et al. (2004) show that the forgone earnings attributable to lost schooling exceed any earnings gain associated with child labor from age 30 onward in Vietnam. This scientific evidence proves that existing research suggests that the long term effects of a reduction in the number of completed years of schooling are not obvious and greatly differentiate according to the context of the study. Thomas et al. (2004) focus on the 1998 Indonesian economic crisis and show how it resulted in a decline in household spending on education, and in turn in significant reductions in school enrollment.

finds that people living in villages surrounding an artisanal cobalt mine had much higher levels of cobalt in their urine and blood than people living in a nearby control area.[17]
On the other hand, potential negative health effects of mining exposure could be offset from the positive impact of the mining boom on the local economies surrounding mining sites, as shown in a recent paper by Benshaul-Tolonen (2018). Specifically, Benshaul-Tolonen (2018) finds that the booms in gold mining in the Sub-Saharan african region was associated to a reduction in infant mortality rates, although some limitations arise on the possible mechanisms of such effect.

Finally, the so called "resource course" economic literature also relates to the present study. The term "resource course" suggests that the abundant presence of mineral and agricultural resources is generally associated with low economic development (Hausmann and Rigobon, 2003; Sachs and Warner, 1995).[18] Subramanian and Sala-i Martin (2003) focus on the deleterious long run impact of oil abundance on institutional quality for the case of Nigeria. Similarly, Tsui (2010) focuses on high quality oil discoveries and their negative impact on democracy in Iraq.

The main limitation of the paper is linked to data availability. Since the cobalt mining boom occurred relatively recently, (i.e in 2007), and the last wave of surveys in the DRC conducted by the Demographic Health Surveys (DHS) took place in 2014, the present data make possible to assess the effects of cobalt mining after a period of seven years. This data limitation constitutes an issue when assessing the long term effects of cobalt mining on future wealth. This, because possible long run effects of a decreased education attainment on wealth could not be soon visible, rather they might need a few more years to show (as in Beegle et al. (2004)). On the other hand, this is not an issue concerning the effects on education attainment of those individuals who at the time of cobalt mining boom were between 6 and 14, since after seven years these individuals have completed their primary education.[19]

The remainder of the paper is organized as follows. Section 2 provides background information about global demand of electric batteries and cobalt production in the DRC. Section 3 describes the data. In Section 4, I present a brief conceptual framework showing the relationship between child labor and fertility decisions. Section 5 describes the empirical strategy examining the effects of cobalt mining boom on education attainment and fertility rates. Section 6 shows the baseline results from the analysis. Section 7 presents the robustness checks. Finally, Section 8 concludes.

[17]The differences were most pronounced for children, in whom Nkulu et al. (2018) found evidence of exposure related DNA damage.

[18]Berman et al. (2017); Dube and Vargas (2013); Angrist and Kugler (2008) exploit how mineral concentration in one region and the relative scarcity in a neighboring region is related to conflicts.

[19]The DHS data show that about 95% of the individuals complete their education before turning 15.

## 2 Background and Institutional Context

In this section I provide information on the geographical and institutional context relevant for the present study. I will start with information regarding the worldwide adoption of the modern cobalt-based lithium-ion batteries and the gradual substitution of the old nickel-based electric batteries. I will then proceed with the geographical distribution of cobalt deposits in the world along with the production of this crucial mineral by country. Third, I will summarize various reports such as Amnesty International (2016, 2017); Unicef (2017) showing the participation of children as young as six in artisanal cobalt mine deposits in the Democratic Republic of Congo. These reports provide evidence on the correlation of cobalt mining and child labor which is then exploiting with a rigorous causal evidence and the relative mechanisms behind it in Section 5.

### 2.1 Electric Batteries and Cobalt

Currently the most popular technology of the battery sector is that of the lithium-ion battery. This modern type of electrical battery gradually substituted the old-fashioned nickel-based battery types which were greatly used in the past. Compared to nickel-based battery types, lithium-ion batteries have superior energy, power density and superior cycling ability Cobalt Institute (2019). These major advantages of the lithium-ion batteries make them first choice for the manufacture of new electronic vehicles, nowadays. Figure 11 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-aluminium-oxide (NCA) and lithium-nickel-manganese-cobalt-oxide (NMC) technology supplying almost 70% of the global lithium-ion battery market.

The possible applications of modern lithium-ion batteries are manifold and depend upon the minerals used. Specifically, the most popular lithium-ion technology is the lithium-cobalt oxide (LCO) battery. The main feature of the LCO battery is the high energy density translating into a long run-time. This characteristics 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 LCO batteries are not particularly suitable for large and heavy devices since their principal disadvantage consists in having a low life span, and a 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 particularly focusing on the LCO and constant improvements are being made in terms of greater durability and safety. The second most popular lithium-ion battery type is the lithium-nickel-manganese-cobalt-oxide (NMC) which contains about 20% of cobalt. 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 their particularly long-life makes them 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[20]. Finally, the lithium-nickel-cobalt-aluminum-oxide (NCA). This particular type of lithium-ion battery shares similar qualities with NMC batteries in that it also has a high specific energy, specific power and a long life span. Downsides to the technology of NCA is that it is expensive and has poor safety. For these reasons NCA batteries are mainly used in industry, medical devices and also in electric power trains.

Common denominator of the vast majority of all 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 of cobalt surged.US Geological Survey (2019) shows that in 2015 global cobalt demand increased to 90 Mt, from about 50 Mt registered before 2007. Moreover, according to the CRU commodity consulting agency, the global demand of cobalt will further accelerate in the next years to reach 155 Mt in 2025. Cobalt has therefore been listed has a critical mineral (Alves Dias et al., 2018). Figure 1 shows that approximately 9,000 Mt of cobalt (which account for about 90% of total worldwide current reserves) are deposited in the Democratic Republic of Congo, making the Sub-Saharan the country with the highest reserves of cobalt in the world (SP Global Market Intelligence, 2018). Moreover, Darton Commodities (2017) estimates that more then 65% of total worldwide cobalt currently supplies comes from the Democratic Republic of Congo (DRC), with the second biggest supplier of cobalt in the world is Russia with just 6% of the total cobalt production (see Figure 13). This highlights the importance of the DRC as producer of such a critical material for our modern era.

Where does the cobalt produced go? Figure 12 shows that about half of all cobalt produced is used to fuel modern batteries with the other half being used for the construction of superalloys, hard metals (capable of withstanding high temperatures) tires and magnets.

[20]Considering no major 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 needed 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 simply to supply its electric-car plants.

## 2.2 Cobalt Mining and Child Labor in the DRC

Cobalt is contained in almost 70% of all modern lithium-ion batteries. The Democratic Republic of Congo is naturally rich of such a critical mineral, with roughly 65% of the world's cobalt production coming from the DRC's southeastern province of Lualaba, near the border with Zambia (as shown in Figure 18). The DRC only supplies cobalt from mining and does not refine it since it lacks the basic technology needed to refine minerals[21]. The mining sector, indeed represents about 80% of total DRC's earnings. However, despite intense mining activities of tin, gold, nickel, copper, and now cobalt, the World Bank reckons that the average person in the DRC earns just 700 USD a year. The Sub-Saharan African country therefore suits as a good example of "mineral resource curse".

Figure 2 shows that since data on cobalt production from mining were available for the DRC, the production of the core minerals was stable at around 20 million tonnes per year. This despite the noteworthy country political instability. The boom of cobalt mining has occurred very fast and came overwhelmingly from outside the DRC. In fact, starting from 2007 with the sharp increase in the use of modern lithium-ion batteries, China entered in the market of cobalt by importing supplies of the mineral directly from the DRC. The production of the african country remarkably increased, 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 then 60 Mt (Figure 2). These levels remained constant until 2016 when the increasing pressure for modern Electric Vehicles (EVs) has determined a second cobalt boom which is not over yet[22]. US Geological Survey (2019) forecasts that production of cobalt from mining in the DRC will be 90 Mt in 2020 and will reach 125 Mt by 2025 putting even more pressure to the already unstable national institutions. Nowadays, around 70 Mt of the total world cobalt production is mined in the DRC (US Geological Survey, 2019) which makes the unstable country the largest world supplier of the critical mineral. Other producers are China which accounts for the 8% of the total world production of cobalt, Canada (6%), Russia and Cuba (4% each). Remarkably, the top four cobalt mining sites are located in the provinces of Katanga and Lualaba, and account for 80% of the total cobalt production of the african

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

[22] Data accuracy of cobalt mining statistics of the DRC is an important issue. There exist different sources on cobalt production from mining in the DRC each showing slightly different numbers. For instance, the DRC Chamber of Mines (Chambre des Mines 2015) reported a cobalt production of 69,328 tons for 2015, whereas CRU (2016) indicated a production of 66,120 tons. US Geological Survey (2019) instead reported a total cobalt production of 63,000 tons. However, all of those figures do not consider artisanal produced cobalt which is considered to account for 15-20% of the total production of cobalt in the DRC. CRU (2016) 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 considering also artisanal based production.

country and 43% of the total cobalt production in the world. Both the natural presence of cobalt in the DRC and the boom originated in 2007 outside the DRC, created a shock which is independent of local education and fertility choices.

However, the vast mineral wealth has failed to contribute to increase the overall standard of living of the katanga province in the specific case as well as that of the country as a whole. Various reasons concerning the failure of cobalt mining activities to increase the standard of living of the katanga province have been proposed. Cuvelier (2017), for instance points at the unskilled migration waves which occurred since late 2000s. The unskilled labors has contributed to depress wages in cobalt rich regions. As previously stated, the economy of the DRC as well as that of the Katanga province extensively relies on mining activities and in particular in cobalt mining since the last decade.

In 2017 a large portion of the country's cobalt mine production was from cobalt ores mined by industrial or mechanized methods, and a small portion, around 20% was gathered by tens of thousands of artisanal miners by handpicking cobalt-rich ores.[23] Spencer (2016) estimated that artisanal mines in the Democratic Republic of Congo produced approximately 10,500 tons of cobalt in 2015.[24] China represents the leading destination for the DRC cobalt exports, as shown in US Geological Survey (2019). Eight of the 14 largest cobalt mines in Congo are now Chinese-owned, accounting for almost half of the country's output. In a recent article, the Financial Times (2019) also shows consistent evidence that chinese owned cobalt mines hire informal miners. In particular, the report estimates that there are around 200,000 informal cobalt miners in the DRC who in large part work in chinese and DRC owned mines.

The artisanal and small-scale mining (ASM) is generally defined as 'labour-intensive, low-tech mineral exploration and processing activities' Hilson (2011). ASM usually employ independent diggers who have converged on the cobalt rich area to search for the critical mineral, often with primitive tools. The precious mineral is then sold mostly to chinese companies. Various reports[25] 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 chinese and european-owned companies keep this practice. Hence, contributing to the use of children in cobalt mines. Amnesty International (2017) reckons that the cobalt diggers include an unknown number of children[26].

[23] 2017 is the latest year for which public data is available.

[24] A report by Center for International Forestry Research (2013) provides detailed information on how the 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.

[25] Reports also include cctv cameras by the CNN news, Sky news, the Financial Times

[26] Amnesty International (2017) interviews different children working in cobalt mines. Remarkable is the

Assessing the long term effects of child labor has been a crucial task for social scientists as well as for clinical researchers. Nevertheless, what distinguish children working on cobalt mining sites to other forms of child labor such as farming and housework activities is that while the latter forms of child labor constitutes 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 children 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.[27] For this reason the possible negative impacts of harmful child labor practices on the education attainment of children might be greater then that shown from other forms of child labor.

What makes cobalt mining a good example of such illegal child labor forms is that it is suitable for children work since it is mostly mined in the surface rather than underground like the rest of the minerals mined in the DRC (e.g. gold, diamond, silver, zinc and copper)[28]. Moreover, the typical job assigned to children consists in washing the tiny cobalt matters from the dust. They typically do this operation in large groups in swaps and small lakes.[29]. This is perceived by parents as a safe child labor practice, rather than working underground, and makes them more willing to send their children to work in cobalt mines rather than in any other type of mine.[30]

Unicef (2017) estimated in 2014 that approximately 40,000 boys and girls work in cobalt mines across the whole of Katanga province. This is more than the double the number of children reported working in rest of the DRC provinces. Finally,

While 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 and uncertain task. For example, Basu and Van (1998) child labor depresses adult wages, making child labor necessary and more persistent over time. The effects of being rich of critical minerals on child labor and child cognitive development is an empirical question. It

example of the 11-year-old Lukasa, who support his family by digging small quantities of cobalt by hand

[27]Faber et al. (2017) conducted a set of representative large-scale 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.

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

[29]Such child labor practices in the DRC are reported by the CNN news, Sky news, the Financial Times

[30]Unicef (2017) reports children either collecting the mineral from the mountains of tailings in active and inactive industrial mining concessions, or working in streams and lakes close to the concessions where they washed and sorted the stones or in some case even carrying bags weighing between 20 to 40 kg to earn between one and two dollars a day.

will depend 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 to be sent to the mines thus subtracting time and energies from school. For this reason, I also examine the effects of cobalt mining on the wealth of those individuals who grew up close to active cobalt deposits. Additionally, as a recent survey conducted by Faber et al. (2017) shows, a higher number of children working in cobalt mines is associated to higher fertility rates. Hence, this paper wants to clearly assess the relationship between cobalt mining, child labor and fertility choices.

# 3 Data

This paper uses two sources of data to assess the effects of cobalt mining on education attainment and women's fertility rates. The first dataset which includes the geographical location of all mineral deposits in the Democratic Republic of Congo, is retrieved from the US Geological Survey (2019). This dataset is then matched with gps data of all Congolese individuals surveyed in the Demographic and Health Surveys (2014) to compute the distance between each individuals and the nearest cobalt mine deposit, which is the main treatment variable. Demographic and Health Surveys (2014) also provides data on completed level of education of each individual, along with the associated wealth index and additional individual-level controls. Finally, women's fertility rates are also provided by the Demographic and Health Surveys (2014) data.

## 3.1 Cobalt Mines Data

The geographical location of all deposits of cobalt along with other minerals mined in the DRC are jointly obtained from the digitization of data from Ghosh Banerjee et al. (2014) and the US Geological Survey (2019). Additionally, data for the actual production of cobalt for different mines were retrieved from the Cobalt Cobalt Institute (2019).[31] Figure 3 shows the location of all mining sites of minerals in the DRC. Most cobalt mines are located in the southeastern part of the DRC near the border with Zambia. The four biggest cobalt mine deposits account for about 80% of the total cobalt mined in the country and are located in the provinces of Katanga and Lualaba. On the other hand, the rest of mineral deposits in the DRC are mainly located in the far eastern part of the country, close to the border with Uganda, Rwanda and Burundi. Data on location of cobalt mining deposits in Zambia, combined with the actual production time-series data of the mineral, allows to perform a placebo test on education attainment and fertility rates of Zambians living in cobalt mining

[31]More information on the data used in the analysis are found in the Appendix

areas. Additionally, data on location of all mining deposits in the DRC allows to compare the effects of being exposed to cobalt mining activities during childhood against any other type of mine.[32]

The geographical variation of cobalt mining deposits in the DRC, combined with the geo-referenced data on individuals surveyed, allows to compute to define the treatment and control groups. Sub Saharan African regions and in particular the Democratic Republic of Congo are naturally abundant of crucial minerals and since the geographical presence of cobalt deposits are defined also before the worldwide diffusion of lithium-ion batteries, they are plausibly exogenous with respect to the main outcome variables of the study over the period of analysis. Moreover, even opening a new cobalt mine requires that a stable deposit of cobalt must be present underground. This is also exogenous to education achievement, cognitive skills and women's fertility rates of the area of analysis.

### 3.2 Education Attainment Data

I examine weather the exposure to cobalt mining during childhood leads to early school dropout, and consequently lower education attainment using survey data from the Demographic Health Surveys (henceforth DHS). The DHS provide data on health, completed education level, as well as the evaluation of cognitive skills of all individuals in the Democratic Republic of Congo. I use two waves of DHS: the first wave which took place in 2007 constitutes the period pre cobalt mining boom, while the second wave constructed in 2014 represents the period post cobalt extraction boom[33]. All surveyed individuals for both 2007 and 2014 wave are recorded with gps. These confidential data come with a separate dataset and in order to protect the privacy of the individuals have an error ranging from two to five kilometers.[34] For this reason the DHS does not recommend researchers to restrict their studies to less than 5 kilometers distance[35]. These data on completed year of education, matched with place of residence and place of birth, allows me to compute the distance from the place in which each individual grew up as a child and the nearest cobalt mine deposit in order to identify which cohorts have been exposed to high production of cobalt from mining. I exploit variation of birth year and town or village of birth for each individual to assess the negative impacts of cobalt mining on education.

[32]This comparison is performed since parents are generally reluctant to send their children to work underground. On the other hand cobalt is mainly mined on surface and most jobs involving children consists in washing cobalt matters from the dust. These activities are perceived as safer from the parents which are more likely to let their children go to the cobalt mines.

[33]A third set of surveys conducted in 2018 is expected to be available in 2020

[34]The error is randomly assigned to each individual

[35]See the relevant appendix on DHS data and privacy restrictions of the corresponding gps locations to have more information of the gps errors.

I construct a database of a total of 43,385 individuals in the DRC who were born between 1960 and 1999. From this sample, I keep people who were born within 100 kilometers from the nearest cobalt mine deposit and still living at the same village or town at the time of the interview[36]. Individuals who were born from 1993 onward (who at the time of the boom of cobalt were at most 14) and lived within 10 kilometers from a cobalt mine deposit constitute the treatment group, while those born until 1992 (i.e. they were already 15 years old in 2007, therefore not falling in the child labor definition of the International Labor Organization) are part of the control group.

The distance is computed using GIS software and gps coordinates of individuals recorded during the surveys and the exact position of the mine. 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 effects of mining activities propagate to approximately 10 kilometres within each mine. Aragón and Rud (2015) find that the effects of pollution due to mining are felt up to 20 kilometres with a mineral mine, while Benshaul-Tolonen (2018) finds that gold mines within 10 kilometres have positive effects on infant health due to better local development. In the particular case of cobalt mines a sufficient number of observations (i.e. children and women) is located within 10 kilometres from a cobalt mine. Therefore, treatment group is defined as all children who were born and live within 10 kilometres from the closest active cobalt mine and were between 6 and 14 at the time of the cobalt boom (i.e. were born since 1993).

We expect that by increasing the distance from the individual to the nearest cobalt mine the effect of cobalt mining of our variables of interest would decrease. As argued in Benshaul-Tolonen (2018) I limit the individuals living in villages within 100 kilometres from a cobalt mine, as well as controlling for sub-regional changes over time, in order to exclude confounding factors along with any other change occurred in 2007 beside the boom in cobalt mining.

Table 1 reports summary statistics of relevant variables pre and post 2007 for villages within 10 kilometres from the closest cobalt mine deposit and between 10 and 100 kilometers. The average number of years of education completed by young adults in the DRC is less then four. DHS data reveals that six years of education, represents the highest education level for adults in the DRC and it is reached by about 18% of the total adult population[37]. Data also shows that almost 95% of those individual typically complete their primary education level

[36]The DHS do not provide information on places where individuals moved during his life. In other words, each individual is asked about the place of residence and if he or she ever moved from that place. Therefore, if an individual reports to have moved in past it is not know which village was coming from. For this reason I only keep those individuals who reported to had never migrated from the place of birth.

[37]DHS shows that 761 out of 9,452 adult individuals complete six years of schooling in their life

before they turn 15. The final sample contains 1322 individuals, who lived within 10 km from a cobalt mine deposit and 3056 individuals who lived beyond 10 km from a cobalt mine. 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.

### 3.3 Women's Fertility Data

Data for fertility rates of women were also provided by the DHS. The analysis considers all women during their fertile period (i.e. between 15 and 39 years old). Each of the interviewed woman states the number of total children and their respective birth year. I do not differentiate from the total number of children ever born and the number of stillbirths, since the aim of the empirical investigation is to assess the effect that cobalt mining boom had on the willingness to have more children and not on the effective health of the children.[38]

I consider two measure of fertility for each woman: the five-year fertility rate and three-year fertility rate. The first measure of fertility considers the number of children ever born for each woman in the last five year preceding the interview, that is for all women surveyed in the 2007, the number of children born in the period between 2002 and 2007, while for all women surveyed in 2014, the number of children ever born during the period 2009-2014. The second measure of fertility considers the number of children ever born from each woman during the last three year before the interview. Since, DHS for the DRC is available in two waves, all women surveyed in the 2007 wave constitute the pre treatment group. Treatment is again based on the proximity of the village of residence of each woman interviewed and the closest active cobalt deposit.

I construct a database of a total 21,816 women from the DRC between during their fertile period (i.e. aged between 15 and 39), among which 844 women reported living within 100 kilometres from a cobalt mine deposit at the time of the survey and 277 lived within 10 kilometres from a cobalt mine.

Table 2 reports summary statistics of relevant fertility related variables pre and post 2007 for villages within 10 kilometres and between 10 and 100 kilometers from the closest cobalt mine deposit. On average, while five-year fertility rate of women living beyond 10 kilometers from a cobalt mine increase by approximately 10% after the boom of cobalt mining, the five year fertility rate of women living within 10 kilometers from a cobalt mine deposit increased by over 32% over the same period of time.[39]

[38]Health effects of cobalt mining go beyond the scope of this paper. Moreover, differently from Benshaul-Tolonen (2018) this paper does not consider infant mortality rates and other measures of health, since one of the goals of the following study is to assess the relationship between child labor in cobalt mines and women's fertility in those areas through a lower opportunity cost of having a new child.

[39]Similarly, the three-year fertility rate of women living beyond 10 kilometers from a cobalt mine surveyed

## 4 Conceptual Framework

Establishing the causal effect of cobalt mining on child labor is crucial to understand the persistent low education attainment of areas exposed to cobalt mining. However, it also has an important consequence, that is fertility decisions by families. When deciding whether to send the child to a paid job rather than investing their resources by sending their child to school, families generally take into account their valuation of both factors that raise the future return to schooling of their child and present child's wages and choose accordingly. Thus, the choice to send a child to work outside the domestic environment may be encouraged by a shock that raises the family's valuation of the present child's wages (Hazan and Berdugo, 2002).

Doepke and Zilibotti (2005) first propose a positive theoretical model of child labor regulation (CLR) in which when families decide to have a child or not, they consider both the expected economic returns of their child education and the short term positive income shock from sending their child to work. As a result, the effects of child labor on family's income is not trivial. As Doepke and Zilibotti (2005) state, child labor has a double effect on income. On one hand, parents whose children are working might experience an immediate additional source of income. On the other hand, child labor depresses unskilled labor wages.

To this regard, this paper wants to provide empirical evidence of the theoretical literature on the relationship between child labor and fertility choices. In other words: do families that live close to a cobalt mining site decide to have more children? If so, does child labor provide a short-term boost to household income?

The cobalt mining boom occurred in 2007 in the Democratic Republic of Congo represents a good example of such a shock and serves as an instrument to fully comprehend the extent to which the boom of cobalt production has affected child labor and in turn how families have responded to it by modifying their fertility choices. This represents a novelty of this paper since no previous economic study has empirical investigated to which extent an increase in child labor translates in fertility rates of women's in sub-saharan african economies.

## 5 Empirical Strategy

The study focuses on the effects of cobalt mining boom which occurred in the Democratic Republic of Congo after 2007 on education attainments and of individuals that at the time of the cobalt production boom were between 6 and 14 years of age and were living in areas surrounding a cobalt mining deposit.

in 2014 increase by approximately 6% compared to those surveyed in 2007; while that for those women living within 10 kilometers from a cobalt mine deposit increased by over 50%.

The boom in the demand of cobalt was caused by the electrification revolution which allowed the diffusion of modern lithium-ion batteries. Lithium-ion batteries are principally contained in modern smartphones, electric vehicles and PCs and heavily rely on cobalt as primary material to function properly.

To this regard, the boom of cobalt mining which started since 2007 due to the worldwide increase in demand of modern lithium-ion batteries largely contained in modern smartphones, PC and EVs serves as a quasi-experiment to understand how education attainment, wealth and consequently fertility rates have changed with intensive cobalt extraction since it came overwhelmingly from outside the DRC, notably from the most advanced economies. Therefore, it is reasonable to assume the exogeneity of cobalt mining boom with any other variable affecting child labor trends in the DRC. In particular, the effects on wealth are not trivial. On one hand children might be subtracted from school to work in the mines[40]. However, on the other hand, by working they might contribute to their family standard of living or alleviate the conditions of poverty they live in. Moreover, child labor also depresses wages since children are generally paid less than adults. To this regard, the economic burden of artisan-based cobalt mining is ambiguous. It is, therefore crucial to evaluate both short term effects of cobalt mining on household wealth as well as long term impacts.

In the analysis, children who were between 6 and 14 and lived within 10 kilometres away from a cobalt mine define the treatment group. The control group is then defined as all individuals who during their childhood were not exposed to cobalt mining (i.e. between 10 and 100 km away from the nearest cobalt deposit). Those differences in differences estimates show that school achievement of children living close to cobalt mines decreased after 2007 compared to those children living beyond 10 kilometers from any cobalt mine.

The second goal of this paper is to investigate if child labor in cobalt mining villages has increased fertility rates of these areas through a reduced opportunity cost for families to have a child. If cobalt mining provides an immediate source of income, than families would find more convenient to have an additional child to send him to work as a cobalt miner as soon as he turn six rather than investing in the education of their child. As a result, the possible increase in fertility rates in areas within 10 kilometres away from a cobalt mine might have crucial implications on the long-term socio-economic growth of those areas.

The main specification that allows to identify the effects of cobalt mining on education attainment and fertility rates is presented as follows:

[40]Or in the best case scenario they might still be able to attend school, but dedicate less hours to studying, consequently they will have lower cognitive skills compared to their peers who attend school full time

$$\begin{aligned}\text{Outcome}_{i,c,d,t} = \alpha + \beta_1\ (Post)_t \times (\text{Cobalt Mine})_c + \beta_2\ (\text{Cobalt Mine})_c + \\ + \gamma\ \mathbf{X}_i' + \delta_t + \sigma_{1,d} + \sigma_{2,dtrend} + \epsilon_{i,c,d,t}\end{aligned} \tag{1}$$

where the outcome variable $Outcome_{i,c,d,t}$ represents either the number of completed school years of individual $i$ and the measures of fertility rates of woman $i$, of born in year $t$, living in DHS cluster $c$, in the sub-regional district $d$. $(Post)_t$ indicates whether the individual $i$'s birth year was later than 1992 (people born after 1992 were at most 14 years old in 2007 and therefore possible cobalt miners) or earlier than 1992 (individuals born until 1992 was at least 15 at the time of the boom and is not considered as a child). Variable $(Post)_t$ is interacted with $(\text{Cobalt Mine})_c$ which represents the measure of distance between the cluster of residence $c$ of individual $i$ and the nearest active cobalt deposit. If the nearest cobalt mine was distant within 10 kilometres from cluster $c$ and the individual $i$'s birth year was 1992 or later, he would be considered as treated. Otherwise he would fall in the control group. The regressions control for differences among different sub-regional districts in the DRC between the seven years of the two DHS waves $\sigma_{2,dtrend}$; birth year cohort-fixed effects $\delta_t$ and a vector of parents education levels, along with individual-specific characteristics $\mathbf{X}_{i,c}'$ such as, his/her gender, if the individual $i$ lives in a rural of urban area, if he or she ever migrated from their native village. Additionally, since a limitation of the present study is constituted by the relatively short time period between the onset of the cobalt mining boom in the DRC (i.e. 2007) and the last DHS wave conducted in the Sub-Saharan African country (i.e 2014), those individuals who at the time of the boom were between 6 and 14, in 2014 aged between 15 and 22 years old. As a result, a possible concern that individuals between 15 and 22 years of age might still be enrolled in a primary school arises. To alleviate this concern, I introduce an individual specific control variables which takes into account if the individual "$i$" is still in primary school. However, this is not an issues since DHS data show that about 95% of the people interviewed who are 15 years old state that they have already completed their primary education.

Different factors such as business environment, policies, corruption, education expenses might vary at district level and over time. For this reason the specification 1 also controls for sub-regional[41] districts time trends. Finally, opening a cobalt mine requires that a stable deposit of cobalt must be present underground. This is exogenous to our outcome variables such as education achievement, cognitive skills and women's fertility rates. Our coefficient of interest is $\beta$ which represents the difference-in-difference estimate of cobalt boom on children

[41] 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

school achievements.

1. If the boom in cobalt production from mining has caused children in the DRC who were going to school to drop out earlier and hamper their cognitive abilities;

2. if cobalt mining boom has caused individuals who grew up in cobalt mining areas during the boom of cobalt to show worse wealth conditions later in life.

Finally, a limitation of the present economic strategy is represented by the fact that evaluating the effects of cobalt mining on the education attainment we will miss those children who would not go to school other than working as cobalt miners. Those children generally help their families in running their business, farms and any type of domestic work activities. This data however, do not allow to quantify how many of those children "switch" from not harmful child labor to harmful child labor. Nevertheless, this is not an issue since the inclusion of those children will likely increase the effect of cobalt mining on child labor.

### 5.1 Parallel Trends Assumption

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 the control groups, defined as those individuals living between 10 and 100 kilometers away from a cobalt mine and the treatment group, composed of those individuals living within 10 kilometers away from cobalt mine, would have shared the same pattern in our outcomes of interest (i.e. education attainment and fertility rates). Therefore, by verifying the validity of the parallel trends assumption we want to exclude that any other event which occurred before the cobalt boom affected school achievements in the control or in the treatment group.

I use both linear, non-parametric techniques and regressing the dependent variables on the full sample using the control variables, sub-regional district time trends and fixed effects defined in the main specification. First, I limit the sample until the onset of the cobalt boom and subsequently limiting the sample to years following the cobalt boom. Figure 15 shows the local polynomial smooth estimates of education attainment on the y-axis of each birth-year cohort, represented on the x-axis. Individuals living in cobalt mining villages and those living in non-cobalt mining areas are shown to be on similar trends in education attainment for all birth-cohorts until 1992 (graph on the left). This is confirmed considering those individuals living in other-mining villages as a second control group (graph on the right).

Figure 16 shows the average number of children per woman for each village on the y-axis at a given year, from 2000 to 2013, on the x-axis. Women living in cobalt mining villages and those living in non-cobalt mining areas are shown to have similar trends of number of children born per year until 2010 (approximately 3 years since the boom of cobalt). This is confirmed considering those women living in other-mining villages as a second control group. In addition, I also regress the dependent variables on the full sample using the same control variables, sub-regional district time trends and fixed effects defined in the baseline Equation 1. Results are shown in Figures 5 and 6.

In Figure 5 I run the main specification provided in Equation 1 limiting the sample of children between 6 and 14 surveyed in 2007 only (pre boom cohorts) and in the 2014 wave only. The only difference with the baseline specification is that I consider current schooling year instead of completed education since children in those ages are still going to school. 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:

$$\text{Outcome}_{i,c,d,t} = \alpha + \beta \left(\text{Cobalt Mine}\right)_c + \gamma \, \mathbf{X}^{'}_{i,c} + \delta_t + \sigma_{1,d} + \epsilon_{i,c,d,t} \tag{2}$$

Since, I first limit the sample to only individuals surveys in the 2007 DHS wave, and to those interviewed in the 2014 wave after, the indicator variable $\left(\text{Cobalt Mine}\right)_c$ indicating the presence of a cobalt deposit within 10 kilometers from the village where individual $i$ is living, is not interacted with a Post indicator variable. Therefore, this time the coefficient of interest $\beta$ reveals the relationship of being 10 kilometers away from a cobalt deposit and the education level of children or women's fertility rates.

If nothing occurred in cobalt-mining areas prior to 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 5 shows the effects of proximity to a cobalt mine deposit on current education attainment of children aged between 6 and 14. On a similar note, I run Equation 2 considering only women surveyed in 2007 (i.e. pre cobalt boom) first, and only those surveyed in 2014 (i.e. post cobalt boom), then. As for children's education we would expect that being within 10 kilometres from a cobalt mine deposit should have no effect on fertility rates before 2007, while a positive and statistically significant effect on fertility only for women interviewed in 2014. Figure 6 shows the effects of proximity to a cobalt mine deposit on 5 year and 3 year fertility rates.

# 6 Results and Mechanisms

## 6.1 Long Term Effects on Education Attainment

I begin by examining the results of the baseline Equation 1. The beta coefficient resulting from this specification compares education attainment of individuals who grew up in cobalt mining areas with those individuals, who during their childhood, were living in non mining areas, before and after the cobalt boom.

Table 3 reports beta coefficients of the effect of the boom of cobalt on educational attainment based on Equation 1. Column (1) presents results from a specification with year of birth fixed effects. In this first specification, I find a significant effect of cobalt mining on schooling achievements later in life, with a coefficient of -0.569 (and a standard error of 0.226). Columns (2)-(3) add other controls and fixed effects sequentially. The addition of individual-specific controls such as gender, type of residence along with a dummy variable indicating if the individual surveyed has ever migrated and if he or she is still attending primary education, in column (2) have small effects on the estimated coefficient, which is now -0.505 (and a standard error of 0.197). Finally, specification in column (3) includes a set of fixed effects, i.e. survey year and sub-regional district by time fixed effect. Results, confirm what shown in columns (1)-(2), with a coefficient of -0.496 (and a standard error of 0.185). Taken together, these results imply that the cobalt mining boom during school-going years led to an average of 0.5 fewer years of completed schooling in areas surrounding a cobalt mine deposit.

Overall, I observe that the cobalt mining activities reduce educational attainment in areas surrounding a cobalt deposit. The estimates imply that the boom of cobalt led to a decline in completed schooling of approximately 0.5 year of those individuals born since 1993 (post boom cohorts) and growing up in areas surrounding a cobalt deposit, compared to those individuals who were born until 1992 (pre boom cohorts)[42]. Additionally, results show no effect of cobalt mining on future wealth of individuals who grew up within 10 kilometres away from the nearest cobalt mine compared to those who during their childhood lived between 10 kilometres and 100 kilometres from a mine.

Important to notice is that some children did not go to school before the cobalt mining boom, for example because they were helping their parents in housework activities or with their farm. Those children might have shifted from not harmful child labor to the cobalt

[42] 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. On the other hand individuals who were born *since* 1993 were at most 14 years old in 2007, when the cobalt mining boom occurred. These are considered as post-boom birth years cohorts

mines (i.e. harmful child labor). The methodology presented does not consider this effect.[43]

A potential channel that might bias the results is endogenous migration. To this regard, I check if the distance to a cobalt mine deposit has attracted more migrants after the cobalt mining boom. First, summary statistics presented in Tables 1 and 2 show that only 2% of individuals surveyed were not born in the same village in which they lived. These small figures are unlikely to bias the baseline results. Moreover, Tables 14 and 15 show that there is no statistical relationship between the distance to a cobalt mine and the probability to migrate of individuals surveyed in the DHS.[44] Additionally, 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 DRC and its cobalt production did not increase over the time of the analysis. The principal reason of such a stagnation in the production of the crucial mineral is that its reserves are estimated to be only one tenth of those of the DRC. As a results, chinese investments on cobalt mining in Zambia did not surge after 2007 (British Geological Survey, 2018).[45] Results of the placebo test on Zambia are reported in Table 13. Second, I check that cobalt mining exposure did not affect secondary education, since cobalt mining mainly involves children between six and 14. Results of the placebo test on secondary education are reported in Table 12.

In section 7 I implement different robustness checks to further test the validity of the results. These imply a cohort analysis, as well as a spatial lag model to allow for non liner relationships between distance from a cobalt mine and education attainment. Finally, I also test if the negative effects of cobalt exposure on completed years of education are due to artisanal small-scale cobalt mines or Chinese or European and American-owned cobalt mines.

### 6.2 Short Term Effects on Education Attainment

I now proceed by examining the results of the baseline Equation 1 in which the treatment group is composed of children between 6 and 14 living in cobalt mining areas and surveyed in the second wave of the DHS, in 2014. Children surveyed in the first DHS wave, in 2007, constitute the control group. The beta coefficient resulting from this specification compares

[43] However, since housework activities as well as farming are often compatible with school attendance, the decline in completed years of education might also in part reflect the possible switch from not-harmful to cobalt mining work.

[44] As a robustness check the methodology additionally excludes individuals who were born beyond 10 kilometres from a cobalt mine and moved closer to a cobalt mine later in their life. In this way, I control for migration patterns which might be due to the boom of cobalt mine in the DRC. This further restriction is done since families in the DRC might migrate because of the greater availability of mining jobs in areas surrounding deposits of cobalt. Results of this restriction are shown in section A.6 and further confirm the negative impact that cobalt boom had on education achievement of children living in areas around cobalt mines.

[45] I also test if the lower education attainment of individuals in the DRC is due to chinese owned cobalt mine. Results of this test are presented in section 7.5.

current year of education of children who currently live in cobalt mining areas with those living in non mining areas, before and after the cobalt boom.

Table 6 reports summary statistics of relevant variables for all children aged between 6 and 14 in the 2007 DHS survey wave and in the more recent 2014 wave of surveys. This is for all villages within 10 kilometres from the closest cobalt mine deposit and between 10 and 100 kilometers. From Table 6 we observe that the current year of education by children in the DRC is around three.

Column (1) of Table 4 presents results from a specification with no individual controls, sub-regional district time trends, or fixed effects. In this first specification, I find a negative but not effect of cobalt mining on current schooling , with a coefficient of -0.692 (and a standard error of 0.549). Columns (2)-(3) add other controls and fixed effects sequentially. The addition of individual-specific controls such as gender, type of residence, an indicator variable showing if the mother and the father are respectively alive, type of job performed by the father, along with a dummy variable indicating if the children has ever migrated, in column (2) have a negative effects on the estimated coefficient, which is now -0.44 (and a standard error of 0.32). Finally, specification in column (3) includes a set of fixed effects, i.e. survey year and district by time fixed effect. This specification further controls for the year of birth of each individual surveyed. Results, confirm what shown in columns (1)-(2), with a coefficient of -0.565 (and a standard error of 0.198). Taken together, these results imply that the cobalt mining boom during school-going years leads to an average of 0.5 fewer years of current schooling years in areas surrounding a cobalt mine deposit. This results on the short-term effects of cobalt mines confirm what shown in the long term analysis: children actively work in cobalt mines as soon as they turn 6.

Columns (4-6) show the effects of cobalt mining exposure on current years of education of children. Results shown in these specifications strengthen the conclusions achieved in Hazan and Berdugo (2002) first and Doepke and Zilibotti (2005) later on the positive effect of child labor on the short term. Overall, I observe that the cobalt mining activities reduce current schooling in areas surrounding a cobalt deposit also in the short term. The estimates imply that children whose age falls within the ILO definition of child labor and live in cobalt mining areas complete on average, 0.5 years of education less than their peers who live in non-cobalt mining areas. Nevertheless, in the short run they achieve greater wealth conditions which fade away later in life.

Children who drop out from school to work, increase the income level of their families. This is found in Column (6) of Table 4. However, the greater wealth experienced in the short term fades away once they become adult. While the differential in wealth between households that send their children to work as cobalt miners compared to those instead opting for investing in their children education is due to the short term increase in family income caused by children paid job, the reason why wealth indexes level out in the long term is not due to better standards of living of those individuals, who have finished their education (on average their wealth is constant over time as shown in table ??) but on worse wealth conditions of those individuals who abandoned school early in order to work as miners (on average their wealth index decreases from 4.7 to 4.5 in seven years). This result shows that in a context of low economic development such that of the Democratic Republic of Congo higher years of education are not associated to higher wealth in future life. Rather, most cobalt mining activities are child specific[46]. As a consequence, once they have become adult they lack the ability to perform the same tasks and need to find other types of jobs.

### 6.3 Fertility

I now move to examine the results of the baseline Equation 1 in which the treatment group is composed of women between 15 and 39 living in cobalt mining areas and surveyed in the 2014 DHS wave. Women surveyed in the 2007 DHS wave, constitute the control group. In this specification the outcome variables are defined as five year fertility and three year fertility rates. This time, the beta coefficients resulting from this specification compare the two measure of fertility of women living in cobalt mining areas with those women, living in non mining areas, before and after the cobalt boom.

Table 5 reports beta coefficients of the effect of the boom of cobalt on women's fertility rates based on Equation 1. Columns (1) and (4) presents results on 5 year and three year fertility, respectively from a specification with only woman's age fixed effects and no woman-specific controls, sub-regional district time trends, or fixed effects. In these first specifications, I find positive and significant effects of cobalt mining on the two measures of women's fertility, with a coefficient of 0.407 (and a standard error of 0.138) for five year fertility and a coefficient of 0.333 (and a standard error of 0.105 for three year fertility). Columns (2) and (5) and add other controls and fixed effects sequentially. The addition of woman-specific controls such as woman's education, type of residence along with a dummy variable indicating if the woman surveyed has ever migrated, in columns (2) and (5) have small effects on the estimated coefficients, which are now 0.363 (and a standard error of 0.134) and 0.3 (and a standard error of 0.103) on five year and three year fertility rates, respectively.

Finally, specification in columns (3) and (6) include a set of fixed effects, i.e. survey year and district by time fixed effect. Results, partially confirm what shown in columns (1)-(2) and (5)-(6), with a coefficient of 0.325 (and a standard error of 0.198) on five year fertility rate and a coefficient of 0.276 (and a standard error of 0.137) on three year fertility rate.

[46]Children are needed due to their small hands in order to wash the tiny cobalt matters from the dust.

Taken together, these results imply that the cobalt mining boom during woman's fertile period led to an average of 0.3 more children during the last five years preceding the interview and an average of 0.28 more children during the last three years preceding the interview in areas surrounding a cobalt mine deposit. This means that almost all the increase in fertility experienced in cobalt-mining areas after 2007 started from 2010 (i.e. three years after the onset of the boom in cobalt mining). Little of the total impact of cobalt mining on fertility is due to years five and four preceding the interview. This expected result is explained by the time period families need to adapt to the shock. Results suggest that women's were more likely to have approximately 0.3 children during the five years preceding the date of the interview and after the cobalt mining boom. This translates in an increase of approximately 0.06 children per year per woman.

# 7 Addressing Potential Concerns

In this section I present potential concerns and how I address them. I will start by implementing a cohort analysis based on the year of birth of each individual from 1960 to 1999. I will then, address the possibility that some other change might have caused the education attainment of individuals in the control group through the use of a spatial lag model. I also estimate the effects of any other type of mining on primary education attainment.

## 7.1 Cohort Analysis

A cohort-specific relationship between pre-cobalt boom and children education achievements is also included in the paper. The cohort-specific relationship allows for a visual and clear representation of the effects of cobalt booming. Hence, the following Equation is estimated:

$$\text{Outcome}_{i,c,d,k} = \alpha + \sum_{k} \beta_k \times (\text{Cobalt Mine})_c + \gamma_k \, \mathbf{X}_i^{'} + \sigma_{1,d} + \sigma_{2,dtrend} + \epsilon_{i,c,d,k} \qquad (3)$$

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 and cognitive skills. Treatment group is unchanged, i.e. those children born since 1993, thus being at most 14years old at the time of cobalt boom in 2007. On the other hand children born until 1992, were older than 14and thus constitute the control group. If the boom of cobalt effectively subtracted children from school, then a break from the preexisting trend of $\beta_k$ should start only from children born after 1993. In other words the analysis must not yield any statistically significant relationship between distance from a cobalt mine and education attainment of all children born before 1992. While, for children born since 1993 a negative and statistically significant relationship should appear.

I now examine graphically the relationship between childhood exposure to cobalt mining and completed years of education. The coefficients obtained from Equation 3 compare the trends in schooling over time in villages with different distance from a cobalt mine deposit. Figure 7 plots the coefficients and respective 95 percent confidence intervals. To have a robust estimates, I group birth cohorts in three-year groups. For instance, I group individuals born in 1960, 1961 and 1962 in one cohort and so on until individuals born in 1998 and 1999. I group birth cohorts in order to avoid the limited data sample available. To focus on individuals of relevant birth cohorts (i.e. born since 1993), the last four birth cohorts are two years long [47].

Figure 7 shows no differential trends in education attainment among cohorts who were born between 1960 and 1992 across villages more or less distant from a cobalt mine deposit. Given these cohorts were exposed to relatively stable and similar trends in cobalt production from mining during their childhood, this lack of association provides reassuring evidence that there were no pre-existing differential trends in schooling achievements across areas within and beyond 10 kilometers from a cobalt mine and. For the cobalt boom cohorts, those born since 1993, there is a statistically significant decline in schooling in cobalt mining areas compared to non cobalt mining areas.

### 7.2 Spatial Analysis

To exclude the possibility that some other change might have caused the education attainment of individuals in the control group (i.e. beyond 10 kilometers from a cobalt mine) to increase after 2007, such as any change in the number of schools in the control group, I use a spatial lag model that allows for non-linear effects on education attainment and fertility with distance from the cobalt mine.

Our concern here, is that the effects of cobalt mining boom on education attainment might be biased upward. If no other shock beside the cobalt mining boom which has affected education attainment of people in the control group occurred after 2007 then we would expect the impact of cobalt mining boom to be only limited to those living within 10 kilometres from the nearest cobalt mine deposit, while no effect should be for those people living beyond 10 kilometres. Hence, the following Equation is estimated:

[47] The cohort of people born in 1994 actually groups individuals born in 1993 and 1994. Cohort 1996 considers individuals born in 1995 and 1996. Cohort 1998, instead considers those born in 1997 and 1998. Finally, cohort 2000 considers individuals born in 1999 and 2000

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

for $b \in \{0-10, 10-20, ..., 40-50, 50-70\}$ .

This spatial lag model allows for non-linear effects with distance from the nearest cobalt mine. Each individual is recorded to a distance bin: 0–10 kilometres, 10–20 kilometres, etc. and compared with the reference category 70–100 kilometres away[48]. 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 Figures 8 and 9 for education attainment and fertility, respectively.

In addition, I also consider a further cohort-specific relationship between pre-cobalt boom and children education attainment in a spatial lag model. This combination of a cohort analysis in a spatial lag model allows for a robust comparison between children born in the same year in different locations without assuming linear effects with distance from a cobalt deposit. This further specification test allows for a better understanding of both temporal and geographic distribution of the effects on education attainment. See Figure 10 in the Appendix.

### 7.3 Birth-Cohort Relationship in a Spatial Lag Model

Here I consider a further cohort-specific relationship between pre-cobalt boom and children education attainment in a spatial lag model. This further specification test allows for a better understanding of both temporal and geographic distribution of the effects on education attainment. Differently from the spatial lag model presented in Equation 4 in Section 5, this time each individual is recorded to a slightly different distance bin: 0–10 kilometres, 10–30 kilometres, 30-50 kilometers and 50-70 kilometers and compared with the reference category 70–100 kilometres away. I consider 20 kilometer distance bins to allow for a greater number of individuals to compare across birth years. 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 10. The regression is specified as follows:

$$\text{Outcome}_{i,c,d,k} = \alpha + \sum_b \sum_k \beta_{b,k} \times (\text{Cobalt Mine})_c + \gamma\, \mathbf{X}_i' + \sigma_{1,d} + \sigma_{2,dtrend} + \epsilon_{i,c,d,k} \tag{5}$$

[48] The adoption of a spatial lag model to show evidence of the spatial diffusion of the effects of mining activities is in spirit very similar to Benshaul-Tolonen (2018)

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

### 7.4 Cobalt Mining vs Other Mining

In order to clearly identify that the effects on child labor is entirely due to cobalt mines and not being a consequence of any other type of mine, I identify a second set of control group which is constituted by children being far from a cobalt mine but within 10 kilometres to *any other* mine in the DRC.

This robustness check was possible since mines in the DRC are sparsely located as shown in Figure 3. Comparison from children within 10 kilometres from a cobalt mine and children within 10 kilometres from any other mine leads to similar results of those obtained in the benchmark regression. The cobalt mining boom has caused children in areas surrounding cobalt mines to achieve lower education rates and cognitive skills to decrease with respect to children and households living in areas surrounding any other mine in the DRC.

Tables 10 and 9 report beta coefficients of the effect of the boom of cobalt on individual's education attainment and women's fertility rates, respectively based on baseline Equation 1 where individuals living in villages within 10 kilometers away from *any* other types of mine now compose the control group.

Column (1) of Tables 10 and 9 presents results of the effects of living within 10 kilometers away from a cobalt mine deposit on the outcome variables of interest from a specification with only birth year fixed effects and no individual-specific controls, sub-regional district time trends, or fixed effects. In this specification, I find a negative and significant effects of cobalt mining on the education attainment of individuals who grew up in cobalt-mining areas compared to those who spent their childhood in general-mining areas.

I obtain a coefficient of -0.452 (and a standard error of 0.173). Columns (2)-(3) add other controls and fixed effects sequentially. The addition of individual-specific controls such as gender, type of residence along with a dummy variable indicating if the individual surveys has ever migrated. In column (2) I have small effects on the estimated coefficient, which is now -0.41 (and a standard error of 0.176). Finally, specification in column (3) I further control for the year of birth of each individual surveyed. Results, confirm what shown in columns (1)-(2), with a coefficient of -0.433 (and a standard error of 0.179).

Taken together, these results imply that the cobalt mining boom during school-going years led to an average of 0.433 fewer years of completed schooling of those individuals born since 1993 (post boom cohorts) and living in areas surrounding a cobalt mine deposit compared to individuals living in other-mining areas. Once again, results show no effect of cobalt mining on future wealth of individuals who grew up within 10 kilometres away from the nearest cobalt mine compared to those who during their childhood lived between 10 kilometres and

100 kilometres from a mine.

Table 9 reports beta coefficients of the effect of the boom of cobalt on women's fertility rates based on Equation 1 where individuals living in villages within 10 kilometers away from *any* other types of mine now compose the control group. Here, columns (1) and (4) presents results on 5 year and three year fertility, respectively from a specification with only woman's age fixed effects and no woman-specific controls, sub-regional district time trends, or fixed effects. In these first specifications, once again, I find positive and significant (although slightly lower in magnitude compared to those obtained when comparing individuals within 10 kilometers away from a cobalt mine with those living between 10-100 kilometers from a cobalt mine deposit) effects of cobalt mining on the two measures of women's fertility, with a coefficient of 0.389 (and a standard error of 0.145) for five year fertility and a coefficient of 0.315 (and a standard error of 0.105 for three year fertility). Columns (2) and (5) add other controls and fixed effects sequentially. Finally, results presented in columns (3) and (6), partially confirm what shown in columns (1)-(2) and (4)-(5), with a coefficient of 0.433 (and a standard error of 0.171) on five year fertility rate and a coefficient of 0.255 (and a standard error of 0.104) on three year fertility rate.

Overall, these results imply that the cobalt mining boom during woman's fertile period led to an average of 0.4 more children during the last five years preceding the interview and an average of 0.25 more children during the last three years preceding the interview in areas surrounding a cobalt mine deposit compared to women of the same age living within 10 kilometers away from any other mine in the DRC.

### 7.5 Artisanal vs Not-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 born due to the sudden boom in the demand of cobalt. While 70% of total production of cobalt in the DRC is owned by chinese companies were active actions and controls to prevent child labor are officially states although no data are 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 takes into account the ownership of each mine by interacting the distance from a cobalt mine with its ownership country. This because DRC owned and artisan based cobalt mines might be less compelling with the law and therefore 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 to cobalt mines owned by countries outside Africa.

Tables 10 and 11 report beta coefficients of the effect of the boom of cobalt on individual's education attainment and women's fertility rates, respectively based on Equation 1.

Column (1) of Tables 10 and 11 presents results of the effects of living within 10 kilometers away from *any* cobalt mine 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, a indicator variable showing if the individual has ever migrated and type of residence. On the other hand, Column (2) of Tables 10 and 11 presents results of the effects of living within 10 kilometers away from *an artisanal or Chinese owned* cobalt mine 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 a negative and significant effects of cobalt mining on the individual's education 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.

Concerning the effect of cobalt mining and artisanal cobalt mining in fertility rates: I find a positive and significant effects of cobalt mining on the three year women's fertility (Column (3) of Table 11), with a coefficient of 0.276 (and a standard error of 0.137) and a coefficient of 0.295 (and a standard error of 0.131) for artisanal cobalt mining effect.

Taken together, these results imply that the artisanal cobalt mining activities, have similar but slightly greater effects on both education attainment and women's fertility rates compared to all types of cobalt mining. In other words, the results from this sample restriction seem to further confirm that the although the unethical child labor uses in cobalt mines are practices diffuses in all cobalt mines, those which are completed unsupervised such as the artisanal-based ones, are associated with ever lower education attainments of those individuals who during their childhood were exposed to the boom in the production of cobalt. Consequently, fertility rates in areas surrounding artisanal-based cobalt mines seem to be slightly higher compared to any type of cobalt-mining areas.

# 8 Conclusion

This paper provides evidence that exposure to cobalt mining activities during childhood subtracts children from school, thus leading to lower education attainment later in life. I also shed light on the greater negative effects on children education caused by harmful child labor practices compared to not-harmful ones, such as housework activities and farming which are often compatible with school attendance. As a result of the increasing use of child labor due to cobalt mining, I also show that the cost-opportunity of having an additional child for families living nearby cobalt-mining areas decreases, hence pushing fertility rates upwards. I contribute to the literature by showing that geographic conditions, naturally richer of critical minerals, and technological advancements leading to modern lithium-ion electric batteries can generate, through the increase in child labor practices, higher fertility rates providing an explanation for the persistence of low education attainment of individuals living in cobalt mining areas.

I then provide evidence that these effects are generally greater in artisanal-based cobalt mining areas, where there is a substantial lack of labor supervision. Moreover, the results indicate that the use of children is strictly associated to cobalt mines rather than any other type of mine. In a cobalt mine, children are not sent underground to search for cobalt, instead they wash the tiny mineral matters from the dust. To perform this relatively not dangerous job, small hands are needed[49]. The results show that the effects are concentrated within 10 kilometres from a cobalt mine deposit. Cobalt is considered one of the most important minerals for the technological development of the next decade, and since its production is predicted to double by 2025[50] it is crucial to regulate artisanal small-scale cobalt mining in the DRC to alleviate long term negative health and wealth effects of individuals exposed to cobalt mining activities.[51]

To this regard, the second half of the present study provides evidence that more efficient labor supervision (through the comparison of artisanal cobalt mines and European and American owned cobalt mines) might mitigate the effects of the exposure to cobalt mining activities on both education and fertility choices.

Overall, this paper provides a first step at understanding how harmful child labor practices, represented by cobalt mining, greatly affect the education attainment of children exposed as well as parental fertility decisions, motivating the use of strict child labor controls in artisanal cobalt mines.

[49]See the reports by Amnesty International (2017)

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

[51]For a clarification of health effects on children caused from cobalt exposition, see Nkulu et al. (2018).

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# 9 Figures and Tables

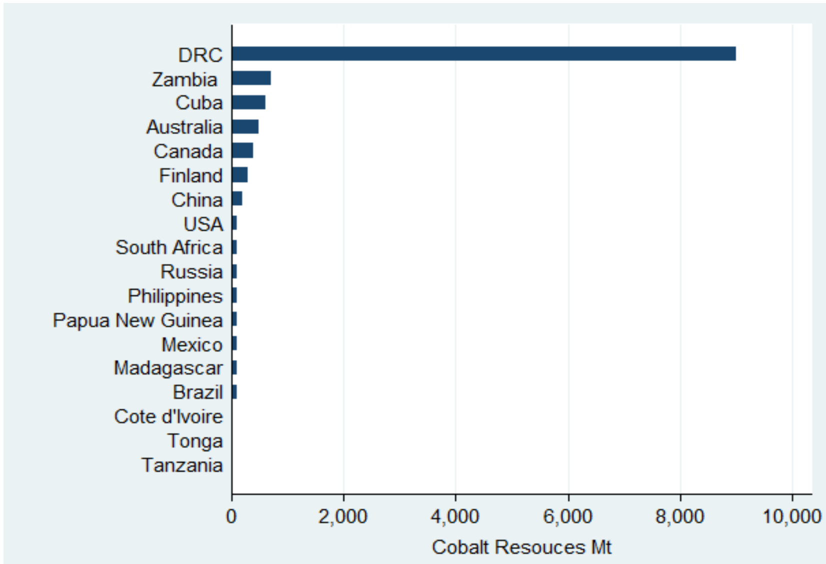


Figure 1: Estimated Cobalt Reserves by Country in 2018. Million Tons

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

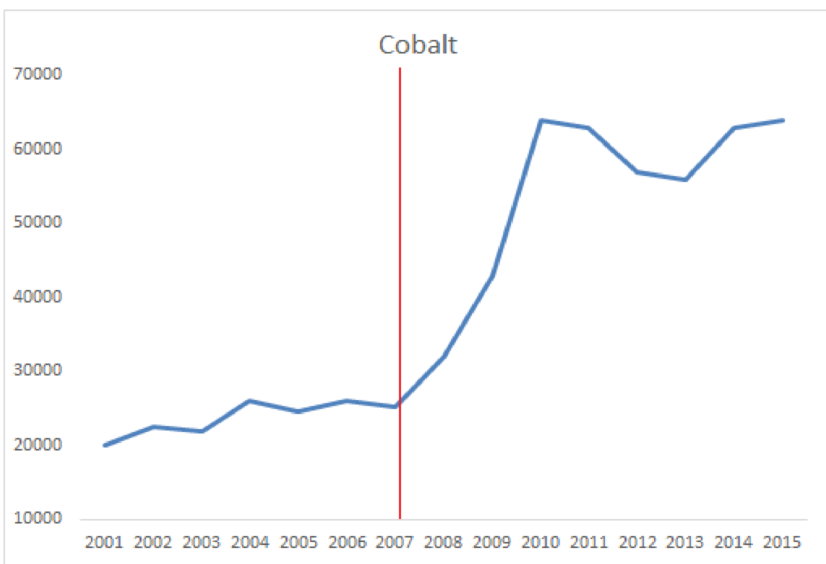


Figure 2: Total Cobalt Production from Mining in DRC. Metric Tons

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

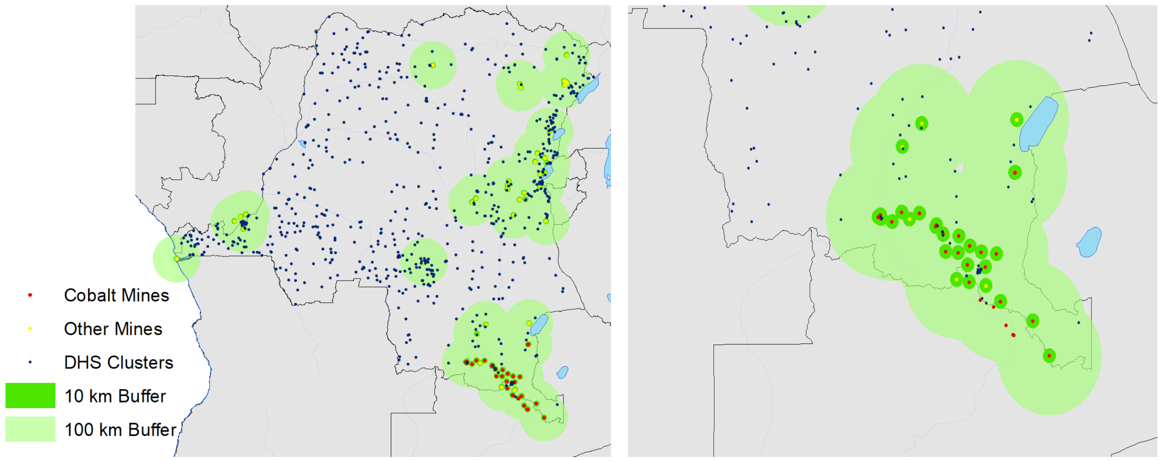


Figure 3: Location of all Mining Deposits in the DRC and gps of all Individuals Surveyed in the 2007 and 2014 DHS waves

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

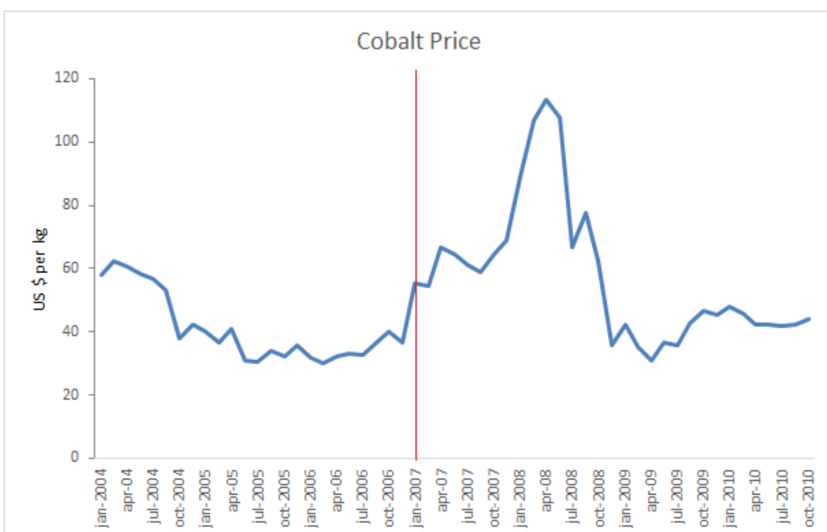


Figure 4: Cobalt Price Trends. US dollars per kilogram.

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

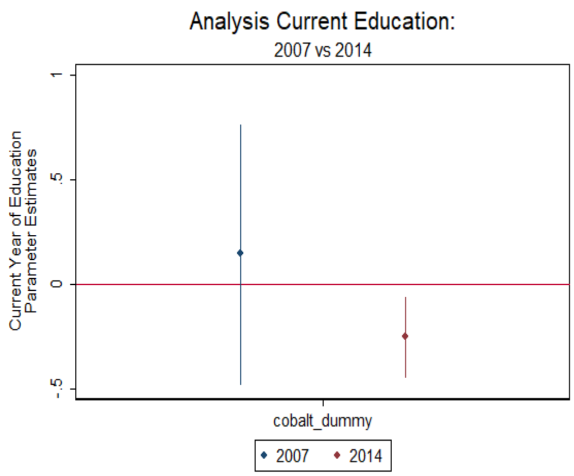


Figure 5: Pre-Cobalt Boom and Children's Education Attainment

*Notes:* This Figure shows the relationship between living within 10 km from 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

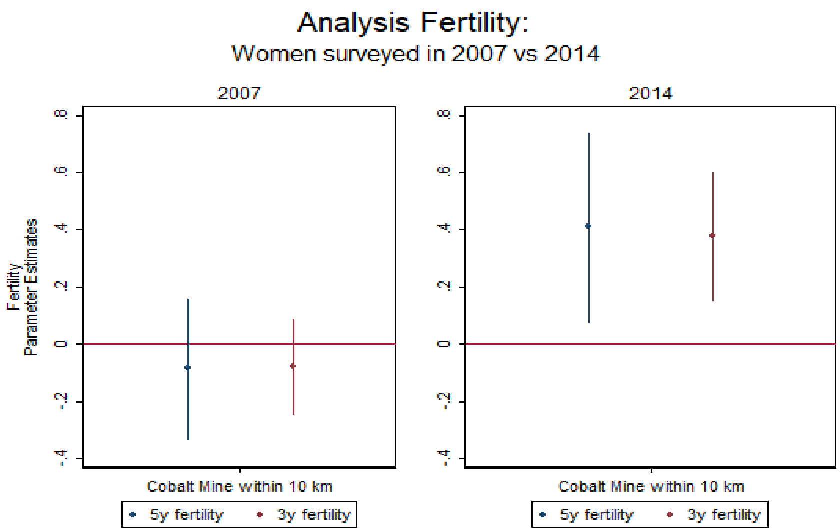


Figure 6: Pre-Cobalt Boom and Women's Fertility Rates

*Notes:* This Figure shows the relationship between living within 10 km from a cobalt deposit and women's fertility rates, for all women surveyed pre cobalt boom, in 2007 (left) and for all women surveyed post cobalt boom, in 2014 (right) using the baseline set of control variables and 95% confidence intervals. The sample is all women who at time of the DHS surveys were between 15 and 39. Regressions also included all individual specific controls and sub-regional district fixed effects

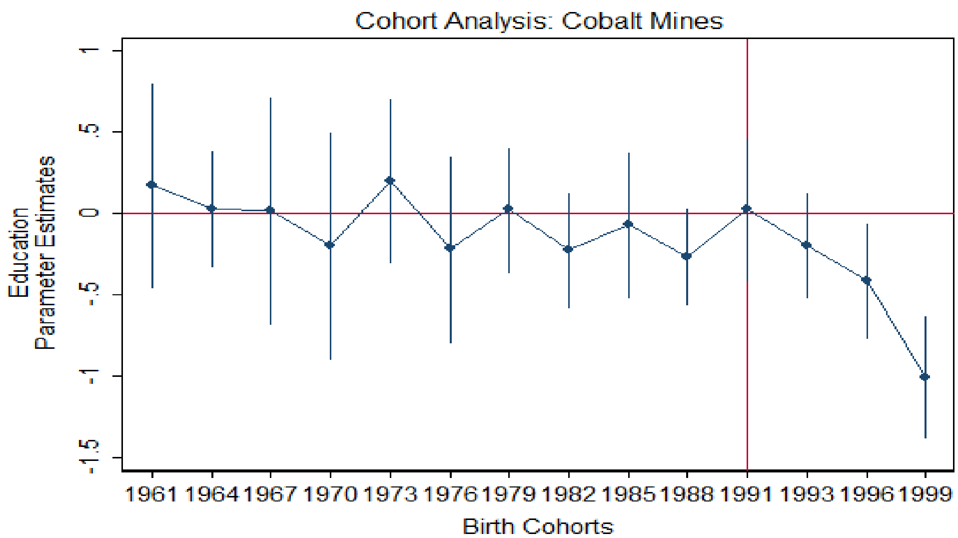


Figure 7: Pre-Cobalt Boom and Completed Years of Education; Three-Year Cohort-Specific relationships for all Individuals Born between 1960 and 1999

*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. 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.

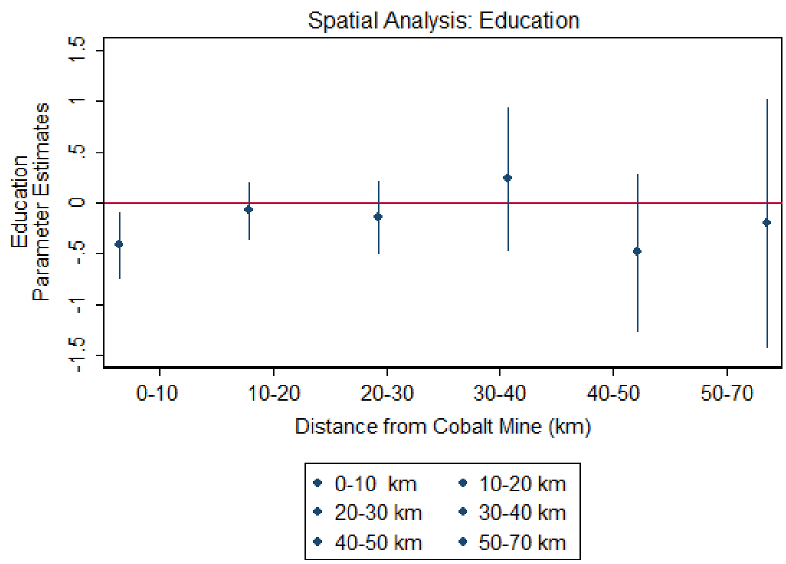


Figure 8: Non Linear Distance from Cobalt Mine: Education Attainment

*Notes:* This Figure shows the results from a spatial lag model with 10 kilometres 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. Regressions also included all individual specific controls, survey year and sub-regional district by time fixed effects

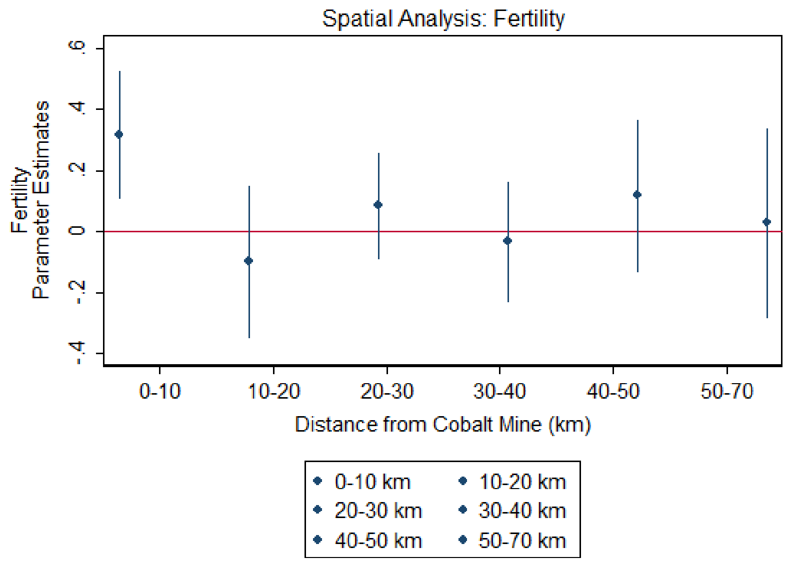


Figure 9: Non Linear Distance from Cobalt Mine: Women's Fertility Rate

*Notes:* This Figure shows the results from a spatial lag model with 10 kilometres distance bins using the baseline set of control variables and 95% confidence intervals. The sample is all women who at time of the DHS surveys were between 15 and 39, pooling DHS datasets of 2007 and 2014. Regressions also included all women specific controls, survey year and sub-regional district by time fixed effects

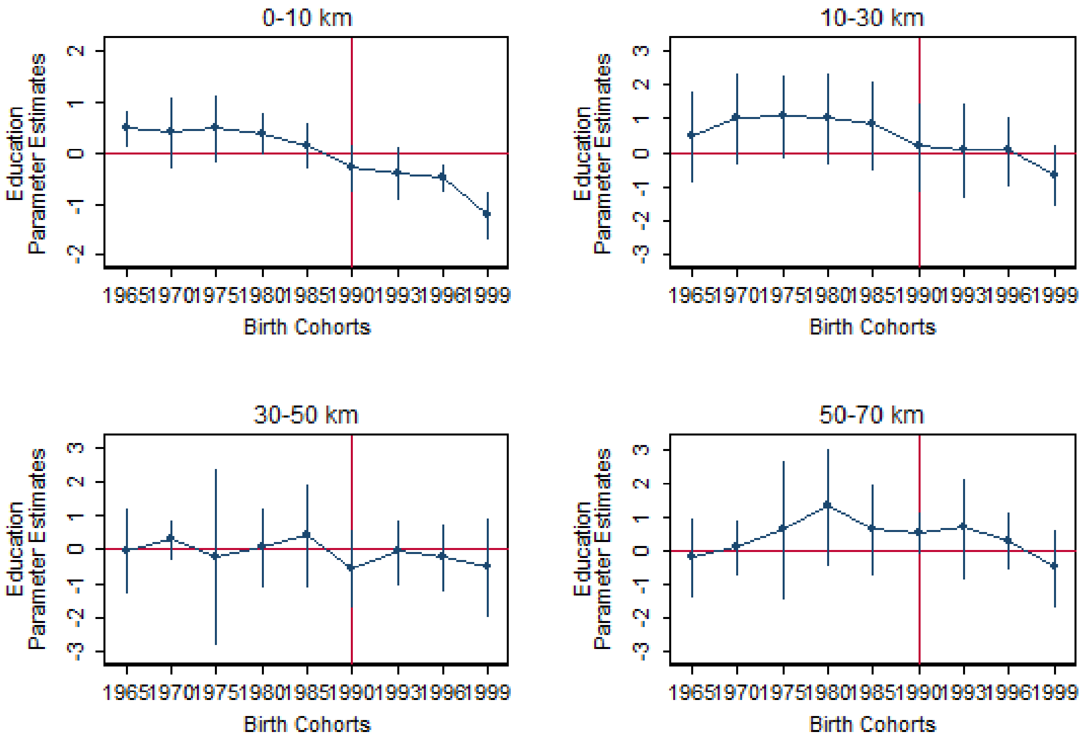


Figure 10: Birth Cohorts in a Spatial Lag Model: Education Attainment. Five-Year Cohort-Specific relationships for all Individuals Born between 1960 and 1999

*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 a spatial lag model with 20 kilometres 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. 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 - adults born from 1960 to 1999

| | Pre 1993 < 10 km | Pre 1993 > 10 km | Pre 1993 any mine | Post 1993 < 10 km | Post 1993 > 10 km | Post 1993 any mine |
|---|---|---|---|---|---|---|
| | Mean | Mean | Mean | Mean | Mean | Mean |
| ***Education*** | | | | | | |
| Highest Year of Education | 3.98 | 3.79 | 3.75 | 2.97 | 3.27 | 3.17 |
| ***Controls*** | | | | | | |
| Female | 1.46 | 1.50 | 1.53 | 1.55 | 1.49 | 1.49 |
| Urban | 1.08 | 1.33 | 1.32 | 1.17 | 1.28 | 1.29 |
| Attending Primary School | 0.02 | 0.02 | 0.02 | 0.05 | 0.05 | 0.06 |
| Age | 30.81 | 32.54 | 31.39 | 17.81 | 17.76 | 17.85 |
| ***Wealth*** | | | | | | |
| Wealth Index | 4.68 | 4.10 | 3.99 | 4.49 | 4.29 | 4.24 |
| ***Health*** | | | | | | |
| Hospitalized | 0.10 | 0.07 | 0.12 | 0.10 | 0.05 | 0.07 |
| Received Treatment | 0.14 | 0.12 | 0.14 | 0.13 | 0.06 | 0.07 |
| Observations | 1063 | 854 | 1544 | 259 | 243 | 415 |

Table 2: Extensive Descriptive Statistics - Women between 15 and 39

| | Pre < 10 km | Pre > 10 km | Pre any mine | Post < 10 km | Post > 10 km | Post any mine |
|---|---|---|---|---|---|---|
| | Mean | Mean | Mean | Mean | Mean | Mean |
| ***Fertility*** | | | | | | |
| Births in the last 5 years | 0.77 | 0.98 | 1.04 | 1.02 | 1.10 | 0.94 |
| Births in the last 3 years | 0.45 | 0.63 | 0.63 | 0.67 | 0.68 | 0.60 |
| Births in the past year | 0.14 | 0.23 | 0.24 | 0.24 | 0.27 | 0.22 |
| ***Wealth*** | | | | | | |
| Wealth Index | 4.78 | 3.60 | 3.86 | 4.58 | 3.85 | 4.20 |
| ***Controls*** | | | | | | |
| Woman's Education | 3.66 | 3.41 | 3.55 | 3.37 | 3.51 | 3.46 |
| Urban | 1.00 | 1.37 | 1.32 | 1.13 | 1.42 | 1.27 |
| Age | 28.73 | 27.93 | 28.24 | 26.77 | 27.83 | 27.59 |
| Observations | 121 | 401 | 371 | 180 | 689 | 589 |

Table 3: Childhood Cobalt Mining Exposure and Education Attainment: Benchmark Results

| | Education | Education | Education | Wealth | Wealth | Wealth |
|---|---|---|---|---|---|---|
| | Coef./SE | Coef./SE | Coef./SE | Coef./SE | Coef./SE | Coef./SE |
| Post x Cobalt Deposit | -0.569** | -0.505** | -0.496** | 0.033 | -0.070 | -0.065 |
| | (0.226) | (0.197) | (0.185) | (0.305) | (0.130) | (0.126) |
| Cobalt Mine within 10 km | 0.186 | 0.087 | 0.071 | 0.556** | 0.086 | 0.097 |
| | (0.161) | (0.128) | (0.124) | (0.259) | (0.092) | (0.100) |
| 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 | 1828 | 1822 | 1822 | 1904 | 1898 | 1898 |

Notes: This table presents results of the effects of childhood exposure to cobalt mining production on completed years of primary 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 ***$p< 0.01$, **$p< 0.05$, *$p< 0.1$.

Table 4: Children Cobalt Mining Exposure and Current Education Attainment: Benchmark Results

| | Current Edu. Coef./SE | Current Edu. Coef./SE | Current Edu. Coef./SE | Wealth Coef./SE | Wealth Coef./SE | Wealth Coef./SE |
|---|---|---|---|---|---|---|
| Post x Cobalt Deposit | -0.692 | -0.445 | -0.558*** | -0.262 | 0.015 | 0.302* |
| | (0.549) | (0.321) | (0.194) | (0.569) | (0.214) | (0.172) |
| Year of Birth FE | No | No | Yes | No | No | Yes |
| Survey Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| District x Time FE | No | No | Yes | No | No | Yes |
| Female | No | Yes | Yes | No | Yes | Yes |
| Urban | No | Yes | Yes | No | Yes | Yes |
| Father's Job | No | Yes | Yes | No | Yes | Yes |
| Mother Alive | No | Yes | Yes | No | Yes | Yes |
| Father Alive | No | Yes | Yes | No | Yes | Yes |
| Observations | 1423 | 1418 | 1418 | 1424 | 1419 | 1419 |

Notes: This table presents results of the short-term effects of exposure to cobalt mining on current year of education for children between 6 and 14 years old . The baseline specification is presented in Equation (1). Column (1) presents the results controlling for survey year fixed effects. Column (2) adds controls for gender differences, place of residence and if the child's mother or father are alive. Column (3) adds year of birth fixed effects and subregional district fixed effects. Columns (4)-(6) show the immediate effects of cobalt mining exposure on household wealth. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

Table 5: Cobalt Mining Exposure and Fertility Rate: Benchmark Results

| | 5y<br>Fertility<br>Coef./SE | 5y<br>Fertility<br>Coef./SE | 5y<br>Fertility<br>Coef./SE | 3y<br>Fertility<br>Coef./SE | 3y<br>Fertility<br>Coef./SE | 3y<br>Fertility<br>Coef./SE |
|---|---|---|---|---|---|---|
| Post x Cobalt Deposit | 0.407*** | 0.363** | 0.325 | 0.333*** | 0.300*** | 0.276* |
| | (0.138) | (0.134) | (0.198) | (0.105) | (0.103) | (0.137) |
| Cobalt Mine within 10 km | -0.287* | -0.182 | -0.074 | -0.186* | -0.101 | -0.025 |
| | (0.151) | (0.149) | (0.139) | (0.099) | (0.097) | (0.080) |
| Woman's Age FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Survey Year FE | No | No | Yes | No | No | Yes |
| District x Time FE | No | No | Yes | No | No | Yes |
| Urban | No | Yes | Yes | No | Yes | Yes |
| Woman's Education | No | Yes | Yes | No | Yes | Yes |
| Ever Migrated | No | Yes | Yes | No | Yes | Yes |
| Observations | 844 | 790 | 790 | 844 | 790 | 790 |

Notes: This table presents results of the relationship between distance to a cobalt mine deposit and fertility rates of women interviewed in the DHS data Column (1) presents the results controlling for women's year of birth fixed effects. Column (2) adds controls for education level and place of childhood residence . Column (3) adds survey year fixed effects and subregional district fixed effects. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

# A Appendix

## A.1 Additional Results and Statistics

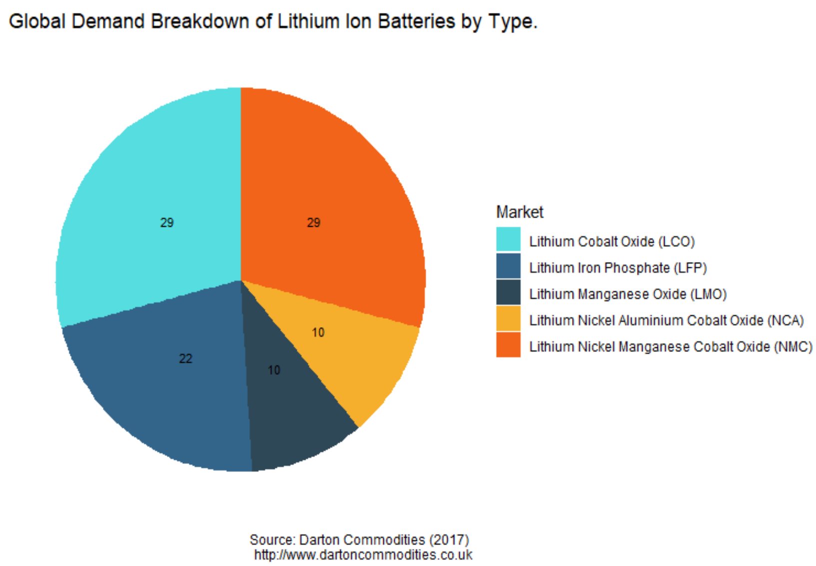


Figure 11: Global Demand Breakdown of Lithium-ion Batteries by Type

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

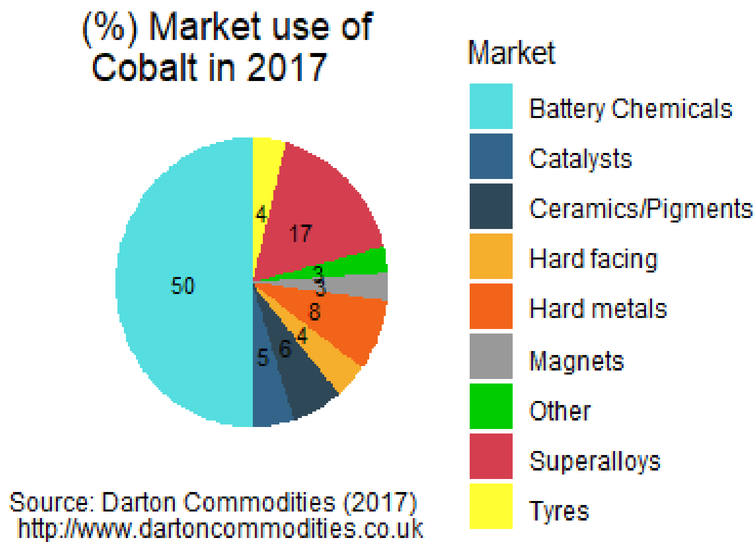


Figure 12: Market Use of Cobalt in Percentage

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

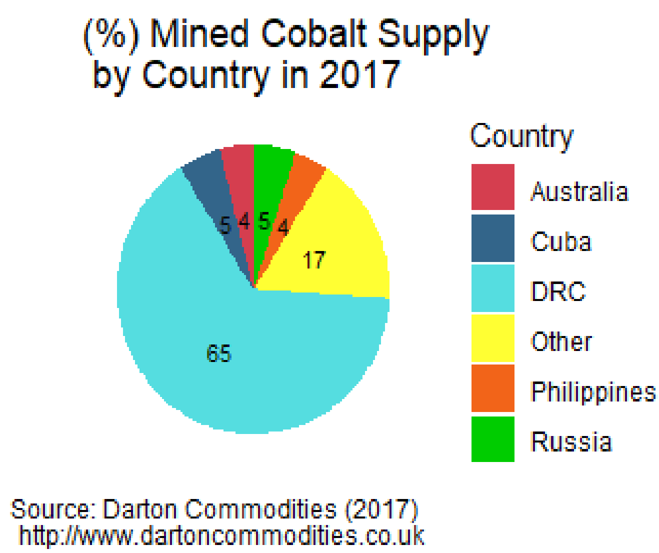


Figure 13: Mined Cobalt Supply by Country in Percentage

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

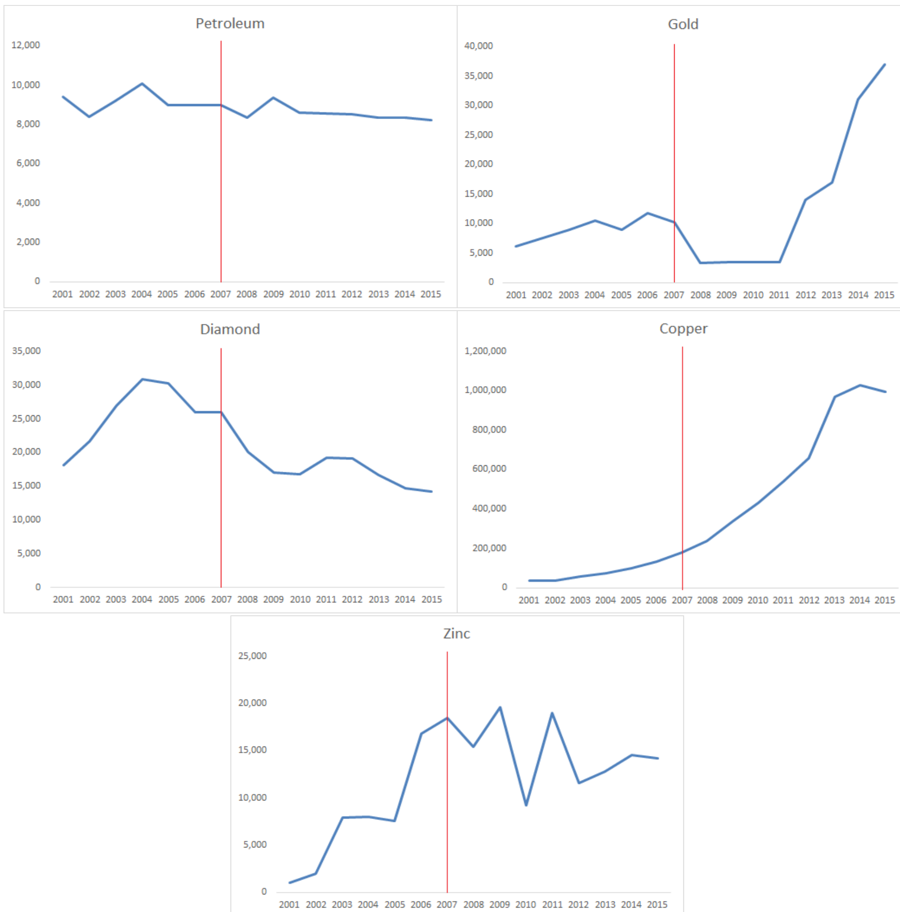


Figure 14: Total Production of Major Minerals in DRC. Metric Tons

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

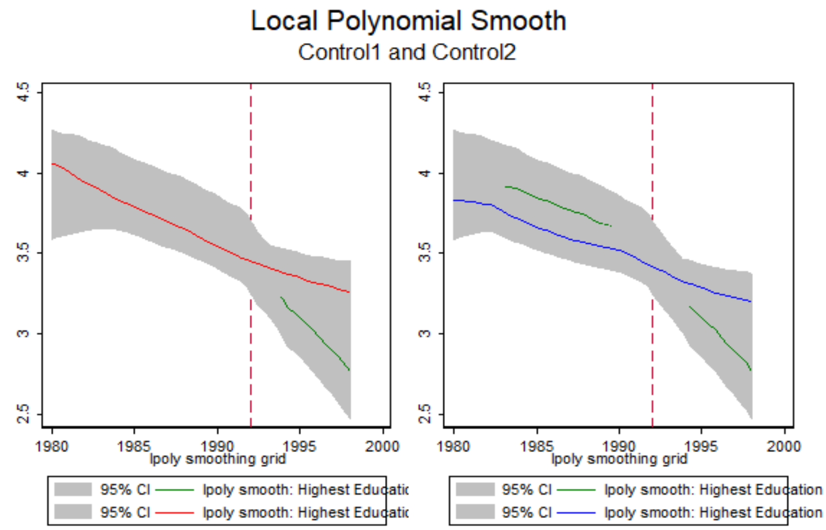


Figure 15: Local Polynomial Smooth Function

*Notes: Birth cohorts and education attainment are shown on the horizontal and vertical axis, respectively. Birth cohorts range from 1960 to 1999. The treatment group is defined as individuals, at the time of the survey, living within 10 kilometres away from the closest active cobalt mine deposit. The first control group is composed of individuals, at the time of the survey, living between 10 and 100 kilometres away from a cobalt mine (red line, left graph). The second control group considers individuals, at the time of the survey, living within 10 kilometres away from any closest mine except cobalt (blue line, right graph). The Figure provides 95% confidence intervals. No control variables, fixed effects or sub-regional district linear trends were considered.*

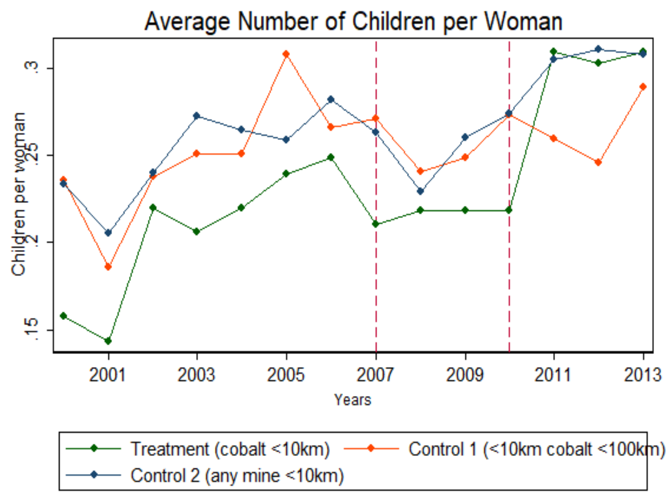


Figure 16: Average Number of Children born per Woman at a Given Year

*Notes: Children birth years and average number of children per woman are shown on the horizontal and vertical axis, respectively. Children birth years range from 2000 to 2013. The treatment group is defined as women surveyed in 2014, who at the time of the survey, were living within 10 kilometres away from the closest active cobalt mine deposit. The first control group is composed of women surveyed in 2007, who at the time of the survey, were living between 10 and 100 kilometres away from a cobalt mine (red line). The second control group considers women surveyed in 2014, who at the time of the survey, were living within 10 kilometres away from any closest mine except cobalt (blue line). No control variables, fixed effects or sub-regional district linear trends were considered.*

Table 6: Extensive Descriptive Statistics - Children between 6 and 14

| | DHS 2007 < 10 km Mean | DHS 2007 > 10 km Mean | DHS 2007 any mine Mean | DHS 2014 < 10 km Mean | DHS 2014 > 10 km Mean | DHS 2014 any mine Mean |
|---|---|---|---|---|---|---|
| ***Education*** | | | | | | |
| Completed Year of Education | 2.93 | 2.22 | 2.28 | 2.98 | 2.98 | 3.01 |
| ***Wealth*** | | | | | | |
| Wealth Index | 4.75 | 4.24 | 3.97 | 4.56 | 4.28 | 4.13 |
| ***Controls*** | | | | | | |
| Age | 10.43 | 10.08 | 10.42 | 10.20 | 10.38 | 10.46 |
| Urban | 1.00 | 1.26 | 1.28 | 1.14 | 1.26 | 1.25 |
| Female | 1.54 | 1.47 | 1.46 | 1.46 | 1.50 | 1.50 |
| Ever Migrated | 1.00 | 1.00 | 0.99 | 0.99 | 0.99 | 1.00 |
| Mother Alive | 0.98 | 0.96 | 0.96 | 0.96 | 0.95 | 0.96 |
| Father Alive | 0.94 | 0.95 | 0.90 | 0.98 | 0.89 | 0.92 |
| ***Cog.Dev.*** | | | | | | |
| Speech not normal | | | | 0.15 | 0.03 | 0.04 |
| Retard | | | | 0.19 | 0.02 | 0.01 |
| ***Work*** | | | | | | |
| Heavyloads | | | | 0.24 | 0.17 | 0.28 |
| Exposed to dust/fumes | | | | 0.21 | 0.07 | 0.20 |
| Observations | 122 | 278 | 401 | 206 | 612 | 751 |

## A.2 Cobalt Mines vs Other Mines

Table 7: Childhood Mining Exposure and Education Attainment: Placebo Treatment

| | Education Coef./SE | Education Coef./SE | Education Coef./SE | Wealth Coef./SE | Wealth Coef./SE | Wealth Coef./SE |
|---|---|---|---|---|---|---|
| Post x Mine Deposit | -0.133 | -0.137 | -0.048 | 0.230 | 0.144 | 0.016 |
| | (0.116) | (0.105) | (0.101) | (0.180) | (0.155) | (0.139) |
| Mine within 10 km | -0.078 | -0.165** | -0.082 | 0.394** | 0.120 | 0.710*** |
| | (0.087) | (0.081) | (0.075) | (0.189) | (0.115) | (0.122) |
| 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 | 15931 | 15800 | 15800 | 17893 | 17757 | 17757 |

Notes: This table presents results of a placebo test on the effects of childhood exposure to *any type of mining activity* on completed years of primary 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 ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 8: Childhood Cobalt Mining Exposure and Education Attainment: Cobalt Mines vs All Mines

| | Education | Education | Education | Wealth | Wealth | Wealth |
|---|---|---|---|---|---|---|
| | Coef./SE | Coef./SE | Coef./SE | Coef./SE | Coef./SE | Coef./SE |
| Post x Cobalt Deposit | -0.465** | -0.444** | -0.481*** | -0.400* | -0.277* | -0.255* |
| | (0.174) | (0.172) | (0.176) | (0.233) | (0.143) | (0.150) |
| Cobalt Mine within 10 km | 0.163 | 0.141 | 0.231 | 0.789*** | 0.395*** | 0.326 |
| | (0.122) | (0.118) | (0.144) | (0.201) | (0.103) | (0.229) |
| 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 | 2016 | 2000 | 2000 | 2149 | 2133 | 2133 |

Notes: This table presents results of the effects of childhood exposure to cobalt mining production on completed years of primary school. The baseline specification is presented in Equation (1) where control group is constituted by all individuals who during their childhood lived within 10 km from any mine deposit in the DRC. 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.

Table 9: Cobalt Mining Exposure and Fertility Rate: Benchmark Results. Cobalt Mines vs Any Mine

| | 5y Fertility Coef./SE | 5y Fertility Coef./SE | 5y Fertility Coef./SE | 3y Fertility Coef./SE | 3y Fertility Coef./SE | 3y Fertility Coef./SE |
|---|---|---|---|---|---|---|
| Post x Cobalt Deposit | 0.389** | 0.337** | 0.433** | 0.315*** | 0.290** | 0.255** |
| | (0.145) | (0.145) | (0.171) | (0.109) | (0.110) | (0.104) |
| Cobalt Mine within 10 km | -0.292** | -0.227 | 0.785*** | -0.217** | -0.175* | 0.463*** |
| | (0.140) | (0.143) | (0.153) | (0.088) | (0.090) | (0.108) |
| Woman's Age FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Survey Year FE | No | No | Yes | No | No | Yes |
| District x Time FE | No | No | Yes | No | No | Yes |
| Urban | No | Yes | Yes | No | Yes | Yes |
| Woman's Education | No | Yes | Yes | No | Yes | Yes |
| Ever Migrated | No | Yes | Yes | No | Yes | Yes |
| Observations | 1013 | 927 | 927 | 1013 | 927 | 927 |

Notes: This table presents results of the placebo test on the relationship between distance to *any mine deposit* and fertility rates of women interviewed in the DHS data Column (1) presents the results controlling for women's year of birth fixed effects. Column (2) adds controls for education level and place of childhood residence . Column (3) adds survey year fixed effects and subregional district fixed effects. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

## A.3 Artisanal Cobalt Mines

Table 10: Childhood Cobalt Mining Exposure and Education Attainment: Artisanal Mining

| | Education Coef./SE | Education Coef./SE | Wealth Coef./SE | Wealth Coef./SE |
|---|---|---|---|---|
| Post x Cobalt Deposit | -0.496** | | -0.066 | |
| | (0.185) | | (0.127) | |
| Post x Art. Cobalt Deposit | | -0.502*** | | -0.009 |
| | | (0.176) | | (0.117) |
| Female | Yes | Yes | No | No |
| Urban | Yes | Yes | Yes | Yes |
| Ever migrated | Yes | Yes | Yes | Yes |
| Current Student | Yes | Yes | Yes | Yes |
| Survey Year FE | Yes | Yes | Yes | Yes |
| District x Time FE | Yes | Yes | Yes | Yes |
| Year of Birth FE | Yes | Yes | Yes | Yes |
| Observations | 1822 | 1822 | 1898 | 1898 |

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.

Table 11: Cobalt Mining Exposure and Fertility Rate: Artisanal Mining

| | 5y Fertility Coef./SE | 5y Fertility Coef./SE | 3y Fertility Coef./SE | 3y Fertility Coef./SE |
|---|---|---|---|---|
| Post x Cobalt Deposit | 0.325 | | 0.276* | |
| | (0.198) | | (0.137) | |
| Post x Art. Cobalt Deposit | | 0.380** | | 0.295** |
| | | (0.184) | | (0.131) |
| Woman's Age FE | Yes | Yes | Yes | Yes |
| District x Time FE | Yes | Yes | Yes | Yes |
| Survey Year FE | Yes | Yes | Yes | Yes |
| Woman's Education | Yes | Yes | Yes | Yes |
| Urban | Yes | Yes | Yes | Yes |
| Ever Migrated | Yes | Yes | Yes | Yes |
| Observations | 790 | 790 | 790 | 790 |

Notes: This table presents results of the relationship between distance to an artisanal cobalt mine deposit and fertility rates of women interviewed in the DHS data Column (1) presents the results controlling for women's year of birth fixed effects. Column (2) adds controls for education level and place of childhood residence . Column (3) adds survey year fixed effects and subregional district fixed effects. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

## A.4 Effects on Secondary Education

Table 12: Childhood Cobalt Mining Exposure and Secondary Education: Placebo Test

| | Sec. Education Coef./SE | Sec. Education Coef./SE | Sec. Education Coef./SE |
|---|---|---|---|
| Post x Cobalt Deposit | 0.118 | 0.035 | 0.039 |
| | (0.144) | (0.030) | (0.031) |
| Cobalt Mine within 10 km | 0.022 | -0.021** | -0.019** |
| | (0.071) | (0.008) | (0.009) |
| Female | No | Yes | Yes |
| Urban | No | Yes | Yes |
| Ever migrated | No | Yes | Yes |
| Current Student | No | Yes | Yes |
| Survey Year FE | No | No | Yes |
| District x Time FE | No | No | Yes |
| Year of Birth FE | Yes | Yes | Yes |
| Observations | 1904 | 1898 | 1898 |

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.5 Cobalt Mining in Zambia

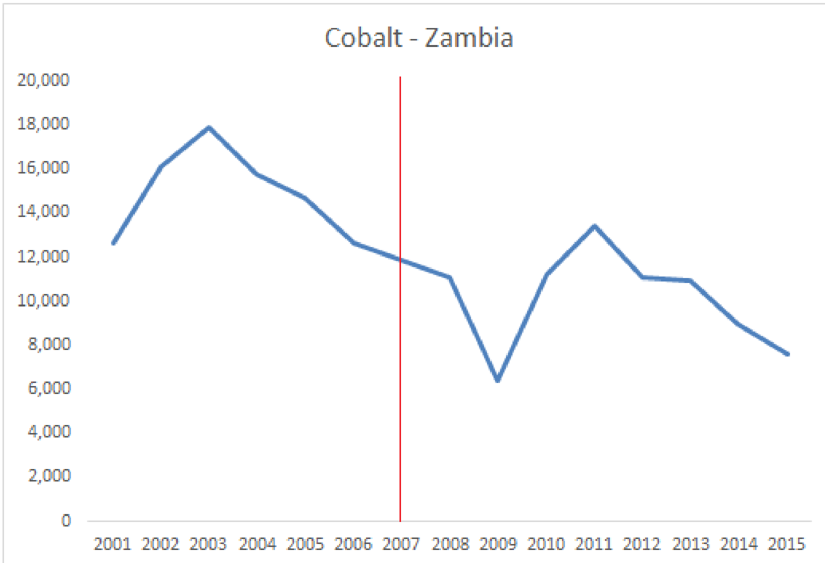


Figure 17: Total Cobalt Production from Mining in Zambia. Metric Tons

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

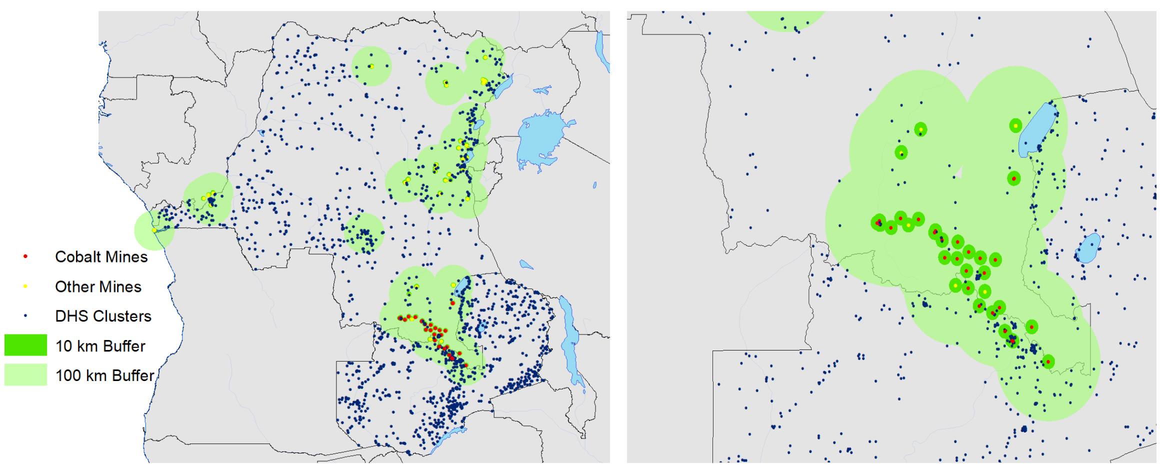


Figure 18: Location of Cobalt Mines in DRC and Zambia

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

Table 13: 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 Mine within 10 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.

## A.6 Selective Migration

As Tables 14 and 15 below show, those individuals living within 10 kilometers from a cobalt mine were actually born in the same village (cluster) where they were surveyed and never migrated. However, we cannot exclude that endogenous migration did not play an important role in explaining the reduction of the education achievement post cobalt boom. Next I control for selective migration.

Table 14: Childhood Cobalt Mining Exposure and Migration

| | Migration<br>Coef./SE | Migration<br>Coef./SE | Migration<br>Coef./SE |
|---|---|---|---|
| Post x Cobalt Deposit | -0.011 | -0.011 | -0.010 |
| | (0.008) | (0.009) | (0.009) |
| Cobalt Mine within 10 km | 0.009 | 0.010 | 0.012 |
| | (0.010) | (0.011) | (0.010) |
| Gender | No | Yes | Yes |
| Type of Residence | No | Yes | Yes |
| Current Student | No | Yes | Yes |
| Survey Year FE | No | No | Yes |
| District Linear Trend | No | No | Yes |
| Birth Cohort FE | Yes | Yes | Yes |
| Observations | 1796 | 1790 | 1790 |

Notes: This table presents results of the relationship between distance to a cobalt mine 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 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. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

The analysis also takes into account the possibility that some people migrated to the treatment group to work in a cobalt mine. This, might bias either upward of downward the impact of being close to a cobalt deposit and education attainment. Consider the following cases:

1. Consider the extreme case in which only the poorest people migrated from control group (i.e. $> 10km$ from the nearest cobalt deposit) to the treatment group (i.e. $< 10km$ from the nearest cobalt deposit) after the cobalt mining boom occurred in 2007. This scenario is actually very plausible since those people without a job might see the opening of a mine as an opportunity to work. If this is the case then, since poorest people are often associated with low education levels, this might result in a reduction in education attainment in the treatment group and at the same time in an increase in the control

Table 15: Cobalt Mining Exposure and Selective Women Migration

| | Ever Migrated<br>Coef./SE | Ever Migrated<br>Coef./SE | Ever Migrated<br>Coef./SE |
|---|---|---|---|
| Post x Cobalt Deposit | 0.015 | 0.016 | -0.011 |
| | (0.010) | (0.011) | (0.016) |
| Cobalt Mine within 10 km | -0.012* | -0.014 | 0.010 |
| | (0.007) | (0.009) | (0.007) |
| Woman's Age FE | Yes | Yes | Yes |
| Survey Year FE | No | No | Yes |
| District x Time FE | No | No | Yes |
| Urban | No | Yes | Yes |
| Woman's Education | No | Yes | Yes |
| Observations | 844 | 790 | 790 |

Notes: This table presents results of the relationship between distance to a cobalt mine deposit and probability to migrate of women interviewed in the DHS data Column (1) presents the results controlling for women's year of birth fixed effects. Column (2) adds controls for education level and place of childhood residence . Column (3) adds survey year fixed effects and subregional district fixed effects. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

group. The result of this first migration flow would be an overestimation of the negative impact of cobalt mining activities on the education achievements.

2. The opposite direction of migration might also play a crucial role. Consider that only richest individuals migrated from the treatment group to the control group after 2007. Richest people are associated with higher education attainment. If this is the case, then following the same reasoning of above, the education of those individuals who stayed in the treatment group would decrease while those in the control group would have completed more years of schooling. This second migration flow would again overestimate the negative impact of cobalt mining activities on the education achievements.

Combining the two cases we obtain the worst scenario in terms of selective migration from the treatment group and to the treatment group. Therefore, by dropping only those individuals who were surveyed in a village belonging in the control group who migrated and show high values of wealth and at the same time dropping those individuals who were surveyed in a village in the treatment group, who migrated and show low values of wealth we would estimate the lower bound of the relationship between living in a village within 10 kilometers from a cobalt mine and education achievements later in life. In other words, if by considering the above mentioned two selective migration flows we still obtain a significant negative effect of distance from a cobalt mine and education rate, then this relationship would be robust to any selective migration flow in and out the treatment group.

Table 16 reports beta coefficients of the effect of the boom of cobalt on individual's education attainment and wealth based on Equation 1. This time, I exclude from the sample the poorest 20%[52] of people who migrated *to* the treatment group (i.e. $< 10km$ from the nearest cobalt deposit) from the control group (i.e. between 10 and 100 kilometers away from the nearest cobalt deposit) after the cobalt mining boom occurred in 2007 and only the richest 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[53].

Here, column (1) presents results on highest completed education year from a specification with only individual's birth cohort fixed effects and no other individual-specific controls, sub-regional district time trends, or fixed effects. Columns (2) adds other controls and fixed effects sequentially. Finally, column (3) shows results from the specifications considering all individual-specific control variables, district linear trends and survey year fixed effects. Results from these specifications show that the patterns observed for individuals education attainment later in life when excluding selective migrants are similar to those in the full sample. With a coefficient of -0.443 (and a standard error of 0.149) for the restricted sample, compared to the beta coefficient of -0.496 (and a standard error of 0.185) for the full sample.

Table 17 instead, reports beta coefficients of the effect of the boom of cobalt on women's fertility rates based on Equation 1 where I consider the extreme scenario in which only the poorest people migrated *to* the treatment group (i.e. $< 10km$ from the nearest cobalt deposit) from the control group (i.e. between 10 and 100 kilometers away from the nearest cobalt deposit) after the cobalt mining boom occurred in 2007 and only richest individuals migrated *from* the treatment group to the control group after 2007.

Here, columns (1) and (4) present results on five year and three year fertility, respectively from a specification with only woman's age fixed effects and no woman-specific controls, sub-regional district time trends, or fixed effects. Columns (2) and (5) add other controls and fixed effects sequentially. Finally, columns (3) and (6) show results from the specifications considering all woman-specific control variables, district linear trends and survey year fixed effects. Once again, I find positive and significant effects of cobalt mining on the two measures of women's fertility (although slightly lower in magnitude compared to the baseline specification, considering the full sample of women), with a coefficient of 0.397 (and a standard error

[52] 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.

[53] I also run a further specification in which I exclude the poorest 40% (i.e. with wealth index $\leq 2$ ) of people who migrated *to* the treatment group (i.e. $< 10km$ from the nearest cobalt deposit) from the control group (i.e. between 10 and 100 kilometers away from the nearest cobalt deposit) after the cobalt mining boom occurred in 2007 and only the richest 40% ((i.e. with wealth index $\geq 4$ )) of those individuals who migrated *from* the treatment group to the control group after 2007. Results are shown in the Appendix and confirm the similar pattern observed in the baseline specification

of 0.188) for five year fertility and a coefficient of 0.301 (and a standard error of 0.136 for three year fertility). Thus, we conclude that the patterns observed for women's fertility rates when excluding selective migrants are similar to those in the full sample.

Table 16: Childhood Cobalt Mining Exposure and Education Attainment: Selective Migration

| | Education | Education | Education | Wealth | Wealth | Wealth |
|---|---|---|---|---|---|---|
| | Coef./SE | Coef./SE | Coef./SE | Coef./SE | Coef./SE | Coef./SE |
| Post x Art. Cobalt Deposit. | -0.343** | -0.444*** | -0.443*** | 0.227 | -0.081 | -0.079 |
| | (0.167) | (0.153) | (0.149) | (0.303) | (0.102) | (0.101) |
| Cobalt Mine within 10 km | 0.114 | 0.044 | 0.028 | 0.515* | 0.073 | 0.085 |
| | (0.132) | (0.107) | (0.107) | (0.275) | (0.084) | (0.094) |
| Gender | No | Yes | Yes | No | Yes | Yes |
| Type of Residence | No | Yes | Yes | No | Yes | Yes |
| Migrant | No | Yes | Yes | No | Yes | Yes |
| Current Student | No | Yes | Yes | No | Yes | Yes |
| Survey Year FE | No | No | Yes | No | No | Yes |
| District Linear Trend | No | No | Yes | No | No | Yes |
| Birth Cohort FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1705 | 1699 | 1699 | 1776 | 1770 | 1770 |

Notes: This table presents results of the relationship between distance to a cobalt mine deposit during childhood and probability to migrate compared to the distance to any other mine in the DRC. 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. Significant at ***p< 0.01, **p< 0.05, *p< 0.1.

Table 17: Cobalt Mining Exposure and Fertility Rate: Selective Migration

| | 5y Fertility Coef./SE | 5y Fertility Coef./SE | 5y Fertility Coef./SE | 3y Fertility Coef./SE | 3y Fertility Coef./SE | 3y Fertility Coef./SE |
|---|---|---|---|---|---|---|
| Post x Art. Cobalt Deposit | 0.274* | 0.399*** | 0.397** | 0.224* | 0.323*** | 0.301** |
| | (0.159) | (0.121) | (0.188) | (0.127) | (0.097) | (0.136) |
| Cobalt Mine within 10 km | -0.191 | -0.183 | -0.090 | -0.105 | -0.097 | -0.022 |
| | (0.173) | (0.136) | (0.126) | (0.124) | (0.088) | (0.078) |
| Woman's Age FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Survey Year FE | No | No | Yes | No | No | Yes |
| District x Time FE | No | No | Yes | No | No | Yes |
| Urban | No | Yes | Yes | No | Yes | Yes |
| Woman's Education | No | Yes | Yes | No | Yes | Yes |
| Observations | 810 | 756 | 756 | 810 | 756 | 756 |

### A.6.1 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 kilometres from a cobalt mine deposit, while no effect for those people living beyond 10 kilometres. Hence, the following Equation is estimated:

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

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 kilometres, 10–30 kilometres, etc. and compared with the reference category 70–100 kilometres 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 19.

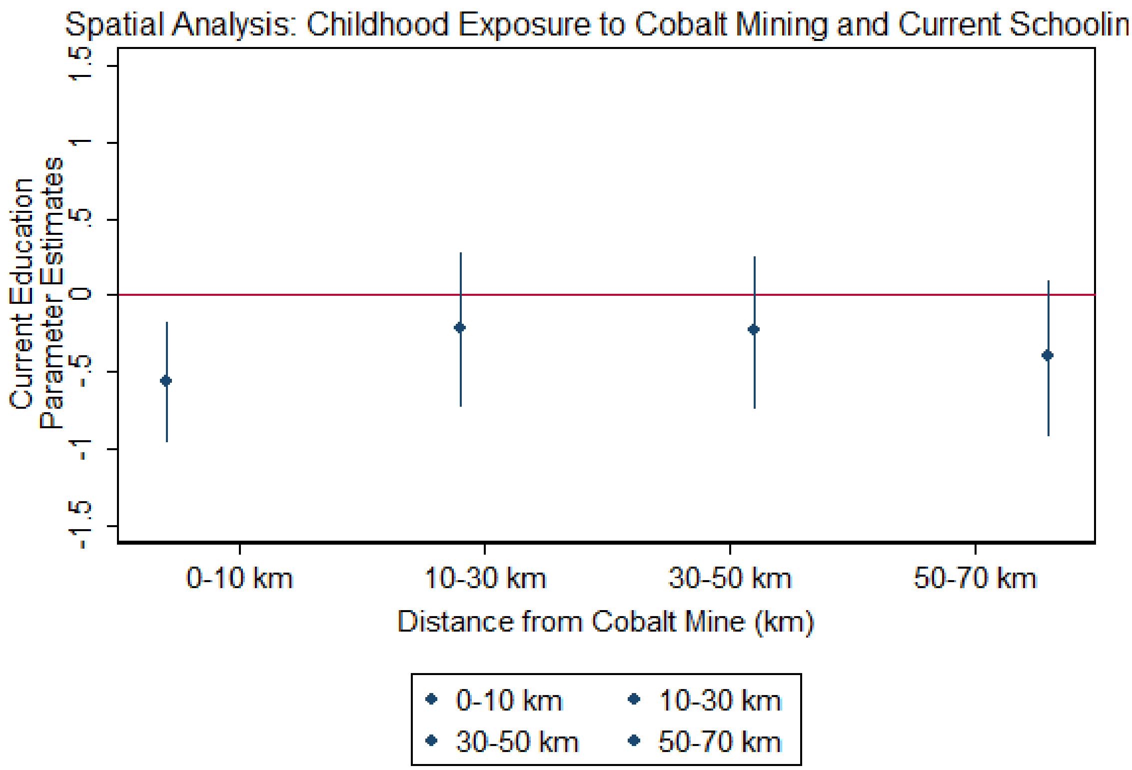


Figure 19: Current Year of Education for all Children between 6 and 14 years old

*Notes:* This Figure shows the results from a spatial lag model with 20 kilometres 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

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