MISUM
WORKING PAPER SERIES

NO. 2023-14, NOV 2023

ECONOMIC OPPORTUNITIES AND HUMAN CAPITAL INVESTMENTS: EVIDENCE FROM ARTISANAL GOLD MINING IN AFRICA

Avenia Ghazarian
Mistra Center for Sustainable Markets (Misum)
Stockholm School of Economics

Akib Khan
Mistra Center for Sustainable Markets (Misum)
Stockholm School of Economics

Economic Opportunities and Human Capital Investments: Evidence from Artisanal Gold Mining in Africa*

Avenia Ghazarian†
Stockholm School of Economics
Mistra Center for Sustainable Markets (Misum)

Akib Khan‡
Stockholm School of Economics
Mistra Center for Sustainable Markets (Misum)

August 14, 2025

Abstract

How does human capital investment respond to local economic opportunities? Income gains can increase the demand for schooling, while new jobs raise the opportunity costs. We investigate this question in the context of rapid growth in artisanal gold mining in sub-Saharan Africa. We compile 45 waves of Demographic and Health Surveys covering 1.2 million individuals from 14 countries in this region. Identification comes from two sources of variation: one in the global gold price and the other in the exposure of households to places that are geologically suitable for artisanal gold mining. We find that a near-tripling of the global gold price, reflecting changes between 2005 and 2010, leads to a decline in school attendance: by 2.6 percentage points for 11–15-year-olds and by 3.3 percentage points for 16–20-year-olds who live near gold-suitable areas. These declines translate into lower completed years of schooling in the long run. We can rule out migration, industrial mining, and conflict as alternative explanations. The results underscore the potential human capital costs of resource-driven economic booms.

Keywords: Artisanal gold mining; Human capital investment; sub-Saharan Africa
JEL codes: J24, O15, Q32

*We thank Niklas Bengtsson, Martina Björkman Nyqvist, Victoire Girard, Andreas Madestam, Torben Mideksa, Niklas Moneke, Jon de Quidt, Abhijeet Singh, Lucas Tilley, Leonard Wantchekon, Céline Zipfel, Olof Åslund, Björn Öckert, and seminar participants at Stockholm School of Economics and Uppsala University for valuable comments and helpful discussions. We are grateful to Mistra Center for Sustainable Markets (Misum) for financial support.
†avenia.ghazarian@hhs.se
‡akib.khan@hhs.se

1 Introduction

How do positive labor demand shocks affect human capital accumulation in low-income countries? With higher income, parents are more likely to keep children in school. However, as returns to labor increase, so does the opportunity cost of schooling. Which effect dominates is an empirical question, and the effects may vary across contexts [Atkin, 2016, Adukia et al., 2020]. We study this question leveraging one of the largest local labor market shocks in sub-Saharan Africa (SSA) over the last two decades: the rise in artisanal and small-scale gold mining.

Artisanal and small-scale mining (ASM) is a labor-intensive, low-tech mineral extraction and processing industry. This is a thriving industry in Africa that directly employs at least 60 million people, including children, and indirectly supports an additional 130 million [World-Bank, 2019].[1] Artisanal gold mining, which generates 20% of the global gold supply, is considered the predominant employer in the African ASM industry [Girard et al., 2022]. Moreover, the surge in gold prices over the last two decades has further fueled the growth of this sector. Between 2000 and 2020, the price of gold increased by about 530%, from USD 279 to 1,769 per ounce. During the same period, direct employment in artisanal gold mining more than tripled.

How does schooling investment respond to these changes in local economic opportunities? While a small and growing body of studies has investigated the effects of ASM on local economic activity, household wealth as well as on the environment [Girard et al., 2022, Poignant, 2022, Bazillier and Girard, 2020], there is limited evidence of its impact on children's schooling outcomes.[2]

In this paper, we study whether the emergence of job opportunities in artisanal and small-scale mining, induced by the rise in the global gold price, affects the schooling decisions of children and young individuals in sub-Saharan Africa. New jobs in the local mining sites, typically labor-intensive, raise the opportunity cost of staying in school. On the other hand, higher parental earnings from mining can increase the demand for schooling. This is particularly relevant for parents who are credit or liquidity-constrained, which characterizes the majority of the households in the region with widespread poverty and imperfect credit markets. The direction of net effects, therefore, is theoretically ambiguous and an empirical question.

Addressing this question, however, poses multiple challenges. First, most countries lack

[1] For an overview of the use of child labor in ASM, see O'Driscoll [2017].

[2] There is an extensive, mostly descriptive, interdisciplinary literature—especially in anthropology, human geography, and development studies—documenting ASM as a livelihood and examining mobility/de-agrarianization, agrarian–mining linkages, gendered labor, environmental and health risks, and (in)formal governance. See, e.g., Jønsson and Bryceson [2009], Bryceson and Jønsson [2010], Bryceson and Geenen [2016], Heemskerk [2002], Tschakert and Singha [2007], Hilson and Garforth [2012], Hilson [2016], Hilson and McQuilken [2014], Maconachie and Binns [2007], Maconachie and Hilson [2011], Geenen [2012], Lahiri-Dutt [2008].

a database of artisanal mining sites as many of these sites operate informally. Second, the timing of the opening of mining sites and their location could depend on characteristics that are also correlated with schooling outcomes. For instance, remote areas with limited school access and a larger out-of-school population may make it more profitable to start a mining site due to the relative abundance of inexpensive labor. We address these challenges by combining temporal variations in international gold prices with spatial differences in household exposure to areas that are geologically suitable for small-scale gold mining.

Our empirical strategy uses two sources of variation. First, instead of the location of realized mining sites, we use data on the *suitability* of a particular location for artisanal gold mining. This provides spatial variation in the households' access to potential mining opportunities. Second, since artisanal gold miners are mostly price takers, we combine this spatial variation with temporal fluctuations in the global gold price, which directly determines ASM revenues. Intuitively, this is similar to a difference-in-differences design where one difference corresponds to comparisons of households across regions with high and low gold-suitability whereas the second difference entails comparing periods of (unexpectedly) high and low gold prices.[3] We also control for a set of predetermined individual and household characteristics.

We combine three data sources. First, to measure gold suitability, we use a pan-African dataset developed by Girard et al. [2022], which maps the geological suitability of bedrock for artisanal gold mining.[4] The dataset draws on recent geophysical mapping that captures the contours, age, and chemical composition of bedrock and identifies 18% of the continent as suitable for artisanal gold extraction. As an alternative measure, we also use a machine-learning-based index of gold potential from Rigterink et al. [2025].

Second, for schooling and demographic outcomes, we pool 45 waves of the Demographic and Health Surveys (DHS), covering nearly 1.2 million individuals aged 6–25 across 14 Sub-Saharan African countries between 2000 and 2018. The inclusion of GPS coordinates for household clusters allows us to calculate each household's proximity to the nearest gold-suitable location and, in turn, their potential exposure to mining opportunities.

Third, we incorporate a time series of global gold prices to capture temporal variation in economic incentives linked to artisanal gold mining.

Overall, higher international gold prices adversely affect school attendance of adolescents and young adults living near gold-suitable areas.[5] For instance, if the gold price nearly

[3] Notable examples of combining heterogeneous geographical suitability and temporal variation include Girard et al. [2022], Nunn and Qian [2011], and Sviatschi [2022].

[4] We are immensely grateful to Girard et al. [2022] for generously sharing this data.

[5] For our main analysis, we dichotomize proximity using a threshold of 10 kilometers, i.e., households within 10 kilometers of gold-suitable locations are considered exposed to potential ASM activities, while those farther away serve as the comparison group. This distance is manageable for daily access, requiring less than two hours on foot or about 30 minutes by bicycle.

triples[6], reflecting the change between the years 2005 and 2010, individuals aged 11-15 years are 2.6 percentage points less likely to be attending school ($p < 0.01$; 3.4% of the sample mean for this age group). The corresponding decline for the age group 16-20 is 3.3 percentage points ($p < 0.01$; 7.3% of their sample mean).

We find no significant gender differences in the effects of gold price shocks on school attendance across age groups. However, attendance declines are notably larger among early adolescents from households where the head has no formal education, suggesting that the opportunity-cost mechanism may play a stronger role in poorer households.

To assess the robustness of our findings, we employ a series of sensitivity analyses. First, we explore alternative definitions of exposure to gold-suitable areas. We partition treatment clusters into distance bands of 0-10 km, 10-20 km, and 20-30 km from gold-suitable locations (with clusters beyond 30 km as controls). The estimated effects diminish and become statistically insignificant beyond 20 km, suggesting that the impacts are concentrated among the most exposed households. As another alternative, we replace the binary exposure variable with the log-transformed distance to the nearest gold-suitable region, obtaining estimates that align with the primary results both in relative magnitude and statistical significance. Finally, to accommodate potential cross-border mobility restrictions, we redefine exposure using within-country distances only, confirming that cross-border considerations do not influence our results substantively.

We also address potential endogeneity from selective migration, specifically the possibility that poorer, low-education households may relocate to gold-suitable areas to engage in mining, which could lead us to overestimate any adverse schooling effects. Given limitations in DHS migration data, we examine household composition changes during gold price booms and find no evidence of systematic demographic shifts in resident households—no changes in household size, age and gender composition, or educational characteristics of the household head—suggesting our results reflect behavioral responses of incumbent households rather than selective in-migration.

Changes in global gold price can also affect industrial mining activity in ways that might independently influence schooling outcomes. We test whether the observed impacts on schooling could be driven by industrial mining through two complementary approaches. First, using the S&P Global/SNL Metals & Mining database, we implement progressively stricter exclusions: restricting analysis to the SNL coverage period (2000-2010), excluding clusters with active industrial gold mines within 100 km in the survey year, and excluding clusters that ever had such mines during the study period. Second, we employ machine-learning predic-

[6] An increase of 172%, to be precise, which corresponds to an increase of one log point.

tions that identify areas suitable for both artisanal and industrial mining based on geological characteristics, excluding clusters predicted to host overlapping mining activities. This approach is particularly relevant given evidence that 31-55% of mining-related conflict stems from competition between large-scale and artisanal miners. Across both sets of tests, our estimates remain virtually unchanged, indicating that industrial mining dynamics and associated conflict channels do not drive our results.

Individuals aged 21–25 show no schooling response to gold price shocks in our main results, which is unsurprising given that their educational decisions, typically about tertiary education, are unlikely to be influenced by low-skilled artisanal mining opportunities. We therefore use them as another comparison group in a triple-difference specification, enabling within-cluster comparisons. Results remain robust under this approach, including when allowing for flexible country-by-year or region-by-year trends.

Finally, we conduct placebo tests by randomly reassigning gold suitability and permuting gold prices across 1,000 iterations, finding that the resulting coefficient distributions are centered around zero under random assignment, while our original estimates remain statistically significant.

As a secondary analysis, using a sample of young adults, we assess the long-term effects of gold price shocks during the different phases of childhood and adolescence. Identification comes from the differences in gold price trajectories across the different cohorts combined with their exposure to gold-suitable locations. We find that higher prices during primary schooling age lead to lower completed schooling for individuals growing up in gold-suitable areas, suggesting lasting adverse effects on human capital accumulation.

Our findings contribute to three strands of literature. First, we add to the literature on how changes in employment opportunities shape human capital investments. Consistent with our results, Atkin [2016] finds an increase in school dropouts in response to the rapid expansion of the export manufacturing sectors in Mexico. Similarly, Kovalenko [2023] documents that the U.S. fracking boom reduced schooling among high school students, particularly those with lower academic performance, as increased earnings opportunities drew them into the labor force. Santos [2018] finds analogous effects in Colombia, where gold price booms increased child labor and reduced school attendance. Ahlerup et al. [2020] also show that adolescents exposed to industrial gold mines during adolescence in Africa attain significantly fewer years of schooling in adulthood.[7] In contrast, Adukia et al. [2020] finds that new roads connecting

[7] Our contribution differs from Ahlerup et al. [2020] in several key respects. First, we focus on artisanal rather than industrial mining. This distinction is important because artisanal and small-scale mining accounts for a much larger share of the mining labor force, particularly in Sub-Saharan Africa [Girard et al., 2022]. Second, instead of relying on the timing and placement of actual mine openings—which may be endogenous—we use plausibly exogenous variation from geological gold suitability interacted with global gold price shocks. Finally, we study contemporaneous school attendance across a wide age range using repeated cross-sections from nationally repre-

villages with urban labor markets increase middle-school enrollment in India. Given the different *and* counteracting mechanisms at play for a positive labor demand shock, such as a higher opportunity cost of schooling and a positive income effect, these mixed results point toward the importance of the contextual specifics in determining the net effects [Bau et al., 2020, Shah and Steinberg, 2017]. Jobs in artisanal gold mining are typically low-tech and labor-intensive, hence widely accessible for school-age individuals, especially in the absence of effective child labor restrictions [O'Driscoll, 2017]. On the other hand, the positive income effects might be rather weak given the potentially low returns to secondary schooling in the region [Duflo et al., 2021].

We also add to the literature on the impact of natural resources on the process of development (see Sachs and Warner [2001] for a review). Our results highlight an important mechanism through which natural endowments can impede growth by reducing human capital investments. Lastly, our findings add to the growing literature on artisanal mining and its socioeconomic effects [Girard et al., 2022, Poignant, 2022, Bazillier and Girard, 2020, Guenther, 2018, Kotsadam and Tolonen, 2016, Geenen et al., 2021].

The remainder of the paper is organized as follows. Section 2 provides background information on artisanal and small-scale mining in sub-Saharan Africa. We describe the data in Section 3 and the empirical strategy in Section 4. Section 5 presents the results and robustness checks. Section 6 concludes.

2 Background: Artisanal gold mining in sub-Saharan Africa

Artisanal and small-scale mining (ASM) refers to low-tech, labor-intensive small-scale mining activities that are usually carried out by individuals or small groups of miners [Hilson and Maconachie, 2020]. ASM can be differentiated from industrial and large-scale mining, which is typically licensed, capital-intensive, and uses advanced technology.

For geological reasons, ASM is particularly prevalent in sub-Saharan Africa. The livelihoods of at least 60 million people are directly dependent on the revenues of ASM, and 130 million people indirectly rely on the sector to earn their livelihoods [WorldBank, 2019].

Both men and women participate in ASM activities. Women's direct participation in such mining varies across the world. In Asia, less than 10% of miners are women, whereas the corresponding figure for Latin America is higher, approximately 10-20%. In Africa, the share of female artisanal miners is the highest, ranging from 40 to 50% [Hinton et al., 2003]. There are also children actively working in the sector. The more remote or informal the activity, the

sentative household surveys.

more likely children are to be involved [Hilson, 2003]. The informality of the sector, however, makes it hard to estimate the total number of children involved. In 2019, ILO estimated that about one million children worked in the ASM sector. In Burkina Faso, for instance, estimates suggest that children constitute up to 30 to 50% of the entire ASM workforce [ILO, 2021].

There are four key steps involved in the process of artisanal gold mining. First, gold ore is excavated from the soil, rock, and surrounding water tributaries. The gold ore is then processed and concentrated[8] by gravity methods (sluice, shaking table[9], etc.). It is then combined with elemental mercury, which forms a gold–mercury amalgamation. This amalgam is subsequently burned, removing the mercury as vapor and leaving a relatively pure gold alloy, which can be further refined [Allan-Blitz et al., 2022].

The market for ASM products is not well-organized, with the majority of miners[10] selling to individual collectors at a negotiated price [Chupezi et al., 2009]. In Cameroon, for example, the majority of miners sell their gold to individual collectors, with only a small share selling to agents that set prices based on factors such as the carat value of the gold and the percentage of gold lost during smelting [Funoh, 2014]. The payment methods to artisanal miners differ based on factors such as ownership of the mining site and whether they work independently or as part of a group. Typically, mining sites operate under individual ownership. Individual miners who own the mining site may employ family labor and/or hire wage laborers. Wage payments are often based on informal or verbal agreements and are paid in cash or kind (a percentage of their produced gold) or a combination of both. Miners who work in groups split their earnings among the members according to each member's contribution [Funoh, 2014].

ASM activities can generate income and consumption gains for participating households [Guenther, 2018, Bazillier and Girard, 2020]. On the other hand, ASM may have detrimental effects on the environment through increasing deforestation and adversely affecting vegetation health [Girard et al., 2022, Morgane et al., 2018]. Moreover, poor working conditions (e.g., risk of collapse due to the absence of proper structural support, exposure to toxins such as mercury or arsenic, etc.) pose serious threats to the physical health and safety of the miners [Hentschel, 2003].

The industry may continue to exist, buoyed by persistently high gold prices, and not the least because there is still widespread poverty in the region [Hentschel, 2003]. Making a comprehensive assessment of the impacts of ASM, however, is challenging since, in most countries, the sector is highly informal with significant bureaucratic barriers to formalization [Morgane et al., 2018]. Consequently, ASM activities are frequently associated with child labor and ex-

[8] A method used for increasing the amount of gold in ore, by selectively removing lighter particles.
[9] A shear flow process equipment that separates particle grains of its feed material based on the differences in their specific gravity, density, size, and shape.
[10] 66.67% in Cameroon and 93.75% in the Central African Republic

ploitation that might put children's health, safety, and future at risk [ILO, 2019]. Therefore, it is critical that we investigate how these mining activities affect children's outcomes such as schooling, which plays an important role in the development of their human capital and in addressing the intergenerational transmission of poverty [Jensen, 2000].

2.1 ASM and schooling

Human capital investments are critical for long-run economic growth [Mankiw et al., 1992, Edmonds and Pavcnik, 2006, Lucas Jr, 1988]. Artisanal mining activities, like any other source of income, can improve schooling outcomes by enabling households to send their children to school, especially in contexts with binding liquidity or credit constraints. On the other hand, in the presence of child labor, these mining opportunities increase the opportunity cost of staying in school. Hence, the theoretical prediction for the net effects is ambiguous and depends on the relative strength of these two different mechanisms.

There are other channels through which ASM may affect schooling outcomes. Considering the hazardous working conditions and the pay structure that is often tied to gold production, children may still indirectly experience adverse effects due to the insufficient time and energy that parents can invest in them while working in the mines.

Developing countries have made remarkable progress in school enrollment rates in the last two decades. In sub-Saharan Africa, where the progress lags behind other regions, primary school enrollment has risen from 73% in 1990 to 99% in 2019. Secondary enrollment has increased as well, from 23% in 1990 to 44% in 2019 (UNESCO Institute for Statistics). Nevertheless, positive labor demand shocks may threaten school enrollment rates by raising the opportunity cost of schooling.

Schooling responses to the arrival of job opportunities depend on the prevalence of child labor [Bau et al., 2020] as well as the nature of the jobs in terms of the returns they offer to education [Adukia et al., 2020]. Job opportunities in the ASM sector generally do not offer high returns to schooling, as most roles are low-skilled and labor-intensive. As such, formal education may not significantly enhance productivity or earnings in this context. While age or gender may not systematically confer broad comparative advantage across all occupations, there is scope for gendered specialization within the sector, depending on the physical demands of specific tasks. For example, men may be more likely to engage in extraction activities that are particularly brawn-intensive, whereas women might concentrate in relatively less physically demanding tasks such as sorting or processing.

3 Data description

3.1 Gold-suitable locations

To determine the extent to which households are exposed to ASM job opportunities, we measure the distance from where a household lives to the nearest gold-suitable location. The suitability of the land is exogenously determined by geological features. Certain geological properties can indicate the likelihood of gold deposits within a particular bedrock. In the African continent, primary and alluvial gold deposits are found almost exclusively in certain geological formations [Goldfarb et al., 2017].

By leveraging recent mapping of the contours, age, and chemical composition of African geological bedrocks, Girard et al. [2022] constructs a dataset to identify areas where artisanal gold mining may take place. We rely on this dataset to determine the potential exposure of households to artisanal gold mining opportunities. Figure 1c shows the map of the geological gold-suitability of bedrock across Africa (in gold).

As an illustrative validation, Figure A4 overlays gold-suitable areas with documented artisanal mining sites in Burkina Faso. The strong spatial correspondence between the geological suitability and realized mining activity captured by satellite imagery and field surveys [Effigis, 2018], provides visual support for the use of geological features as a basis for exposure classification. We cannot, however, use this kind of data in our analysis: beyond concerns around the endogeneity of mining site locations, data on realized artisanal mining activity is rarely available in consistent or high-quality form for other countries in our sample.

3.2 Schooling and demographic characteristics of households

The Demographic and Health Surveys (DHS) provide data on schooling and other demographic information at both individual and household levels. A subset of these surveys also provides GPS coordinates for clusters[11], which allows us to determine the (linear) distance from the location of the cluster where a household lives to the nearest location that is geologically suitable for artisanal gold mining. This provides us with variations in the extent to which households are exposed to the potential emergence of ASM job opportunities. Presumably, traveling to places where ASM activities take place incurs costs that are likely to increase with distance. Thus, the closer a household resides to gold-suitable locations, the smaller the costs of accessing them, which may raise the likelihood of engaging in ASM. We restrict our sample to the surveys conducted between 2000 and 2018 as some preceding survey rounds rarely

[11] Defined as groupings of household participants in the survey living in one or several close villages or in an urban neighborhood.

collect geo-coordinates. The rise in the gold price accelerated in 2007. To account for this, we further restrict the sample to countries that have at least one DHS wave available before 2007 and at least one afterward, which results in a sample of 45 DHS waves from 14 countries in sub-Saharan Africa [Boyle et al., 2022]. The blue dots in Figure 1c present the distribution of the DHS clusters from the latest round of DHS for each of the countries in the sample. Note that, for any given country, each survey wave represents a repeated cross-section.

As discussed earlier, schooling responses to the arrival of new job opportunities may differ by age, as the costs of dropping out of school vary across the age distribution. Our analysis primarily focuses on three age cohorts: 6–10, 11–15, and 16–20 years, corresponding broadly to primary, lower secondary, and upper secondary education levels, respectively. We also report estimates for the 21–25 age group. Individuals within this age bracket typically have completed their secondary education and are pursuing higher education aligned with long-term career goals requiring advanced qualifications. Given the low-skilled and labor-intensive nature of artisanal mining, it is unlikely to attract those with higher educational ambitions, as the opportunity cost of entering this sector would be particularly high. With substantial educational investments already undertaken, these individuals are unlikely to abandon further studies in favor of short-term employment in mining. Consequently, this group can serve effectively as a placebo. [12] Figure 1b illustrates school attendance rates by age and gender, showing the expected age gradient in attendance as well as a modest gender gap that emerges during adolescence, with girls attending at slightly lower rates than boys.

The main outcome of our analysis is school attendance – specifically, whether an individual is attending school during the survey year. This is a *flow* variable, capturing contemporaneous schooling decisions. To assess long-term effects, we also use completed years of schooling, which is the corresponding *stock* variable. In the main analysis, we take 10 kilometers as the threshold for exposure, i.e., households living within 10 km of the nearest gold-suitable locations are considered to have access to potential ASM activities, whereas households living further away constitute the comparison group. On average, it takes less than 2 hours to walk for 10 km and around 30 minutes to cycle, so it is not too costly to do on a daily basis. Table A1 describes the sample size divided by country and survey year, and Table A2 presents some descriptive statistics across the age groups.

[12] Alternatively, employing a triple-differences design, this age group can act as a comparison cohort to account for broader secular changes in schooling outcomes within gold-suitable regions. It also facilitates robustness checks with more stringent fixed effects, such as cluster and household fixed effects, allowing for more precise comparisons. We report the corresponding results in Section 5.2.

3.3 Global gold price

The global gold price is a direct determinant of the revenues of ASM activities. As presented in Figure 1a, over the past two decades, the global gold price has experienced a sharp increase, of about 530% from 2000 to 2020. This has led to a surge in public and private interest in the ASM sector. The estimated number of people directly involved in the activity increased from 13 million in 1999 to 40.5 million in 2017 [Morgane et al., 2018]. Given the small-scale and decentralized nature of the sector, artisanal miners are considered to be price takers in the international gold market. Hence, changes in global prices may impact artisanal mining, both on the extensive margin, in terms of the number of people who work in the mines, and on the intensive margin, on the level of effort they put into mining activities [Girard et al., 2022].

4 Empirical Strategy

4.1 School attendance

To investigate whether the emergence of job opportunities in artisanal gold mining affects school attendance, we exploit two sources of variation. One is the temporal variation in the global gold price, with the underlying assumption that the local ASM transactions do not have an effect on the international price. The second source of variation is spatial: the differential exposure of the households to these job opportunities as measured by their proximity to the nearest gold-suitable location. For our preferred specification, we take 10 kilometers to dichotomize this exposure.[13,14]

We estimate the following model for the *flow* measure of schooling, namely school attendance:

$$Y_{ict} = \alpha(\text{Gold}_c \times \text{Price}_{t-1}) + \nu \text{ Gold}_c + \mathbf{X}_i + FE_{region} + FE_t + \epsilon_{ict}, \tag{1}$$

where Y_{ict} is the outcome of individual i who lives in cluster c and responds to the survey in year t. The outcome is a binary variable indicating whether an individual is attending a school in year t. Gold_c indicates if cluster c is located within 10 km of the closest gold-suitable location. Price_{t-1} is the one-year-lagged international gold price in US dollars (in log terms). $\mathbf{X}_i$ is a vector of predetermined covariates at the individual and household levels: whether individual i is female, household size, whether the household head is female, and whether the household lives in a rural area. Fixed effects for regions or sub-national units, FE_{region},

[13] In other words, households who live within 10 kilometers of the closest gold-suitable location constitute the treatment group while those who live further away are considered the comparison group. We relax this definition by gradually increasing the threshold. We also use an alternative measure of exposure: distance to the nearest gold-suitable location. We report and discuss the results below in Section 5.2.1.

[14] Note that this is similar in spirit to the reduced form of a shift-share design with potentially endogenous shares and exogenous shocks [Borusyak et al., 2022].

account for time-invariant differences between regions. For any given country, all regions are represented across all survey rounds.[15] Year fixed effects, FE_t, control for changes over time that are common to the study population. ϵ_{ict} is the error term clustered at the DHS-cluster level. A cluster often represents a village or a similar agglomeration of households, which is a reasonable proxy for a local labor market. Clustering the standard error at this level, therefore, allows us to account for local labor market shocks coinciding with the changes in gold price [Abadie et al., 2023]. However, as Figure 1c shows, gold suitable areas can cover a larger spatial area and span multiple clusters. Reassuringly, the conclusions remain the same when we cluster at the region level (Table A5, Panel C), which is often a considerably larger unit than a cluster.

We estimate this model separately for the age groups 6-10, 11-15, 16-20, and 21-25 years. The parameter of interest is α, which captures the age-specific effects of living near gold-suitable locations in periods with higher international gold prices. This is important as both access and returns to schooling might differ across these age groups.

4.2 Years of schooling

For the stock measure, namely completed years of schooling, we are interested in the long-run effects of labor market shocks from childhood through adolescence. Hence, we restrict our sample to individuals aged 21-30 years. Combining price variation across cohorts with differential gold-suitability of a location, we estimate the following specification[16]:

$$\begin{aligned} Y_{ict} = \sum_{k=1}^{3} \beta_k (\text{Gold}_c \times \text{Price\_at\_Age}_k) + \\ \mu \, \text{Gold}_c + \sum_{k=1}^{3} \pi_k \, \text{Price\_at\_Age}_k + \mathbf{X}_i + FE_{region} + FE_t + \epsilon_{ict}, \end{aligned} \tag{2}$$

where Y_{ict} represents the total years of schooling completed by individual i living in cluster c and surveyed in year t. Price_at_Age_k represents the log average price of gold when an individual is 6-10, 11-15, or 16-20 years old. Gold_c indicates if cluster c is located within 10 km from the closest gold-suitable location. $\mathbf{X}_i$ is a vector of predetermined covariates at the individual and household levels: whether individual i is female, household size, whether household head is female, and whether the household lives in a rural area. Finally, FE_{region} and FE_t are region and year fixed effects, respectively. ϵ_{ict} is the error term clustered at the

[15] Table A3 reports the number of regions and clusters for the study countries as well as the respective average sample sizes. The regions generally correspond to administrative units at the GADM-1 level. As mentioned above, DHS surveys consist of repeated cross-sectional data for each country rather than longitudinal data, which means it is not possible to follow the same individuals or households over time.

[16] This is similar to the model that Sviatschi [2022] uses to estimate the long-term effects of shocks to coca prices during different schooling ages on adult incarceration.

DHS-cluster level.

The parameters of interest are β_k, which capture the long-term schooling effects of price shocks that individuals in gold-suitable areas experience when they are 6-10, 11-15, or 16-20 years old. Identification comes from the differences in gold price trajectories across the different cohorts combined with their exposure to gold-suitable locations. For instance, β_1, the coefficient on (Gold$_c$ × Price_at_Age$_{6_10}$), uses two comparison groups: individuals who belong to the same cohort but are not exposed to gold-suitable areas and individuals from other cohorts living in gold-suitable areas who do not experience a gold price shock when they are 6-10 years old.

It is important to note that, in both cases, our estimates potentially provide intention-to-treat effects of ASM on schooling since our definition of exposure is based on the *suitability* of a location for mining activities but not on the realized mining opportunities.[17] This means our estimates capture the effect of living in areas where artisanal gold mining could potentially emerge during gold price booms, rather than the effect of definite exposure to active mining. To the extent that only a fraction of geologically suitable areas experience actual mining activity, our estimates represent a lower bound of the true effect of ASM on schooling outcomes.

5 Results

5.1 Effect on school attendance

We begin by examining how gold price shocks affect contemporaneous school attendance. Panel A, Table 1 reports the main results, with columns 1–4 presenting the estimates for the age groups 6–10, 11–15, 16–20, and 21–25, respectively. All models use region and year fixed effects along with the individual and household-level covariates, as detailed in equation 1.

Overall, higher international gold price adversely affects the school attendance of adolescents living near gold-suitable areas. For instance, a one log point increase in the gold price—equivalent to the near-tripling observed between 2005 and 2010[18]—lowers school attendance by 2.6 percentage points for 11–15-year-olds ($p < 0.01$) and by 3.3 percentage points for 16–20-year-olds ($p < 0.01$) living within 10 km of a gold-suitable area. These magnitudes represent declines of roughly 3.4% and 7.3% relative to the respective sample means. Put differently, during a gold boom of this scale, around one in every 30 children in lower secondary school and one in every 14 youths in upper secondary school leave school in these high-exposure

[17] For privacy protection, DHS randomly displaces the clusters in a mean-zero way. This can introduce classical measurement error in our definition of exposure to gold-suitable areas and, in turn, may attenuate our estimates toward zero.

[18] An increase of 172%, to be precise.

areas. Given that artisanal mining employs over 60 million people across Africa [WorldBank, 2019], these individual-level effects can translate into substantial aggregate human capital losses.

In contrast, there is no detectable effect on younger children (ages 6–10), whose school attendance rates are relatively high, likely reflecting both the compulsory nature of primary education in most study countries and the lower physical capacity of very young children for the demanding work typical in artisanal mining [Carr, 2022, Bansah and Adonteng-Kissi, 2025]. We also find no significant effects on the oldest group (21–25), most of whom may have already completed their initial education.

Using two-year age groups instead of five-year age groups, Figure 2 reports the corresponding estimates, which show that the declines in attendance are driven by ages 12-19.

Two features of these patterns are noteworthy. First, the concentration of effects in the 12–19 age range (Figure 2) aligns with the idea that older adolescents face both a higher opportunity cost of time and a greater set of physically feasible tasks in artisanal mining. Second, the absence of effects on the 21–25 group provides a useful placebo: this cohort is unlikely to be on the margin of leaving school for low-skill work, so any estimated effect here would suggest unobserved confounding.

We investigate heterogeneity along two key dimensions: gender of the child and the educational attainment of the household head, which we use as a proxy for the household's pre-existing socioeconomic status.[19] Gender is a particularly relevant factor, as boys may possess a comparative advantage in mining activities that are typically brawn-intensive, potentially making them more responsive to labor market shocks in this sector. In contrast, the household's socioeconomic position may shape which underlying mechanisms predominate—whether the income effect, which can relax budget constraints and enable continued schooling, or the opportunity cost channel, whereby the returns to child labor become relatively more attractive and draw children out of school.

Using the same specification as above, columns 1-4 in Panel B investigate gender heterogeneity in the effects of gold price shocks. Broadly, we do not find any significant gender differences for any of the age groups. Panel C, on the other hand, shows that attendance declines are larger among adolescents living in households where the head has no formal education (37% of the sample). In particular, among early adolescents aged 11–15 years, the

[19] Two factors limit our ability to conduct heterogeneity analysis at the household level. First, we are working with a repeated cross-sectional design, which precludes the use of baseline characteristics. Second, many of the household characteristics available in these repeated cross-sections are likely themselves affected by the treatment (for example, household wealth, which Girard et al. [2022] has shown tends to increase in years with high prices). One household characteristic that is less likely to suffer from this issue, and that can serve as a proxy for pre-existing socioeconomic conditions, is the educational attainment of the household head, whose schooling would have been completed before the onset of any price shocks.

decline in attendance is roughly twice as large in these households. This provides suggestive evidence that the opportunity cost mechanism may be more important for poorer households.

While the DHS does not track detailed labor market outcomes for children under 15, evidence from older cohorts supports this interpretation. Using the sample of 16 to 25-year-olds, Table A4 (Columns 1-2) estimates equation 1 with employment as an outcome, i.e., whether an individual has been employed in the last 12 months, excluding household labor.[20] We find an increase in employment in years with higher gold prices among individuals aged 16-20 years who live in gold-suitable areas – by 3.3 percentage points ($p < 0.01$; 15% of this age group's sample mean). Interestingly, this matches, in absolute value, the estimate for attendance for this group earlier (Column 3, Panel A, Table 1). We also see an increase in employment, albeit smaller in both absolute and relative terms, for the ages 21-25. [21]

Overall, the results from this section point to economically meaningful reductions in school attendance during gold price booms, concentrated among adolescents in poorer households, with suggestive evidence of direct reallocation of time from schooling to work.

5.2 Robustness

In what follows, we subject our results to a battery of sensitivity and robustness checks.

5.2.1 Alternative definitions of exposure to gold-suitable areas

First, as an alternative measure of exposure to gold-suitable areas, we estimate our preferred specification (equation 1) replacing the indicator variable, Gold_c, with distance to the nearest gold-suitable region (in log terms). The estimates, reported in Panel A, Table A5, are consistent with our main results in terms of relative magnitude across the different age groups and retain statistical significance.

Second, we redefine treatment groups based on finer distance thresholds to the nearest gold-suitable locations. Specifically, we restrict the control group to clusters situated more than 30 kilometers from any gold-suitable area, selecting this cutoff to ensure adequate control sample availability across all countries. We then partition the treatment clusters into three mutually exclusive distance bands reflecting increasing proximity to potential gold deposits: 0–10 km, 10–20 km, and 20–30 km. Figure A5 presents the corresponding results. Reassuringly, for households in the 20–30 km band, the estimated effects for the 11–15 and

[20] Note that this information is available for a subset of individuals who were surveyed separately. The attendance information, on the other hand, comes from the household roster that is more comprehensive.

[21] Ideally, we would analyze sector-specific employment. However, DHS does not consistently collect granular data on the sector of employment. Among the broad sectors that DHS surveys have information on for the study countries, 'skilled' and 'unskilled labor' probably best match the jobs in ASM. In Columns 3-4 in Table A4, we use employment in these sectors as an outcome. The estimates suggest that over 12% (16-20-year-olds) and 50% (21-25-year-olds) of the increases in overall employment are driven by employment in these sectors.

16–20 age groups diminish in magnitude and become statistically insignificant, suggesting that the estimated impacts are concentrated among populations with the greatest exposure to gold-suitable locations.

Lastly, we redefine the distance to the nearest gold-suitable location by restricting it to within-country commutes, as frequent cross-border travel may not be feasible in some countries. This changes the treatment status of a few clusters that are close to borders (see Figure A2 for an illustrative example). However, results from this exercise (see Panel B, Table A5) are broadly similar to the benchmark estimates.

5.2.2 Migration

Another identification concern is endogenous permanent migration, where poorer, less-educated households might migrate to gold-suitable areas specifically to participate in mining activities. Such selective migration would introduce a downward bias in our estimates, leading us to overestimate the adverse effects on school attendance.

DHS migration data is insufficient for comprehensively addressing this concern. Migration information is available for only 8 of our 14 study countries and is limited to individuals aged 15 or older surveyed in the men's or women's modules, excluding the broader household roster. Moreover, DHS surveys define household members as those who usually reside in the household, systematically excluding seasonal migrants who maintain primary residence elsewhere while temporarily working in mining areas.

This limitation is particularly problematic given the seasonal nature of artisanal and small-scale mining (ASM). Bazillier and Girard [2020] demonstrate that ASM activities in Burkina Faso are highly seasonal, with extractive work peaking during the dry season when agricultural labor demands are minimal. Their analysis reveals notable quarterly variation in the share of workers in the extractive sector, indicating temporary migration patterns that remain invisible to standard DHS surveys.

Given these data limitations, we examine changes in household composition to detect migration effects more robustly. If permanent in-migration were driving our results, we should observe systematic demographic shifts in resident households during gold-price booms: larger household sizes, higher shares of young adult males, or lower educational attainment among household heads.

We therefore re-estimate equation 1 using household demographic characteristics as outcomes: head's years of education and gender, household size, female share, and age-group shares we study (6-10, 11-15, 16-20, 21-25). The coefficients, reported in Table A6, are uniformly small and statistically insignificant, with only a marginal reduction in the 6-10 age share.

This evidence aligns with the predominantly seasonal rather than permanent nature of artisanal mining. ASM follows agricultural cycles, with households using mining to diversify income sources without permanently abandoning farming [Bazillier and Girard, 2020, Werthmann, 2017]. During the rainy season, artisanal mining often becomes dangerous or legally prohibited due to mine collapse risks, forcing miners to return to their home communities. This seasonality, combined with the informal and uncertain nature of mining income, encourages circular rather than permanent migration.

The absence of compositional changes in our data, combined with documented ASM seasonality, suggests that the adverse schooling impacts we identify reflect behavioral responses of incumbent households rather than inflows of households with different educational preferences or characteristics.

5.2.3 Industrial mining and conflict

To ensure that the schooling effects we estimate are not an artifact of industrial-mine spillovers, we conduct two progressively stricter tests, with the results summarized in Figure 3 and detailed in Table A7.

First, using the S&P Global / SNL Metals & Mining database assembled by Berman et al. [2017], we restrict the sample to DHS rounds that fall within the SNL coverage window (2000–2010) (black-shaded estimates in Figure 3; Panel A, Table A7). We then exclude, in turn, clusters with an *active* industrial gold mine within 100 km in the survey year (blue-shaded estimates; Panel C, Table A7) and clusters that have ever had such a mine within that distance during any year between 2000 and 2010 (green-shaded estimates; Panel D, Table A7). Across these specifications, the point estimates remain virtually unchanged.

Second, we repeat the exercise using the machine-learning (ML) measures of artisanal and industrial mining from Rigterink et al. [2025]. These measures are based on a random-forest classifier trained on artisanal-mine censuses from eastern DRC, western Tanzania, and Burkina Faso, combined with continent-wide geological covariates—bedrock age and lithology, surface rock type, fault lines, and aeromagnetic anomalies—to predict where artisanal mining of gold, diamonds, "3T" minerals (tin–tungsten–tantalum), and "2C" minerals (copper–cobalt) is technically feasible. Out-of-sample accuracies range from 72% to 93%. Overlaying these suitability maps with the SNL industrial-mine layer, they show that price shocks increase conflict mainly where large-scale mining (LSM) and artisanal-scale mining (ASM) overlap, with 31–55% of the overall mining–conflict link attributable to violent LSM–ASM competition. Using these ML grids, we first replace the Girard et al. [2022] gold-suitability measure with the

ML-based suitability measure (red-shaded estimates; Panel B, Table A7), and then exclude clusters located in cells predicted to host both ASM and an industrial gold mine in the survey year (purple-shaded estimates; Panel E, Table A7) before re-estimating the benchmark. The key conclusions remain robust.

These two layers of evidence—industrial-mine proximity and ML-predicted ASM–LSM overlap—show that our main findings are not entirely driven by industrial mining or by the conflict channel documented in Berman et al. [2017] and Rigterink et al. [2025].

5.2.4 Placebo tests

Finally, we conduct a placebo test to assess the robustness of our inference. The test proceeds in two stages: first, we randomly reassign gold-suitability status to 43% of clusters across 100 iterations, preserving the original proportion of gold-suitable clusters in our sample. Second, for each random allocation, we permute the gold price vector 10 times, generating 1,000 total iterations. Figure A6 reports the relevant results. This alternative attempt at inference yields the same conclusions. The resulting distributions of coefficient estimates are centered around zero, indicating no systematic effect under random assignment, and the original estimates are highly statistically significant when compared to these placebo distributions.

5.2.5 Canonical two-period difference-in-differences

Finally, given the persistently high gold price in the latter part of the study period, we estimate a canonical two-period difference-in-differences model, splitting the time periods into low-price (before 2007) and high-price (2007 and onward). Panel D in Table A5 reports the corresponding estimates, which are broadly similar to those from our preferred specification.

5.2.6 Within-cluster comparison and flexible trends

As noted earlier, the absence of panel data precludes the use of cluster fixed effects to make within-cluster comparisons. In a setting with repeated cross-sections, such comparisons would require a within-cluster control group. Across both the main specification and a range of robustness checks, we find no evidence of schooling responses to gold price shocks among individuals aged 21–25. This is perhaps unsurprising, as their key schooling decision — whether to pursue tertiary education — is unlikely to be influenced by job opportunities in the artisanal mining sector. By this age, most individuals have completed secondary education and are considering further study aligned with longer-term career goals that require advanced qualifications. Given that artisanal mining jobs are low-skilled and physically demanding, they may be unattractive to this group, who likely perceive the opportunity cost of entering the sector as particularly high. Having already invested in their education, these individuals are less likely to forgo additional schooling for short-term employment in mining. As such, the 21–25 age group may serve as a credible within-cluster comparison group, allowing us to estimate models with cluster fixed effects.

We implement this approach in Table A8 using a triple-difference specification.[22] Column 1 includes cluster and year fixed effects. Columns 2 and 3 further allow for more flexible temporal trends by replacing year fixed effects with country-by-year and region-by-year fixed effects, respectively, in addition to cluster fixed effects. Reassuringly, the estimates for the adolescents, albeit smaller, retain their statistical and practical significance across all these—arguably more demanding—specifications.

5.3 Long-run impacts on completed schooling

What are the long-term effects of labor-market shocks during childhood and adolescence? Using equation 2, we address this question using young adults aged 21-30 years living in gold-suitable areas who experience different trajectories of gold prices during their childhood. Note that, this age restriction, while essential to ensure that a substantial share has completed their schooling investments, excludes younger individuals who experienced the gold price surge around 2010 but are not yet old enough to be included in this analysis. This also limits the scope for comparing these results with those for school attendance. We acknowledge this limitation.[23]

Table 2 reports the relevant results. Column 1 uses the full sample whereas Columns 2 and 3 use the male and female sub-samples, respectively. Price shocks earlier in childhood appear to have higher long-term effects. One log point higher gold price when an individual living in a gold-suitable area was 6-10 years old leads to a decline in completed years of schooling by almost half a year ($p < 0.1$; 7.9% of the sample mean). The corresponding estimates for shocks during ages 11-15 and ages 16-20 are reductions of 0.25 years ($p < 0.05$; 4% of the sample mean) and 0.146 years, respectively ($p < 0.1$; 2.3% of the sample mean).

[22] In particular:

$$\begin{aligned} Y_{icgt} = \sum_{g=1}^{3} \alpha_g \text{ Gold}_c \times \text{Price}_{t-1} \times \text{Age}_g + \sum_{g=1}^{3} \gamma_g \text{ Price}_{t-1} \times \text{Age}_g + \\ \nu \text{ Gold}_c \times \text{ Price}_{t-1} + \sum_{g=1}^{3} \lambda_g \text{ Gold}_c \times \text{Age}_g + \sum_{g=1}^{3} \theta_g \text{ Age}_g + \mathbf{X}_i + FE_{cluster} + FE_t + \epsilon_{ict}, \end{aligned} \tag{3}$$

where Y_{icgt} is the outcome of individual i who lives in cluster c, belongs to the age group g, and responds to the survey in year t. Age_g represents one of the age groups 6-10, 11-15, and 16-20 years. The omitted age group is 21-25.

[23] Another caveat relates to migration. Migration rates are higher for this age group compared to their younger counterparts. However, we do not have sufficiently granular information on the origin of these young adults. This may introduce noise to our measures of their exposure to gold-suitable areas when they were growing up.

The gender-specific estimates in Columns 2 and 3 reveal a suggestive pattern of differential vulnerability. For boys, the largest penalty occurs when price shocks are experienced in late adolescence (16–20 years), consistent with their greater likelihood of taking up physically demanding mining work at that age. For girls, the schooling loss is more pronounced when high gold prices occur earlier, during ages 6–15, a period when they may be drawn into auxiliary mining roles or increased household responsibilities in response to rising labor demand in mining communities.

These results suggest that the contemporaneous declines in attendance in response to higher prices that we observe in Section 5.1 may translate into long-term losses in completed years of schooling. In settings where average schooling is already low—just over six years—losing a quarter to half a year of education represents a substantive loss of human capital. Figure A7 corroborates this pattern using a canonical event-study design. Defining the cohort born in 1990—age 17 in 2007, when gold prices begin their sharp rise—as the first to experience relatively higher prices over the study period, we find that younger cohorts born after 1990 complete significantly fewer years of schooling, consistent with the long-run effects implied by our main estimates.

6 Conclusion

This paper examines how artisanal and small-scale gold mining (ASM) in sub-Saharan Africa affects human capital investment. Exploiting variation in potential ASM activity, we find that resource booms reduce schooling among adolescents and young adults, with larger effects for poorer households. These results suggest that the income gains from ASM documented by Girard et al. [2022] may be insufficient to offset higher opportunity costs, especially when jobs offer low returns to education, echoing Atkin [2016] evidence from low-skill manufacturing. By contrast, contexts where new jobs reward education [Adukia et al., 2020] can yield the opposite effect. Weak enforcement of child labor laws may further amplify schooling losses.

Policy responses that lower the opportunity cost of schooling—such as conditional cash transfers or stricter labor regulation—could mitigate these effects, particularly for the poorest. More broadly, our findings contribute to the resource curse literature by highlighting human capital erosion as a channel through which resource booms can slow long-run development. While ASM's impacts are context-specific, the underlying mechanism—a shift from schooling to low-skill work during economic booms—is likely relevant in other low-income labor markets.

References

Alberto Abadie, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge. When should you adjust standard errors for clustering? *The Quarterly Journal of Economics*, 138(1):1–35, 2023.

Anjali Adukia, Sam Asher, and Paul Novosad. Educational investment responses to economic opportunity: evidence from indian road construction. *American Economic Journal: Applied Economics*, 12(1):348–76, 2020.

Pelle Ahlerup, Thushyanthan Baskaran, and Arne Bigsten. Gold mining and education: a long-run resource curse in africa? *The Journal of Development Studies*, 56(9):1745–1762, 2020.

Lao-Tzu Allan-Blitz, Charlotte Goldfine, and Timothy B Erickson. Environmental and health risks posed to children by artisanal gold mining: A systematic review. *SAGE Open Medicine*, 10:20503121221076934, 2022.

David Atkin. Endogenous skill acquisition and export manufacturing in mexico. *American Economic Review*, 106(8):2046–2085, 2016.

Kenneth Joseph Bansah and Obed Adonteng-Kissi. Child labor in artisanal and small-scale mining: Implications for health, development and poverty. *The Extractive Industries and Society*, 21:101577, 2025.

Natalie Bau, Martin Rotemberg, Manisha Shah, and Bryce Steinberg. Human capital investment in the presence of child labor. 2020.

Remi Bazillier and Victoire Girard. The gold digger and the machine. evidence on the distributive effect of the artisanal and industrial gold rushes in burkina faso. *Journal of Development Economics*, 143:102411, 2020.

Nicolas Berman, Mathieu Couttenier, Dominic Rohner, and Mathias Thoenig. This mine is mine! how minerals fuel conflicts in africa. *American Economic Review*, 107(6):1564–1610, 2017.

Kirill Borusyak, Peter Hull, and Xavier Jaravel. Quasi-experimental shift-share research designs. *The Review of Economic Studies*, 89(1):181–213, 2022.

Elizabeth Heger Boyle, Miriam King, and Matthew Sobek. Ipums-demographic and health surveys: Version 9, 2022.

Deborah Fahy Bryceson and Sara Geenen. Artisanal frontier mining of gold in africa: Labour transformation in tanzania and the democratic republic of congo. *African Affairs*, 115(459): 296–317, 2016. doi: 10.1093/afraf/adw013.

Deborah Fahy Bryceson and Jesper Bosse Jønsson. Gold digging careers in rural east africa: Small-scale miners' livelihood choices. *World Development*, 38(3):379–392, 2010. doi: 10.1016/j.worlddev.2009.09.003.

Olivia G Carr. Promoting priorities: Explaining the adoption of compulsory schooling laws in africa. *International Journal of Educational Development*, 88:102523, 2022.

Tieguhong Julius Chupezi, Verina Ingram, and Jolien Schure. *Impacts of artisanal gold and diamond mining on livelihoods and the environment in the Sangha Tri-National Park landscape.* CIFOR, 2009.

Esther Duflo, Pascaline Dupas, and Michael Kremer. The impact of free secondary education: Experimental evidence from ghana. Technical report, National Bureau of Economic Research, 2021.

Eric V Edmonds and Nina Pavcnik. International trade and child labor: cross-country evidence. *Journal of international Economics*, 68(1):115–140, 2006.

Effigis. Cartographie des principaux sites miniers artisanaux. Technical report, Projet d'Appui au Développement du Secteur Minier du Burkina Faso (PADSEM), Ouagadougou, Burkina Faso, 2018.

Kevin N Funoh. *The impacts of artisanal gold mining on local livelihoods and the environment in the forested areas of Cameroon*, volume 150. CIFOR, 2014.

Sara Geenen. A dangerous bet: The challenges of formalizing artisanal mining in the DRC. *Resources Policy*, 37(3):322–330, 2012. doi: 10.1016/j.resourpol.2012.02.004.

Sara Geenen, Nik Stoop, and Marijke Verpoorten. How much do artisanal miners earn? an inquiry among congolese gold miners. *Resources Policy*, 70:101893, 2021.

Victoire Girard, Teresa Molina-Millán, Guillaume Vic, et al. Artisanal mining in africa. Technical report, Universidade Nova de Lisboa, Nova School of Business and Economics, NOVAFRICA, 2022.

Richard J Goldfarb, Anne-Sylvie André-Mayer, Simon M Jowitt, and Gavin M Mudd. West africa: The world's premier paleoproterozoic gold province. *Economic Geology*, 112(1):123–143, 2017.

Martin Guenther. Local effects of artisanal mining: Empirical evidence from ghana. In *Presentation at the international conference'environmental economics: a focus on natural ressources', orléans*, 2018.

Marieke Heemskerk. Livelihood decision-making and environmental degradation: Small-scale gold mining in the suriname amazon. *Society & Natural Resources*, 15(4):327–344, 2002. doi: 10.1080/089419202753570819.

Thomas Hentschel. Artisanal and small-scale mining: challenges and opportunities. 2003.

Gavin Hilson. Farming, small-scale mining and rural livelihoods in sub-saharan africa: A critical overview. *The Extractive Industries and Society*, 3(2):547–563, 2016. doi: 10.1016/j.exis.2016.02.003.

Gavin Hilson and Chris Garforth. 'agricultural poverty' and the expansion of artisanal mining in sub-saharan africa: Experiences from southwest mali and southeast ghana. *Population Research and Policy Review*, 31(3):435–464, 2012. doi: 10.1007/s11113-012-9229-6.

Gavin Hilson and Roy Maconachie. Artisanal and small-scale mining and the sustainable development goals: Opportunities and new directions for sub-saharan africa. *Geoforum*, 111:125–141, 2020.

Gavin Hilson and James McQuilken. Four decades of support for artisanal and small-scale mining in sub-saharan africa: A critical review. *The Extractive Industries and Society*, 1(1): 104–118, 2014. doi: 10.1016/j.exis.2014.01.002.

Gavin M Hilson. *The socio-economic impacts of artisanal and small-scale mining in developing countries*. CRC Press, 2003.

Jennifer Hinton, Marcello M Veiga, and Christian Beinhoff. Women and artisanal mining: Gender roles and the road ahead. *The socio-economic impacts of artisanal and small-scale mining in developing countries*, pages 149–188, 2003.

ILO. Child labor in mining and global supply chains. 2019.

ILO. Children's work in the artisanal and small-scale gold mining sector in timor-leste: Baseline research report, 2021.

Robert Jensen. Agricultural volatility and investments in children. *American Economic Review*, 90(2):399–404, 2000.

Jesper Bosse Jønsson and Deborah Fahy Bryceson. Rushing for gold: Mobility and small-scale mining in east africa. *Development and Change*, 40(2):249–279, 2009. doi: 10.1111/j.1467-7660.2009.01514.x.

Andreas Kotsadam and Anja Tolonen. African mining, gender, and local employment. *World Development*, 83:325–339, 2016.

Alina Kovalenko. Natural resource booms, human capital, and earnings: Evidence from linked education and employment records. *American Economic Journal: Applied Economics*, 15(2): 184–217, 2023.

Kuntala Lahiri-Dutt. Digging to survive: Women's livelihoods in south asia's small mines and quarries. *South Asian Survey*, 15(2):217–244, 2008. doi: 10.1177/097152310801500204.

Robert E Lucas Jr. On the mechanics of economic development. *Journal of monetary eco-*

nomics, 22(1):3–42, 1988.

Roy Maconachie and Tony Binns. 'farming miners' or 'mining farmers'? diamond mining and rural development in post-conflict sierra leone. *Journal of Rural Studies*, 23(3):367–380, 2007. doi: 10.1016/j.jrurstud.2007.01.003.

Roy Maconachie and Gavin Hilson. Artisanal gold mining: A new frontier in post-conflict sierra leone? *The Journal of Development Studies*, 47(4):595–616, 2011. doi: 10.1080/00220381003599402.

N Gregory Mankiw, David Romer, and David N Weil. A contribution to the empirics of economic growth. *The quarterly journal of economics*, 107(2):407–437, 1992.

Fritz Morgane, James McQuilken, Nina Collins, and Fitsum S Weldegiorgis. Global trends in artisanal and small-scale mining: A review of key numbers and issues. 2018.

Nathan Nunn and Nancy Qian. The potato's contribution to population and urbanization: evidence from a historical experiment. *The quarterly journal of economics*, 126(2):593–650, 2011.

Dylan O'Driscoll. Overview of child labour in the artisanal and small-scale mining sector in asia and africa. 2017.

Adrian Poignant. Small-scale mining and agricultural development: Evidence from north-western tanzania. *Available at SSRN 4082121*, 2022.

Anouk S Rigterink, Tarek Ghani, Juan S Lozano, and Jacob N Shapiro. Mining competition and violent conflict in africa: Pitting against each other. *The Journal of Politics*, 87(1):000–000, 2025.

Jeffrey D Sachs and Andrew M Warner. The curse of natural resources. *European economic review*, 45(4-6):827–838, 2001.

Rafael J Santos. Blessing and curse. the gold boom and local development in colombia. *World Development*, 106:337–355, 2018.

Manisha Shah and Bryce Millett Steinberg. Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy*, 125(2):527–561, 2017.

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

Petra Tschakert and Kamini Singha. Contaminated identities: Mercury and marginalization in ghana's artisanal mining sector. *Geoforum*, 38(6):1304–1321, 2007. doi: 10.1016/j.geoforum.2007.05.002.

Katja Werthmann. The drawbacks of privatization: Artisanal gold mining in burkina faso

1986–2016. *Resources Policy*, 52:418–426, 2017.

WorldBank. Shining a light on a hidden sector. *World Bank*, 2019.

7 Tables

Table 1: ASM and school attendance

	Dependent variable:			
	School Attendance			
	6-10	11-15	16-20	21-25
	(1)	(2)	(3)	(4)
Panel A: ASM and school attendance				
gold×price	0.001	-0.026^{***}	-0.033^{***}	-0.001
	(0.006)	(0.006)	(0.006)	(0.004)
Observations	419,684	332,315	261,979	203,157
Panel B: Heterogeneity by gender				
gold×price	0.001	-0.030^{***}	-0.028^{***}	-0.001
	(0.007)	(0.007)	(0.007)	(0.004)
gold×price×male	0.0003	0.007	-0.010	0.002
	(0.005)	(0.006)	(0.008)	(0.006)
Observations	419,684	332,315	261,979	203,157
Panel C: Heterogeneity by household head's education				
gold×price	-0.0001	-0.015^{***}	-0.032^{***}	-0.002
	(0.005)	(0.005)	(0.007)	(0.005)
gold×price×no_education	0.008	-0.021^{**}	-0.001	0.003
	(0.009)	(0.009)	(0.010)	(0.007)
Observations	415,084	328,505	258,934	201,002
Covariates	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
	School Attendance: Mean (SD)			
	6-10	11-15	16-20	21-25
All	0.69	0.77	0.45	0.11
	(0.46)	(0.41)	(0.49)	(0.32)
Male	0.70	0.78	0.52	0.16
	(0.46)	(0.41)	(0.49)	(0.37)
Female	0.69	0.76	0.38	0.08
	(0.46)	(0.42)	(0.48)	(0.27)

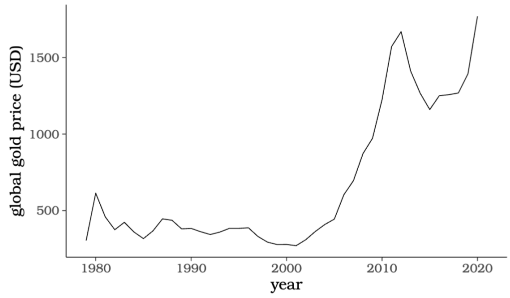
Note: Estimates based on equation 1, separately for the four age groups. The sample includes individuals aged 6 to 25 years surveyed across 45 waves of Demographic and Health Surveys (DHS) covering 14 countries in SSA and spanning 2000-2018. The outcome is school attendance, i.e., whether an individual is attending school in the year of the survey. The 'price' variable is the global gold price in US dollars in logs, lagging by a year. The 'gold' variable indicates whether a cluster is located within 10 km of the nearest gold-suitable location. 'male' indicates male individuals. 'no_education' indicates whether the household's head has zero years of schooling (37% of the sample). Standard errors clustered at the DHS cluster level are in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Table 2: ASM and long-run effects on completed schooling

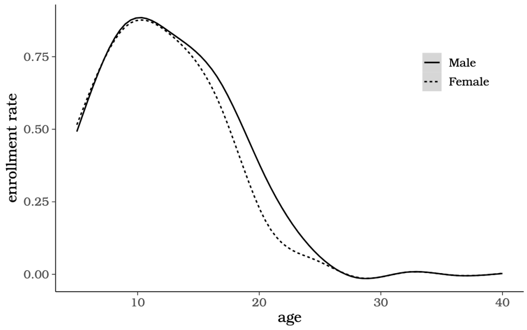
	Dependent variable:		
	Years of Schooling		
	All	Male	Female
	(1)	(2)	(3)
gold×ln_avgprice_6_10	−0.493*	−0.324	−0.609*
	(0.278)	(0.393)	(0.319)
gold×ln_avgprice_11_15	−0.250**	−0.067	−0.389***
	(0.105)	(0.143)	(0.122)
gold×ln_avgprice_16_20	−0.146*	−0.191*	−0.070
	(0.084)	(0.110)	(0.091)
Region FE	✓	✓	✓
Year FE	✓	✓	✓
Covariates	✓	✓	✓
Observations	427,588	188,652	238,936

Note: Estimates based on equation 2. The sample in column (1) includes individuals aged 21 to 30 years who are surveyed across 45 waves of Demographic and Health Surveys (DHS) covering 14 countries in SSA and spanning the period 2000-2018, while column 2 (3) includes males (females) only. The outcome is completed years of schooling. The average years of schooling for the sample is 6.24 (sd 5.04). For the male (female) sample, the average is 7.15 (5.53), and the standard deviation is 4.98 (4.97). The 'gold' variable indicates whether a cluster is located within 10 km of the nearest gold-suitable location. The 'ln_avgprice_6_10' variable, for example, captures the average of the global gold price in US dollars in logs when these individuals were 6-10 years old. The standard errors are clustered at the DHS cluster level and are reported in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

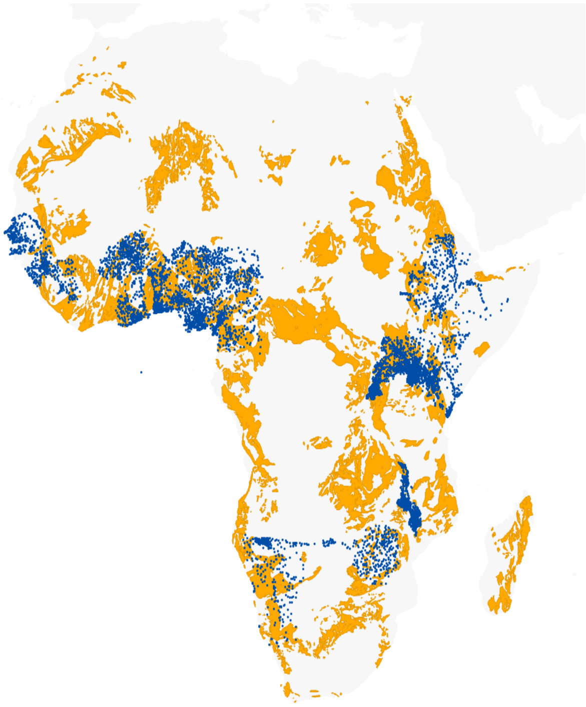
8 Figures



a Trend in global gold price



b School attendance by age and gender



c Gold-suitability & DHS clusters

Figure 1

Note: Panel (a) plots the global gold price in US dollars over the period 1980-2020. Panel (b) plots the school attendance rates by age, separately for males and females. The solid (dotted) line shows the age profile for males (females). The sample comprises the latest available waves of Demographic and Health Surveys (DHS) covering 14 countries in SSA. Panel (c) plots a map of Africa highlighting regions with bedrock suitable for gold mining (in gold) overlaid with the GPS coordinates of DHS clusters from the countries included in the sample (in blue).

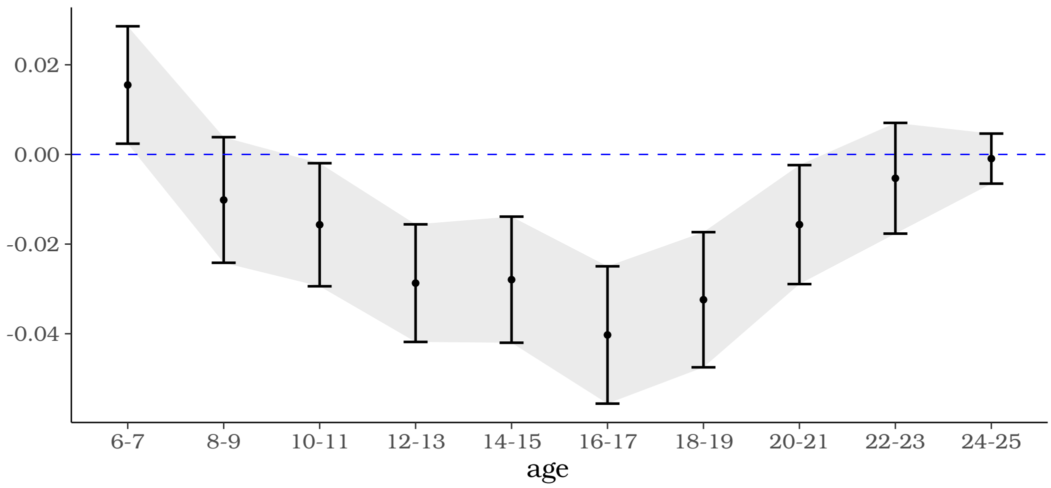


Figure 2: Effects on school attendance across ages

Note: Using equation 1, the figure displays the estimated effects (point estimates and 95% confidence intervals) on school attendance for each two-year age group between ages 6 and 25. The standard errors are clustered at the DHS cluster level.

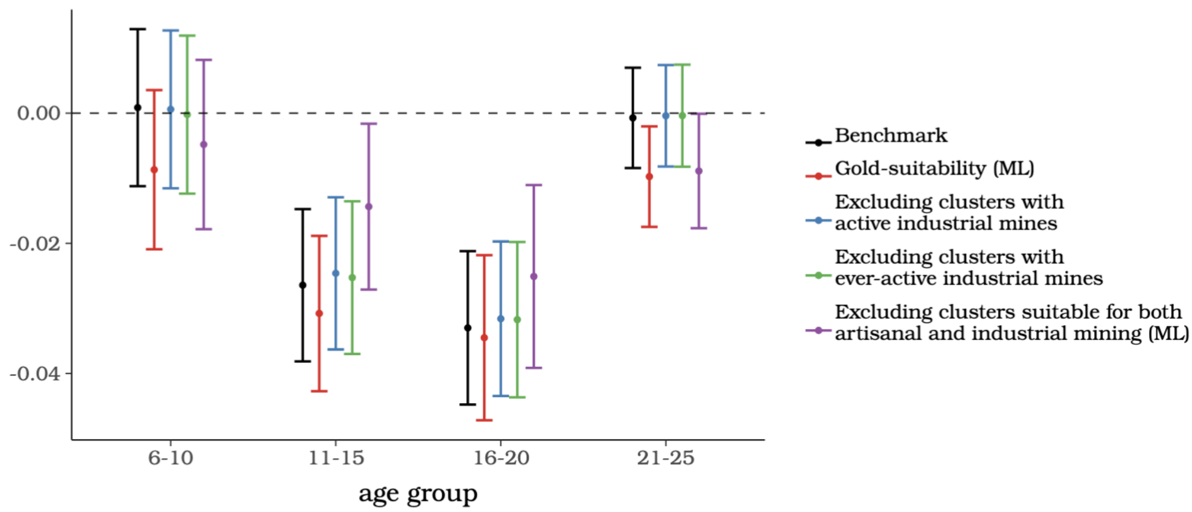


Figure 3: ASM and school attendance: Robustness to industrial mining and conflict

Note: The figure displays estimates for the effects on school attendance, separately for four age groups, and with the following sample definitions. Black points and confidence intervals represent the benchmark specification. Red points represent estimates using an alternative treatment definition based on proximity to gold-suitable locations identified through a machine learning (ML) classification from Rigterink et al. [2025]. Blue points use the original definition of gold-suitability but exclude clusters located within 100 kilometers of an active industrial gold mine in the same year the cluster was surveyed. Green points exclude clusters that have ever had an active mine operating within 100 kilometers during any year in the study period. Purple points exclude clusters that are classified as suitable for both industrial and artisanal gold mining through the machine learning (ML) classifications from Rigterink et al. [2025]. The corresponding sample sizes are reported in Table A7

Appendix

Table A1: Sample size by DHS wave

country	year	observations	country	year	observations
Senegal	2005	30,144	Nigeria	2003	15,791
	2010	34,466		2008	65,487
	2015	18,918		2013	73,664
	2016	19,086		2018	75,183
	2017	35,987			
			Malawi	2000	29,896
Ethiopia	2000	32,165		2004	5,981
	2005	32,433		2010	53,885
	2011	35,763		2016	58,621
	2016	34,218			
			Uganda	2001	16,188
Kenya	2003	17,492		2006	19,701
	2008	17,100		2011	21,227
	2014	71,779		2016	41,850
Ghana	2003	11,582	Guinea	2005	11,019
	2008	20,356		2012	20,657
	2014	18,391		2018	22,128
Rwanda	2005	22,417	Namibia	2000	14,004
	2010	26,293		2006	18,357
	2014	25,056		2013	17,229
Zimbabwe	2005	8,898	Benin	2001	13,788
	2010	18,307		2011	38,132
	2015	18,685			
			Burkina Faso	2003	28,457
Cameroon	2004	23,832		2010	34,685
	2011	31,571			

Note: The table shows the sample size for individuals aged 6 to 25 who are surveyed across 45 waves of Demographic and Health Surveys (DHS) covering 14 countries in SSA and spanning the period 2000-2018.

Table A2: Summary Statistics

	Sample	Distance to Gold-suitable Land <=10 km	>10 km	Sample	Distance to Gold-suitable Land <=10 km	>10 km
	age group: 6-10			age group: 16-20		
N	427,275	178,967	240,717	266,470	108,071	153,908
Female (%)	49.5	49.6	49.5	51.8	51.3	52.2
Rural (%)	75.2	76.7	73.9	66.5	68.5	64.9
HH-head female (%)	23.9	23.3	27.5	27.8	28.2	27.5
HH size	7.91	7.26	8.38	7.40	6.70	7.89
	age group: 11-15			age group: 21-25		
N	338,221	141,163	191,152	206,502	84,867	118,290
Female (%)	49.7	49.7	49.8	55.6	55.4	55.6
Rural (%)	72.5	74.5	70.9	62.7	64.6	61.2
HH-head female (%)	27.3	28.1	26.7	23.0	23.0	23.2
HH size	7.90	7.29	8.35	6.40	5.60	6.95

Note: Summary statistics for the different age groups stratified by exposure to gold-suitable locations. The sample comprises 45 waves of Demographic and Health Surveys (DHS) covering 14 countries in SSA. See Table A1 for details.

Table A3: Sample Description of Aggregation Units

Country	Region	Cluster	N	N (per Region)	N (per Cluster)
Benin	12	991	51,920	4,327	52
Burkina Faso	13	937	63,142	4,857	67
Cameroon	10	1,040	55,403	5,540	53
Ethiopia	11	2,251	134,579	12,234	60
Ghana	16	1,228	50,329	3,146	41
Guinea	8	983	53,804	6,726	55
Kenya	47	2,371	106,371	2,263	45
Malawi	28	2,745	148,383	5,299	54
Namibia	13	1,290	49,590	3,815	38
Nigeria	37	3,510	230,125	6,220	66
Rwanda	5	1,438	73,766	14,753	51
Senegal	14	1,566	138,599	9,900	89
Uganda	58	1,685	98,966	1,706	59
Zimbabwe	10	1,185	45,890	4,589	39

Note: The table presents, for each study country, the number of administrative regions and DHS clusters as well as the average number of sample respondents per each of these units across all survey rounds.

Table A4: ASM and employment

	Dependent variable:			
	Employment		Skilled & unskilled	
age groups	16-20	21-25	16-20	21-25
	(1)	(2)	(3)	(4)
gold×price	0.033***	0.013**	0.004***	0.007***
	(0.005)	(0.005)	(0.001)	(0.001)
Covariates	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	119,538	79,785	119,538	79,785

Note: Estimates based on equation 1, separately for the two age groups. The sample includes individuals aged 16–20 (21–25) in columns 1 and 3 (2 and 4), surveyed across 45 waves of Demographic and Health Surveys (DHS) covering 14 Sub-Saharan African countries spanning the period 2000-2018. The outcome variable in columns 1–2 indicates whether an individual has been employed in the past 12 months (excluding household labor), and in columns 3–4, it indicates whether the individual has worked in an occupation characterized in the DHS data as 'skilled or unskilled labor'. The 'price' variable is the global gold price in US dollars in logs, lagging by a year. The 'gold' variable indicates whether a cluster is located within 10 km of the nearest gold-suitable location. Standard errors, clustered at the DHS cluster level, are reported in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A5: School Attendance and Gold Exposure: Alternative treatment definitions and clustering of standard errors

	Dependent variable: School Attendance			
age groups	6–10	11–15	16–20	21–25
	(1)	(2)	(3)	(4)
Panel A: Distance to the Nearest Gold-Suitable Location				
log_distance×price	−0.001	0.009***	0.011***	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Panel B: Within-Country Distance				
gold_bord×price	0.001	−0.026***	−0.033***	−0.001
	(0.006)	(0.006)	(0.006)	(0.004)
Panel C: Clustering at the Region Level				
gold×price	0.001	−0.026***	−0.033***	−0.001
	(0.009)	(0.009)	(0.009)	(0.007)
Panel D: Canonical Two-Period DiD				
gold×high_price	0.008	−0.027***	−0.026***	0.002
	(0.007)	(0.007)	(0.008)	(0.005)
Covariates	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	419,684	332,315	261,979	203,157

Note: Estimates are based on OLS regressions, separately for the four age groups. The sample includes individuals (with age groups specified in the column headers) surveyed across 45 waves of Demographic and Health Surveys (DHS) conducted in 14 Sub-Saharan African countries between 2000 and 2018. The outcome variable is school attendance, defined as whether an individual is attending school in the year of the survey. ***Panel A*** *applies the benchmark specification but replaces the proximity dummy with 'log_distance'—the logarithm of one plus the distance (in kilometers) to the nearest gold-suitable location.* ***Panel B*** *uses a proximity dummy defined within national borders ('gold_bord').* ***Panel C*** *uses the benchmark specification but clusters standard errors at the region level.* ***Panel D*** *estimates a canonical two-period difference-in-differences model using a post-2007 high-price dummy. Across all panels, 'price' is the global gold price in US dollars in logs, lagging by a year. The 'gold' variable indicates whether a cluster is located within 10 km of the nearest gold-suitable location. The standard errors are clustered at the DHS cluster level and are reported in parentheses.* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A6: ASM and household composition

	Dependent variable:							
	size	head_edyears	head_female	share_female	share_age_6_10	share_age_11_15	share_age_16_20	share_age_21_25
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
gold×price	−0.014	0.097	0.004	0.003	−0.004***	−0.001	−0.001	−0.0005
	(0.025)	(0.061)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Region FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	596,203	590,966	596,203	596,203	596,203	596,203	596,203	596,203
	Summary statistics							
	size	head_edyears	head_female	share_female	share_age_6_10	share_age_11_15	share_age_16_20	share_age_21_25
Mean	4.96	5.2	0.27	0.5	0.12	0.1	0.09	0.09
SD	3.26	5.13	0.44	0.26	0.15	0.14	0.17	0.19

Note: Estimates are based on equation 1. The sample includes individuals (with age groups specified in the column headers) surveyed across 45 waves of Demographic and Health Surveys (DHS) conducted in 14 Sub-Saharan African countries between 2000 and 2018. Each column corresponds to a different household-level outcome variable: total household size (column 1), years of education of the household head (2), indicator for female household head (3), share of females in the household (4), and shares of household members in four age groups—6–10, 11–15, 16–20, and 21–25 years old (columns 5–8). 'price' is the global gold price in US dollars in logs, lagging by a year. The 'gold' variable indicates whether a cluster is located within 10 km of the nearest gold-suitable location. The standard errors are clustered at the DHS cluster level and are reported in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A7: ASM and school attendance: Robustness to industrial mining and conflict

	Dependent variable: School Attendance			
	6-10	11-15	16-20	21-25
	(1)	(2)	(3)	(4)
Panel A: Benchmark (Panel A, Table 1)				
gold×price	0.001	-0.026***	-0.033***	-0.001
	(0.006)	(0.006)	(0.006)	(0.004)
Observations	419,684	332,315	261,979	203,157
Panel B: Gold-suitability [Rigterink et al., 2025]				
gold×price	-0.009	-0.031***	-0.035***	-0.010**
	(0.006)	(0.006)	(0.006)	(0.004)
Observations	427,262	338,211	266,464	206,499
Panel C: Excluding clusters near active industrial mines				
gold×price	0.001	-0.025***	-0.032***	-0.0004
	(0.006)	(0.006)	(0.006)	(0.004)
Observations	416,399	329,497	259,335	200,889
Panel D: Excluding clusters near ever-active industrial mines				
gold×price	-0.0002	-0.025***	-0.032***	-0.0004
	(0.006)	(0.006)	(0.006)	(0.004)
Observations	414,671	328,077	258,178	199,939
Panel E: Excluding clusters suitable for both ASM & industrial mining [Rigterink et al., 2025]				
gold×price	-0.005	-0.014**	-0.025***	-0.009**
	(0.007)	(0.006)	(0.007)	(0.004)
Observations	327,399	260,952	206,319	160,512
Covariates	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Note: Table corresponding to Figure 3 Estimates based on equation 1, separately for the four age groups. The benchmark sample includes individuals aged 6 to 25 years surveyed across 45 waves of Demographic and Health Surveys (DHS) covering 14 countries in SSA and spanning 2000-2018. The outcome is school attendance, i.e., whether an individual is attending school in the year of the survey. The 'price' variable is the global gold price in US dollars in logs, lagging by a year. The 'gold' variable indicates whether a cluster is located within 10 km of the nearest gold-suitable location. ***Panel A*** *presents the benchmark where 'gold' indicates clusters within 10 km of a gold-suitable location according to Girard et al. [2022].* ***Panel B*** *shows estimates using an alternative treatment definition based on proximity to gold-suitable locations identified through a machine learning (ML) classification from Rigterink et al. [2025].* ***Panel C*** *uses the main definition of gold-suitability but excludes clusters located within 100 kilometers of an active industrial gold mine in the same year the cluster was surveyed.* ***Panel D*** *excludes clusters that have ever had an active mine operating within 100 kilometers during any year in the study period.* ***Panel E*** *excludes clusters that are classified as suitable for both industrial and artisanal gold mining through the machine learning (ML) classification in Rigterink et al. [2025]. Standard errors clustered at the DHS cluster level are in parentheses.* * *p<0.1;* ** *p<0.05;* *** *p<0.01.*

Table A8: ASM and school attendance: Within-cluster comparison and flexible trends

	Dependent variable:		
	school attendance		
	(1)	(2)	(3)
gold×price×age_6_10	−0.001	−0.001	−0.001
	(0.009)	(0.009)	(0.009)
gold×price×age_11_15	-0.019^{**}	-0.019^{**}	-0.019^{**}
	(0.008)	(0.008)	(0.008)
gold×price×age_16_20	-0.012^{*}	-0.012^{*}	-0.012^{*}
	(0.007)	(0.007)	(0.007)
Cluster FE	✓	✓	✓
Year FE	✓		
Country×Year FE		✓	
Region×Year FE			✓
Covariates	✓	✓	✓
Observations	1,217,135	1,217,135	1,217,135

Note: This table estimates a triple-difference specification using Equation 3, where individuals aged 21–25 serve as a within-cluster comparison group. The coefficients report the differential effect of gold price shocks in gold-suitable areas for younger age groups (6–10, 11–15, and 16–20 years) relative to the 21–25 group. All specifications include cluster fixed effects. Column 1, in addition, includes year fixed effects; columns 2 and 3 replace these with country-by-year and region-by-year fixed effects, respectively. Standard errors clustered at the DHS cluster level are in parentheses. * *p<0.1;* ** *p<0.05;* *** *p<0.01.*

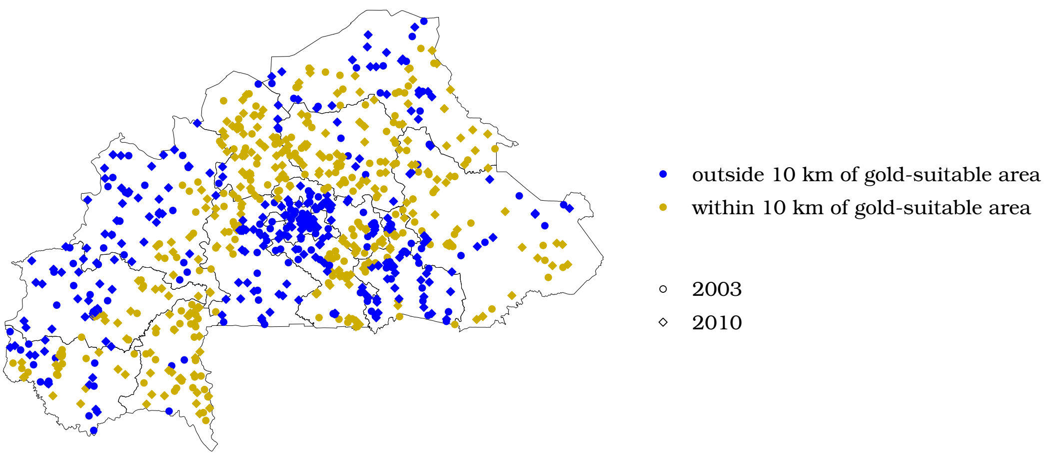


Figure A1: Location of treatment and control clusters in Burkina Faso

Note: As an example, this map displays the geographic location of DHS clusters in Burkina Faso for the years 2003 and 2010. Each point represents a cluster, with the color indicating whether the cluster lies within 10 kilometers of a gold-suitable location.

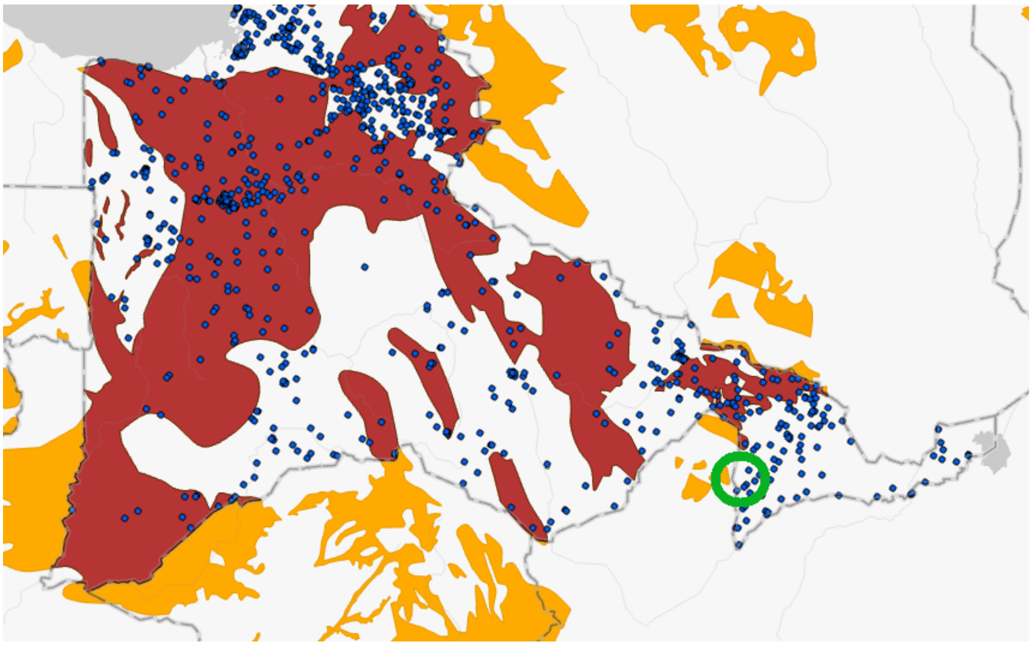


Figure A2: Illustrative example of accounting for country borders: Cameroon (rotated)

Note: The figure shows the map of Cameroon rotated 90 degrees. The blue dots represent the DHS clusters. The red areas are the gold-suitable locations within Cameroon whereas the yellow areas are those outside Cameroon. The clusters that are located within the green circle are considered to be in the Treatment group in the original analysis as they are within 10 km from the closest gold-suitable location. Taking the country's borders into account, these clusters are considered controls.

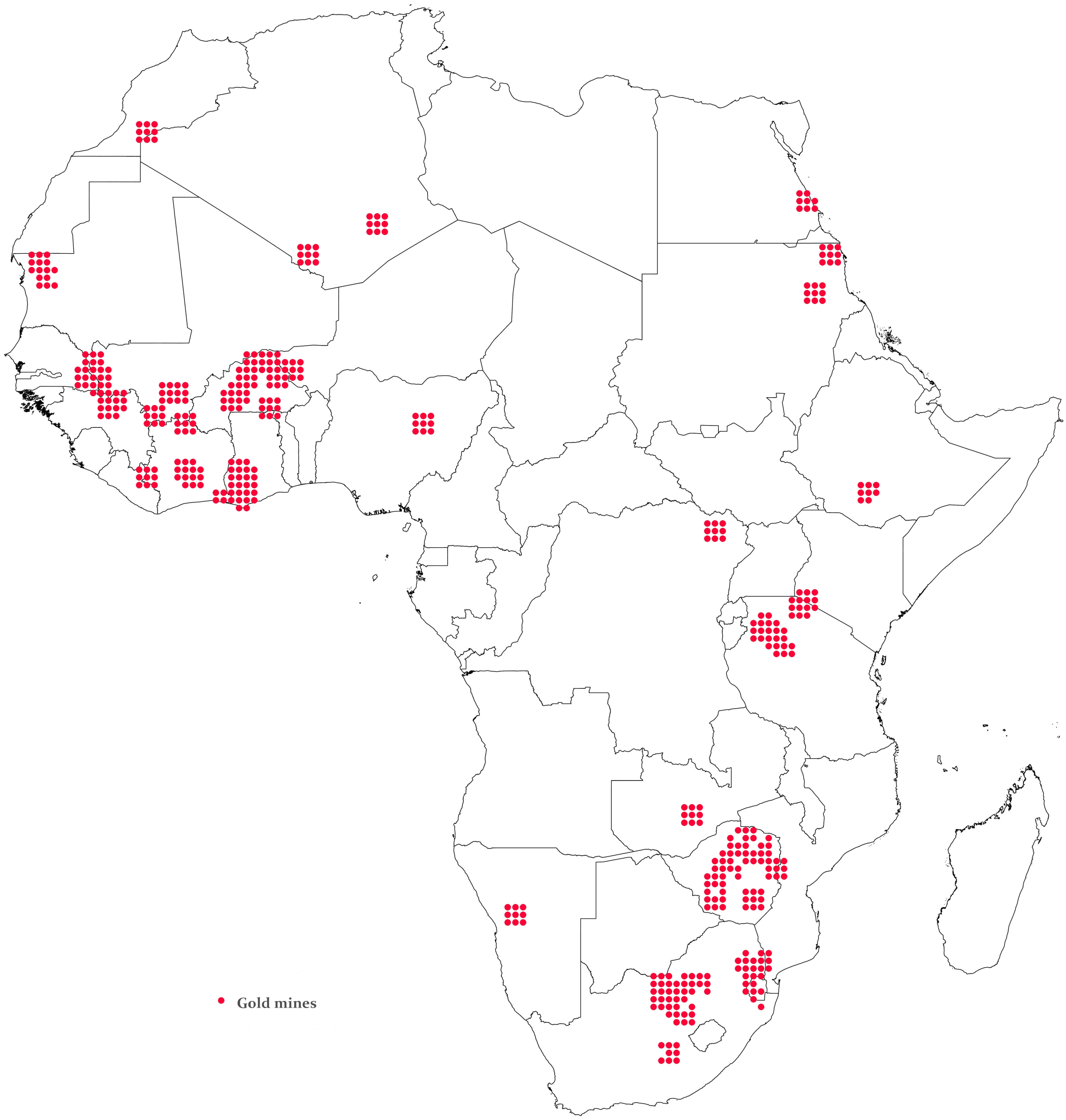


Figure A3: Location of industrial gold mines (2000-2010)

Note: The map shows the locations of industrial gold mines that are active between 2000 and 2010. Source: Berman et al. [2017].

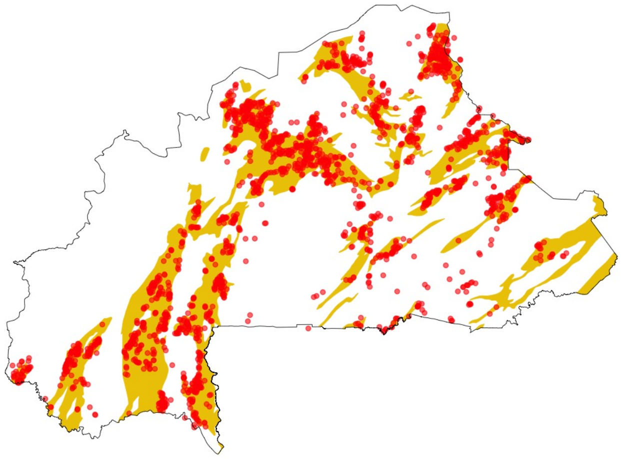


Figure A4: Burkina Faso: Gold-suitable areas and documented artisanal mining sites

Note: The map overlays the yellow-shaded gold-suitable areas with locations of artisanal gold mines marked by red-shaded circles. Originally collected by Effigis [2018], the dataset on mining sites combines manual satellite image analysis with field surveys to identify and geolocate major artisanal mining sites across the country in 2017-18 [Rigterink et al., 2025].

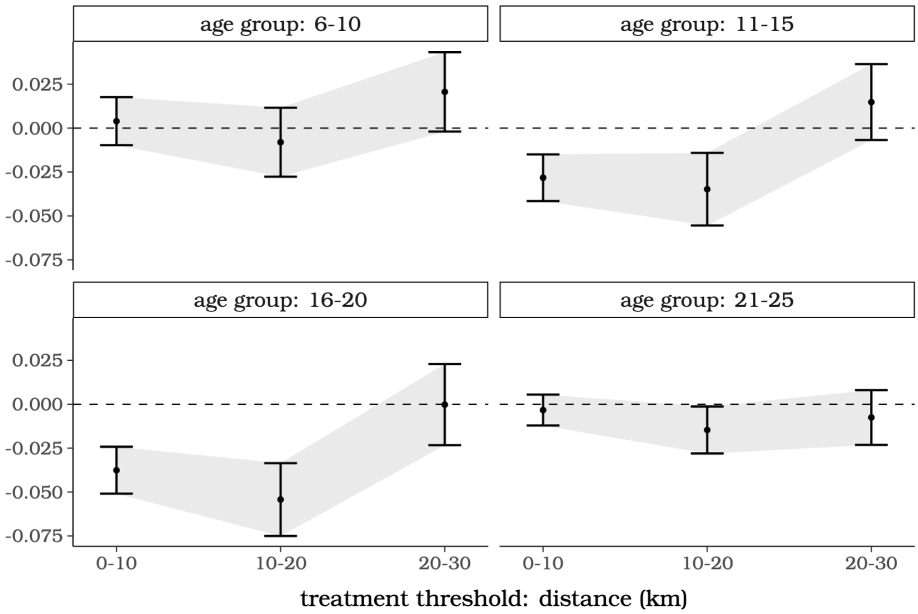


Figure A5: Robustness to Treatment Definition Using Varying Distance Bands

Note: The figure displays point-estimates and 95% confidence intervals for an exercise that keeps clusters located farther than 30 kilometers from the nearest gold-suitable location as the control group. The treatment groups are defined based on the proximity of the clusters to the nearest gold-suitable locations, using three distance bands: 0–10km, 10–20km, and 20–30km. All estimates use the benchmark specification, equation 1

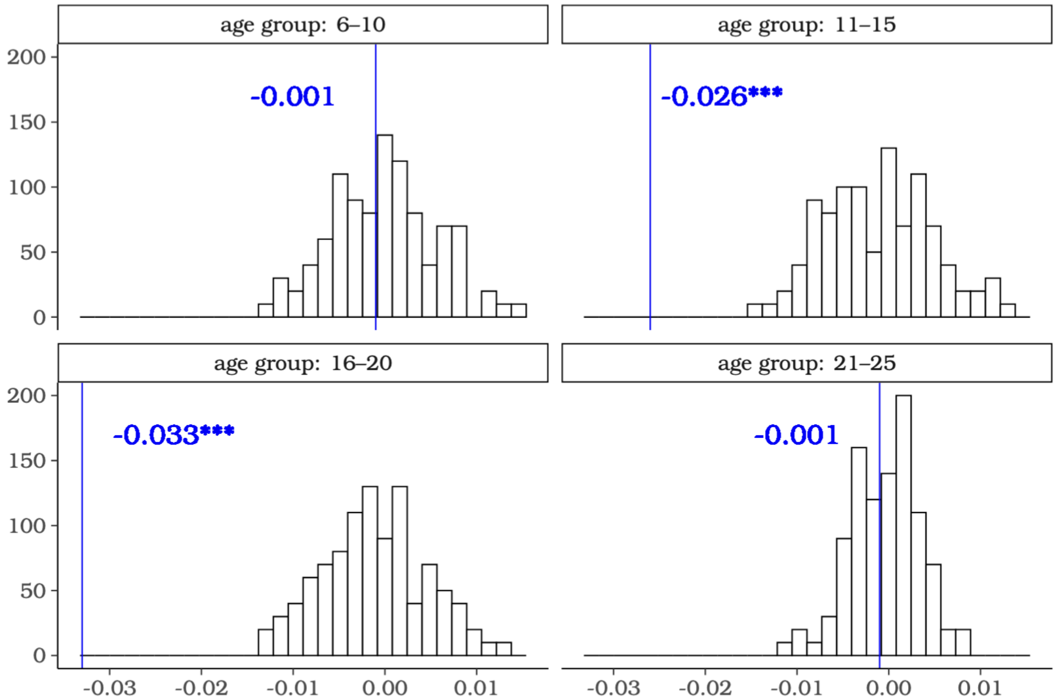


Figure A6: Inference permuting gold-suitability across clusters and gold-price across time

Note: The figure shows the distribution of the coefficients on `gold` × `price`*, based on 1,000 permutation regressions per age group. For each of the four age groups, we randomly reassign gold-suitable status across clusters 100 times. For each reassignment, we additionally permute the vector of lagged gold prices 10 times, resulting in 1,000 total draws per age group. The outcome is school attendance, i.e., whether an individual is attending school in the year of the survey. All specifications also include covariates and fixed effects as specified in equation 1. The vertical blue lines indicate the coefficients from the main analysis, i.e., columns (1)-(4) in Table 1.*

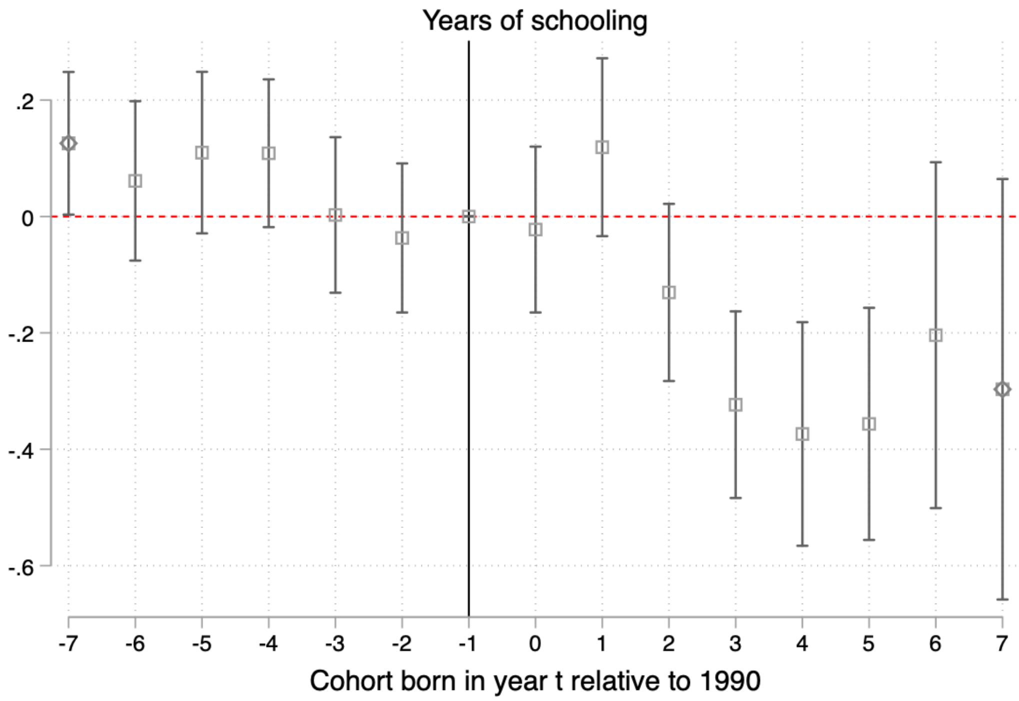


Figure A7: Event study estimates for completed years of schooling

Note: N=427,573; Sample: 21-30 years old born between 1970 and 1997. To supplement the analysis on the long-term effects in Section 5.3, this Figure presents the event-study estimates using the following specification:
$y_{ict} = \sum_{t \in (-7,+7),\ t \neq -1} \theta_t Gold_c + \boldsymbol{\tau} \boldsymbol{X}_i + \boldsymbol{\mu}_c + \boldsymbol{\lambda}_t + \epsilon_{ict}$,
where we normalize the periods relative to the cohort born in 1990 ($t = 0$), with the cohort born in 1989 $t = -1$ as the reference point. We assume that the individuals born in 1990, who are 17 in 2007 when the rise in gold price accelerates, are the first relevant cohort to experience relatively higher prices over the study period. y_{ict} is completed years of schooling for individuals born in year t and living in cluster c. $Gold_c$ is a binary variable indicating whether an individual is living within 10 km of a gold-suitable area. μ_c stands for cluster fixed effects and λ_t represents birthyear/cohort fixed effects. X_i comprises the same set of covariates used in the main analysis (except the urban-rural indicator, as that is the same for individuals living in the same cluster) as well as age-at-survey fixed effects. The vector of coefficients plotted are $\boldsymbol{\theta}_t$ $[t \in (-7, +7),\ t \neq -1]$.