Mining and Educational Outcomes in Ghana*

Justice Tei Mensah[1], George Adu[2], Franklin Amuakwa-Mensah[1] and George Marbuah[1]

[1]Swedish University of Agricultural Sciences
[2]Kwame Nkrumah Univ of Science and Technology

March 10, 2017

Preliminary Draft, Please Do Not Cite
Click here for latest version of the paper

Abstract

The socioeconomic impact of mining activities has gained keen interest in development discourses. Extant studies on the local impacts of mining have so far focused on the effects on individual and community outcomes such as income, employment, and the spillover effects of mining on other sectors particularly, agriculture. However, an important question that remains unanswered so far is: to what extent does the mining activities affect human capital accumulation in host communities? In an attempt to address this issue, this paper presents evidence from Ghana on the impact of gold mining on educational outcomes of individuals living in mining communities. Using comprehensive and unique geo-referenced survey and administrative datasets from 1998 to 2013, we find a negative effect of mine opening on years of schooling, but no effect on literacy outcomes. Taken together our results suggest a negative spillover of gold mining activities on the educational sector, which is largely driven by the negative effect of mining on income of households particularly those engaged in agricultural related activities, thereby limiting their investments in education.

JEL Codes: 013,A20, C21, 012
Keywords: Mining, Education, Ghana, Difference-in-Difference

*Corresponding Author: Justice Tei Mensah. Email:justice.tei.mensah@slu.se

1 Introduction

For many years the debate on what became known as the "resource curse hypothesis" inundated academic and policy discourses particularly in relation to resource endowed developing economies around the world. The hypothesis asserts that natural resource endowment exerts negative socioeconomic impacts on host economies often evidenced by lower growth, conflicts, weak institutions, and poor governance (Sachs and Warner, 1995, 2001) . This view point though popular, has been challenged by other studies (see: Mehlum et al., 2006). Nonetheless, the issue of the real impact of natural resources on host economies remains an empirical conundrum with varying impacts across space and time.

In recent past however, a new strand of the literature has emerged albeit still nascent. Following the mining boom in the last two decades or so around the world, there has been growing attention among economists and development institutions on the localized impacts of natural resources exploitation, particularly, mining(see for instance: Word Bank, 2015; Aragón and Rud, 2015; Aragona et al., 2015; Tolonen, 2015; Chuhan-Pole et al., 2015; Kotsadam and Tolonen, 2016; Adu et al., 2016). These studies unequivocally show that inspite of the varying direction of impacts, the effects of natural resource exploitation are much more discernible at local and subnational level than national level. On the one hand, mining for instance has been shown to affect local economies positively via boosting local incomes, employment, labor reallocation, gender empowerment, etc., (Aragón and Rud, 2013; Tolonen, 2015). On the other hand, there are evidence of localized negative impact of mining activities such as reducing agricultural productivity, pollution and its effect on human health, HIV-AIDS, *inter alia* (Corno and de Walque, 2012; Aragón and Rud, 2015)

Despite the large number of studies on the effect of mining on the local economies, the effect of mining on human capital accumulation (education) in host communities has not been investigated empirically. The present study fills this gap using household and administrative level data on Ghana. How do mining activities affect educational outcomes in host communities? At least two possible sources have been advanced. One line of argument is that mining booms are associated with increased the economic activities in host economies thereby improving income of local residents and child health (Tolonen, 2015; Aragón and Rud, 2015). This effect is likely to incentivize households to increase their investments into education and health of their children thereby improving education and learning outcomes of children in mining districts. Additionally, corporate social responsibility programs of large mining companies and mineral royalties to local governments will, other things being equal, lead to an improvement in social infrastructure such as provision of new school blocks, teachers accommodation, community library, water and sanitation and road access. These social investments have the potential of improving educational outcomes in mining areas relative to non-mining areas.

On the contrary, the existence of small scale and artisanal gold mining activities (often informal and unregulated) have the potential of drawing children of school going age to engage in mining or ancillary activities, with associated negative effects on enrollment and schooling outcomes in mining areas. Even in areas dominated by large scale mines, the existence of interlinkages between the mining and other sectors of the local economy, particularly services, implies that mining booms are likely to generate increased economic activities. As a result children or in some cases parents will motivate their children to skip school to participate in the labor market in anticipation of high short term economic returns. Another channel via which mining activities affect enrollment is the increase in social vices such as robbery, prostitution, teenage pregnancy, conflicts and the consequent rise in school dropouts. These arguments suggest that the exact impact of mining on educational outcomes is an empirical conundrum, hence the need for investigation.

In this paper we examine the total effect of mining on human capital accumulation using household and administrative data from Ghana between 1998 and 2013. To our knowledge, this is the first study on the local impact of mining on education. Given the important role of education in fighting poverty, knowledge about how mining affects education is relevant for understanding the current and future trends in poverty and development in mining areas, even after the closure of the mine. Again it offers an intriguing perspective on the long run impacts of mining on host communities, given the fact that returns to education are largely realized in the long run.

In order to capture the effect of mining on education, we define our treatment indicator(s) based on the distance thresholds between individual's place of residence and mine location. The following thresholds are used in defining our treatment: 20, 25, 30, 50 and 70 kilometer radius from an open mine. Our identification strategy exploits the spatio-temporal variation in the timing mine of opening and closure to estimate the effect of mining on education outcomes. Therefore with the aid of the difference-in-difference estimator, we compare the educational attainments of individuals within the respective distance thresholds with comparable individuals living outside the distance thresholds.

Two broad measures of educational attainments are considered in this paper. They include years of schooling and literacy skills (i.e. ability of the respondent to read, write and solve a standard mathematics problem set). We interpret these outcomes as measures of quantity and quality of education respectively. Also, we focus on children within the ages of 6 to 30 year old, with a key focus on the cohort between the ages of 6 and 18 years which directly corresponds to individuals in the basic and senior high school categories. To sufficiently understand the educational impact of mining activities, we explore the potential channels of impact such as the probability of the child engaging in economic activities, access to school and social infrastructure, and the effects of mining on household income and educational expenditure.

Findings from the paper can be summarized as follows: first, we find a negative effect of mining on years of schooling, suggesting that mine opening reduces the incentives of children in mining communities to attend school. Second, contrary to the findings of the effect on years of schooling, we do not find any effect of mining on literacy skills. These results put together provides suggestive evidence that mining offers a "quantity" but no "quality" effect on educational outcomes. Thirdly, there are no discernible gender disparities in the impact of mining on education. Further, the negative effect of mining on education is only concentrated in mining intensive communities i.e. communities within a maximum of 20-25km radius from an open mine. Finally, the effect is largely driven by the negative effect of mining on income of households thereby reducing their expenditure on education. This is particularly among households employed in agriculture which is the dominant sector of employment in the study area employing nearly 50% of the populace.

The rest of the paper is structured as follows. Section 2 presents a review of the relevant literature on mining impacts. The empirical strategy and data description are outlined in sections 3 and 4. The results are presented and discussed in section 5, while section 6 concludes the paper.

2 Related Literature

This paper is related to at least two strands of the literature on the economic development impact of natural resources endowments in developing countries. The first is the growing but inconclusive literature on the so called curse of natural resources hypothesis (see for instance Sachs and Warner, 1995, 2001; Gylfason, 2000, 2001; Gylfason and Zoega, 2002). At the macro level, rich natural resource endowments become a curse when they distort the efficient allocation of resources and undermine the efficient functioning of institutions (Dubé and Polèse, 2015). One of the important mechanisms through which natural resource wealth affect national economies is human capital accumulation. Dubé and Polèse (2015) argue that revenues generated by resource rents retard the introduction of effective tax systems and cause governments to neglect investments in human capital. Gylfason (2001) report a negative relationship between the weight of natural resources in national economies and various indicators of educational attainment.

The present paper is also very closely related to the literature that examines the development impact of resource extraction on local economies. In particular, the literature on socioeconomic impact of mining. Chuhan-Pole et al. (2015) and Aragón and Rud (2015) contains detail reviews of studies on the local economic impacts of natural resource extraction; interested readers may consult these studies and references therein. Mining is noted to cause considerable amount of pollution in the catchment areas, poverty and social vices. However, there is a growing realization that mining activities can be undertaken in a manner whereby the economic contributions (income and employment) are maximized; social conditions (e.g. health and education outcomes) are improved and damages to the environment (land, air and water pollution) are minimized. Kitula (2006) documents that mining improves access to infrastructure (road and water), market opportunities for food crop farmers; improved incomes through direct employment in mines and indirect employments; but the effect on the environment and socio-cultural impacts (displacement, unemployment, child labour, accidents, theft and prostitution) are negative. These findings by Kitula (2006) suggest that mining offers both positive and negative impacts. However, the study was purely descriptive and thus could not compare the costs and the benefits in other to estimate the overall impact of mining on the community and how this is distributed across different socio-economic groups. Kotey and Rolfe (2014) revealed that mining statistical local areas (SLAs) in remote communities in Australia tend to have larger populations and workforce, fewer indigenous people and lower unemployment. Mining SLAs also have relatively smaller primary and social services sectors, but a larger construction sector and tend to accumulate more human capital with more residents having tertiary qualifications and technical occupations (Kotey and Rolfe, 2014). Kotey and Rolfe (2014) further document that incomes are higher and more equitably distributed in mining than non-mining SLAs. Hajkowicz et al. (2011) also reports lack of any systematic negative associations between quality of life and the gross value of mineral production. Hajkowicz et al. (2011) instead documents evidence that mining has positive impact on incomes, housing affordability, communication access, education, and employment across regional and remote Australia. However, the above conclusions are based on mere correlation analysis and should not be interpreted as evidence of causal impact of mining to the quality of life indicators.

The literature studying the local economic impact of resources extraction has emphasized on the important of backward linkages as the main means by which the economic benefits of resource extraction are felt by those living close to the resource. This theoretical postulation has been the central idea in many empirical studies on the local economic impact of resource abundance. For instance, Lippert et al. (2014) studies the economic benefits of Copper Belt mine in Zambia on the neighboring households. The central result of the study is that an increase in local copper output improves measures of living standards in the respective constituencies through the mines' backward linkages. The positive effect of natural resource extraction on the local economy contrasts sharply with the enclave thesis that date back to Hirschman (1958). While the empirical estimates appear to be robust, there is still much less understanding of the distribution of the burden and the benefits of resource extraction. Kotsadam and Tolonen (2016), for instance, in a study based on household level data from selected mineral producing countries in Africa, documents evidence of increased female employment from mine opening. They also find evidences for a shift of women into the service sector, although the effect dissipates with distance; and asymmetric effect of mine closure and suspension, with women not fully returning to the agricultural sector, whereas overall employment levels remain low.

Aragón and Rud (2013) find evidence of positive effect of large scale mining operations on real income of households of local communities in Peru through the demand for local inputs. Aragón and Rud (2013) also report that local price of nontradable goods such as housing respond positively to mining. These findings underscore the potential backward linkages from the extractive industries to engender positive spillovers in less developed economies. It however remains a question whether their findings hold for other developing countries. Loayza et al. (2013) also reported positive impact of mining on producing districts. The authors find evidence that mineral producing districts have better average living standards than otherwise similar districts: larger household consumption, lower poverty rate and higher literacy. However, Loayza et. al. (2013) document that the positive impacts of mining dissipates significantly with administrative and geographic distance from the mine, while district level consumption inequality increases in all districts belonging to producing province. They reckon that the inequalizing effect of mining engenders social discontent and violence that is common in most mining areas in the developing world. In a study that explores the relationship between non-oil and gas extraction on economic growth for non-metropolitan U.S. counties for the period 2000 to 2007, Deller and Schreiber (2012) found that non-oil and gas mining is associated with lower population growth, and a positive impact on per capita income, but has no impact on employment growth.

In a more recent econometric study on Ghana, Chuhan-Pole et al. (2015) reveled that men are more likely to benefit from direct employment as miners while women are more likely to gain from indirect employment opportunities in services. They also show that mining improves access to infrastructure (such as electricity and radios) and health outcomes of the children of long established households relative to migrants. Chuhan-Pole et al. (2015) al also report that infant mortality rates significantly decrease in mining communities relative to non-mining areas. On the contrary, Aragón and Rud (2015) have reported that farmers located near mines experienced a relative reduction in total factor productivity of almost 40% between 1997 and 2005, with pollution emanating from mining as the most plausible explanation for the agricultural productivity slowdown in mining areas. With agriculture as the backbone of rural economies, the findings of Aragón and Rud (2015) suggest that mining generates negative welfare effects on majority of rural households, which conflicts with the findings reported by Chuhan-Pole et al. (2015) and Aragón and Rud (2013)). Also, Adu et al. (2016) finds a negative impact of mining on income and welfare of households living close to a mine in Ghana. In addition, they observed an income reducing effect of mining activity and this heavily falls on households at bottom of the income distribution.

Despite the growing volume of empirical studies on the localized impact of natural resource wealth, the impact of resource extraction on human capital accumulation has not been investigated at the micro level (individual/household and district level). The present paper therefore attempts to provide rigorous analysis on the spillover effects of natural resource extraction on the education of individuals living host communities, using the gold mining as a case study.

3 Empirical Strategy

The main goal of this paper is to evaluate the effect of "living close to a large scale mine" on a set of educational outcomes of individuals living in the proximity of a mine. To achieve this aim, our identification strategy is to exploit two main sources of variations: first, even though the geographic distribution of mineral deposits are naturally determined, discovery and exploitation of the resources vary across space and time. Also, there are significant variations in the size of mineral deposits across space, therefore the lifetime of mining activities vary across space and time. These factors create spatio-temporal variations in mine opening and closure. Secondly, the geographic distance between communities and mine locations also vary across space. Therefore, the identification strategy of this paper is to exploit the time and spatial variations in mine opening (closure) and distance to communities to causally estimate the impact of mining activities on our set of outcome variables.

These sources of variation together with the repeated-cross sectional data allows us to use a difference-in-difference (diff-in-diff) approach to causally estimate the impact of mining on educational outcomes. Using varying distance thresholds, we define $Mine \in [1, 0]$ as a treatment indicator equal to 1 for communities within a given distance threshold from a mine, and zero for communities outside the threshold, and *Open* equal to 1 if the mine is open and 0 if otherwise. Our baseline model can be expressed as:

$$y_{igjt} = \alpha + \beta Mine_j + \delta Open_t + \gamma Mine_j \times Open_t + \theta_0 K_{igjt} + \theta_1 Z_{jt} + \psi_r + \eta_d + \lambda_t + \mu_{d*t} + \epsilon_{ijt} \quad (1)$$

where y_{igjt} is the outcome variable for individual i in household g living in community j in year t; K and Z is a vector of household (individual) and community characteristics respectively; while ψ, η, λ and μ represent respectively, regional, district, year and district-year fixed effects. Within the diff-in-diff framework, γ measures the causal effect of living close to an open mine on the outcome variable(s). The dummy variables $Mine$, $Open$ and $Mine_j \times Open$ captures the difference in the outcome variable between living in and out of mining area, and before and after mine opening.

The identification of causal impact however requires a valid control group for the treatment group. In this study, we restrict our sample to individuals living within a 100 km radius from a mine. Within this sample, we vary our treatment group by changing the distance threshold from 20km, 25km, 30km, 50km and 70km; even though our baseline analysis confines the treatment group to individuals living within a 20km radius from a mine. Also, in all regressions we include region, district, year and district-year fixed effects. Inclusion of district and regional fixed effects allows us to control for any time invariant institutional, cultural and administrative factors. Again, by doing so, we net out any effects from fiscal transfers, to for example the educational sector, which might confound our analysis, as we compare individuals within the same district and region (Chuhan-Pole et al., 2015). In addition, these fixed effects enable us to capture spillovers effects in the neighborhood of the mine (Chuhan-Pole et al., 2015). The year fixed effects also enables us to control for time varying factors that may confound the results, while the district-year fixed effect measuring district specific time trends captures essentially changes in (un)observable district specific attributes over time.

The validity of our identification strategy within the diff-in-diff framework relies on the assumption that the population remains the same before and after the mine opening. This assumption is however difficult to validate particularly given that the study relies on repeated cross sectional data. Mining areas are known to be hot spots for intra-migration patterns. Mine opening and the associated boom in the local economy tend to attract labor (skilled and unskilled), sometimes together with their families, into host and nearby communities. Out-migration is however limited, at least until the mine closure. To assess the validity of this assumption and its effect in driving the results, we conduct robustness by testing whether there are any significant differences in the educational outcomes between migrants and natives[1], and also whether these differences are induced by the mine opening. Thus by so doing, we are able to control the effect of in-migration on the results. Again, there are concerns that the population in the control communities may be dissimilar to the population in the treatment communities. Therefore, the effect obtained by comparing the outcome variable between treatment and control groups may be driven by factors other than the mine opening. We address this issue also by controlling for region and district fixed effects (Kotsadam and Tolonen, 2016). Also, we vary our control group by extending the geographic limit from the 100 km radius in the baseline to a 200 km radius. A further validity test is done by dropping the distance restriction on the composition of the control group (i.e., on the entire national dataset). Thus, conditional on our identifying assumptions, the results should not vary significantly with the extension of the control group (see the appendix on robustness checks).

Another threat to our identification strategy is that the estimations could capture some changes in the education sector that could have otherwise occurred even in the absence of the mine opening (i.e. the so-called "parallel trends" assumption). For example, government policies such as the "School Feeding Program", "Free School Uniforms and Sandals ", targeted social intervention programs, expansion in education infrastructure, among other education reforms have over the years been implemented with the aim of improving schooling

[1]defined in this study as individuals whose household head was born in the same community.

outcomes. Most of these programs were (sometimes) targeted, so it possible the targeted districts fall within the treatment areas. Therefore, changes in education outcomes could be attributed to these programs other than mining. We adopt several strategies to address this challenge. One of such strategies is to control for the district time trend which captures some of these developments and policy changes across the districts over time. We address these concerns further in detail in Section 5.5

All individual and household level estimations are clustered at the primary sampling unit (PSU) which allows us to control for intra-cluster spatial correlation among households. Community level estimations are however clustered at district level to account for inter household spatial correlation in the same district.

4 Data

This study combines data from a geo-referenced household survey with geo-data on the location of gold mines in Ghana. Specifically, we utilize the three most recent waves of the Ghana Living Standards Survey (GLSS 4 (1998/99), GLSS 5 (2005/06), & GLSS 6 (2012/2013)) covering the period 1998-2013. This dataset is a nationally representative repeated cross-sectional survey of households in Ghana, and conducted by the Ghana Statistical Service with support from the World Bank and other agencies. The sampling unit for the survey is the population living in private households in Ghana. The above sample unit is further divided into two: primary and secondary sampling units. The primary sampling unit (PSU) is defined as the census enumerated areas (EAs) that are stratified into the ten administrative regions of Ghana based on proportional allocation using the population in each of the ten regions. The secondary sampling unit on the other hand is defined as the households living in the EAs. The survey design follows a two-stage stratified random sampling technique.

All the data in the three waves used in the study are geo-referenced, at the PSU level otherwise referred to as clusters. In other words, they contain the GPS coordinates of the communities within which households are located rather than the exact location of the households. This is largely due to privacy concerns of the households interviewed. Thus our implicit assumption is that households in the same cluster share the same location. Nonetheless, this does not pose any (serious) limitation to our study in the sense that the use of community location suffices in determining whether a household is located in a mining community or otherwise. The same approach has been widely used by studies such as Tolonen (2015); Aragón and Rud (2015); Chuhan-Pole et al. (2015); Adu et al. (2016), and Kotsadam and Tolonen (2016)

Further, by using GPS location of formal large scale gold mines in Ghana obtained from Aragón and Rud (2015) and Chuhan-Pole et al. (2015), we match the location of the mines to the household data and then compute the geographic distances of each cluster to the mines. The data on mine location from Aragón and Rud (2015) and Chuhan-Pole et al. (2015) also contain information on whether the mine is open or closed. We also updated the status of some mines that were not yet open during the time of compilation of the mine list by Aragón and Rud (2015). The status of these mines were determined using information from various sources including the financial statement of the mines, annual reports, and newspaper reports. In all, the location and status of 26 registered large scale mines are used in the analysis. Table 14 in appendix provides detailed information on the status of these mines. Figure 1 shows a map of the mine location and the 100 km buffer zone for the baseline sample used in this paper.

By pooling data across the three rounds of the survey, we obtain a sample of 72,423 individuals of which 54% (39,528) live within the 100 km buffer zone from a mine. However, given that we focus only on people of school going age, we further restrict the sample to individuals aged between 6 and 30, which consists of 26,213 individuals. Summary statistics of the chosen sample are shown in Table 1. Average years of schooling is 5[2]; there is gender parity in the sample with 50% of the sample being female. There are also high infrastructural

[2] corresponding to grade 5 of primary school

gaps among the communities in the sample. With the exception of road network, access to health facilities, electricity, and pipe-borne water remain low with access rates of 25%, 48%, and 17% respectively. Access to Primary and Junior High School (JHS) are fairly high. About 19% and 34% of the sample do not have access to primary and JHS schools in their communities respectively. Agriculture is the dominant sector of employment with over 54% of individuals in the sample having their household heads employed in the sector. Meanwhile, only 2% of household heads in the data are employed in mining and allied sectors. We also include three measures of literacy as proxies for the quality of education. These include the ability of respondents to perform basic standardized math calculations, read and write a complete sentence in English[3]. These variables are dummies equal to 1 if the individual can perform the assigned task (i.e. math, read, write) and equal to 0 if otherwise. Overall, more than half of the individuals in the sample can perform the respective task.

5 Results

In this section we present results on the estimation of the effects of mine opening on educational outcomes using the empirical strategy outlined in section 3. This section is structured into three main parts: first, we investigate the impact of mining on years of schooling; second, the effects on literacy as a measure of the quality of education. In the third part, we examine the potential channels through which mining affect the education sector.

5.1 Effects on Educational Attainment

To what extent does mining activities affect schooling outcomes of individuals in mining communities? To sufficiently address this question, our analysis focuses on children of school going age. As a result, five (5) age groups are considered including the: 6-12 year, 6-18 year,

[3]and or French. English is the main medium of instruction in the Ghanaian education sector. Students in most parts of the country are also taught French, even though proficiency rate is very low. In this case, greater emphasis is given to the ability of the student to speak and write in English rather than French

6-20 year, 12-20 year, and 6-30 year cohorts. Our baseline specification however focuses on the 6-18 year age cohort. This group largely relates to children within the primary, junior and senior high schools. Again, unless otherwise stated, a mining community is defined as one located within a 20km radius from a mine. The results presented herein restricts the control group to individuals within a maximum distance threshold of 100km from a mine.

As highlighted in Section 3, the coefficient associated with the interaction between $Mine$ and $Open$,γ, gives the causal estimate of the effect of mine opening on the outcome variable (years of school). Estimates of this impact for the various age cohorts are shown in Table 2. The results, reveal a significant and negative impact of mining activities on years of schooling of individuals (young adults) of school going age (maximum age of 20 years) living in mining communities. For instance, Column 1 of Table 2 suggest that mine opening results in a 1.14 year reduction in years of schooling for individuals within the ages of 6-18 years and living in a mining community relative to individuals in the same age cohorts living in non-mining. Similarly, a reduction of 1 and 1.4 years is observed for the 6-20 and 12-20 year cohorts. What do these results imply? The current education structure in Ghana (since 1993) requires "compulsory" schooling for children 6 years and above, therefore by age 18, the representative child should have completed senior high school, other things being equal[4]. Thus, our results provide suggestive evidence of a negative impact of mining on pre-tertiary education,at least within the Ghanaian context, with an associated impact of approximately 1 year reduction in schooling. The mechanisms underlying the negative effect of mining activities on years of school as observed in our results are explained in details in Section 5.3

For post-secondary education, we do not expect any impact of mining due to the following reasons. First, enrollment in tertiary education is relatively low compared to basic and secondary school enrollment, mainly due to issues such as cost and high entrance requirements. Second, the post secondary schools are unevenly distributed across the country,

[4]The average completion age for pre-tertiary education is likely to be higher for students in the old educational system, i.e. the O-and-A level Certificate system, which run concurrently with the current JHS/SHS system in the 1990s.

and are often located in cities and urban centers, so more often than not, students will have to travel outside their district and/or regions to attend tertiary school. In this case, it is reasonable not to expect any impact of mining on schooling outcomes at the tertiary level, hence their exclusion from this analysis.

We extend the analysis further, by looking at the heterogeneous impact of mining on education of the baseline cohort at varying distance thresholds. The results of the impact are summarized in Figure 2 with full details of the results presented in Table 9 in the Appendix. The results reveal varying impacts of mining on years of schooling with the impacts exhibiting a distant-decay process. On the one hand, we observe that mining exerts a negative impact on years of schooling in communities within a 20-25km radius from an open mine (i.e., mining intensive communities); while on the other hand, a positive effect is observed on years of schooling for individuals in communities within a 50 and 70 km radius from an open mine. Specifically, we observe that mine opening reduces years of schooling by 1 year for children living within 20 from an open mine.

5.1.1 Gendered Differences in Impact of Mining on Education

To further understand the impact of mining on educational attainment, we proceed to assess the differences in the impact between male and female age cohorts (see: Table 3). In Columns (1-2) of Table 3, we estimate the model for the 6-18 and 12-20 year cohorts while controlling for the gender of the individual and the interaction between the gender and the measure of mine impact ($Mine \times Open$). For instance, the coefficient of the term $Male \times Mine \times Open$, measures the impact of a male individual living in a community with (or in the neighborhood) of an open mine on the years of schooling of the individual. Put differently, the interaction measures the relative impact of open mines on education of males compared to females in the respective age cohorts. As seen in the results, we find no evidence of a significant difference in the impact between male and females. This result appear unsurprising particularly given the fact that documented evidence suggest that both sexes play active roles in mining and ancillary activities (Hentschel et al., 2003; ILO, 2007; Tolonen, 2015). Even in instances where girls are not directly engaged in mining, they are often engaged in ancillary services like selling food and supply of inputs to the mining sector. As a result there are very little reasons, if any, to motivate a significant difference in the impact of mining on education between males and females. In columns (3-4) and (5-6) we split the sample into male and female respectively. Thus in these cases we assess the impact of mining activities by comparing the educational outcomes of males(females) living in a mining community with their counterparts in a non-mining community. Once again, we observe a negative impact of mining on the educational attainment of both male and females living in mining areas. The effect is however more pronounced on females. The results indicate that the years of schooling of females in the 6-18 year cohort and living in communities are 1.4 years lower than their counterparts in non-mining communities. Similar results is obtained for females in the 12-20 year cohorts. In relation to the results on males, we only find (weak) significant effect on individuals within 12-20 cohorts. Juxtaposing the results in Tables 2 and 3, it is clear that while the effect of mining on education is undeniable, there are no marked differences in the impact in terms of gender.

5.2 Effects on Literacy

Education experts argue that while a "quantitative" measure of schooling outcomes such as years of schooling is important, an even more important outcome is the quality of education. The ability of the educational system to produce students with high cognitive skills is an important factor that cannot be over emphasized. Cognitive skills such as ability to read and write, and knowledge of mathematics are important skills that a well functioning educational system should inculcate into its students. In addition, these skills signals the potential productivity of the educated labour force.

Therefore, in search of the impact of mine opening on schooling outcomes, it is instructive to investigate the effect of mine opening on literacy skills. Holding the quality of the educational system constant, more years of schooling should lead to accumulation of literacy skills, other things being equal. In Table 4, we estimate the impact of mining on the ability of individuals to perform basic tasks in reading, writing and mathematics. The results however shows, no evidence of the impact of mining on literacy. Hence, we conclude that the effect of mining falls largely on amount of schooling rather than quality of schooling.

5.3 Channels of Mining Impact on Education

To ascertain the possible channels via which mining affect the educational outcomes, we estimate the impact of mine opening on i. the probability of the individual in engaging in employment activities, as a proxy for child labor activities; ii. access to schooling and complementary social infrastructure such as road, electricity, pipe-borne water, and health care facilities; and iii. household income and educational expenditure.

In Table 5, we estimate the impact of mining on the probability of the individual engaging in economic activities either as paid labor or unpaid labor. Anecdotal evidence suggest that mining booms and the associated boost in the local economy tend to attract children to engage in paid employment or support parents and family relations in the labor market, thereby resulting in low attendance in schools and eventually leading to students dropping out of school. In some cases, children are often seen to be engaged directly in mining operations especially in the informal gold mines which is mostly unregulated. Our results however, fails to confirm this assertion as we do not find any evidence of mining induced child-labor activities. A possible reason for this result is the current study focuses on the large scale mining areas. In Ghana, large scale mining is regulated and mining firms are expected to adhere to labor laws, thereby reducing the probability of minors to be employed in mining and quasi-mining activities. Engagement of children in such activities may possibly be more pronounced in areas dominated by the informal, unregulated and illegal small scale mines, otherwise known as "*galamsey*". Nonetheless, we do also acknowledge that many of the areas with large scale mining are also hotspots for small scale mining activities.

On access to schooling infrastructure, we estimate the impact of mining on access to Primary, Junior High School (JHS) and Senior High School(SHS). In addition to our dif-in-diff estimates, we complement our analysis with OLS[5] estimations. The OLS estimates measures the correlation between living in a mining community and access to schooling infrastructure. From the results, we observe a negative correlation between access to schooling and living in a mining area. The results from the Diff-in-Diff estimates (Column 5-8) however indicates that while the impact is negative, they are not statistically significant. In other words, there is no causal impact of mine opening on access to schooling in the study area. By extending the analysis to access to complementary infrastructure such as electricity, pipe-borne water, road and health post, our results (Table 7) again shows no evidence of the impact of mining activities on access to these infrastructure. In other words, there are no statistical differences between mining and non-mining communities in relation to access to critical infrastructural services such as schools, road, electricity, health care and pipe-borne water.

Next, we examine the possibility of households' income and education expenditure as channels through which mining affects the educational outcomes of individuals in host communities. To this end, we estimate the effects of mining on households' educational expenditure and income, and also the impact conditional on the sector of employment of the household head. The latter is key in identifying whether the impact through these channels is also contingent on the sector of employment of the key decision maker in the household, i.e., the household head. In Table 8, we observe interesting results on the impact on income. Mine opening is shown to exert a positive impact on employment income, and this is particularly for households with the head working in the mining sector. Agricultural households' are however disadvantaged, as we observe a negative and significant impact. This result is similar in spirit to the findings of Aragón and Rud (2015) who report that mining activities

[5]Ordinary Least Squares

results in lower agricultural productivity in mining communities in Ghana and consequently resulting in lower welfare of farm households. Thus, in communities where agriculture is the dominant sector of employment, mining booms is likely to reduce aggregate welfare through the displacement effect resulting from pollution and or conversion of agricultural lands for mining activities. Column (4) is indicative of this impact as the impact on overall household income is negative. Consequently, Columns (1-2) shows a negative impact of mine opening on household expenditure on education. Taken together, we can conclude that conditional on community and household characteristics, the negative impact of mining on educational attainment as observed in this study, is driven to a large extent on the negative impact of mining on household incomes. This therefore reduces households' educational investments with the attendant effect of lowering schooling outcomes.

5.4 Robustness Checks

The identification strategy outlined in this paper faces two main threats which could confound the estimations. First, it is possible that the negative impact derived in the paper could be driven largely by the fact that mining booms results in the inflow of low skilled and educated migrants and therefore reduces the probability of sending their children to school rather than purely as a result of the mining activities (i.e. the so-called endogenous migration problem). Additionally, within the diff-in-diff framework, the choice of the control group is critical as it is important to ensure that the sampling units in the treatment and control groups before and after mine opening are relatively similar. As a result, a change in the composition of the control group, may influence the result. If these cases hold, then our results cannot be confidently attributed to the impact of mining activities.

To this end, this section presents a test of these claims and show the robustness of the results to these potential confounding factors. In addressing the issue of "endogenous migration", we test whether being a native or migrant has any effect on the educational outcomes of the individual. Due to data limitations, we define "native" as an individual whose household head was born in the same community or otherwise. Thus our identifying assumption is that households' whose head was born and have lived in the same community are more likely to be natives of the community or at least have lived and settled in the community for a long time while households whose head was born elsewhere have a higher probability of being migrants. This has been widely used to measure migration status of individuals in the extant literature (Amuakwa-Mensah et al., 2016; Ackah and Medvedev, 2012). From the results (Table 10 in Appendix), we show that the effect of mine opening on education is not conditional on whether the individual is a migrant or native. In other words, we rule out the possibility of endogenous migration confounding our results.

Further we conduct a set of placebo test by extending to sample from the initial 100km threshold to 200km. In so doing we compare the outcome variables of individuals living within 20km from an open mine (treatment group) to individuals between 20km and 200km from an open mine (control group). Finally, we also estimate an additional model without any restriction on the distance threshold. Results of these tests are shown in Tables 11 12, and 13. The estimates from these additional tests affirm the robustness of the estimated impact of mining on educational outcomes, as the variations in the definition of the control group yields no effect on the estimated impact(s).

Therefore, we can conclude that this paper provides concrete suggestive evidence of the negative impact of mining on human capital accumulation in host communities in Ghana, with the effect largely driven by the negative impact of mining activities on household income thereby resulting in lower investment into education.

5.5 Extension to the Paper

The next phase of this study is to complement the analysis with administrative data on school enrollment, exam performance. Indeed, we have secured access to unique data on student examination performance at the Junior Secondary School(JHS) and Senior Secondary School(SHS) level from the West African Examination Council (WAEC) over the period 2000-2014. This data provides the exam score of students in basic and secondary schools across the country. Additionally, we have obtained unique data on "Early Grade Reading Assessment" (EGRA) from Eddata. This is an oral student assessment designed to measure the most basic forms of literacy at early grades. The measure include ability of students to recognize letters of the alphabet, read simple words, understand sentences and paragraphs, and listening with comprehension. Therefore by matching this data with the geocoded data on mine and school location we will examine the effect of mining activities on student performance. This will be complemented by analysis of data on student enrollment to fully ascertain the impact of mining activities on the educational sector.

Thus, we believe that conducting further analysis with the additional data, together with the previous results, will provide more rigorous evidence on the impact of mining on education outcomes in Ghana.

6 Conclusion

How do natural resource extraction influence human capital accumulation in developing countries? This is the main question the paper seeks to address, by analyzing the effects of mining activities on the educational outcomes of children and youth in host communities. To achieve this goal, we combine a unique set of household and administrative data on individuals in Ghana from 1998-2013, to estimate the impact of mine opening on a set of educational outcomes using a quasi-experimental econometric technique.

Findings from the paper provide suggestive evidence of a negative effect of mine opening on years of schooling. In other words, mining decreases the incentives of children in mining communities to go to school. This effect is largely driven by the negative impact of mining activities on income of households particularly, in the agricultural sector, thereby resulting in lower household investments in to education of their children. However, an interesting revelation from the paper is that in spite of this negative impact on years of schooling, there is no improvement or deterioration in the quality of education following the mine opening.

A major limitation of this paper is that it focuses solely on the impact of large-scale registered mines, largely due to data constraints on the location and operation of small-scale illegal mines. As a result, the results herein may not reflect the impact of the overall mining sector on the education sector. Nonetheless, we do not anticipate a reverse impact in areas dominated by the small-scale unregulated mining activities.

That aside, the results from this paper suggest a negative spillover of natural resource extraction on human capital accumulation. The results further, imply that greater efforts may be needed to ensure that the socioeconomic gains from the extraction of natural resources to host communities are fully optimized.

References

Ackah, C. and Medvedev, D. (2012). Internal migration in ghana: determinants and welfare impacts. *International Journal of Social Economics*, 39(10):764–784.

Adu, G., Amuakwa-Mensah, F., Marbuah, G., Mensah, J. T., et al. (2016). Effect of gold mining on income distribution in ghana. Technical report.

Amuakwa-Mensah, F., Boakye-Yiadom, L., and Baah-Boateng, W. (2016). Effect of education on migration decisions in ghana: a rural-urban perspective. *Journal of Economic Studies*, 43(2):336–356.

Aragón, F. M. and Rud, J. P. (2013). Natural resources and local communities: evidence from a peruvian gold mine. *American Economic Journal: Economic Policy*, 5(2):1–25.

Aragón, F. M. and Rud, J. P. (2015). Polluting industries and agricultural productivity: Evidence from mining in ghana. *The Economic Journal*.

Aragona, F. M., Chuhan-Pole, P., and Land, B. C. (2015). The local economic impacts of resource abundance: What have we learned? *World Bank Policy Research Working Paper*, (7263).

Chuhan-Pole, P., Dabalen, A., Kotsadam, A., Sanoh, A., and Tolonen, A. (2015). The local socioeconomic effects of gold mining: evidence from ghana. *World Bank Policy Research Working Paper*, (7250).

Corno, L. and de Walque, D. (2012). Mines, migration and hiv/aids in southern africa. *Journal of African Economies*, 21(3):465.

Deller, S. and Schreiber, A. (2012). Mining and community economic growth. *The Review of Regional Studies*, 42(2):121.

Dubé, J. and Polèse, M. (2015). Resource curse and regional development: Does dutch disease apply to local economies? evidence from canada. *Growth and Change*, 46(1):38–57.

Gylfason, T. (2000). Resources, agriculture, and economic growth in economies in transition. *Kyklos*, 53(4):337–361.

Gylfason, T. (2001). Natural resources, education, and economic development. *European economic review*, 45(4):847–859.

Gylfason, T. and Zoega, G. (2002). Inequality and economic growth: Do natural resources matter?

Hajkowicz, S. A., Heyenga, S., and Moffat, K. (2011). The relationship between mining and socio-economic well being in australias regions. *Resources Policy*, 36(1):30–38.

Hentschel, T., Hruschka, F., and Priester, M. (2003). *Artisanal and small-scale mining: challenges and opportunities*. Iied.

Hirschman, A. O. ((1958)). *The Strategy of Economic Development*. Yale University Press, New Haven, CT.

ILO (2007). Girls in mining: Research findings from ghana, niger, peru and united republic of tanzania. Technical report, International Labour Organization.

Kitula, A. (2006). The environmental and socio-economic impacts of mining on local livelihoods in tanzania: A case study of geita district. *Journal of cleaner production*, 14(3):405–414.

Kotey, B. and Rolfe, J. (2014). Demographic and economic impact of mining on remote communities in australia. *Resources Policy*, 42:65–72.

Kotsadam, A. and Tolonen, A. (2016). African mining, gender, and local employment. *World Development*, 83:325–339.

Lippert, A. et al. (2014). Spill-overs of a resource boom: evidence from zambian copper mines. Technical report, Oxford Centre for the Analysis of Resource Rich Economies, University of Oxford.

Loayza, N., Mier y Teran, A., and Rigolini, J. (2013). Poverty, inequality, and the local natural resource curse. *World Bank Policy Research Working Paper*, (6366).

Mehlum, H., Moene, K., and Torvik, R. (2006). Institutions and the resource curse*. *The Economic Journal*, 116(508):1–20.

Sachs, J. D. and Warner, A. M. (1995). Natural resource abundance and economic growth. Technical report, National Bureau of Economic Research.

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

Tolonen, A. (2015). Local industrial shocks, female empowerment and infant health: Evidence from africas gold mining industry. In *2015 Fall Conference: The Golden Age of Evidence-Based Policy*. Appam.

Word Bank, T. (2015). Socioeconomic impact of mining on local communities in africa. Technical report, AFRCE, The World Bank.

Tables

Table 1: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Log of HH Income (real 2013 GHS)	26213	3.28	1.39	0	9.14
Log of HH Educational Expenditure	13641	.72	.93	0	5.56
HH Educ Expend. per student(real 2013 GHS)	8461	2.02	4.72	0	137.41
Educational Expend/Total HH Expenditure	13641	.06	.08	0	.93
Parent(s) with Secondary School or Higher	14082	.1	.3	0	1
Mother Lives in the HH	26199	.64	.48	0	1
Father Lives in the HH	26213	.47	.5	0	1
HH Size	26213	5.89	2.75	1	22
Child Engages in Paid/Unpaid Work	25025	.37	.48	0	1
Male Headed HH	16500	.67	.47	0	1
Age of HH head	16500	44.92	14.22	15	99
Health Post in Community	16125	.25	.44	0	1
Electricity in Community	16125	.48	.5	0	1
Road in Community	16125	.91	.29	0	1
Pipe-borne Water in Community	16125	.16	.36	0	1
Access to Primary School	16125	.81	.39	0	1
Access to JHS	16125	.66	.48	0	1
Access to SHS	16042	.37	.48	0	1
School (i.e. primary, JHS or SHS) in Community	16102	.9	.31	0	1
Rural	26213	.63	.48	0	1
Gender (1 male)	26213	.5	.5	0	1
Age	26213	15.41	6.71	6	30
Years of Schooling	26213	4.89	4.01	0	19
Mine_20km	26213	.19	.39	0	1
Mine_25km	26213	.29	.46	0	1
Mine_30km	26213	.36	.48	0	1
Mine_50km	26213	.65	.48	0	1
Mine_70km	26213	.83	.38	0	1
Mine×Open_20km	26213	.14	.35	0	1
Mine×Open_25km	26213	.22	.41	0	1
Mine×Open_30km	26213	.26	.44	0	1
Mine×Open_50km	26213	.48	.5	0	1
Mine×Open_70km	26213	.6	.49	0	1
HHH Employed in Agric	12518	.54	.5	0	1
HHH Employed in Mining	12518	.02	.15	0	1
HHH Employed in Manufacturing	12518	.09	.29	0	1
HHH Employed in Services	12518	.33	.47	0	1
HHH Employed in other sector	12518	.02	.14	0	1

Table 2: Effects of Mine Opening on Education at Different Age Cohorts

	Age Groups					
	6-18yrs	6-20yrs	6-12yrs	12-20yrs	6-30yrs	All Ages
	(1)	(2)	(3)	(4)	(5)	(6)
Mine	0.600*	0.340	0.0221	0.545	0.0493	-0.384
	(0.357)	(0.381)	(0.335)	(0.503)	(0.445)	(0.330)
Open	0.272	0.120	0.146	0.279	0.0581	0.00791
	(0.310)	(0.335)	(0.191)	(0.387)	(0.264)	(0.156)
Mine×Open	-1.142***	-1.007***	-0.265	-1.385***	-0.654	0.123
	(0.340)	(0.374)	(0.322)	(0.498)	(0.424)	(0.308)
Constant	3.464***	3.699***	0.705	4.263***	4.576***	3.039***
	(1.105)	(1.153)	(0.937)	(1.401)	(1.071)	(0.760)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes	Yes	Yes
Community Controls	Yes	Yes	Yes	Yes	Yes	Yes
District, Region & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.150	0.169	0.180	0.141	0.280	0.267
Obs	2884	3231	1518	2021	5250	10488

Notes: Robust standard errors in parentheses clustered at PSU. Dependent variables is years of schooling. All regressions include characteristics such as gender, real HH income, HH size, education of mother and father, whether the parents live in same HH. Community characteristics such as, presence of a school in community, access to electricity, road , pipe-borne water, and rural/urban status of the community. Distance cutoff is 20km.

* Significant at 10 percent level

** Significant at 5 percent level

*** Significant at 1 percent level

Table 3: Gendered Impact of Mine Opening on Education

	All		Male		Female	
	Age Groups					
	6-18yrs	12-20yrs	6-18yrs	12-20yrs	6-18yrs	12-20yrs
	(1)	(2)	(3)	(4)	(5)	(6)
Mine	0.605*	0.542	-0.364	-0.136	1.574***	1.518**
	(0.359)	(0.506)	(0.680)	(0.652)	(0.425)	(0.715)
Open	0.273	0.278	-0.271	-0.372	0.515	0.683*
	(0.310)	(0.388)	(0.510)	(0.750)	(0.401)	(0.374)
Mine×Open	-1.283***	-1.556***	-0.599	-1.320*	-1.419**	-1.447**
	(0.412)	(0.534)	(0.548)	(0.632)	(0.750)	(0.714)
Male	-0.138	-0.0447				
	(0.142)	(0.184)				
Male × Mine ×Open	0.253	0.337				
	(0.394)	(0.389)				
Constant	3.507***	4.313***	3.263**	4.722**	2.909**	4.767***
	(1.111)	(1.403)	(1.565)	(2.169)	(1.411)	(1.712)
Indiv. controls	Yes	Yes	Yes	Yes	Yes	Yes
HH controls	Yes	Yes	Yes	Yes	Yes	Yes
Community Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region,District & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.150	0.141	0.164	0.147	0.127	0.116
Obs	2884	2021	1449	1031	1435	990

Notes: Robust standard errors in parentheses clustered at PSU level. Dependent variables is years of schooling. All regressions include characteristics such as real HH income, HH size, education of mother and father, whether the parents live in same HH, and whether the individual is engaged in any economic activity (ie. paid or non-paid work),. Community characteristics such as, presence of a school in community, access to electricity, road , pipe-borne water, and rural/urban status of the community. Distance threshold is 20km.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table 4: Effects of Mine Opening on Literacy

	(1) Reading	(2) Writing	(3) Mathematics
Mine	0.0553	0.111	-0.0896
	(0.0792)	(0.0672)	(0.0786)
Open	0.0128	-0.00361	0.0176
	(0.0397)	(0.0394)	(0.0504)
Mine×Open	-0.0305	-0.0967	0.104
	(0.0778)	(0.0753)	(0.0884)
Constant	0.332**	0.327***	0.572***
	(0.133)	(0.125)	(0.140)
Indiv. Controls	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes
Community Controls	Yes	Yes	Yes
Region,District & Year FE	Yes	Yes	Yes
DistrictXYear FE	Yes	Yes	Yes
Adj R^2	0.130	0.125	0.164
Obs	2871	2871	2871

Notes: Robust standard errors in parentheses clustered at PSU level. All regressions include characteristics such as gender, real HH income,HH size, education of mother and father, whether the parents live in same HH. Community characteristics such as, presence of a school in community, access to electricity, road , pipe-borne water, and rural status of the community. Dependent variables: math is a discrete variable equal to 1 if respondent is able to do a specified math exercise and 0 if otherwise; read is equal to 1 if respondent is able to read in English or French; write equals 1 if respondent is able to write in english and zero if otherwise. Distance cutoff is 20km
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table 5: Effects of Mine Opening on the Probability of Working

	All		Male	Female
	(1)	(2)	(3)	(4)
Mine	-0.0204	-0.0185	-0.148	0.0334
	(0.0874)	(0.0868)	(0.0978)	(0.125)
Open	0.0251	0.0258	-0.0551	0.0699
	(0.0933)	(0.0933)	(0.130)	(0.0936)
Mine×Open	0.0698	0.175	0.0827	0.149
	(0.103)	(0.112)	(0.118)	(0.136)
Male	0.00487	0.0352		
	(0.0218)	(0.0227)		
Male×Mine×Open		-0.208***		
		(0.0612)		
HH controls	Yes	Yes	Yes	Yes
Community Controls	Yes	Yes	Yes	Yes
Region,District & Year FE	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes
Adj. Rsq	0.240	0.246	0.279	0.256
Obs	2021	2021	1031	990

Notes: Robust standard errors in parentheses clustered at PSU. All regressions include characteristics such as gender, real HH income,HH size, education of mother and father, whether the parents live in same HH. Community xtics such as, presence of a school in community, access to electricity, road , pipe-borne water, and rural status of the community. Dependent variable is work=1 if the individual is engaged in work(paid and unpaid) and equal 0 if otherwise. Estimations are done for 12-20 age groups. Distance cutoff is 20km

* Significant at 10 percent level

** Significant at 5 percent level

*** Significant at 1 percent level

Table 6: Effects of Mining on Communal Access to Schooling

	OLS				Diff-in-Diff			
	School	Primary	JHS	SHS	School	Primary	JHS	SHS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mine	-0.065**	-0.081**	-0.087*	-0.033	-0.038	-0.051	0.045	-0.029
	(0.027)	(0.034)	(0.048)	(0.024)	(0.047)	(0.059)	(0.091)	(0.041)
Open					-0.00037	0.028	0.15***	0.0010
					(0.031)	(0.041)	(0.052)	(0.023)
Mine×Open					-0.036	-0.043	-0.19	-0.0048
					(0.064)	(0.087)	(0.12)	(0.042)
Constant	1.22***	1.41***	0.61	0.47**	1.22***	1.40***	0.55	0.47**
	(0.35)	(0.42)	(0.48)	(0.24)	(0.35)	(0.42)	(0.47)	(0.23)
Community Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.072	0.010	0.001	0.809	0.068	0.007	0.013	0.808
Obs	455	461	461	458	455	461	461	458

Notes: Robust standard errors in parentheses clustered at District level. All regressions include real average income of households in the community, rural/urban status of the community, region and year fixed effects. Dependent variables: School is a dummy variable with 1 if the community has a school i.e., primary, Junior High, or Senior High, and 0 if otherwise; Primary is equal to 1 if community has a primary school and 0 if otherwise; JHS is equal to 1 if community has a Junior High School and 0 if otherwise; SHS is equal to 1 if community has a Senior High School and0 if otherwise. Columns 1-4 are estimated via OLS while Columns 5-8 are estimated via DID Distance cutoff is 20km.

* Significant at 10 percent level

** Significant at 5 percent level

*** Significant at 1 percent level

Table 7: Effects of Mining on Communal Access to Social Infrastructure

	OLS				Diff-in-Diff			
	(1) Electricity	(2) Pipe-borne Water	(3) Road	(4) Health Post	(5) Electricity	(6) Pipe-borne Water	(7) Road	(8) Health Post
Mine	-0.058	-0.019	0.058*	-0.032	0.084	-0.025	0.077	0.068
	(0.057)	(0.045)	(0.032)	(0.046)	(0.095)	(0.060)	(0.058)	(0.088)
Open					0.099	0.0029	0.030	0.019
					(0.061)	(0.039)	(0.033)	(0.051)
Mine×Open					-0.20*	0.0083	-0.029	-0.14
					(0.11)	(0.068)	(0.060)	(0.11)
Constant	0.0029	0.37	2.05***	0.55	-0.027	0.36	2.04***	0.56
	(0.54)	(0.42)	(0.27)	(0.46)	(0.55)	(0.42)	(0.27)	(0.46)
Community Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	461	461	461	461	461	461	461	461
Adj. R^2	0.067	0.035	0.054	0.032	0.071	0.031	0.052	0.031

Notes: Robust standard errors in parentheses clustered at District level. All regressions include real average income of households in the community, rural/urban status of the community, region and year fixed effects. Dependent variables: Whether the Community has access to electricity, pipe-borne water motorable road, and health post respectively.Distance cutoff is 20km.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table 8: Effect of Mine Opening on Households' Education Expenditure and Income

	Expend	Expend per capita	Expend Share	Income	Employment Income		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mine	1.819**	0.913**	0.0114	0.556***	-0.993**	-0.897*	-0.965**
	(0.860)	(0.399)	(0.0117)	(0.180)	(0.470)	(0.484)	(0.471)
Open	0.363	0.376	0.00216	0.0642	-0.378	-0.393	-0.396
	(0.675)	(0.285)	(0.00718)	(0.133)	(0.249)	(0.249)	(0.248)
Mine $\times$Open	-1.864**	-0.818**	-0.0160	-0.451**	1.532***	1.393***	2.208***
	(0.857)	(0.389)	(0.0116)	(0.189)	(0.440)	(0.458)	(0.553)
# of students	1.322***	-0.0479	0.0231***				
	(0.200)	(0.0642)	(0.00145)				
HHH Mining	-2.221	-1.510	-0.0208	0.973***	1.923***	1.365*	1.744**
	(2.900)	(1.564)	(0.0223)	(0.301)	(0.738)	(0.699)	(0.720)
Mine $\times$Open$\times$HHH mining						1.341	
						(1.256)	
HHH Agric	-2.195	-1.498	-0.0230	0.315	-1.692***	-1.695***	-1.535***
	(2.759)	(1.581)	(0.0210)	(0.252)	(0.447)	(0.447)	(0.443)
Mine $\times$Open$\times$HHH Agric							-0.987**
							(0.467)
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Community Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region,District & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes		
Adj R^2	0.189	0.126	0.244	0.771	0.232		
Obs	3598	3598	3598	5467	5467		

Robust standard errors in parentheses clustered at PSU. All regressions include Household controls such as gender of HH head, age of HH head, real HH income (except in columns 4-6), HH size, years of schooling of household head, sector of employment for HH head. Community controls also include the: presence of a school , access to electricity, road , and pipe-borne water in community, as well as the rural/urban status of the community. Dependent variables: Expend refers to the real HH expenditure on education; Expend per capita refers to the education expenditure per student in the HH; Expend Share is the share of education expenditure in total HH expenditure; Income is the real HH income; Empl Income refers to real HH income from employment. Distance cutoff is 20km.

* Significant at 10 percent level

** Significant at 5 percent level

*** Significant at 1 percent level

List of Figures

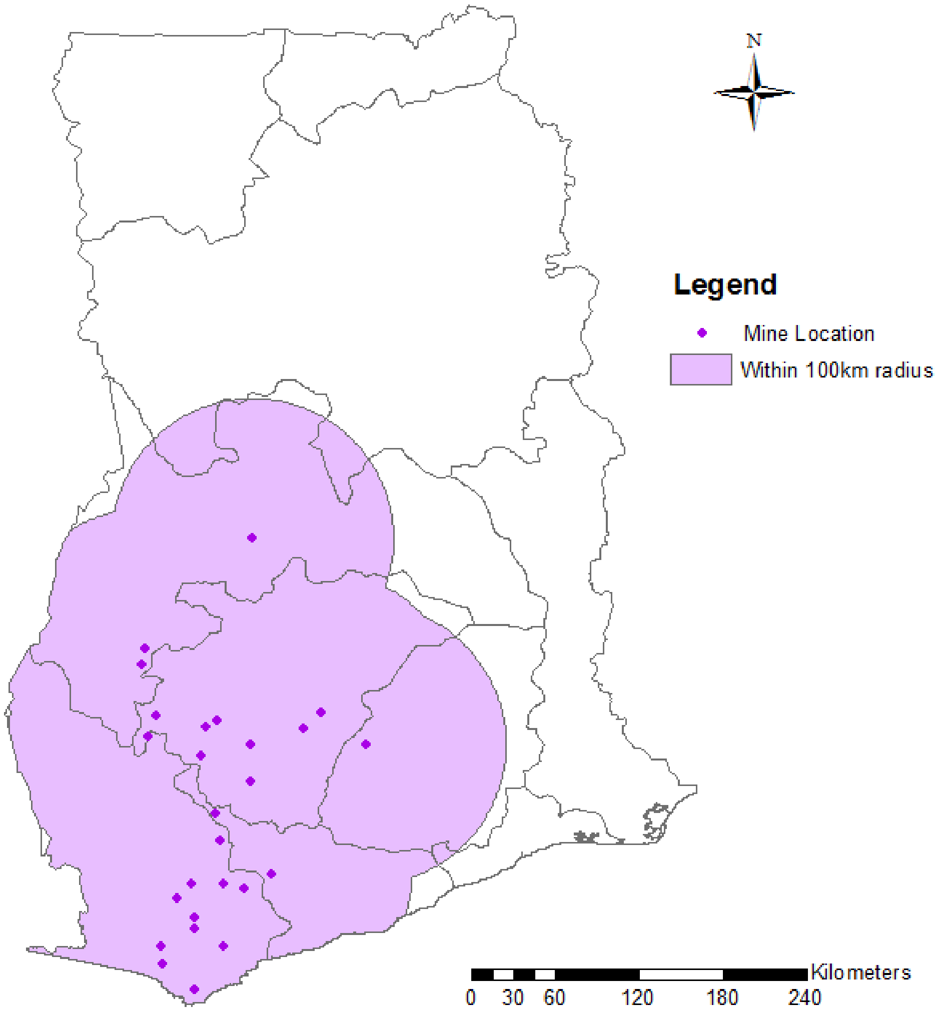

Figure 1: Study Area within 100km radius from a mine

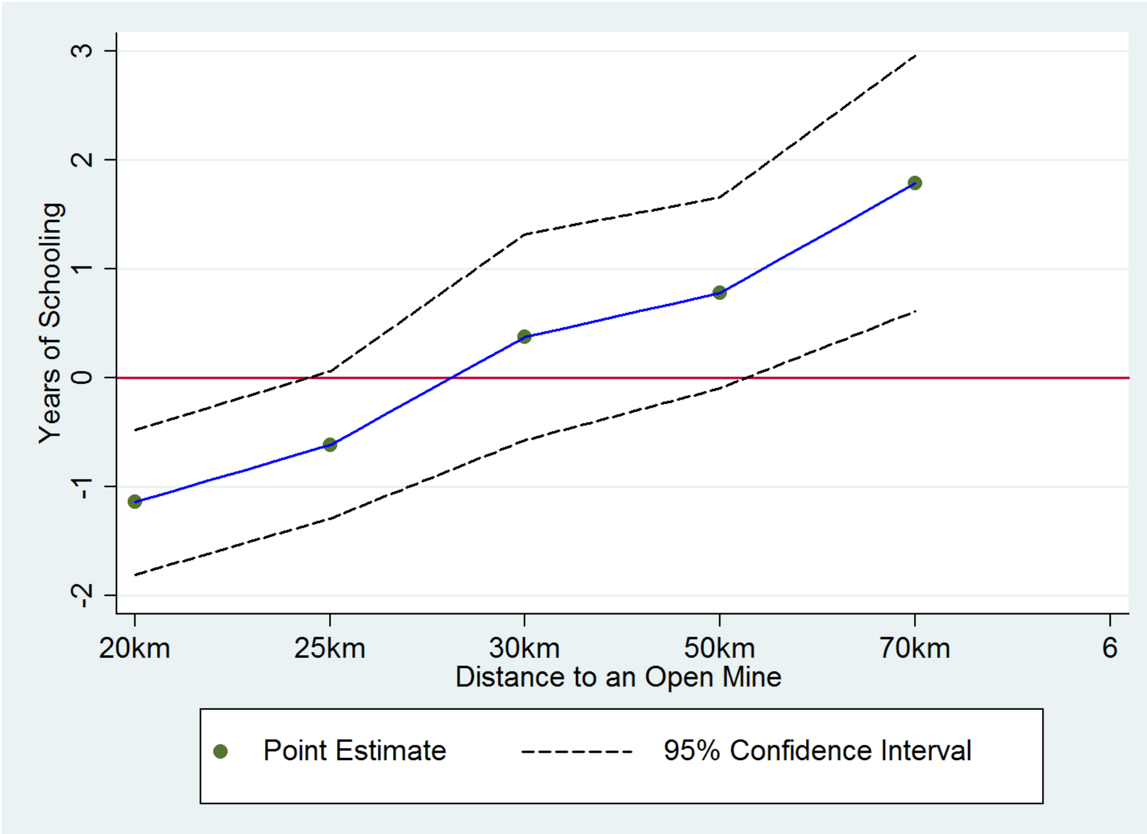

Figure 2: Effect of Mine Opening on Years of Schooling, by Distance to the Mine

Appendix

Table 9: Effects of Mine Opening on Education at Various Distance Thresholds

	Distance Thresholds				
	20km	25km	30km	50km	70km
	(1)	(2)	(3)	(4)	(5)
Mine	0.600*	0.938**	0.950*	-0.0514	-1.119**
	(0.357)	(0.370)	(0.483)	(0.435)	(0.449)
Open	0.272	0.161	-0.0127	-0.314	-1.066**
	(0.310)	(0.309)	(0.310)	(0.325)	(0.435)
Mine×Open	-1.142***	-0.615*	0.374	0.782*	1.785***
	(0.340)	(0.345)	(0.482)	(0.447)	(0.598)
Constant	3.464***	3.708***	2.632**	3.507***	4.096***
	(1.105)	(1.110)	(1.156)	(1.171)	(1.222)
Ind. Controls	Yes	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes	Yes
Community Controls	Yes	Yes	Yes	Yes	Yes
Region,District & Year FE	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.150	0.150	0.153	0.151	0.152
Obs	2884	2884	2884	2884	2884

Notes: Robust standard errors in parentheses clustered at PSU. Dependent variables is years of schooling. All regressions include characteristics such as gender, real HH income, HH size, education of mother and father, whether the parents live in same HH. Community characteristics such as, presence of a school in community, access to electricity, road , pipe-borne water, and rural/urban status of the community.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table 10: Effects of Mine Opening on Education Conditional on Migration

	(1)	(2)	(3)
	20km	25km	30km
Mine	0.268	0.811*	0.787
	(0.447)	(0.528)	(0.502)
Open	0.183	0.172	0.145
	(0.345)	(0.346)	(0.347)
Mine×Open	-0.932*	-0.962*	-0.556
	(0.556)	(0.528)	(0.567)
Native	0.0269	-0.00428	-0.0577
	(0.217)	(0.227)	(0.239)
Native × Mine ×Open	0.921	0.805	0.759*
	(0.618)	(0.497)	(0.427)
Constant	4.014***	4.216***	4.011***
	(1.421)	(1.398)	(1.453)
Individual Controls	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes
Community Controls	Yes	Yes	Yes
Region,District & Year FE	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes
Adj R^2	0.163	0.164	0.165
Obs	1639	1639	1639

Notes: Robust standard errors in parentheses clustered at PSU. Dependent variables is years of schooling. Results relates to individuals within the ages of 6-18 years. Native is measured by whether the HH head was born in the community or otherwise. All regressions include characteristics such as gender of the individual, real HH income, HH size, education of mother and father, whether the parents live in same HH. Community characteristics such as, presence of a school in community, access to electricity, road , pipe-borne water, and rural/urban status of the community. Distance cutoff is 20km.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table 11: Placebo Test C:Effect of Mine Opening on Households' Education Expenditure and Income:Sample 200km from a Mine

	Expend	Expend per capita	Expend Share	Income	Employment Income		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mine	1.622*	0.775**	0.00807	0.628***	-1.073**	-0.992**	-1.040**
	(0.871)	(0.387)	(0.0123)	(0.174)	(0.468)	(0.481)	(0.470)
Open	0.427	0.331	0.00281	0.140	-0.405*	-0.416*	-0.419*
	(0.606)	(0.259)	(0.00659)	(0.124)	(0.236)	(0.236)	(0.235)
Mine ×Open	-1.823**	-0.738*	-0.0145	-0.529***	1.554***	1.436***	2.228***
	(0.868)	(0.378)	(0.0121)	(0.185)	(0.436)	(0.454)	(0.551)
# of students	1.246***	-0.0618	0.0228***				
	(0.168)	(0.0536)	(0.00132)				
HHH Mining	-2.001	-1.142	-0.0199	0.836***	1.822**	1.368**	1.642**
	(2.204)	(1.130)	(0.0178)	(0.280)	(0.723)	(0.682)	(0.707)
Mine ×Open×HHH Mining						1.171	
						(1.239)	
HHH Agric	-2.070	-1.190	-0.0261	0.153	-1.859***	-1.861***	-1.730***
	(2.065)	(1.144)	(0.0160)	(0.235)	(0.467)	(0.467)	(0.466)
Mine ×Open×HHH Agric							-0.990**
							(0.462)
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Community Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region,District & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.190	0.123	0.233	0.769	0.229	0.229	0.230
Obs	4402	4402	4402	6705	6705	6705	6705

Robust standard errors in parentheses clustered at PSU. All regressions include Household controls such as gender of HH head, age of HH head, real HH income (except in columns 4-6), HH size, years of schooling of household head, sector of employment for HH head. Community controls also include the: presence of a school , access to electricity, road , and pipe-borne water in community, as well as the rural/urban status of the community. Dependent variables: Expend refers to the real HH expenditure on education; Expend per capita refers to the education expenditure per student in the HH; Expend Share is the share of education expenditure in total HH expenditure; Income is the real HH income; Empl Income refers to real HH income from employment. Distance cutoff is 20km.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table 12: Placebo Test A: Extending Sample to Individuals Living within 200km of a Mine

	Age Groups					
	6-18yrs (1)	6-20yrs (2)	6-12yrs (3)	12-20yrs (4)	6-30yrs (5)	All Ages (6)
Mine	0.663*	0.420	-0.0160	0.656	0.0989	-0.408
	(0.360)	(0.370)	(0.325)	(0.492)	(0.446)	(0.325)
Open	0.222	0.0936	0.0159	0.276	0.0809	0.000982
	(0.257)	(0.280)	(0.176)	(0.322)	(0.240)	(0.169)
Mine × Open	-1.166***	-1.052***	-0.234	-1.444***	-0.705*	0.135
	(0.336)	(0.364)	(0.319)	(0.491)	(0.423)	(0.304)
Constant	3.798***	4.264***	0.205	4.773***	5.274***	3.439***
	(0.983)	(1.031)	(0.853)	(1.252)	(0.990)	(0.694)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes	Yes	Yes
Community Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region,District & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.138	0.160	0.191	0.131	0.272	0.259
Obs	3535	3955	1874	2469	6419	12859

Notes: Robust standard errors in parentheses clustered at PSU. Dependent variables is years of schooling. All regressions include characteristics such as gender, real HH income, HH size, education of mother and father, whether the parents live in same HH. Community characteristics such as, presence of a school in community, access to electricity, road , pipe-borne water, and rural/urban status of the community. Distance cutoff for the treatment group is 20km.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table 13: Placebo Test B: Without Distance Threshold on Sample

	Age Groups					
	6-18yrs	6-20yrs	6-12yrs	12-20yrs	6-30yrs	All Ages
	(1)	(2)	(3)	(4)	(5)	(6)
Mine	0.702*	0.491	0.0749	0.692	0.226	-0.408
	(0.359)	(0.373)	(0.323)	(0.487)	(0.470)	(0.325)
Open	0.190	0.0607	0.0486	0.228	0.0696	0.000982
	(0.252)	(0.273)	(0.172)	(0.315)	(0.238)	(0.169)
Mine × Open	-1.134***	-1.047***	-0.290	-1.416***	-0.770*	0.135
	(0.335)	(0.357)	(0.321)	(0.489)	(0.439)	(0.304)
Constant	3.890***	4.367***	0.762	4.362***	6.055***	3.439***
	(0.883)	(0.945)	(0.763)	(1.160)	(0.908)	(0.694)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes	Yes	Yes
Community Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region,District & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.131	0.152	0.190	0.129	0.255	0.259
Obs	4112	4632	2157	2911	7684	12859

Notes: Robust standard errors in parentheses clustered at PSU. Dependent variables is years of schooling. All regressions include characteristics such as gender, real HH income, HH size, education of mother and father, whether the parents live in same HH. Community characteristics such as, presence of a school in community, access to electricity, road , pipe-borne water, and rural/urban status of the community. Distance cutoff for the treatment group is 20km.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table 14: Mines and their Open/Close Status during the Survey Years

Mine Name	**1999**	**2005**	**2012**
AHAFO-NTOTOROSO	0	1	1
AKROKERI PROPERTY	0	1	1
BENSO (HBB)	0	0	1
BIBIANI	1	1	1
BOGOSO/PRESTEA	1	1	1
CAPE THREE POINTS	0	0	1
CENTRAL ASHANTI	1	1	0
CHICHIWERE	1	0	0
CHIRANO	0	1	1
DAMANG MINE	1	1	1
DUNKWA (MAMPON)	1	1	1
ESAASE GOLD PROJECT	1	1	1
HWIDiem-AHAFO PROJECT	0	0	1
IDUAPRIEM /TEBEREBIE	1	1	1
NORTH ASHANTI	1	0	1
NOYEM	0	1	1
NZEMA GOLD PROJECT	0	0	1
OBUASI	1	1	1
TARKWA	1	1	1
WASSA	1	1	1
OBOTAN	1	1	0
ESSASE PLACER	1	1	0
KONONG/OBENAMASI	1	1	1
EDIKAN-AYANFURI	1	1	1
JENI-BONTE	1	0	0
PRESTEA SANKOFA	1	0	0

Notes: Entries in the columns "1999, 2005 and 2012" are binary indicator where 1 means the mine is opened and active in that year, 0 otherwise. These years corresponds with the years within which the respective GLSS surveys were undertaken.