Gold Mine Openings and Child Labor in Mali *

Hyuk Harry Son †

July 29, 2021
Click [here] for the latest version of the paper.

Abstract

This study investigates the effect of a natural resource shock on child labor using the opening dates and the location of the industrial gold mines in Mali. Unlike other papers that show mines increase children's work, I find that the opening of mines decreases children's work, specifically the working hours for household tasks while it does not affect the school enrollments. The effects were heterogeneous by age and birth order. I claim that my results stem from the income effects of the mines dominating the substitution effects by presenting the evidence on the adults' employment and occupational choices.

Keywords: child labor, gold mines, education, economic shock, natural resources

*I thank John Hoddinott, Kaushik Basu, Mike Lovenheim, Brian Dillon, Chris Boone and numerous seminar participants at Cornell University and the Center for the Study of African Economics Conference for their helpful comments and suggestions. All errors are on the author.

†Department of Economics, Cornell University. Email: hs924@cornell.edu

1 Introduction

Child labor is one of the activities that hinders investment in children's human capital, a crucial ingredient for economic development. Working children invest less time and effort in schooling; hence, they have poorer educational outcomes both in the short- and long-term (Heady 2003; Beegle et al. 2008; Emerson et al. 2017; DeGraff et al. 2016). Moreover, exposure to hazardous conditions in work leads to poorer health conditions in adulthood (Kassouf et al. 2001; Lee and Orazem 2010). Hence, governments and development organizations have made an effort to reduce child labor, but 264 million children were still at work globally in 2016. These child laborers are not equally populated across countries—the prevalence of child labor is higher in countries with lower GDP per capita (Edmonds 2016).

In some of these low- to middle-income countries, natural resource extraction is a major source of export, but evidence of its effects on economic development is mixed. Macro-level evidence often finds capital-intensive, foreign-owned, large-scale industrial mines[1] as a source of resource curse (Frankel 2012; Sachs and Warner 2001). However, micro-level evidence shows that local economic impact is positive. Specifically, studies show that sectoral shift in employment, and in some cases the structural transformation of the economy, is induced by industrial mines (Aragón and Rud 2013; Fafchamps et al. 2017; Kotsadam and Tolonen 2016). Moreover, the studies on the impact of mining activities on children that lead to a long-term effect of these activities have produced mixed and conflicting results (Benshaul-Tolonen 2019; Santos 2018; von der Goltz and Barnwal 2019; Zabsonré et al. 2018).

This paper investigates the relationship between mining activities and children's work and schooling by empirically examining the opening of industrial gold mines in the West African country of Mali. Theory suggests that when new job opportunities arise as with the mines, there will be two effects. More opportunities for work increase child labor, while higher adult income decreases the need of parents to send their children to work. However, theory cannot predict which effect will dominate, warranting the importance of empirical work, which is what I do in this paper. For the empirical analysis, I exploit two exogenous events: (a) a new mining code introduced in 1991 that resulted in new foreign direct investment in extractive industries (World Trade Organization 1998); and (b) the increase in global gold prices that made such investments profitable (Mainguy 2011). I match geo-coded data on 12,468 children between 5 to 14 years old who were interviewed between 2001 to 2012 with geo-coded information on new gold mine construction and operation.

[1] I refer to industrial mines as highly mechanized, capital intensive, and large-scale gold mines operated by firms that are often large as well. In contrast, artisanal small-scale mines (ASM) are traditional ways to extract gold, and most ASMs are unregistered and operated by local capitals.

It allows us to compare children living in households closer to the mines to those living further from the mines. The comparison is made before and after the closest mines open while controlling for region- and time-specific confounders. By doing so, I capture the effect of opening industrial gold mines on child labor.

My main finding is that the opening of industrial mines reduces children's working hours by 7.6 hours per week, which is a 38.2 percent reduction. The effects were driven by household tasks which decreased by 5.1 hours. The economic activities show qualitatively similar effects, but the magnitude and the precision of the effects are much smaller than for household tasks. The effects are heterogeneous across groups with different demographic characteristics. The reduction in working hours is larger among girls than among boys, contributing to closing the gender gap in children's work. However, first-born children continue to perform more work, resulting in significantly decreased working hours among younger siblings. Moreover, younger siblings are one of the only two demographic subgroups decreased economic activities. Additionally, the first-born children and the older age group children (12-14 years old) are the only two groups that reduced school enrollment.

I find no substantial changes at extensive margins nor improvements in educational outcomes. These results do not resonate with previous findings in the literature of which children increase work participation and decrease school enrollment when a mine opens. It suggests that the industrial mines in Mali only had an indirect impact on children's work through income effects instead of having direct employment effects. I argue that the indirect income effects come from changes in the adults' employment outcomes. Mothers were less likely to work, but were more likely to work in better-quality jobs conditional on work, which is consistent with the findings of Kotsadam and Tolonen (2016). Moreover, adult female employment shifts from agriculture to the sales sector while adult male employment increases in clerical/managerial positions.

Lastly, I show that the results are robust to the changes in the distance threshold, continuous distance measure, and a more conservative measure of child labor. Moreover, I verify that the demographic changes induced by endogenous migration are not the drivers of the results. The average demographic characteristics do not systematically change due to mine openings, and the estimates using the sample of "never movers" after the mine openings show qualitatively the same results.

This paper adds evidence to the mixed literature on the effects of gold mining activities on children's work and schooling. Several papers have investigated the effect of gold mine activities on this topic and found gold mines increase children's work and decrease schooling. Santos (2018) shows that industrial gold mines in Colombia increase child labor and decrease schooling.

Ahlerup et al. (2020) also find that industrial mines decrease adolescent schooling attainments in Sub-Saharan Africa. They remove other candidate mechanism and argue child labor is a likely mechanism, but do not present supporting empirical evidence. My results differ from these studies because I show that children's work—at least within the household—decreases substantially and the effects on schooling are not significant. The results of my study are closer to those of Zabsonré et al. (2018)who find that increases in gold prices had no impact on child labor or on children's schooling in mining communities in Burkina Faso. Nevertheless, my results can be reconciled with those of Santos (2018) and Ahlerup et al. (2020) for two reasons. First, my sample includes children 5 to 14 years old, while the other two papers focus on adolescents who are more likely to be formally employed. In my analysis, I also find that older children (ages 12-14) and first-born children decrease school enrollment, while younger children decrease working hours in economic activities. Second, I include working hours for household tasks in the analysis, and it is a driver of the main results. Even among older children, the hours for household work decreased. Therefore, my results provide rare evidence that an industrialized gold mining activity can reduce the workload of children.

I also contribute to the discussion on the relationship between economic development and children's work. Economic development often increases household income, and a large body of research shows that higher household income decreases children's work participation (Basu and Van 1998; Edmonds 2005; Edmonds and Pavcnik 2005; Edmonds and Schady 2012; Cogneau and Jedwab 2012).[2] However, other studies suggest that economic development may increase children's work in response to a higher demand for labor. For example, households can accumulate productive assets as the economy develops, but children may increase their work to utilize these assets (Basu et al. 2010; Cockburn and Dostie 2007; Edmonds and Theoharides 2020). Urbanization is also associated with an increase in child labor (Fafchamps and Wahba 2006). [3] I analyze the effect of the development of a sector with capital-intensive, heavy machine-operated technologies that expand work availability in the region. My results show that such a development can reduce children's working hours in the region.

Lastly, I address the literature on the economic effects of natural resource extraction. Microeco-

[2] This negative correlation between household income and child labor is also found under negative productivity shocks (Beegle et al. 2006; Duryea et al. 2007), suggesting that some households use children's labor as a way to self-insure against risks.

[3] More productive assets at home (e.g. land, livestock) could decrease the relative value of the alternative use of a child's time and increase the child labor supply (Basu et al. 2010; Cockburn and Dostie 2007; Edmonds and Theoharides 2020). Basu et al. (2010) show that poorer households increase child labor when they have more productive assets at home, but households start to decrease child labor once they have more productive assets than a certain threshold. Additionally, the proximity to an urban area may increase the working hours of children outside of the household as economic opportunities for children increase with proximity (Fafchamps and Wahba 2006).

nomic evidence indicates that mining activities have positive effects on the local economy. Mining activities increase household income (Gajigo et al. 2012; Weng et al. 2013), shift employment from agriculture to manual labor and services (Kotsadam and Tolonen 2016), increase household asset wealth (von der Goltz and Barnwal 2019), on der Goltz and Barnwal 2019), and improve household living standards (Aragón and Rud 2013; Zabsonré et al. 2018) due to the resources and infrastructure they require (Fafchamps et al. 2017). However, the literature on the impact of mining activities on health has produced mixed results. According to von der Goltz and Barnwal (2019), industrial gold mines decrease infant mortality. By contrast, Benshaul-Tolonen (2019) finds that pollution from industrial mines increases the prevalence of chronic undernutrition. This paper provides evidence that the natural resource shock could positively affect children by decreasing children's engagement in work.

This paper proceeds as follows. Section 2 discusses a conceptual framework. Section 3 explains the study setting, and section 4 describes the data set and the empirical strategy used for the estimation. I present the estimated results in section 5 and conclusions in section 6.

2 Conceptual Framework

This section presents a simple framework to structure thinking about the effects of natural resource shock on household labor allocation. Each household decides the amount of children's work depending on adult and children's wage (defined as the value of their work instead of actual market wage), household income, the net benefit of education, and other factors including time and risk preference. Industrial gold mines increase household income and wealth (Aragón and Rud 2013; von der Goltz and Barnwal 2019) through multiple channels. The two potential channels through which industrial mines can increase household income are direct and indirect employment at mines. Indirect employment includes service and sales jobs created through a local multiplier (Moretti 2010). However, neither the cost nor the quality of education will likely change due to the gold mine openings; therefore, unless there is a significant population influx, children's work and schooling are affected by changes in household income or wages as determined by the demand for labor.

Under this setting, the effect on child labor is *a priori* ambiguous. First, the demand for child labor is likely to increase. The direct employment at the mine would be negligible due to the capital-intensive nature of jobs at industrial mines. However, opportunities for indirect employment in service and sales sectors can increase as described by Santos (2018). Similarly, Kotsadam and Tolonen (2016) also found that female adult employment in those sectors increase. Considering that a child typically works for the household farm or business, an increase in the employment of adult females in sales and service sectors increases children's exposure to household jobs. Moreover, the demand for child labor increases within a household as well. As adults experience increased employment opportunities – especially in sectors other than agriculture – vacancies in household farms or household tasks may rise. To the extent that children can substitute adult labor in these tasks, the demand for children's work will increase.

Following the Luxury axiom posed in Basu and Van (1998), increased adult wage income from the labor demand shock may decrease child labor. Moreover, as found in existing studies, increased household income from adult labor will decrease child labor (Cogneau and Jedwab 2012; Edmonds and Schady 2012). The income effect can work through two channels. Assuming that a child's leisure activities are normal good, a household will increase the consumption of children's leisure activities with the increased income. I call this a "direct" income effect. An "indirect" income effect occurs when an increased household income leads to a decrease in the secondary adult income earner's economic activities, and the secondary adult income earner replaces children in household work. In fact, Kotsadam and Tolonen (2016) argue that the decrease in female employment is due to increased household income from a male partner's employment. If this is the case, female adults will replace children's work at home.

Therefore, the direction of the effects on child labor is determined by which effect dominates the other. If the substitution effect dominates, children may work more. On the other hand, child labor may decrease if the income effect dominates. If the income effect dominates, the changes in adult labor outcomes will provide a hint as to which channel the effects of mine openings may work through. The dominant effect cannot be determined theoretically; therefore, addressing the question is an empirical matter.

3 Study Settings

3.1 Gold Mining in Mali

Gold has been an important source of the Malian economy since 1235 when the Mali empire was first established (Dibua 2010; Kusnir 1999). Historically, extraction was on a small-scale, artisanal basis. Two incidents triggered a dramatic growth in gold production in Mali. First, a new mining code introduced in 1991 provided tax and customs advantages to the mining sector to attract foreign direct investments. As a result, seven large-scale industrial gold mines started their operations in the following two decades, and gold production volume increased rapidly. Mali produced only 950 kg of gold in 1987, while production grew to 23,668 kg by 1999. Second, increases in international gold prices that began in 2001 led to further increases in production value and expansion of the mining industry as shown in Figure 1. The gold production industry continued to grow, and the share of gold among Mali's export goods increased to 65 percent by 2019 (International Monetary Fund 2019).

I consider the opening of industrial gold mines to be exogenous for two reasons. First, the initial expansion of the industrial gold mines began with a policy change—a new mining code in 1991 designed to attract foreign direct investments in the Malian mining sector. The global price increase led to the next expansion. Figure 1 also shows that the number of mines increased after 2001 when international gold prices started to increase. Second, industrial gold mines' locations are limited to those places where gold can be extracted on an industrial basis. Figure 2 shows the locations of gold mines in Mali. Mines are concentrated in the western and southern parts of the country. In fact, there are only two regions where all the mines are located—in the Kayes and Sikasso regions.[4] Thus, it is unlikely that the foreign-owned mining companies were attracted to the current locations for characteristics of the local economies, such as the presence of local capital other than the existence of the gold reserves.

3.2 Child Labor Practice in Mali

Child labor is widespread in Mali. Panel A of Figure 3 shows that children's participation in work decreased over time from 80.4 percent in 2001 to 62.5 percent in 2012. The high participation rate comes from helping with household tasks that range from 57 percent to 74 percent. It is consistent with the premise that some parents view a moderate amount of children's work as acceptable or even instructive for their children (Kippenberg 2011). Participation in economic activities is relatively lower, ranging from 20 percent to 58 percent during this period.

Agriculture is the largest employer of children participating in economic activities. Mali's population and housing census indicates that 83 percent of working children work in agriculture. Other sectors, including the mining sector, hire considerably fewer children (Figure A1).

Unlike the participation rate, working hours did not substantially vary across time. In total, children worked 23.4 hours in 2001 and 24 hours in 2012 (conditional on working). Working hours were less than 19 hours per week for economic activities and 24 hours for household tasks. Considering that the International Labour Organization (ILO) and other international organizations use a threshold of 14 hours (for economic activities) and 28 hours (for domestic activities) to define

[4] The geographical data of mines was obtained from a publicly disclosed dataset used in Benshaul-Tolonen (2019).

children's engagement in work as child labor for the older group of children (ages 12–14), the workload is not light. These working hours are long enough to be classified as child labor.

Since economic activities and household tasks comprise child labor together, I examine the effects of the opening of industrial mines on two different types of children's work activities in this paper: (a) economic activity, which includes any income-generating activity that a child is engaged in regardless of payment status or for whom the child is working; and (b) household tasks, which includes cooking, taking care of younger siblings, and fetching water. I also use an aggregate number of hours a child works.

4 Data and Empirical Strategy

4.1 Data

For the main empirical analyses, I combine three data sets, Mali's Demographic and Health Surveys (DHS), information on the location of industrial gold mines in Mali from Benshaul-Tolonen (2019), and opening dates of industrial gold mines from mining companies' official website and Mining Data Online[5]. These data sets provide repeated information on child labor and demographic characteristics over time, information on the geographic location of survey clusters and gold mines, and the opening dates of the mines—all of which are necessary for my analysis.

Mali's Demographic and Health Surveys (DHS) provides information on children's work, education, and demographic background from the 1996, 2001, 2006, and 2012 waves (CPS and DNSI 1996; CPS and DNSI 2002; CPS and DNSI 2007; CPS, INSTAT, and INFO-STAT, 2014). It is a repeated cross-sectional household survey that provides a wide range of data pertaining to population, health, child labor, and education. It also provides GPS coordinates of the survey clusters and collects information on child labor in a standardized manner.

I measure child labor using the working hours of children, ages 5–14, in the 7 days before the interview. The legal minimum working age is 15; hence, 14 years of age is the upper bound of the age range. The DHS data set identifies two types of work in which children are engaged: economic activities and household tasks. Economic activities include tasks children undertake on family land, help for the family business, fetching water and wood, and any other paid or unpaid economic activities outside of the household. Household tasks refer to activities such as cooking, cleaning, and washing clothes. I sum children's working hours for both types of work to measure

[5] https://miningdataonline.com

children's time allocation for work. I set 95 hours per week as an upper bound of all types of children's working hours and coded working hours to be zero if a child did not work in the last 7 days before the interview.[6]

Educational outcomes are measured using years of education and the current year's school enrollment. Years of education is a stock variable, so it is less susceptible to short-term changes than the current enrollment. I treat both "attended school at some point this year" and "attending school now" as currently enrolled to avoid the possibility of measurement error since the survey period typically spans 5–6 months and varies from winter to summer.

To identify a cluster as a mining area, I link the GPS coordinates of the survey clusters and the GPS coordinates of all mines and compute the distance to the closest mine. If the cluster is within a 20 km radius from the industrial gold mines, I identify the cluster as a mining area. Therefore, the survey clusters within a mining area serve as an ever-treated group since they are exposed to the active mine operations at some point in the sample period. As depicted in Figure 2, mines are located at the country's southwestern border where the gold reserves are located. However, it may raise concern regarding the systematic difference between the region and the rest of the country. Therefore, I restrict the sample to the surveyed clusters located within a 100 km radius of the mines. I discuss the choice of the threshold distances in the next section in more detail.

Panel A of Table 1 presents the mean and standard deviation of individual- and household-level characteristics of children in mining and non-mining areas before the mine openings. I use the data from pre-opening years to show the average difference in pre-shock variables between the mining and non-mining areas. Column 1 shows that the children living in the mining area are 9 years old on average and about 51.6 percent are boys. The average household has 9.8 people, with 15.6 percent of households residing in urban areas. The average wealth quintile is 3.01.[7] The average mother is 37 years old and received 0.5 years of education, while the average father is 50 years old with 1.1 years of education. Eighty-nine percent of the children in my sample are living together with their biological mother. Demographic characteristics of non-mining area children and their households are similar to those of mining area children.

Panel B summarizes the pre-shock outcome variables—participation in and working hours for child labor and educational outcomes in mining and non-mining areas. Column 1 shows that in pre-shock mining areas, 84.1 percent of children were engaged in child labor (any type). Specifically, 41.9 percent of the children participated in economic activities and 75.8 percent in household tasks.

[6] One percent of the sample is reported to have worked longer than 95 hours in the previous week, and I check whether the results are robust after dropping this observation.

[7] I construct the wealth index by principal component analysis using indicators of the living standards of respondents (e.g., access to electricity, water, and bathroom; materials used to construct walls and floors of the household.)

Weekly working hours were 20.2 hours for any type of work. Among the 20.2 hours, children spent 2 hours on economic activities and 18 hours on household tasks. On average, children in the mining area received 0.8 years of education, and 39 percent were in school during the previous school year. These pre-shock outcomes in non-mining areas were similar to those of mining areas: Column 3 shows that the school enrollment is higher in mining areas than non-mining areas, with 5 percent statistical significance, but other outcome variables are the same, on average, across areas.

Children's weekly working hours are negatively correlated with the wealth status of their households. Panel A of Figure 4 shows that the wealthier the household is, the fewer children participate in any types of work. Moreover, children's working hours are correlated with their mother's occupational choices. Panel B of Figure 4, shows that the children of mothers working in the agricultural sector work the longest hours in total (18.3 hours per week). They do so by working the longest in both economic activities and household tasks. By contrast, children of non-working mothers work the least number of hours in total (12.3 hours per week). These children work 2.7 hours per week in economic activities, which is longer than the average, but they work the fewest number of hours performing household tasks. It indicates that children's engagement in household tasks is substituted by mothers who are present at home.

In section 4.3, I estimate the pre-shock trends of outcome variables across mining and non-mining areas. I aim to establish the ground for the causal estimation by showing the pre-shock parallel trend. The average differences of pre-shock variables presented in this section provide additional supporting evidence to show that the level difference between the areas was small.

4.2 Empirical strategy

Following Kotsadam and Tolonen (2016) and Benshaul-Tolonen (2019), I use the following equation to estimate the impact of gold mine expansion on child labor and educational outcomes:

$$y_{ijtc} = \beta_0 + \beta_1 20km_j \cdot Open_{jt} + \sum_{d=1}^{5} \text{Distance Bin}_j^d + \sum_{y=1}^{6} \text{Years from open}_t^y + \delta_t + \theta_c + X_{ijct} + \varepsilon_{ijct} \tag{1}$$

where y_{ijtc} is the outcome variable of a child i living in a cluster j located at t years from the opening of the mine; Subscript c denotes the cercle (a sub-regional administrative area); $20km_{jt}$ is an indicator equals one if a cluster j interviewed at t years from mine opening is located within 20 km from an open mine (serves as an ever-treated group indicator). The control group is the children living in clusters located between 20 km and 100 km from the gold mines. $Open_{jt}$ is an indicator equals one if a cluster j was interviewed after the closest mine open. It exploits the differences in the opening year of mines and the survey year and serves as a post dummy in a 2×2 difference-in-difference estimation.[8] Spatial variations are captured by 20 km-bin fixed effect, denoted by $\sum_{d=1}^{5}$ Distance Bin_j^d, and time variations by year-from-mine fixed effect, $\sum_{y=1}^{6}$ Years from open_t^y. Distance Bin_j^d is a series of indicators that groups the distance from the closest mine to the surveyed cluster in 20 km bins. Years from open_t^y is also a series of binary variables which take the value of one if the relative time from the mine opening falls into the 5-year bins. In this equation, β_1 is the coefficient of interest, which I interpret as the changes in child labor in areas in proximity to the active mines compared to the contemporaneous changes in areas farther away from the mines.

I chose geographic proximity – 100 km as a threshold to restrict the sample and 20 km to define the mining area – to measure the effect of mines for several reasons. First, the existing literature on mining suggests that the treatment effects of mines are concentrated in adjacent areas. While Aragón and Rud (2013) find effects in the areas within 100 km of the mine, other papers such as Kotsadam and Tolonen (2016), Benshaul-Tolonen (2019) and von der Goltz and Barnwal (2019) found the effects among the households residing within a 20 km radius of the mines. Evidence on Ghana and Tanzania's commuting behaviors also shows that the impact of mines on local economies can be identified within 5–20 km from the mines (Amoh-Gyimah and Aidoo 2013). Therefore, a threshold of 100 km for sample restriction ensures the comparability of ever-treated and the comparison group. Second, the geocoordinates in the DHS data are randomly displaced up to 5 km and 10 km for 1 percent of the sample to prevent the users from identifying the individual households. DHS also recommends using thresholds larger than 5 km. Third, as discussed in Benshaul-Tolonen (2019), the geocoordinates in the mining data locate the center of the mining area. Thus, using a distance threshold that is too small could introduce more noise or increase the possibility of capturing only the mining sites rather than the communities surrounding the mines. In section 5.4, we assess if our results are robust to changes in these distance thresholds.

To control for the effects from region-specific characteristics and survey-year specific events, I include commune and survey-year fixed effects denoted by θ_c and δ_t.[9] To avoid potential omitted variable bias that may arise from the variables correlated with distance from gold mines and households' child labor supply decisions, I include X_{ijct} as a covariate vector. The vector includes age, sex, birth order, household size, urban status, each parent's age and years of education, whether a child is living with his/her biological parents, and the wealth index of a household. To allow for intra-commune heteroskedasticity of standard errors, standard errors are clustered at the commune

[8] I calculate the years from the mine openings by subtracting the year of mine opening from the interview year. As presented in Table A1, mines open in different years, so the years from mine opening range from -16 to 16 years.

[9] A commune is a smallest sub-region level administrative area identified in the data set.

level.

Since child labor decisions could differ based on the child's age and sex, differential responses from various demographic backgrounds may help understand the effect. To examine this potential heterogeneity of effects, I also estimate:

$$
\begin{aligned}
y_{ijct} = & \beta_0 + \beta_1 20km_j \cdot Open_{jt} \cdot H_{ijt} + \beta_2 20km_j \cdot Open_{jt} + \beta_3 H_{ijt} \\
& + \sum_{d=1}^{5} \gamma_1^d \text{Distance Bin}_j^d + \sum_{d=1}^{5} \gamma_2^d \text{Distance Bin}_j^d \cdot H_{ijt} \\
& + \sum_{y=1}^{6} \gamma_3^y \text{Years from open}_t^y + \sum_{y=1}^{6} \gamma_4^y \text{Years from open}_t^y \cdot H_{ijt} \\
& + \delta_t + \theta_c + X_{ijct} + \varepsilon_{ijct}
\end{aligned} \tag{2}
$$

where H_{ijt} is an indicator of a demographic characteristic equals one if a child i in cluster j at year t from opening satisfies specified characteristics. These characteristics include: male children, children ages 5-11, and the oldest siblings within a household. The coefficient β_1 captures the effect of mine openings on a remaining demographic group (female children, children ages 12-14, and the younger siblings), and β_2 captures the difference of the effect between the two demographic groups. Therefore, β_1+β_2 provides the effect on the specified demographic group. This sum of the two coefficients is also presented at the bottom of Table 4 and 5 depicting the effect on both demographic groups.

4.3 Parallel Pre-trends

The causal interpretation of this paper is based on the assumption that the households in the non-mining area serve as a counter-factual of the households in the mining area. Thus, showing parallel pre-trends between mining and non-mining areas is crucial to establishing the causality of the estimated effects.

Figure 5 is an event-study type figure with the estimated difference of children's working hours across mining and non-mining areas over time. The coefficients are estimated by replacing $Open_{jt}$ with a series of indicators for years from opening from Equation (1), omitting 0–5 years before the mine openings. The horizontal axes show years from mine openings, the vertical axes the estimated coefficients, and the vertical lines show 95 percent confidence intervals. The coefficients of the periods before mine openings are not statistically distinguishable from zero for all outcome variables. That is, I find parallel pre-trends of child labor supply across regions.

Table 2 presents estimates that confirm these results. Since I omit 0–5 years before the mine openings, the test of parallel pre-trend is equivalent to testing the following hypothesis:

$$20km \cdot (11+ \text{ years prior}) = 20km \cdot (6\text{-}10 \text{ years prior}) = 0$$

The p-value for the joint F-test of this difference is presented at the bottom of the table. All p-values are larger than 0.05, so I do not reject the null hypothesis that the two summed coefficients are zero. Taken together, these results satisfy the crucial assumption for the causality of the estimated effects of the opening of industrial gold mines.

5 Results

5.1 Impact on Child labor

Figure 5 suggests that children located in mining areas worked fewer hours after mines open. Table 3 complements this by showing the results of estimating Equation (1). Results in Panel A shows that total working hours decreased by 7.6 hours per week on average when industrial mines open in the local area, and the coefficient is statistically significant at the 1 percent level. The decrease is also economically significant. Children in mining areas worked 19.9 hours before mine opened, so the result indicates a 38.2 percent reduction in total working hours. I find a decrease in hours for economic activities 3.3 hours, which is not precisely estimated statistically (column 2); however, the size of the coefficient is non-negligible, considering that the average working hours were 3.1 hours per week before the mine openings. On the other hand, working hours for household tasks decreased by 5.1 hours per week. The effect is statistically significant at the 5 percent level and is economically large (30.0 percent decrease). All the effects I find on children's working hours are robust to the exclusion of control variables, comparing the estimates presented in Panels A and B; Panel A presents the results with control variables and panel B without control variables. Therefore, I present results estimated with control variables for the rest of the section. On the other hand, I find that the effects were not strong enough to decrease children's work by an extensive margin, as shown in Tables A2 and A3. These results indicate that children who were engaged in household work more intensively decreased their work. Taken together, the results suggest that the income effect dominated the substitution effect. Specifically, the evidence suggests that the indirect income effect is at play since the decrease in hours for household work drives the overall change. I verify this claim in section 5.3 by examining the effects on adults' employment and occupational choices.

To better understand amongst whom the decrease in children's work was concentrated, I examined the heterogeneity of the local effects of large-scale mines across different demographic groups. I do this by estimating Equation 2, using several criteria: sex, age, and birth order. The estimated results are presented in 4.

I first disaggregate by a child's gender. Gender roles in children's work activities are fixed. Girls are more likely to be involved in household work than boys, and vice versa for economic activities. Moreover, girls spend longer hours in household work (17 hours per week) than in economic activities (2.4 hours per week). If the indirect income effect is driving the results, I would find a bigger decrease in household work among girls than among boys, and not in the other types of work. Columns 1 and 2 show that the effects are similar across boys and girls in total working hours and hours for economic activities. In column 3, the difference of the effects between the boys and girls is imprecisely estimated as well; however, it shows that the girls decreased working hours for household tasks substantially (by 3.0 hours)while the effect on boys is much weaker and statistically insignificant. This implies that the mine openings decreased the gender gap in household tasks from 6.2 to 1.9 hours.

Next, I examine heterogeneity across age groups. For this analysis, I define children ages 5–11 as younger children and those ages 12–14 as older children. The definition follows the UNICEF and ILO's convention in child labor measurement where different thresholds of working hours for each age group are used to classify a child's activity as child labor. I find that the effect on total working hours and in economic activities, presented in columns 4 and 5 do not differ substantially across age groups. On the other hand, column 6 shows that household tasks decreased among both age groups. This decrease was more substantial among older children who worked much longer hours initially. Older children worked 26.0 hours while younger children worked 14 hours before the mine opening. This result shows that the gap in working hours across age decreased from 12.2 to 7.6 hours due to mine openings.

Often the oldest siblings start working early to financially support the household and their younger siblings. In many cases, they continue to work even when the household income rises to continue the financial responsibility. In this regard, the first-born children are less likely to be affected by the income effect. In columns 7–9, I find this is the case in my setting. The first-born children do not decrease working hours substantially in all types of work. On the other hand, the younger siblings decreased working hours substantially, and naturally, the effects statistically differ between the first-born and the younger siblings. Therefore, the working hours gap between the siblings increased as a result of mine openings.

5.2 Impact on Education

Child labor is often discussed as an alternative to schooling in children's time use. Therefore, one could expect a decrease in children's working hours will lead to increased educational outcomes, and it is what many studies in this literature find (e.g., Santos (2018)). However, it did not lead to an increase in school enrollment nor years of education in my sample. Figure 6 shows that the trends of educational outcomes – years of education and current enrollment – over time are indistinguishable from zero, consistent with parallel pre-trends. However, the coefficients revolve around zero after the mine openings, suggesting null effects on educational outcomes. Table 5 complements the figure and shows no effect of mine openings on years of education or current enrollment. Years of education was a stock variable so it may not fluctuate concurrently; however, no changes in current enrollment requires further examination.

Heterogeneity analyses presented in columns 6–8 reveal that the key to understanding the effects on the schooling outcome is engagement in economic activities. While I do not find any substantial difference across gender (column 6), children from ages 12 to 14 and first-born children were those with negative and statistically significant effects. The first-born children showed null effects on all types of working hours, which suggests that the elder siblings who cannot reduce working hours have to decrease schooling. On the other hand, the effects on the current enrollment of younger age group children and younger siblings were negligible. These two groups are the only groups that substantially decreased working hours for economic activities. Combining these results, the decrease in children's economic activities prevented schooling reduction while an increase in work led to a decrease in schooling. I suspect that this asymmetry in the effect on schooling is likely due to the difficulty and rarity of returning to school after dropping out.

5.3 A Potential Mechanism: Adult employment

The evidence so far points to a story where the income effects dominate the substitution effects, thus decrease children's time spent on work. This section analyzes the adult employment outcomes to explore this mechanism, using the same empirical framework I used in the previous sections. Panel A of Table 6 suggests that mothers are less likely to work, but the quality of their work improved if they continued working. The probability of mothers working decreases by .3 percentage points, but the coefficient is statistically insignificant. However, the magnitude of the effect is 33.3 percent of the average. Columns 2 and 3 that mothers are more likely to work in paid jobs and be paid in cash, which indicates a better job quality compared to other payment options such as in-kind transfers or no payments. Moreover, columns 4–6 show that mothers are 1 percentage point less likely to work for family members. The evidence supports the income effect story. In order for the substitution effect to increase child labor, an increase in adult employment should precede. It may lead to an increase in demand for child labor since their wage is cheaper, or there would be a need to replace adult labor in the household. The null effects in adult female employment suggest a stronger possibility of no effect or small substitution effects. If anything, female employment seems to be decreasing – suggestive evidence of the secondary income earner decreasing their work (Kotsadam and Tolonen 2016).

The results on adult occupation points in the same direction. Panel B of Table 6 shows that mothers are increasingly choosing sales jobs (column 2). They are 33 percentage point less likely to choose agriculture, but the coefficient is not statistically significant. Changes in other sectors are small and indistinguishable from zero. On the other hand, fathers are not likely to change their occupational choices substantially, except that they are 6.8 percentage points more likely to work in clerical, managerial, and technical positions.

These changes in occupational choices support the story of an increased household income. As shown in Figure 7, the wealthier the household, the more mothers are likely to work in the sales sector and less likely to work in agriculture. Moreover, cash-paying positions are positively correlated with a household's wealth quintile, and work for family members was negatively correlated. Thus, the results suggest that the improved quality of mother's work must be correlated with a household's better economic status. These results are consistent with the findings from previous studies such as Kotsadam and Tolonen (2016) and von der Goltz and Barnwal (2019), and also Aragón and Rud (2013), who argue that the industrial gold mines increase the household income, at least in the short-run.

5.4 Robustness Checks

Although demographic characteristics are balanced across regions and the parallel pre-trends assumption is satisfied, other confounders correlated with unobserved heterogeneity may exist. Here, I report additional robustness checks to address this concern. First, I evaluate the sensitivity of the results based on the threshold distance to define the mining area. I vary the threshold distance from 10 km to 50 km to check whether the estimated results are robust to my definition of threshold distance. As discussed in section 4.2, I expect the 20 km radius to be a reasonable choice and the effects to be mitigated as I move the cutoff further away from mines. The mitigated effects in the same direction would also show that it was the mine driving the effects. Figure A3 shows that the results are robust when I vary the cutoff distance, and that the magnitude of the effects reduces as I use longer distance as a threshold. I also repeat the main analysis by replacing the 20 km dummy with a continuous distance from the closest mine since the figure suggests that the effects gradually decrease with the distance. Tables A4, A5, and A6 show the results are qualitatively the same.

In addition, I assess the potential spillover effects to the neighboring areas by assigning the surrounding area within 30–50 km of the mines as a neighboring area, while the areas 50–100 km from the mines are considered non-mining area. Since the neighboring areas are closer to the mines than the non-mining areas are, while they do not include the mining areas, the estimated coefficients should capture the spillover effects to the neighboring areas. Estimated results presented in Table 7 show that the children from the neighboring areas were not affected by the mine openings. Although the estimated coefficients are negative, their sizes are much smaller than the original estimates and are statistically indistinguishable from zero.

I also examine if the way we define child labor affects the results. My measure of child labor includes children's engagement in work of all intensity. Therefore, it may seem to have weak relevance for children's welfare, especially since I do not find significant changes in children's educational outcomes. To complement this, I repeat the analyses using a more conservative measure of child labor. The measure would define children's economic activity as child labor if they were engaged in economic activities or household tasks for more than certain hours per week, depending on the age group. Therefore, a child would have been engaged in substantial work if classified as a child laborer according to these criteria. I follow the definition used by UNICEF here. Specifically, UNICEF defines children's activity as child labor if children 5–11 years old worked at least 1 hour of economic activity or at least 28 hours of household tasks. For a child 12–15 years old, it is classified as child labor if a child worked at least 14 hours of economic activity or at least 28 hours of household tasks. This follows the ILO convention No. 138, which states that the national laws or regulations should permit the work of children 13–15 years of age for light work, that is, less than 14 hours of economic activities or 21 hours of household tasks (Chaubey et al. 2007). Here, I treat children's working hours as zero if working hours were less than the relevant threshold for each age group and activity. Thus, the result I present here is a more conservative way to measure child labor. Table A7 shows that the effects are similar to what I find in the main analysis, suggesting that the decrease of child labor I find is not coming from children who are within the margin of doing light or no work, but rather from children who were engaged in intensive work.

5.5 Alternative Explanations

Finally, I consider two alternative explanations: endogenous migration and expansion of artisanal small-scale mines (ASMs). I examine the possibility of endogenous migration driving the results in two ways. First, I estimate the effects of mine openings on time-invariant demographic characteristics such as age, gender, household size, gender of the household head, parents' years of education. Table A9 shows that these characteristics did not change substantially due to mine openings except the mothers' years of education is 0.4 years higher in mining areas. Second, I investigate the effects using the sample of children who have never moved since birth (never movers). The interpretation of the result is limited for this analysis since the migration information was collected in 2001 and 2006 only. However, the estimated results presented in Table A10 are qualitatively the same as what I find in my main analysis. The size of the effects is larger for never movers, but combined with the results on demographic change, the evidence suggests that what I found is less likely to be drawn by endogenous migration.

I also explore the possibility of ASM expansion driving the results. Gold deposits are geographically concentrated, thus ASM operations are likely to be affected by the expansion or the opening of industrialized mines. In fact, Hilson (2012) shows that the global gold price increase entailed a boom in small-scale gold mining in southern Mali. Moreover, he also shows that ASMs employ children directly as the parents consider working in mines as a "family affair". I cannot directly test this and rule out this possibility due to the lack of systematic data on the location and operating dates of ASMs in Mali.[10] I instead compare the non-mining area with the region where the mine is located.[11] It is similar to the analysis presented in Table 7, but expanding both the potential spillover and the comparison area. If the ASMs are actually located in the non-mining area surrounding industrial mines and affect child labor substantially, the estimates in Table A11 should indicate the effect. I find that children's work and schooling did not change substantially in non-mining areas, which suggests that the effects from ASMs are not likely mechanisms.

6 Conclusion

This paper provides evidence on the impact of natural resource shocks on child welfare in the specific dimensions of work and schooling. Exploiting plausible exogenous variations in distance from industrial mining sites and the timing of mine openings, I find that an opening of industrial gold mines leads to a substantial decrease in children's working hours. The effects are economically significant as well, considering a 38.2 percent decrease in total working hours is found. In

[10] Dataset on ASM is rare. Several studies overcome the limitation of the ASM data. These include: Bazillier and Girard (2020) who compared the local economic effects of industrial mines and ASMs using a nation-wide administrative data on ASM in Burkina Faso; Zabsonré et al. (2018) who examined the effect of industrial and artisanal mines on child labor; a working paper by Guenther (2019) who used a novel ASM dataset collected by remote sensing over satellite imageries; Parker et al. (2016) and Sánchez de la Sierra (2019) who used survey data on ASMs; and Fourati et al. (2021) using variations of geological bedrocks. Therefore, while the interaction of ASMs and industrial gold mines is important, the investigation is left for future research.

[11] Region is the largest administrative unit of Mali.

contrast, a mine opening did not lead to increased school attendance. The mine openings decreased gender gaps in work while it increased the burden on the oldest siblings. The results are robust with the inclusion of control variables, changes in the distance threshold, a more conservative measure of child labor, and a continuous measure of distance from mines.

The evidence is consistent with a scenario where the income effects dominate the substitution effects. This paper presents results on adults' employment outcomes and occupational choices to support these arguments, which align with the findings of Kotsadam and Tolonen (2016). My results also complement the findings of Cogneau and Jedwab (2012) in the sense that children's work is countercyclical. It contrasts with the main findings of Santos (2018), but he points out a possibility of countercyclicality of child labor when the initial prevalence of child labor is high, which fits my study's setting. Therefore, I can reconcile the results of this paper with other studies that shows child labor increases due to the gold mines (Ahlerup et al. 2020). The results are closer to the findings of Zabsonré et al. (2018), who assert that the gold price shock does not substantially affect child labor or education.

A decrease in children's work that does not lead to an increase in school attendance calls for a more nuanced approach in understanding children's time allocation. A number of papers in the literature on child labor view education as a substitute for labor. Ahlerup et al. (2020) suggested child labor as a strong candidate for decreasing educational attainment after examining various potential channels. Amongst excluded channels were low school supply and endogenous migration, while child labor was suggested without rigorous empirical analysis. Moreover, school construction or incentives for schooling decreased child labor (de Hoop and Rosati 2014; Edmonds and Shrestha 2014). Increased household income has similar effects. It decreased child labor while increasing child schooling (Edmonds 2006; Edmonds and Schady 2012). Unlike other studies, this paper shows that the opening of industrial mines decreases children's work but does not lead to changes in schooling. I include hours spent on household work as working hours, which led to the decrease in total working hours. Since household tasks are more compatible with schooling than economic activities, the inclusion of household work reconciles the difference between my results and the findings in the literature. Moreover, it adds a nuance in examining the effect of an economic change on children's human capital, which should be considered in formulating child labor policy.

References

Ahlerup, Pelle, Thushyanthan Baskaran, and Arne Bigsten. 2020. "Gold Mining and Education: A Long-run Resource Curse in Africa?" Publisher: Routledge _eprint: https://doi.org/10.1080/00220388.2019.169 *The Journal of Development Studies* 56, no. 9 (): 1745–1762. Visited on 08/20/2020. doi:10.1080/00220388.2019.1696959. https://doi.org/10.1080/00220388.2019.1696959.

Amoh-Gyimah, Richard, and Eric Nimako Aidoo. 2013. "Mode of transport to work by government employees in the Kumasi metropolis, Ghana". *Journal of Transport Geography* 31 (): 35–43. Visited on 05/11/2019. doi:10.1016/j.jtrangeo.2013.05.008. http://www.sciencedirect.com/science/article/pii/S0966692313000859.

Aragón, Fernando M., and Juan Pablo Rud. 2013. "Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine". *American Economic Journal: Economic Policy* 5 (2): 1–25. Visited on 04/07/2019. http://www.jstor.org/stable/43189326.

Basu, Kaushik, Sanghamitra Das, and Bhaskar Dutta. 2010. "Child labor and household wealth: Theory and empirical evidence of an inverted-U". *Journal of Development Economics* 91, no. 1 (): 8–14. Visited on 04/07/2019. doi:10.1016/j.jdeveco.2009.01.006. http://www.sciencedirect.com/science/article/pii/S0304387809000029.

Basu, Kaushik, and Pham Hoang Van. 1998. "The Economics of Child Labor". *American Economic Review* 88 (3): 412–27. Visited on 04/07/2019. https://econpapers.repec.org/article/aeaaecrev/v_3a88_3ay_3a1998_3ai_3a3_3ap_3a412-27.htm.

Bazillier, Remi, and Victoire Girard. 2020. "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. Visited on 08/20/2020. doi:10.1016/j.jdeveco.2019.102411. http://www.sciencedirect.com/science/article/pii/S0304387819300586.

Beegle, Kathleen, Rajeev H. Dehejia, and Roberta Gatti. 2006. "Child labor and agricultural shocks". *Journal of Development Economics* 81, no. 1 (): 80–96. Visited on 04/07/2019. doi:10.1016/j.jdeveco.2005.05.003. http://www.sciencedirect.com/science/article/pii/S0304387805000829.

Beegle, Kathleen, Rajeev H. Dehejia, Roberta Gatti, and Sofya Krutikova. 2008. "The Consequences of Child Labor: Evidence from Longitudinal Data in Rural Tanzania". SSRN Scholarly Paper ID 1233053. Rochester, NY: Social Science Research Network. Visited on 07/09/2020. https://papers.ssrn.com/abstract=1233053.

Benshaul-Tolonen, Anja. 2019. "Local Industrial Shocks and Infant Mortality". *The Economic Journal* 129, no. 620 (): 1561–1592. Visited on 06/04/2019. doi:10.1111/ecoj.12625. http://academic.oup.com/ej/article/129/620/1561/5473519.

Cellule de Planification et de Statistique (CPS and Direction Nationale de la Statistique et de l'Informatique (DNSI). 2002. "Enquête Démographique et de Santé au Mali 2001 [Data set]". Calverton, Maryland, USA: CPS/DNSI et Macro International Inc. https://dhsprogram.com/data/dataset/Mali_Standard-DHS_2001.cfm?flag=0.

Cellule de Planification et de Statistique (CPS) and Direction Nationale de la Statistique et de l'Informatique (DNSI). 1996. "Enquête Démographique et de Santé, Mali 1995-1996 [Data set]". Calverton, Maryland, USA: CPS/DNSI et Macro International Inc. https://dhsprogram.com/data/dataset/Mali_Standard-DHS_1996.cfm?flag=0.

Cellule de Planification et de Statistique (CPS) and Direction Nationale de la Statistique et de l'Informatique du Ministère de l'Économie, de l'Industrie et du Commerce (DNSI). 2007. "Enquête Démographique et de Santé du Mali 2006 [Data set]". Calverton, Maryland, USA: CPS/DNSI et Macro International Inc. https://dhsprogram.com/data/dataset/Mali_Standard-DHS_2006.cfm?flag=1.

Cellule de Planification et de Statistique (CPS), Institut National de la Statistique (INSTAT/MPATP),INFO-STAT et ICF International, and INFO-STAT. 2014. "Enquête Démographique et de Santé au Mali 2012-2013 [Data set]". Rockville, Maryland, USA: CPS, INSTAT, INFO-STAT et ICF Internationa. https://dhsprogram.com/data/dataset/Mali_Standard-DHS_2012.cfm?flag=1.

Chaubey, Jay, Mima Perisic, Nadine Perrault, George Laryea-Adjei, and Noreen Khan. 2007. "Child Labour, Education and Policy Options". New York, NY, US: United Nations Children's Fund (UNICEF).

Cockburn, John, and Benoit Dostie. 2007. "Child Work and Schooling: The Role of Household Asset Profiles and Poverty in Rural Ethiopia". Publisher: Oxford Academic, *Journal of African Economies* 16, no. 4 (): 519–563. Visited on 05/29/2020. doi:10.1093/jae/ejl045. https://academic.oup.com/jae/article/16/4/519/775038.

Cogneau, Denis, and Rémi Jedwab. 2012. "Commodity Price Shocks and Child Outcomes: The 1990 Cocoa Crisis in Côte d'Ivoire". Publisher: The University of Chicago Press, *Economic Development and Cultural Change* 60 (3): 507–534. Visited on 05/29/2020. doi:10.1086/664017. https://www.jstor.org/stable/10.1086/664017.

De Hoop, Jacobus, and Furio C. Rosati. 2014. “Does promoting school attendance reduce child labor? Evidence from Burkina Faso’s BRIGHT project”. *Economics of Education Review* 39 (): 78–96. Visited on 07/15/2020. doi:10.1016/j.econedurev.2013.11.001. http://www.sciencedirect.com/science/article/pii/S0272775713001556.

DeGraff, Deborah S., Andrea R. Ferro, and Deborah Levison. 2016. “In Harm’s Way: Children’s Work in Risky Occupations in Brazil”. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/jid.3111, *Journal of International Development* 28 (4): 447–472. Visited on 07/06/2020. doi:10.1002/jid.3111. https://onlinelibrary.wiley.com/doi/abs/10.1002/jid.3111.

Dibua, Jeremiah. 2010. “Mali Empire”. Oxford African American Studies Center. ISBN: 9780195301731. Visited on 08/14/2020. http://oxfordaasc.com/view/10.1093/acref/9780195301731.001.0001/acref-9780195301731-e-47941.

Duryea, Suzanne, David Lam, and Deborah Levison. 2007. “Effects of economic shocks on children’s employment and schooling in Brazil”. *Journal of Development Economics* 84, no. 1 (): 188–214. Visited on 05/29/2020. doi:10.1016/j.jdeveco.2006.11.004. http://www.sciencedirect.com/science/article/pii/S0304387806001908.

Edmonds, Eric V. 2006. “Child labor and schooling responses to anticipated income in South Africa”. *Journal of Development Economics* 81, no. 2 (): 386–414. Visited on 10/15/2020. doi:10.1016/j.jdeveco.2005.05.001. http://www.sciencedirect.com/science/article/pii/S0304387805000799.

– . 2005. “Does Child Labor Decline with Improving Economic Status?” *Journal of Human Resources* XL, no. 1 (): 77–99. Visited on 04/07/2019. doi:10.3368/jhr.XL.1.77. http://jhr.uwpress.org/content/XL/1/77.

– . 2016. “Economic Growth and Child Labor in Low Income Economies” No.3. GLM. https://glm-lic.iza.org/wp-content/uploads/2017/06/glmlic_sp003.pdf.

Edmonds, Eric V., and Nina Pavcnik. 2005. “The effect of trade liberalization on child labor”. *Journal of International Economics* 65, no. 2 (): 401–419. Visited on 05/29/2020. doi:10.1016/j.jinteco.2004.04.001. http://www.sciencedirect.com/science/article/pii/S0022199604000662.

Edmonds, Eric V., and Norbert Schady. 2012. “Poverty Alleviation and Child Labor”. *American Economic Journal: Economic Policy* 4, no. 4 (): 100–124. Visited on 04/07/2019. doi:10.1257/pol.4.4.100. http://www.aeaweb.org/articles?id=10.1257/pol.4.4.100.

Edmonds, Eric V., and Maheshwor Shrestha. 2014. "You get what you pay for: Schooling incentives and child labor". *Journal of Development Economics*, Special Issue: Imbalances in Economic Development, 111 (): 196–211. Visited on 10/15/2020. doi:10.1016/j.jdeveco.2014.09.005. http://www.sciencedirect.com/science/article/pii/S0304387814001047.

Edmonds, Eric, and Caroline Theoharides. 2020. "The short term impact of a productive asset transfer in families with child labor: Experimental evidence from the Philippines". *Journal of Development Economics* 146 (): 102486. Visited on 11/19/2020. doi:10.1016/j.jdeveco.2020.102486. http://www.sciencedirect.com/science/article/pii/S0304387820300614.

Emerson, Patrick M., Vladimir Ponczek, and André Portela Souza. 2017. "Child Labor and Learning". Publisher: The University of Chicago Press, *Economic Development and Cultural Change* 65, no. 2 (): 265–296. Visited on 06/19/2020. doi:10.1086/688895. http://www.journals.uchicago.edu/doi/abs/10.1086/688895.

Fafchamps, Marcel, Michael Koelle, and Forhad Shilpi. 2017. "Gold mining and proto-urbanization: recent evidence from Ghana". *Journal of Economic Geography* 17, no. 5 (): 975–1008. Visited on 04/22/2020. doi:10.1093/jeg/lbw015. http://academic.oup.com/joeg/article/17/5/975/2930589.

Fafchamps, Marcel, and Jackline Wahba. 2006. "Child labor, urban proximity, and household composition". *Journal of Development Economics*, Special Issue in honor of Pranab Bardhan, 79, no. 2 (): 374–397. Visited on 04/22/2020. doi:10.1016/j.jdeveco.2006.01.005. http://www.sciencedirect.com/science/article/pii/S0304387806000071.

Fourati, Maleke, Victoire Girard, and Jeremy Laurent-Lucchetti. 2021. "Sexual violence as a weapon of war". Working Paper 2103. Universidade Nova de Lisboa, Faculdade de Economia, NOVAFRICA.

Frankel, Jeffrey A. 2012. "The Natural Resource Curse: A Survey of Diagnoses and Some Prescriptions". Accepted: 2012-05-08T18:22:10Z Publisher: John F. Kennedy School of Government, Harvard University, *HKS Faculty Research Working Paper Series*. Visited on 11/11/2020. https://dash.harvard.edu/handle/1/8694932.

Gajigo, Ousman, Emelly Mutambatsere, and Guirane Samba Ndiaye. 2012. "Working Paper 147 - Gold Mining in Africa-Maximizing Economic Returns for Countries" 378. African Development Bank. Visited on 04/07/2019. https://ideas.repec.org/p/adb/adbwps/378.html.

Guenther, Martin. 2019. "Local Effects of Artisanal Mining- Empirical Evidence from Ghana". Working Paper.

Heady, Christopher. 2003. "The Effect of Child Labor on Learning Achievement". *World Development* 31, no. 2 (): 385–398. Visited on 06/19/2020. doi:10.1016/S0305-750X(02)00186-9. http://www.sciencedirect.com/science/article/pii/S0305750X02001869.

Hilson, Gavin. 2012. "Family Hardship and Cultural Values: Child Labor in Malian Small-Scale Gold Mining Communities". *World Development* 40, no. 8 (): 1663–1674. Visited on 07/20/2019. doi:10.1016/j.worlddev.2012.03.017. http://www.sciencedirect.com/science/article/pii/S0305750X1200054X.

International Monetary Fund. 2019. "Mali: First Review Under the Extended Credit Facility Arrangement, Request for a Waiver of Nonobservance of a Performance Criterion and Modification of Performance Criteria-Press Release; Staff Report; and Statement by the Executive Director for Mali; IMF Country Report No. 20/8; December 23, 2019". IMF. Visited on 04/23/2020. https://www.imf.org/en/Publications/CR/Issues/2020/01/16/Mali-First-Review-Under-the-Extended-Credit-Facility-Arrangement-Request-for-a-Waiver-of-48954.

Kassouf, A. L., M. McKee, and E. Mossialos. 2001. "Early entrance to the job market and its effect on adult health: evidence from Brazil". *Health Policy and Planning* 16, no. 1 (): 21–28. doi:10.1093/heapol/16.1.21.

Kippenberg, Juliane. 2011. "A Poisonous Mix: Child Labor, Mercury, and Artisanal Gold Mining in Mali". Human Rights Watch. https://www.hrw.org/report/2011/12/06/poisonous-mix/child-labor-mercury-and-artisanal-gold-mining-mali#cb60e7.

Kotsadam, Andreas, and Anja Tolonen. 2016. "African Mining, Gender, and Local Employment". *World Development* 83 (): 325–339. Visited on 04/07/2019. doi:10.1016/j.worlddev.2016.01.007. http://www.sciencedirect.com/science/article/pii/S0305750X1600005X.

Kusnir, Imrich. 1999. "Gold in Mali".

Lee, Chanyoung, and Peter F. Orazem. 2010. "Lifetime health consequences of child labor in Brazil". In *Child Labor and the Transition between School and Work*, ed. by Randall K.Q. Akee, Eric V. Edmonds, and Konstantinos Tatsiramos, 31:99–133. Research in Labor Economics. Emerald Group Publishing Limited. Visited on 07/06/2020. doi:10.1108/S0147-9121(2010)0000031007. https://doi.org/10.1108/S0147-9121(2010)0000031007.

Mainguy, Claire. 2011. “Natural resources and development: The gold sector in Mali”. *Resources Policy* 36, no. 2 (): 123–131. Visited on 07/20/2019. doi:10.1016/j.resourpol.2010.10.001. http://www.sciencedirect.com/science/article/pii/S0301420710000528.

Moretti, Enrico. 2010. “Local Multipliers”. *American Economic Review* 100, no. 2 (): 373–377. Visited on 11/04/2020. doi:10.1257/aer.100.2.373. http://www.aeaweb.org/articles?id=10.1257/aer.100.2.373.

Organization, World Trade. 1998. “Diversification of exports should strengthen Mali’s trade”. Press Release. Visited on 07/09/2020. https://www.wto.org/english/tratop_e/tpr_e/tp088_e.htm.

Parker, Dominic P., Jeremy D. Foltz, and David Elsea. 2016. “Unintended Consequences of Sanctions for Human Rights: Conflict Minerals and Infant Mortality”. Publisher: The University of Chicago Press, *The Journal of Law and Economics* 59, no. 4 (): 731–774. Visited on 04/27/2021. doi:10.1086/691793. http://www.journals.uchicago.edu/doi/full/10.1086/691793.

Sachs, Jeffrey D., and Andrew M. Warner. 2001. “The curse of natural resources”. *European Economic Review*, 15th Annual Congress of the European Economic Association, 45, no. 4 (): 827–838. Visited on 11/11/2020. doi:10.1016/S0014-2921(01)00125-8. http://www.sciencedirect.com/science/article/pii/S0014292101001258.

Sánchez de la Sierra, Raúl. 2019. “On the Origins of the State: Stationary Bandits and Taxation in Eastern Congo”. Publisher: The University of Chicago Press, *Journal of Political Economy* 128, no. 1 (): 32–74. Visited on 04/27/2021. doi:10.1086/703989. http://www.journals.uchicago.edu/doi/full/10.1086/703989.

Santos, Rafael J. 2018. “Blessing and curse. The gold boom and local development in Colombia”. *World Development* 106 (): 337–355. Visited on 08/20/2020. doi:10.1016/j.worlddev.2018.02.016. http://www.sciencedirect.com/science/article/pii/S0305750X18300548.

Von der Goltz, Jan, and Prabhat Barnwal. 2019. “Mines: The local wealth and health effects of mineral mining in developing countries”. *Journal of Development Economics* 139 (): 1–16. Visited on 04/07/2019. doi:10.1016/j.jdeveco.2018.05.005. http://www.sciencedirect.com/science/article/pii/S0304387818304875.

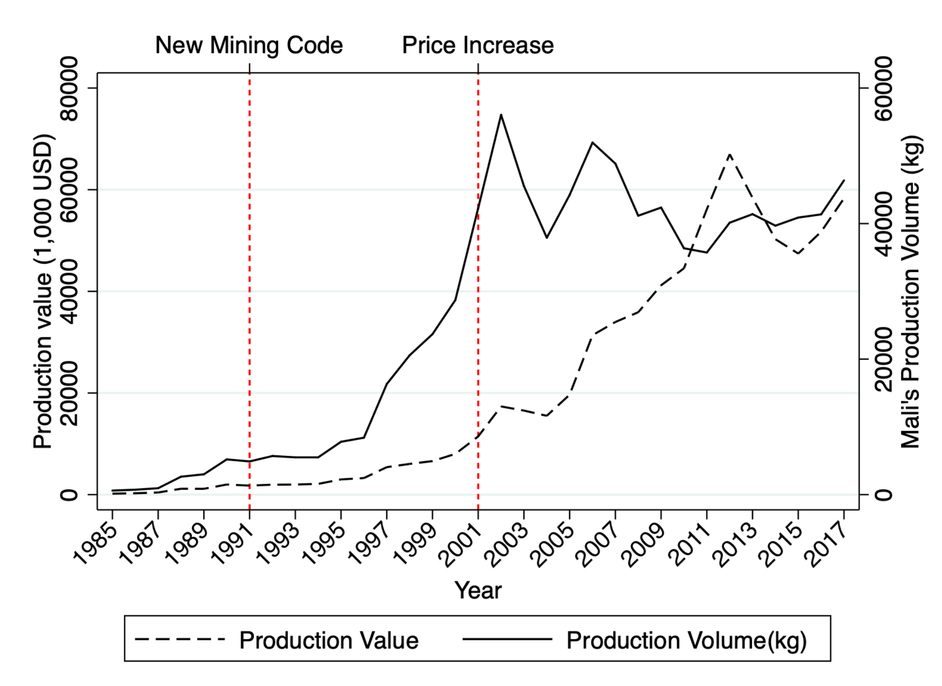
Weng, Lingfei, Agni Klintuni Boedhihartono, Paul H. G. M. Dirks, John Dixon, Muhammad Irfansyah Lubis, and Jeffrey A. Sayer. 2013. “Mineral industries, growth corridors and agricultural development in Africa”. *Global Food Security* 2, no. 3 (): 195–202. Visited on 07/20/2019.

doi:10.1016/j.gfs.2013.07.003. http://www.sciencedirect.com/science/article/pii/S2211912413000357.

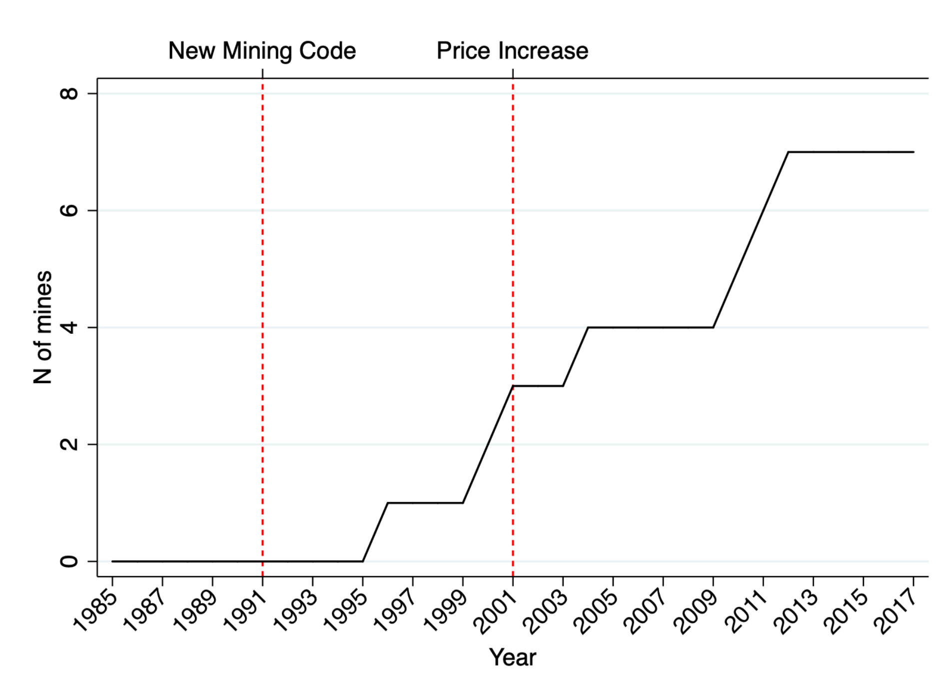
Zabsonré, Agnès, Maxime Agbo, and Juste Somé. 2018. "Gold exploitation and socioeconomic outcomes: The case of Burkina Faso". *World Development* 109 (): 206–221. Visited on 08/20/2020. doi:10.1016/j.worlddev.2018.04.021. http://www.sciencedirect.com/science/article/pii/S0305750X18301402.

Figure 1: Mali's Gold Production

(a) Production volume and value



(b) Number of industrial mines

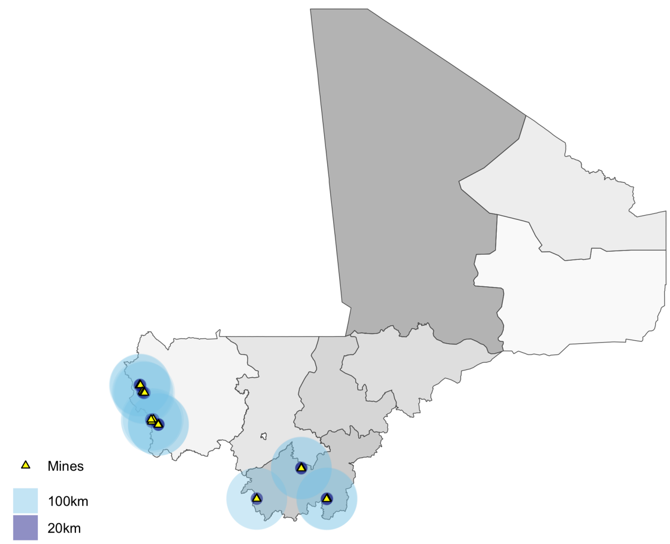


Source: United States Geological Survey Minerals Yearbook

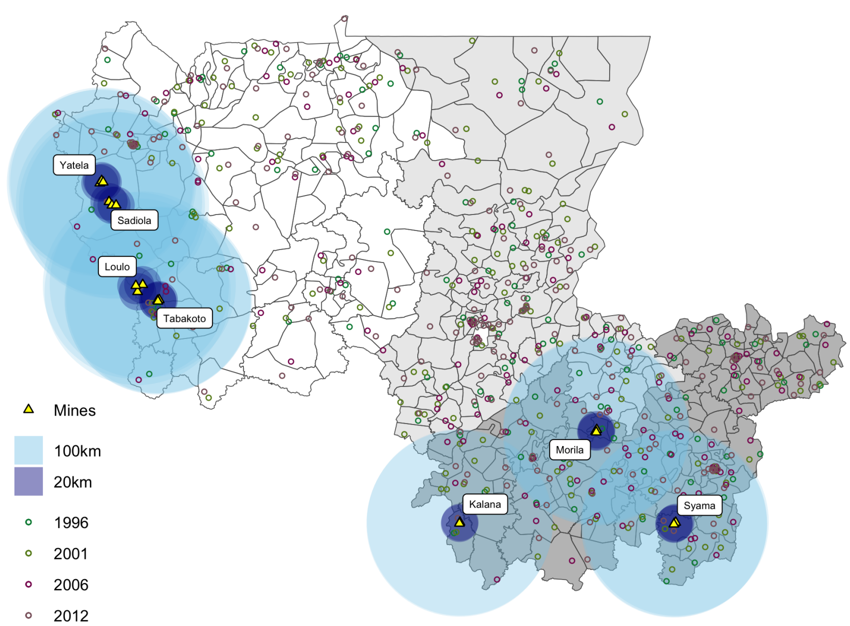
This figure plots trends of global gold prices and Mali's gold production volume. The horizontal axis show years, the vertical axis on the right world price, and the vertical axis on the left Mali's gold production volume. Solid line show the production volume and dashed line the gold price.

Figure 2: Location of Mines, 2018

(a) Mines and its surrounding areas



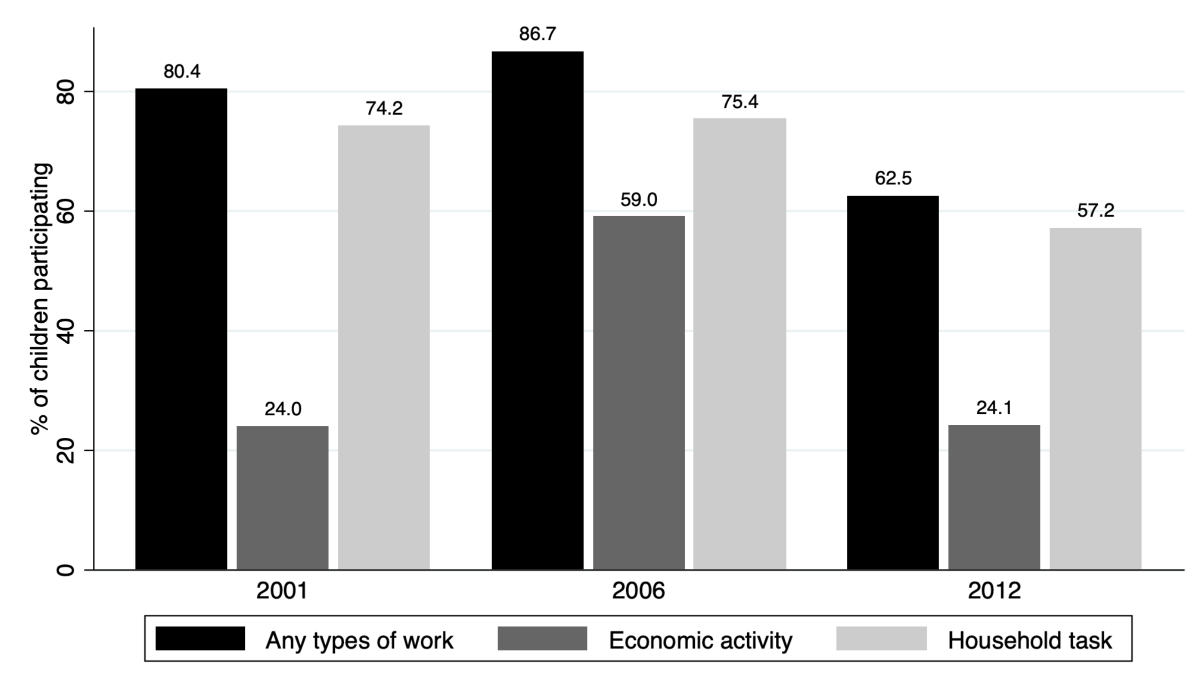
(b) DHS clusters within mining area



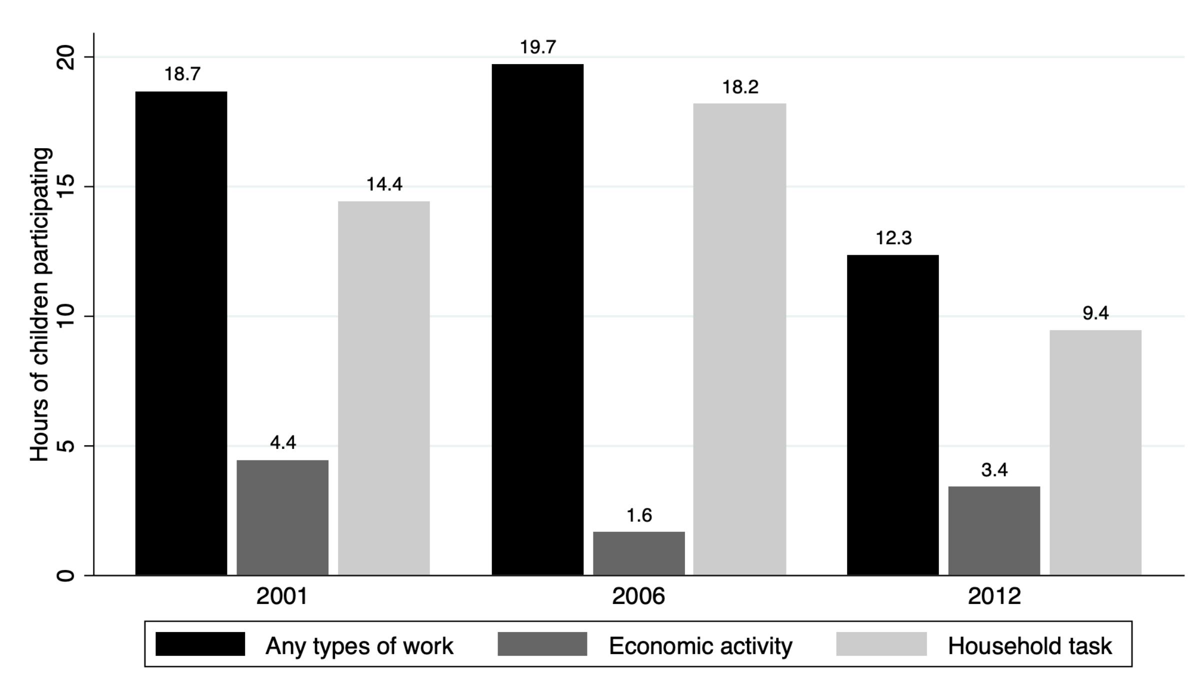
Source: Direction Nationale des Collectivités Territoriales, Demographic and Health Survey 1996-2012, and Benshaul-Tolonen (2019). Panel A plots the boundaries of communes, the lowest level municipality, the location of mines (yellow dots), 20-km radius (dark blue circle) and 100-km radius (light blue circle). Panel B adds the locations of DHS clusters for each rounds, zoomed in around the mine-located regions.

Figure 3: Status of Child Labor

(a) Child employment



(b) Children worked

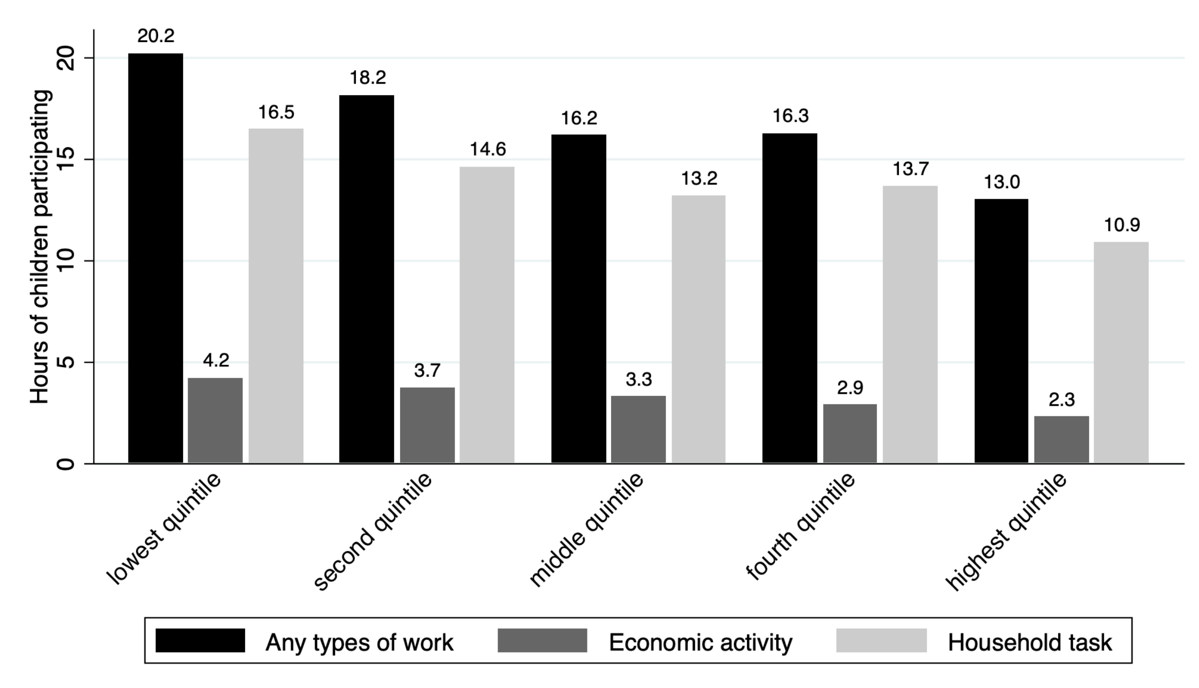


Source: DHS Mali

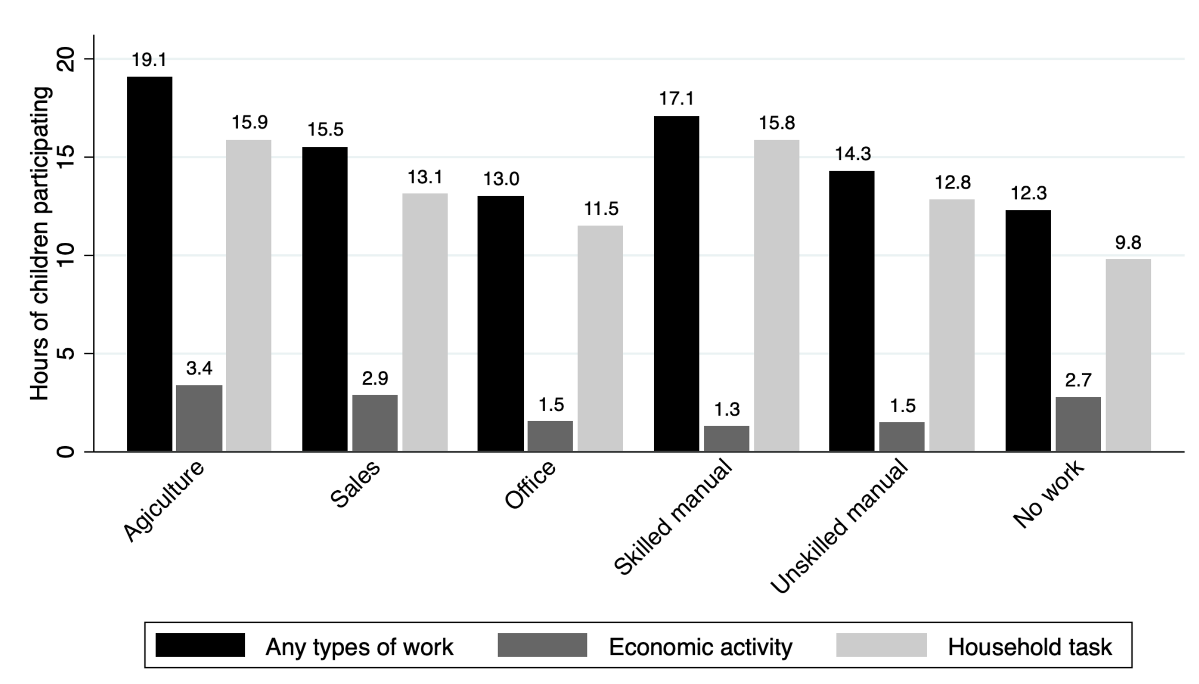
Note: This figure presents the share of working children in Mali. Panel A presents percentage of children participating in the activities among all children aged 5-14 and Panel B presents number of hours children engaged in each activity from 2001 to 2012.

Figure 4: Children's working hours by household characteristics

(a) By Wealth Quintile



(b) By Mother's Occupation

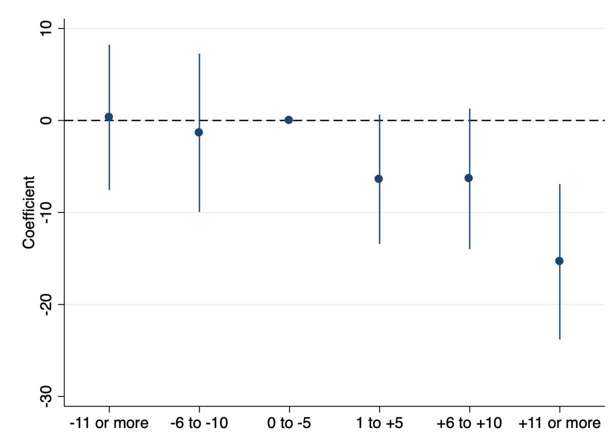


Source: DHS Mali

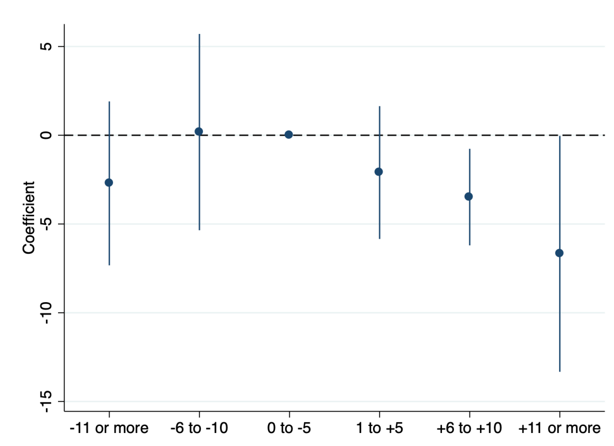
Note: This figure presents the share of working children in Mali. Panel A presents the average number of working hours by each wealth quintile, and Panel B presents the average number of hours children work by mother's sector of work.

Figure 5: Impacts on Working Hours of Children

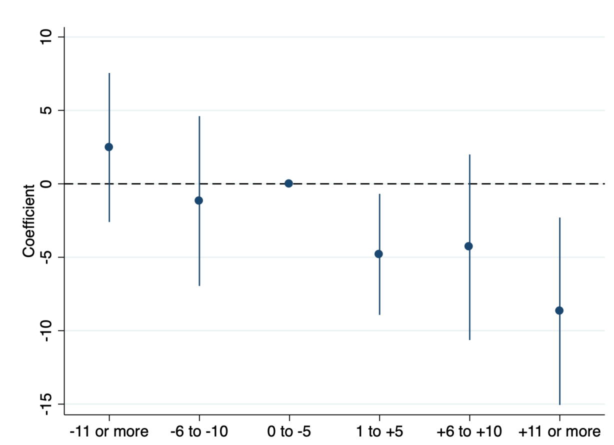
(a) Any types of work



(b) Economic Activities



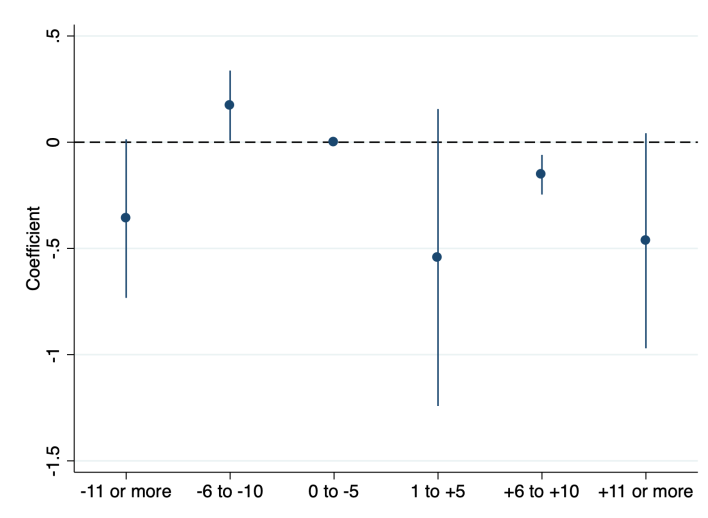
(c) Household work



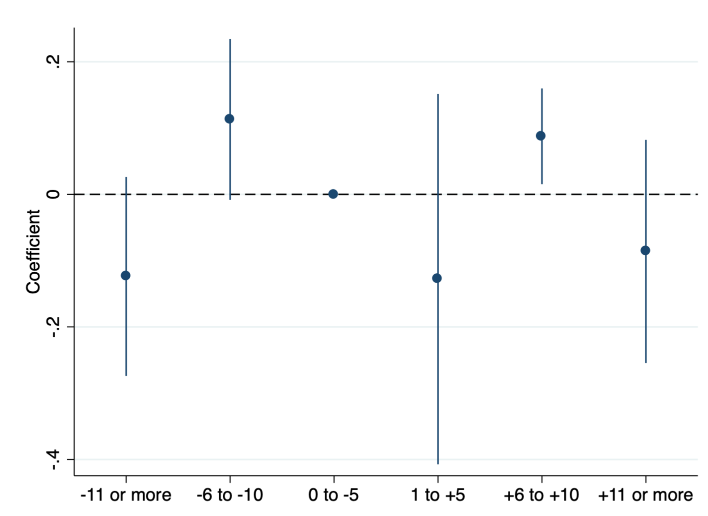
Note: This figure plots estimated effects of mine openings on working hours of children in mining areas. The horizontal axes show years from mine openings and the vertical axes the estimated coefficients. Navy dot show the estimated coefficients and the vertical lines the 95 percent confidence intervals. 0 to 5 years prior to opening is used as a reference period. Panel A, B, and C presents results for working hours for all types of work, economic activities, and household chores.

Figure 6: Impacts on Educational Outcomes

(a) Years of education



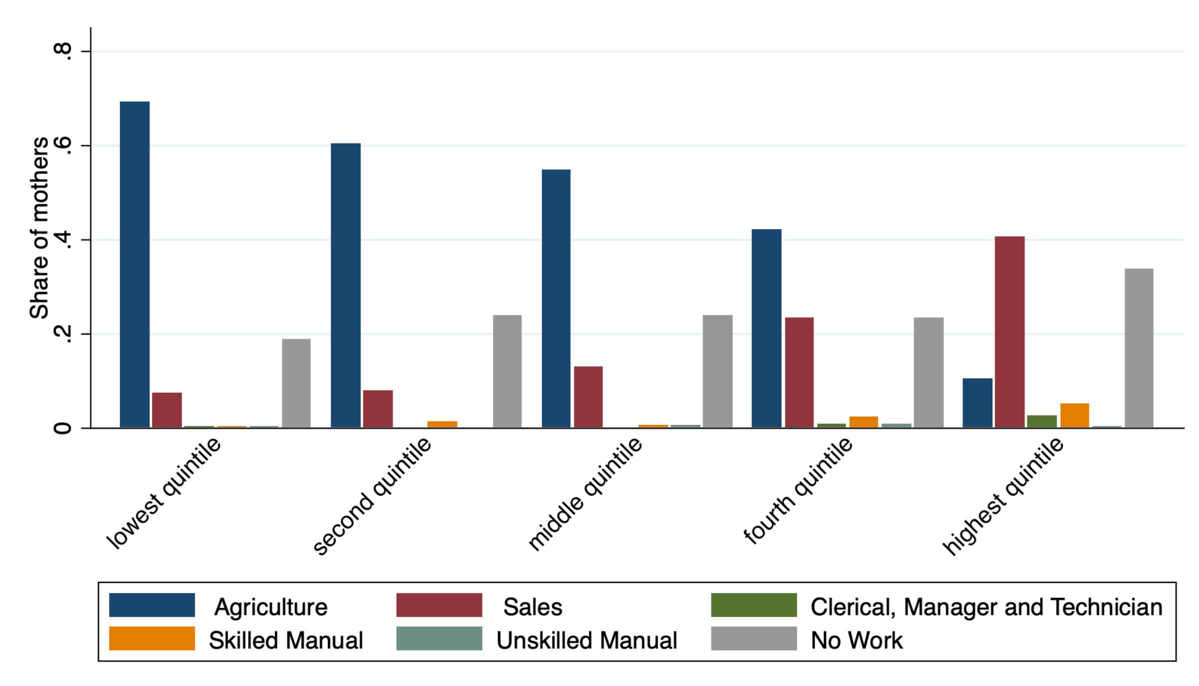
(b) Current year attendance



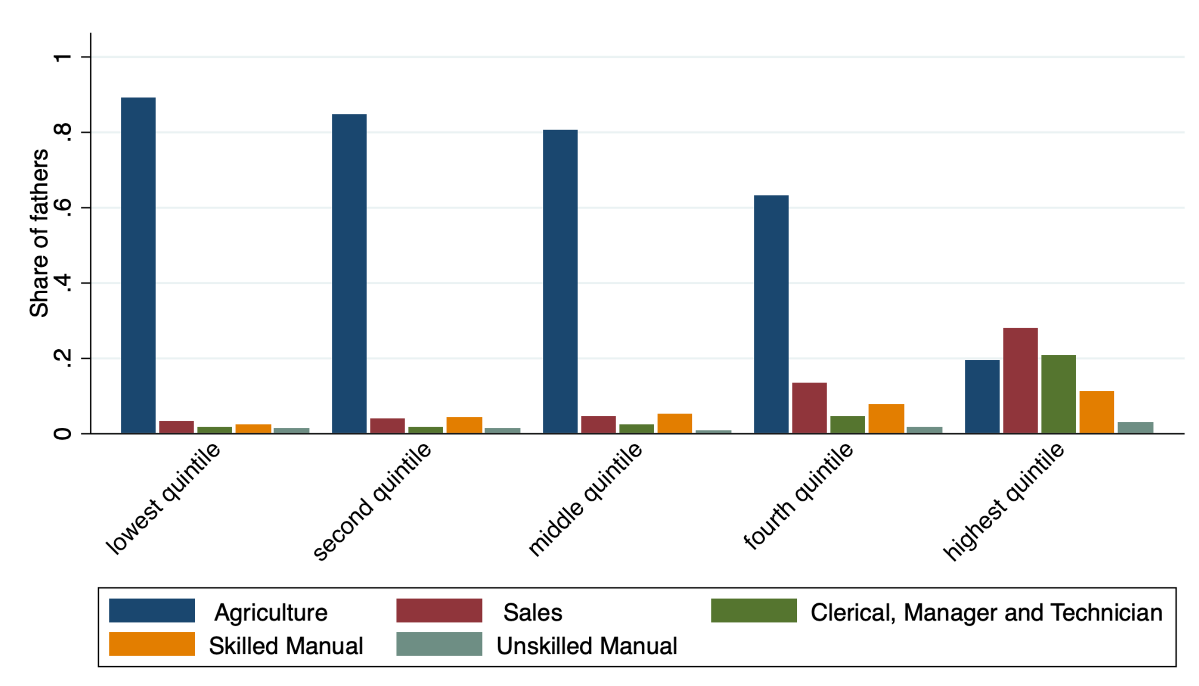
Note: This figure plots estimated effects of mine openings on educational choices of children in mining areas. The horizontal axes show years from mine openings and the vertical axes the estimated coefficients. Navy dot show the estimated coefficients and the vertical lines the 95 percent confidence intervals. Panel A, B, and C presents results for years of education and current year school attendance.

Figure 7: Adult Occupation by Wealth Quintnile

(a) Mothers



(b) Fathers



Source: DHS Mali

Note: This figure presents the share of parents working in each occupation types by wealth quintile of a household. Panel A and B present mothers' and fathers' occupational composition by wealth quintile, respectively.

Table 1: Balance Across Areas

	Mining	Non-mining	Mining vs. Non-mining	N
	(1)	(2)	(3)	(4)
Panel A: Demographic variables				
Age	9.22	9.21	0.00983	6078
	[2.77]	[2.84]	(0.110)	
Male	0.519	0.504	0.0151	6077
	[0.500]	[0.500]	(0.0111)	
N of HH members	9.88	9.47	0.411	6078
	[3.90]	[3.88]	(0.670)	
Live in urban area	0.136	0.160	-0.0238	6078
	[0.343]	[0.366]	(0.133)	
Mother's age	37.4	36.8	0.581	6078
	[10.1]	[9.43]	(0.733)	
Fathers's age	50.4	49.0	1.48	6078
	[10.6]	[10.6]	(1.53)	
Mother's education	0.494	0.658	-0.164	6078
	[1.70]	[1.96]	(0.237)	
Fathers's education	1.10	1.04	0.0591	6078
	[2.59]	[2.55]	(0.422)	
Biological child	0.878	0.886	-0.00827	6078
	[0.328]	[0.318]	(0.0244)	
Panel B: Outcome variables				
Participation: Any work	0.846	0.822	0.0244	3996
	[0.361]	[0.383]	(0.0281)	
Participation: Economic activity	0.495	0.344	0.151	3995
	[0.500]	[0.475]	(0.111)	
Participation: Household work	0.705	0.752	-0.0465	3981
	[0.456]	[0.432]	(0.0498)	
Hours: Any work	23.6	20.4	3.20	3996
	[22.0]	[20.9]	(3.00)	
Hours: Economic activity	7.34	3.17	4.17	3990
	[15.1]	[10.2]	(4.30)	
Hours: Domestic work in HH	16.8	17.3	-0.524	3973
	[18.0]	[18.7]	(2.08)	
Years of education	0.832	0.746	0.0856	5985
	[1.45]	[1.50]	(0.124)	
Currently enrolled	0.395	0.309	0.0856**	6057
	[0.489]	[0.462]	(0.0369)	

Notes: Column 1 and 2 reports means of baseline variables for subjects residing in mining and non-mining areas. Columns 3 report mean differences between the mining and non-mining areas. Standard deviations are in brackets, and standard errors, clustered at the commune level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Notes: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).

Table 2: Hours Worked by Years

	Any work	Economic activity	Household work
	(1)	(2)	(3)
20 km × 11+ yrs prior	0.337	-2.712	2.474
	(3.979)	(2.327)	(2.557)
20 km × 6-10 yrs prior	-1.343	0.177	-1.173
	(4.338)	(2.787)	(2.914)
20 km × 1-5 yrs post	-6.395*	-2.102	-4.804**
	(3.542)	(1.886)	(2.078)
20 km × 6-10 yrs post	-6.351	-3.484**	-4.320
	(3.853)	(1.371)	(3.185)
20 km × 11+ yrs post	-15.357***	-6.685**	-8.676***
	(4.257)	(3.348)	(3.216)
N	11792	11769	11699
R-Squared	0.225	0.130	0.230
Mean of Dep. Var.	19.933	3.084	17.029
P-val.: joint F-test	0.835	0.076	0.303

Notes: All columns include year-from-open, commune and survey year fixed effects. Additional controls include a child's age, birth order, the number of household members, whether a child is the biological children of the household member, living in urban area, mother and father's age and years of education, and wealth index score. Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Source: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).

Table 3: Hours Worked

	Any work	Economic activity	Household work
	(1)	(2)	(3)
Panel A: Demographics controlled			
20 km × Open	-7.624***	-3.299	-5.057**
	(2.686)	(1.987)	(2.407)
N	11792	11769	11699
R-Squared	0.223	0.129	0.228
Mean of Dep. Var.	19.933	3.084	17.029
Panel B: Naive estimates			
20 km × Open	-7.907***	-3.554*	-5.065*
	(2.826)	(2.095)	(2.592)
N	11793	11770	11700
R-Squared	0.092	0.085	0.111
Mean of Dep. Var.	19.933	3.084	17.029

Notes: In Panel A, all columns include control variables listed in the notes of Table 2. In the bottom panel, all fixed effects are included but additional demographic control variables are excluded. Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Source: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).

Table 4: Heterogeneous Effect on Hours Worked

	By gender			By age			By birth order		
	Any work	Economic activity	Household work	Any work	Economic activity	Household work	Any work	Economic activity	Household work
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
20 km × Open	-8.830**	-2.216	-7.325**	-9.763***	-2.336	-8.852***	-9.291***	-3.890*	-6.276**
	(3.379)	(1.552)	(2.884)	(3.537)	(3.554)	(3.109)	(2.749)	(2.186)	(2.430)
20 km × Open × Male	2.505	-1.848	4.340						
	(2.592)	(2.606)	(3.805)						
20 km × Open × Age 5-11				2.306	-1.428	4.652**			
				(2.743)	(3.076)	(1.845)			
20 km × Open × 1st-born							8.386***	3.011	6.032***
							(2.839)	(2.187)	(1.663)
N	11792	11769	11699	11792	11769	11699	11792	11769	11699
R-Squared	0.227	0.135	0.231	0.228	0.136	0.233	0.227	0.132	0.232
Mean of Dep. Var.	22.185	2.205	20.169	30.958	5.380	25.976	18.873	3.008	16.019
20 km · Open + Interaction	-6.325	-4.064	-2.985	-7.457	-3.763	-4.199	-0.905	-0.879	-0.244
P-value.: 20 km · Open + Interaction	0.013	0.168	0.354	0.005	0.046	0.070	0.803	0.678	0.929

Notes: All columns include control variables listed in the notes of Table 2. Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Areas outside of 20 km radius are considered as treated and control area.

Source: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).

Table 5: Educational Outcomes

	Years of Education				Currently enrolled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
20 km × Open	-0.296	-0.203	-0.711	-0.273	-0.106	-0.116	-0.243*	-0.075
	(0.283)	(0.254)	(0.677)	(0.209)	(0.106)	(0.108)	(0.143)	(0.109)
20 km × Open × Male		-0.195				0.016		
		(0.153)				(0.046)		
20 km × Open × Age 5-11			0.578				0.180**	
			(0.536)				(0.070)	
20 km × Open × 1st-born				-0.168				-0.129*
				(0.415)				(0.074)
N	14809	14809	14809	14809	14962	14962	14962	14962
R-Squared	0.333	0.336	0.342	0.336	0.235	0.242	0.242	0.242
Mean of Dep. Var.	0.755	0.755	0.755	0.755	0.318	0.318	0.318	0.318
20 km · Open + Interaction		-0.397	-0.133	-0.440		-0.100	-0.063	-0.203
P-value.: 20 km · Open + Interaction		0.229	0.453	0.444		0.364	0.524	0.076

Notes: All columns include control variables listed in the notes of Table 2. Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Source: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).

Table 6: Parents' Work

Panel A: Mother's Employment Status

	Work	Paid work	Cash-paying work	Self-employed	Work for others	Work for family members
	(1)	(2)	(3)	(4)	(5)	(6)
20 km × Open	-0.257	0.235**	0.447***	0.089	0.044	-0.098*
	(0.163)	(0.104)	(0.145)	(0.054)	(0.027)	(0.052)
N	11856	9716	9139	9067	9114	9114
R-Squared	0.255	0.289	0.371	0.196	0.088	0.231
Mean of Dep. Var.	0.857	0.756	0.463	0.752	0.016	0.169

Panel B: Mother's occupation

	Agriculture	Sales	Clerical, Manager, Technician	Skilled Manual labor	Unskilled Manual labor	Domestic service
	(1)	(2)	(3)	(4)	(5)	(6)
20 km × Open	-0.335	0.167**	-0.005	-0.096**	-0.030	0.001
	(0.225)	(0.082)	(0.006)	(0.039)	(0.031)	(0.001)
N	11856	11856	11856	11856	11856	11856
R-Squared	0.498	0.225	0.118	0.129	0.192	0.010
Mean of Dep. Var.	0.578	0.235	0.011	0.022	0.008	0.000

Panel C: Father's occupation

	Agriculture	Sales	Clerical, Manager, Technician	Skilled Manual labor	Unskilled Manual labor	Domestic service
	(1)	(2)	(3)	(4)	(5)	(6)
20 km × Open	-0.047	-0.087	0.068*	-0.016	-0.030	0.028
	(0.194)	(0.093)	(0.038)	(0.021)	(0.022)	(0.018)
N	11775	11775	11775	11775	11775	11775
R-Squared	0.386	0.187	0.262	0.092	0.062	0.056
Mean of Dep. Var.	0.745	0.102	0.059	0.050	0.010	0.008

Notes: All columns include control variables listed in the notes of Table 2. Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Source: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).

Table 7: Spillover Effects on Areas Farther Away From Mines

	Any work	Economic activity	Household work
	(1)	(2)	(3)
Panel A: Naive estimates			
30-50 km $\times$ Open	-0.292	0.896	-1.578
	(2.991)	(1.397)	(2.912)
N	10113	10092	10026
R-Squared	0.080	0.066	0.101
Mean of Dep. Var.	20.807	2.987	18.002
Panel B: Demographics controlled			
30-50 km $\times$ Open	-0.409	1.085	-1.943
	(2.797)	(1.310)	(2.847)
N	10112	10091	10025
R-Squared	0.215	0.113	0.221
Mean of Dep. Var.	20.807	2.987	18.002

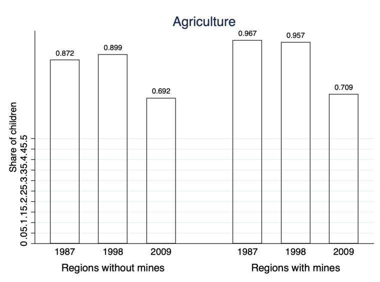
Notes: All columns include control variables listed in the notes of Table 2. Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Areas outside of 20 km radius are considered as treated and control area.

Source: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).

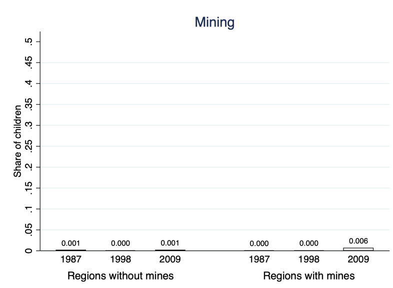
A Additional tables and figures

Figure A1: Child employment in different sectors

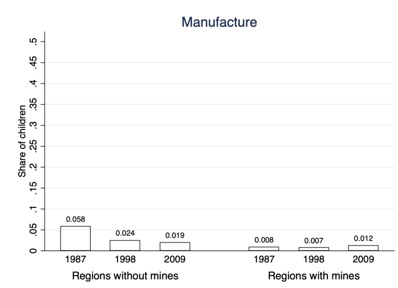
(a) Agriculture



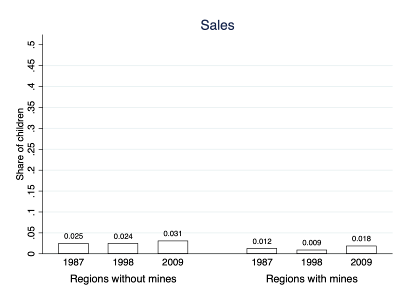
(b) Mining



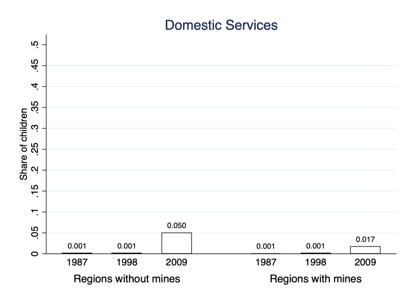
(c) Manufacture



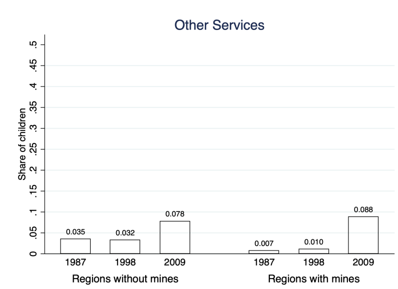
(d) Sales



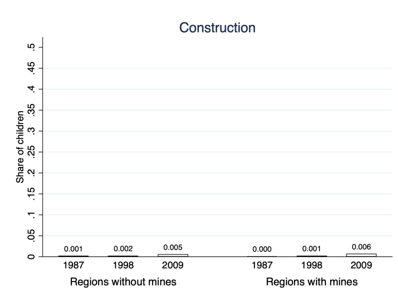
(e) Domestic services



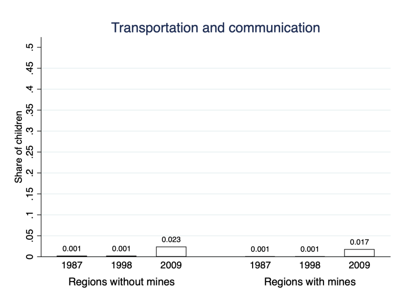
(f) Other services



(g) Construction



(h) Transportation / Communication

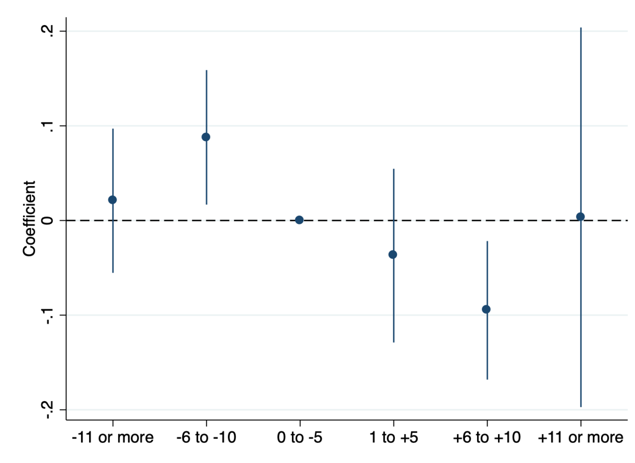


Source: Mali Census

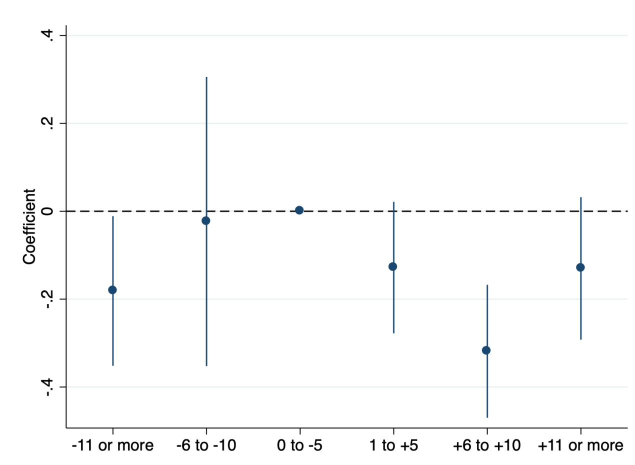
Note: This figure plots the share of children employed each sector among all children aged 5 to 14, in each census wave, by mining and non-mining areas. The horizontal axes show years and areas. and the vertical axes the share of children in each sector.

Figure A2: Impacts on child labor participation

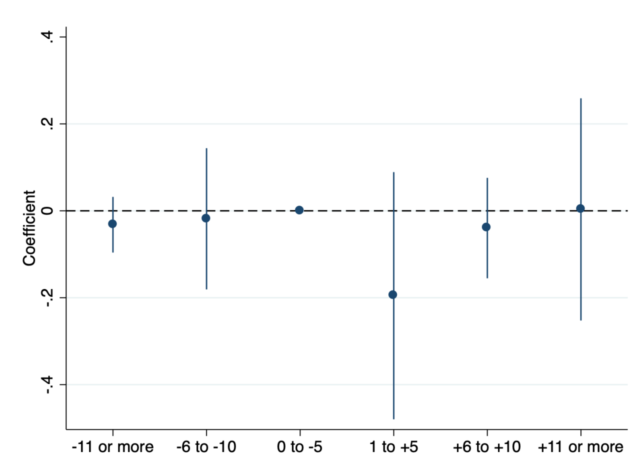
(a) Any types of work



(b) Economic activities



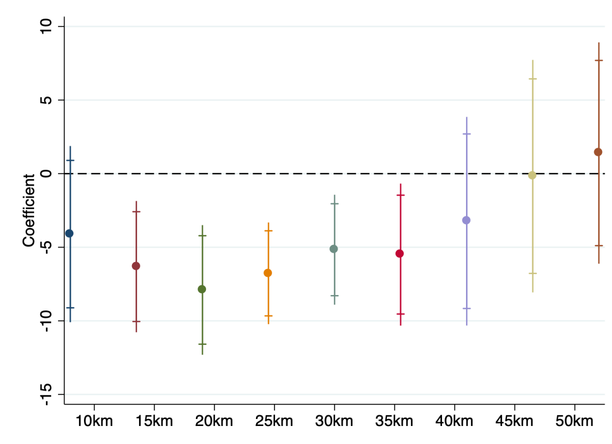
(c) Household work



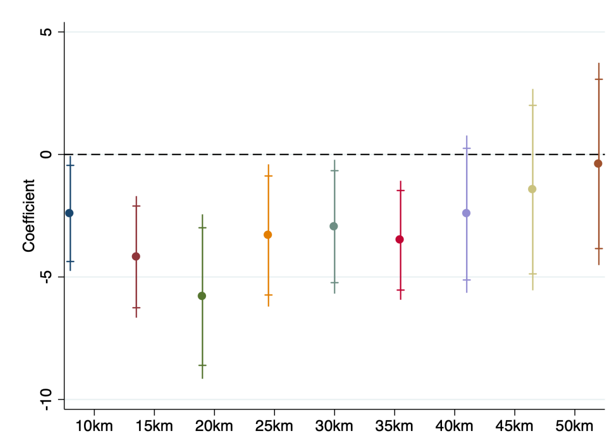
Note: This figure plots estimated effects of mine openings on children's participation in work in mining areas. The horizontal axes show years from mine openings and the vertical axes the estimated coefficients. Navy dot show the estimated coefficients and the vertical lines the 95 percent confidence intervals. 0 to 5 years prior to opening is used as a reference period. Panel A, B, and C presents results for working hours for all types of work, economic activities, and household chores.

Figure A3: Impacts on Working Hours of Children

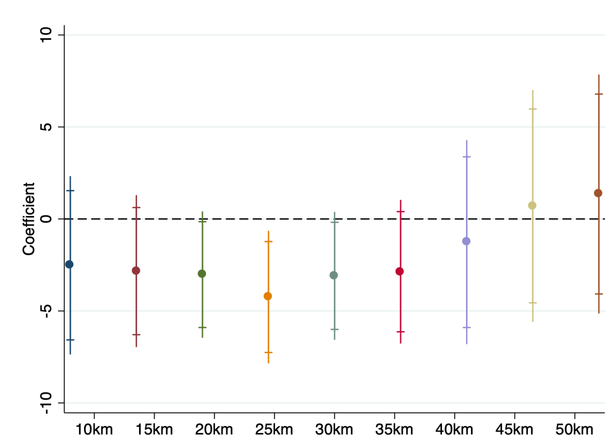
(a) Any types of work



(b) Economic Activities



(c) Household work



Note: This figure plots estimated effects of mine openings on working hours of children in mining areas, varying the threshold distance to define mining area. The horizontal axes threshold distance used to define mining areas and the vertical axes the estimated coefficients. The vertical lines represent the 95 percent confidence intervals. Panel A, B, and C presents results for working hours for all types of work, economic activities, and household chores.

Table A1: List of Gold Mines in Mali

Name	Open	Closed	Re-open
Yatela Pit	2001		
Sadiola Pit	1996		
Loulo Pit	2011		
Tabakoto Pit	2012		
Kalana Pit	2004		
Morila Pit	2000		
Syama Pit	1990	2001	2011

Table A2: Child Worked by Years

	Any work	Economic activity	Household work
	(1)	(2)	(3)
20 km × 11+ yrs prior	-0.014	-0.091	-0.402***
	(0.066)	(0.155)	(0.077)
20 km × 6-10 yrs prior	0.005	-0.133	-0.369***
	(0.079)	(0.197)	(0.077)
20 km × 1-5 yrs post	-0.005	-0.077	-0.260***
	(0.062)	(0.094)	(0.070)
20 km × 6-10 yrs post	-0.051	-0.314***	-0.036
	(0.061)	(0.069)	(0.064)
20 km × 11+ yrs post	0.116	-0.076	-0.187**
	(0.081)	(0.177)	(0.087)
N	11794	11793	11770
R-Squared	0.238	0.283	0.213
Mean of Dep. Var.	0.832	0.343	0.762
P-val.: joint F-test	0.874	0.797	0.000

Notes: All columns include control variables listed in the notes of Table 2. Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Source: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).

Table A3: Child Worked

	Any work	Economic activity	Household work
	(1)	(2)	(3)
Panel A: Demographics controlled			
20 km × Open	0.011	-0.023	0.075
	(0.048)	(0.105)	(0.060)
N	11794	11793	11770
R-Squared	0.234	0.281	0.209
Mean of Dep. Var.	0.832	0.343	0.762
Panel B: Naive estimates			
20 km × Open	0.014	-0.031	0.087
	(0.049)	(0.108)	(0.059)
N	11795	11794	11771
R-Squared	0.109	0.203	0.101
Mean of Dep. Var.	0.832	0.343	0.762

Notes: In Panel A, all columns include control variables listed in the notes of Table 2. In the bottom panel, all fixed effects are included but additional demographic control variables are excluded. Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Source: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).

Table A4: Hours Worked (Using continuous distance)

	Any work	Economic activity	Household work
	(1)	(2)	(3)
Panel A: Demographics controlled			
ln(Distance) × Open	4.080***	0.453	3.830***
	(1.477)	(0.674)	(1.411)
N	11792	11769	11699
R-Squared	0.223	0.130	0.226
Mean of Dep. Var.	19.185	2.891	16.513
Panel B: Naive estimates			
ln(Distance) × Open	4.113***	0.489	3.820***
	(1.558)	(0.765)	(1.434)
N	11793	11770	11700
R-Squared	0.091	0.083	0.109
Mean of Dep. Var.	19.185	2.891	16.513

Notes: In Panel A, all columns include control variables listed in the notes of Table 2. In the bottom panel, all fixed effects are included but additional demographic control variables are excluded. Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A5: Heterogeneous Effect on Hours Worked (Using continuous distance)

	By gender			By age		
	Any work	Economic activity	Household work	Any work	Economic activity	Household work
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Distance) × Open	4.555**	0.119	4.652***	4.802***	0.655	4.555**
	(1.790)	(0.615)	(1.585)	(1.819)	(0.949)	(1.845)
ln(Distance) × Open × Male	-0.934	0.584	-1.563			
	(1.111)	(0.823)	(1.466)			
ln(Distance) × Open × Age 5-11				-0.900	-0.255	-0.924
				(1.361)	(0.864)	(1.217)
N	11792	11769	11699	11792	11769	11699
R-Squared	0.227	0.137	0.229	0.228	0.136	0.231
Mean of Dep. Var.	19.185	2.891	16.513	19.185	2.891	16.513
ln(Distance) · Open + Interaction	3.621	0.703	3.089	3.902	0.400	3.631
P-value.: ln(Distance) · Open + Interaction	0.007	0.430	0.050	0.009	0.585	0.008

Notes: In Panel A, all columns include control variables listed in the notes of Table 2. In the bottom panel, all fixed effects are included but additional demographic control variables are excluded. Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A6: Educational Outcomes (Using continuous distance)

	Years of Education			Currently enrolled		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Distance) × Open	0.070	0.027	0.189	0.027	0.021	0.036
	(0.087)	(0.075)	(0.189)	(0.038)	(0.037)	(0.041)
ln(Distance) × Open × Male		0.086			0.012	
		(0.068)			(0.018)	
ln(Distance) × Open × Age 5-11			-0.166			-0.012
			(0.158)			(0.018)
Control	Yes	Yes	Yes	Yes	Yes	Yes
N	14809	14809	14809	14962	14962	14962
R-Squared	0.338	0.341	0.347	0.240	0.247	0.247
Mean of Dep. Var.	0.779	0.779	0.779	0.322	0.322	0.322
ln(Distance) · Open + Interaction		0.113	0.023		0.033	0.024
P-value.: ln(Distance) · Open + Interaction		0.299	0.703		0.415	0.528

Notes: All columns include control variables listed in the notes of Table 2. Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A7: Child work (Conservative measure of child labor)

	Pr(Participation)			Hours worked		
	Any work	Economic activities	Household chores	Any work	Economic activities	Household chores
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Demographics controlled						
20 km × Open	-0.096	-0.055	-0.057	-7.229**	-3.332*	-4.713**
	(0.073)	(0.091)	(0.039)	(2.820)	(1.976)	(2.373)
N	11794	11794	11794	11794	11794	11794
R-Squared	0.143	0.125	0.190	0.174	0.120	0.168
Mean of Dep. Var.	0.368	0.144	0.248	14.555	2.884	10.802
Panel B: Naive estimates						
20 km × Open	-0.097	-0.053	-0.059	-7.529**	-3.565*	-4.809*
	(0.078)	(0.096)	(0.044)	(2.953)	(2.089)	(2.601)
N	11795	11795	11795	11795	11795	11795
R-Squared	0.074	0.099	0.106	0.076	0.084	0.087
Mean of Dep. Var.	0.368	0.144	0.248	14.555	2.884	10.802

Notes: In Panel A, all columns include control variables listed in the notes of Table 2. In the bottom panel, all fixed effects are included but additional demographic control variables are excluded. Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.
Source: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).

Table A8: Heterogeneous Effect on Hours Worked (Conservative measure of child labor)

	By gender			By age			By birth order		
	Any work	Economic activity	Household work	Any work	Economic activity	Household work	Any work	Economic activity	Household work
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
20 km × Open	-7.757**	-2.363	-6.021**	-12.435***	-2.970	-11.893***	-8.621***	-3.935*	-5.364**
	(3.392)	(1.545)	(2.677)	(3.493)	(3.543)	(2.834)	(2.967)	(2.177)	(2.359)
20 km × Open × Male	1.277	-1.643	2.560						
	(2.439)	(2.605)	(3.364)						
20 km × Open × Age 5-11				6.148**	-0.683	9.006***			
				(2.757)	(3.121)	(1.566)			
20 km × Open × 1st-born							7.428**	2.949	3.995*
							(2.957)	(2.107)	(2.102)
N	11794	11794	11794	11794	11794	11794	11794	11794	11794
R-Squared	0.179	0.127	0.171	0.183	0.127	0.179	0.179	0.123	0.172
Mean of Dep. Var.	14.555	2.884	10.802	14.555	2.884	10.802	14.555	2.884	10.802
20 km · Open + Interaction	-6.480	-4.006	-3.461	-6.288	-3.654	-2.887	-1.193	-0.986	-1.369
P-value.: 20 km · Open + Interaction	0.018	0.172	0.262	0.025	0.054	0.206	0.735	0.628	0.657

Notes: In Panel A, all columns include control variables listed in the notes of Table 2. In the bottom panel, all fixed effects are included but additional demographic control variables are excluded. Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Source: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).

Table A9: Demographic change

	Age	=1 Male	HH size	Live in urban area	Female HH head	Mother's years of education	Father's years of education
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
20 km radius × Open	-0.565	-0.006	-0.767	0.057	-0.014	0.369**	0.298
	(0.626)	(0.023)	(0.663)	(0.091)	(0.033)	(0.159)	(0.368)
N	46634	46659	46660	46660	46660	46660	46660
R-Squared	0.006	0.003	0.079	0.757	0.047	0.062	0.066
Mean of Dep. Var.	20.658	0.488	8.315	0.123	0.041	0.773	1.255

Notes: Standard errors, clustered at commune level, are in parentheses. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.
Source: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).

Table A10: Effects on outcome variables using never movers sample

	Any work	Economic activity	Household Work	Child Labor	Enrolled in School	Mother's work
	(1)	(2)	(3)	(4)	(5)	(6)
20 km × Open	-4.543***	-0.841	-4.359***	0.416***	0.062	-0.591***
	(1.618)	(0.626)	(1.286)	(0.143)	(0.085)	(0.134)
N	5499	5485	5473	7617	7722	7716
R-Squared	0.245	0.171	0.263	0.278	0.220	0.253
Mean of Dep. Var.	21.816	5.063	17.165	0.749	0.369	0.904

Notes: Standard errors, clustered at commune level, are in parentheses. The sample includee 1996 to 2006 survey wave only since the variable asking about the years lived in the current place is not collected in 2012. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.
Source: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).

Table A11: Effects on non-mining areas

	Any work	Economic activity	Household Work	Child Labor	Enrolled in School	Mother's work
	(1)	(2)	(3)	(4)	(5)	(6)
100 km radius × Open	-5.483	-0.369	-5.034	-0.136	-0.040	-0.140
	(4.515)	(0.890)	(3.631)	(0.121)	(0.048)	(0.096)
N	8762	8746	8716	12348	12490	12467
R-Squared	0.120	0.134	0.150	0.117	0.136	0.284
Mean of Dep. Var.	.	.	.	.	.	.

Notes: Standard errors, clustered at commune level, are in parentheses. The sample includee 1996 to 2006 survey wave only since the variable asking about the years lived in the current place is not collected in 2012. Sample weights used were provided by DHS. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Source: Pooled dataset using Demographic and Health Survey (DHS) from 1996, 2001, 2006 and 2012, and the data from Benshaul-Tolonen (2019).