Gold Mine Openings and Child Labor in Mali *

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Abstract

Child labor is prevalent in low-income countries, many of which use natural resource extraction as a major source of exports. The evidence of its effects on children's human captial accumulation is mixed. This paper investigates the effect of a natural resource shock on child labor using the opening of industrial gold mines in Mali as an exogenous shock. The empirical analysis combines data from Demographic and Health Survey (DHS) and mine data from Benshaul-Tolonen (2019), and use difference-in-difference model to estimate the effects. We find that the industrial gold mines decrease children's working hours, specifically the working hours for household tasks. However, we do not find significant changes in educational outcomes. We also find that the effects decrease gender gaps in working hours while increasing the burden on the oldest siblings. The results are robust to various specifications and sensitivity checks. Using the effects on adults' employment and occupational choices, we provide suggestive evidence that our main results are consistent with the scenario where the income effects dominate the substitution effects.

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

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1 Introduction

Human capital investment is crucial for economic development. Child labor is one of the activities that hinder investment in children's human capital. Working children invest less time and effort in schooling; hence have worse educational outcomes both in the short- and long-term (Heady, 2003; Beegle et al., 2008; Emerson, Ponczek, and Souza, 2017; DeGraff, Ferro, and Levison, 2016). Exposure to hazardous conditions in work leads to poorer health conditions in adulthood (Kassouf, McKee, and Mossialos, 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. Moreover, the prevalence of child labor is higher in countries with lower GDP per capita (Edmonds, 2016). Therefore, understanding how economic development affects child labor is an important issue.

Natural resource extraction is a major source of exports in some developing countries, 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 (Sachs and Warner, 2001; Frankel, 2012). However, local economic impacts are often found to be positive (Aragón and Rud, 2013; Fafchamps, Koelle, and Shilpi, 2017). Moreover, studies on the impact of mining activities on children that lead to a long-term effect of these activities has produced mixed and conflicting results (von der Goltz and Barnwal, 2019; Benshaul-Tolonen, 2019; Zabsonré, Agbo, and Somé, 2018; Santos, 2018).

This paper brings new evidence to the literature on the relationship between income and child labor by examining the impact of a natural resource shock, the opening of industrial gold mines in the West African country of Mali, on child labor. We exploit two exogenous events: i) A new mining code introduced in 1991 that resulted in new foreign direct investment in extractive industries (Organization, 1998)); and ii) increases in global gold prices that made such investments profitable (Mainguy, 2011). Child labor is widespread in Mali. For example, 31 percent of children aged 5 to 14 engaged in economic activities in 2009 (Kippenberg, 2011). We match geo-coded data on 12,468 children aged 5 to 14 years old interviewed between 2001 to 2012 with geo-coded information on new gold mine construction and operation. It allows us to compare children from households living closer to the mines to the children living further away from the mines, before and after the closest mines open while controlling for region- and time-specific confounders. By doing so, we capture the effect of opening industrial gold mines on child labor.

[1] We refer industrial mines to highly mechanized, capital intensive, and large-scale gold mines operated by firms - that are often large. In contrast, Artisanal Small-scale Mines (ASM) are traditional ways to extract gold, most of which are unregistered and operated by local capitals.

We find that the opening of industrial mines reduces child labor by 8.6 hours per week in total. The effects were qualitatively similar across different types of activities. Hours for economic activities decrease by 3.7 hours and household tasks 5.7 hours. The effects are heterogeneous across groups with diffrent demographic characteristics. The reduction in working hours is larger among girls than among boys, decreasing the gender gap in working hours, and is larger among older children aged 12 to 14 than among younger children. However, the decrease in working hours did not lead to improvements in educational outcomes such as years of schooling and current enrollment. The results are robust to the changes in the distance threshold and a more conservative measure of child labor.

Consistent with the findings of Kotsadam and Tolonen (2016), we find that mothers are less likely to work but more likely to work in better-quality jobs conditional on work. We also find a sectoral shift of female workers from agriculture to the sales sector and increased adult male employment in clerical/managerial positions. We also confirm that the effects are not driven by the demographic changes induced by migration. Taken together, the results show that the structural shift in the adult labor market accompanied by the mine opening led to decreased children's working hours through higher household income and increased mothers' presence at home.

These findings reconcile mixed evidence on the initial effects of economic development on child labor. Economic development increases household income, and a large body of research on child labor shows that child labor decreases when household income increases (Basu and Van, 1998; Edmonds, 2005; Edmonds and Pavcnik, 2005; Edmonds and Schady, 2012; Cogneau and Jedwab, 2012).[2] Economic development may lead to accumulation of households' productive assets. Evidence shows that child labor increases when households have more productive assets (Basu, Das, and Dutta, 2010; Cockburn and Dostie, 2007; Edmonds and Theoharides, 2020). Urbanization and increases in local labor demand, other aspects of development, have also been associated with increased child labor. (Fafchamps and Wahba, 2006; Manacorda and Rosati, 2011)[3] This paper shows that under a capital-intensive, industry-driven economic development can decrease

[2]This negative correlation between household income and child labor is found in the opposite situation: some studies show that child labor increases facing negative productivity shocks (Beegle, Dehejia, and Gatti, 2006; Duryea, Lam, and Levison, 2007). These results suggest 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 alternative use of a child's time and increase child labor supply (Basu, Das, and Dutta, 2010; Cockburn and Dostie, 2007; Edmonds and Theoharides, 2020). Basu, Das, and Dutta (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. Besides, the proximity to an urban area may increase children's working hours outside of the households as economic opportunities for children increases with the proximity (Fafchamps and Wahba, 2006). In addition, when local labor demand increases, child labor tends to increase despite the income effect that working in favor of decreasing child labor (Manacorda and Rosati, 2011).

children's working hours through changes in adult employment.

Our findings contribute to the discussion of the economic effect of natural resource extraction as well. Previous studies find that mining activities improve household living standards (Aragón and Rud, 2013; Zabsonré, Agbo, and Somé, 2018) and increase household income (Gajigo, Mutambatsere, and Ndiaye, 2012; Weng et al., 2013). Moreover, industrial mines shift employments from agriculture to manual labor and services (Kotsadam and Tolonen, 2016) and increase households' asset wealth (von der Goltz and Barnwal, 2019). Urban areas start to develop around industrial mines[4] due to the resources and infrastructure they require (Fafchamps, Koelle, and Shilpi, 2017). Relatedly, Bazillier and Girard (2020) find that it is Artisanal Small-scale Mines (henceforth ASMs) which increases household consumption. However, the limited literature on the impact of mining activities on child welfare has produced mixed and conflicting results. von der Goltz and Barnwal (2019) show that industrial gold mines decrease infant mortality. By contrast, Benshaul-Tolonen (2019) finds that pollution from industrial mines increases the prevalence of chronic undernutrition. While Santos (2018) show that industrial mines increase child labor and decrease schooling and Ahlerup, Baskaran, and Bigsten (2020) also find that industrial mines decrease adolescent schooling attainments in Colombia and Sub-Saharan Africa, Zabsonré, Agbo, and Somé (2018) find that increases in the price of gold had no impact on child labor in mining communities in Burkina Faso. This paper provides additional evidence that the natural resource shock positively affects child welfare by decreasing children's work engagement, especially household tasks.

The paper proceeds as follows. Section 2 discusses a conceptual framework. Section 3 explains the study setting, and Section 4 describes the dataset and the empirical strategy used for the estimation. We present the estimated results in section 5 and conclude in Section 6.

2 Conceptual Framework

This sections presents a simple framework to structure thinking about the effects of natural resource shock on household labor allocation. A household decide 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, 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 industriaml mines can increase household income exist: direct employment at mines and the

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inderect employments. The indirect employments include service and sales jobs created through local multiplier, as shown in Moretti (2010). However, neither the cost of education nor the school quality will not likely to change due to the gold mine openings. Therefore, unless there is significant population influx, children's work and schooling are to be determined by the changes in household income or the wages 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 shown in Santos (2018). Kotsadam and Tolonen (2016) also shows that female adult employment in these sectors increase. Considering that a child typically work in household farm or business, increase in female adults' employment in sales and service sectors increase children's exposure to these jobs. Moreover, the demand for child labor increases within a household as well. As adults experience increased employment opportunities – especially in sectors other than in 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 childrne's work will increase.

However, following the Luxury axiom posed in Basu and Van (1998), increased wages 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. (Edmonds and Schady, 2012; Cogneau and Jedwab, 2012) The income effect can work through two channels. Assuming that a child's leisure is a normal good, a household will increase the consumption of children's leisure with the increased income. We call this a "direct" income effect. An indirect income effect occurs when an increased household income leads to a decrease in a 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 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 effects dominate the other. If the substitution effect dominates, we may see children work more. On the other hand, child labor will decrease if the income effect dominates. If the income effect dominates, the changes in adult labor outcomes will provide a hint on 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. We implement empirical analyses to estimate the net effect.

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; for example, only 950kg of gold was produced in Mali in 1987. In 1991, a new mining code providing tax and customs advantages to the mining sector to attract foreign direct investments was introduced. As a result, seven large-scale industrial gold mines started their operations in the following two decades, and the gold production volume increased rapidly. By 1999, 23,668kg of gold was being produced annually. Figure 1 shows that increases in international gold prices started in 2001 led to a further increase in production value and a further expansion of the mining industry. Population and Housing Census of Mali shows that the mining sector's employment share in total employment grew from 9 percent in 1999 to 27 percent in 2009. The share of gold among Mali's export goods has increased to 65 percent by 2019 (International Monetary Fund, 2019).

We 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, the 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, it is only two regions where all the mines are located, in Kayes and Sikasso regions.[5] 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 decreases over time from 80.4 percent in 2001 to 62.5 percent in 2012, but the 2012 participation rate is still high. The high participation rate comes from helping with household tasks that ranges from 57 to 74 percent. It is consistent with the story where parents view child labor as acceptable

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

or even instructive for children (Kippenberg, 2011). Participation in economic activities is relatively lower, ranging from 20 to 58 percent during this period, and agriculture is the largest sector employing most of working children. Mali's population and housing census shows that 83 percent of the workign children are in agriculture. Other sectors, including the mining sector, hire few children. (Figure A4).

However, unlike the participation rate, working hours did not vary substantially across time. In total, children worked for 23.4 hours in 2001 and 24 hours in 2012 conditional on working. Working hours are less than 19 hours per week for economic activities and 24 hours for household tasks. Considering that International Labour Organization (ILO) and other international organizations use 14 hours and 28 hours as a threshold to define children's engagement in economic activities and domestic work as child labor for the older group of children (aged 12 to 14), these working hours are not too long.

Since economic activities and household tasks comprise child labor together, we examine the effect of the opening of industrial mines on two different types of activities of children in this paper: i) economic activity, which includes any income-generating activity that a child is engaged in regardless of payment status or whom the child is working for, and household tasks, which includes cooking, taking care of younger siblings fetching water.

4 Data and Empirical strategy

4.1 Data

For the main empirical analyses, we combine three datasets, 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[6]. These datasets 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 our analysis. For the supplementary analyses, we use data from the Population and Housing census of Mali conducted in 1987, 1998, and 2009.

Mali's Demographic and Health Surveys (DHS) provide information on children's work, education, and demographic background from the 1996, 2001, 2006, and 2012 waves.[7] It is a repeated

[6]https://miningdataonline.com

[7]We excluded the 1987 wave from the main analysis because geolocation of survey clusters was not recorded in

cross-sectional household survey that provides a wide range of data in 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.

We measure child labor using working hours of children aged 5 to 14 in the seven days before the interview. The legal minimum working age is 15, hence 14 years old as the upper bound of the age range. The DHS dataset 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 family business, fetching water and woods, and any other paid or unpaid economic activities outside of the household. Household tasks refer to activities such as cooking, cleaning, and washing clothes. We sum up children's working hours for both types of work to measure children's time allocation for work. We 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 seven days before the interview.[8]

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. We 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 to 6 months and varied from winter to summer.

To identify a cluster as a mining area, we 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 20km radius from the industrial gold mines, we identify a 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. However, it may raise the concern of the systematic difference between the region and the rest of the country. Therefore, we restrict the sample to the surveyed clusters located within a 100km radius of the mines. We discuss the choice of the threshold distances in the next section in more detail.

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. We 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 nine years old on average, and about 51.6 percent of them are boys. The average household has 9.8 people, 15.6

the 1987 wave.

[8] 1 percent of the sample is reported to work longer than 95 hours in the previous week, and we check if the results are robust after dropping these observations.

percent of households reside in urban areas, and the average wealth quintile is 3.01.[9] The average mother is 37 years old, received 0.5 years of education, while the average father is 50 years old with 1.1 years of education. 89 percent of the children in our sample are living together with their biological mother. Demographic characteristics of non-mining area children and their households are similar to that of mining area children.

Table 2 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 any type of child labor. Specifically, 41.9 percent of the children participated in economic activities and 75.8 percent in household tasks. 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 in the previous school year. The 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 on average the same across areas.

Children's weekly working hours are negatively correlated with the wealth status of the households. Panel A of Figure 4 shows that the wealthier the household is, the less children participate in all types of work. Moreover, children's working hours depend on mother's occupational choices as well. Panel B of Figure 4, plots that children of a mother working in agricultural sector works the longest hours in total (18.3 hours per week). They do so by working the longest in both economic activities and household tasks. On the other hand, children with mothers do not work the least number of hours in total (12.3 hours per week). These children work 2.7 hours per week for economic activities that is longer than the average but they work the least number of hours for household tasks. It indicates that children's engagement in household tasks are substituted by mothers with mothers present at home.

In Section 4.3, we estimate the pre-shock trends of outcome variables across mining- and non-mining areas. We 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 provides additional supporting evidence to show that the level difference between the areas was small.

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

4.2 Empirical strategy

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

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

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 20km from an open mine. It serves as a ever-treated group indicator. The control group is the children living in clusters located between 20 and 100km 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.[10] Spatial variations are captured by 20km-bin fixed effect, denoted by $\sum_{d=1}^{5} \text{Distance Bin}_j^d$, and time variations by year-from-mine fixed effect, $\sum_{y=1}^{6} \text{Years from open}_t^y$. Distance Bin_j^d is a seriese of indicators, which groups the distance from the closest mine to the surveyed cluster in 20km bins. $\text{Years from open}_t^y$ 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 our coefficient of interest which we interpret as the changes in child labor in areas in proximity to the active mines, compared to the contempraneous changes in areas farther away from the mines.

We use 100km as a threshold to restrict the sample and 20km to define the mining area. We use geographic proximity 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 100km 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 20km radius of the mines. Evidence on Ghana and Tanzania's commuting behaviors also shows that mines' impact on local economies can be identified within 5–20 kilometers from the mines (Amoh-Gyimah and Aidoo, 2013). Therefore, a threshold of 100km for sample restriction ensures the comparison and ever-treated group's comparability and reduces potential biases due to the systematic difference between the two groups.

[10] We 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.

Second, the geocoordinates in the DHS data are randomly displaced up to 5km and 10km for 1 percent of the sample to prevent the users from identifying the individual households. DHS also recommends using thresholds larger than 5 kilometers. Third, as disccussed in Benshaul-Tolonen (2019), the geocoordinates in the mining data locates the center of the mining area. Thus, using a distance threshold that is too small could introduce more noise or increases 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, we include commune- and survey-year fixed effects denoted by θ_c and δ_t.[11] To avoid potential omitted variable bias, which may arise from the variables correlated with distance from gold mines and households' child labor supply decisions, we 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, if a child is living with his/her biological parents, and wealth index of a household. To allow for intra-commune heteroskedasticity of standard errors, standard errors are clustered at the commune 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, we 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 and children aged 5 to 11. The coefficient β_1 captures the effect of mine openings on a remaining demographic group (female children and children aged 12 to 14), β_2 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 the results table

[11] A commune is a smallest sub-region level administrative area identified in the dataset.

to show 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 from the non-mining area serve as a counter-factual of the households of 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 working hours of children 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 to 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 the 95 percent confidence intervals. The coefficients of the periods before mine openings are not statistically distinguishable from zero, for all outcome variables. That is, we find parallel pre-trends of child labor supply across regions.

Table 3 presents estimates that confirm these results. Since we omit 0 to 5 years before the mine openings, the test of parallel pre-trend is equivalent to testing the following hypothesis:

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

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 we 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 Impacts on Child labor

Figure 5 also suggests that children located in mining areas worked fewer hours after mines open. Table 4 complements this by showing the results of estimating Equation (1) with (Panel A) and without (Panel B) control variables. 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. We find a decrease in hours for economic activities by 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 was 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 of the effects we find on children's working hours are robust to the inclusion of control variables, comparing the estimates presented in Panel A and B. Therefore, we present results estimated with control variables for the rest of the section. On the other hand, we find that the effects were not strong enough to decrease children's work at the extensive margin, as shown in Table A2 and A3. These results indicate that children who were engaged in household work more intensively decreased their work. Taken together, the results suggests 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. We verify this claim in section 5.3 by examining the effects on adults' employment and occupational choices.

To better understand among whom the decrease in children's work was concentrated, we examine the heterogeneity of the local effects of large-scale mines across different demographic groups. We do this by estimating Equation (2), using several criteria: sex, age, and birth order. The estimated results are presented in Table 5.

We first disaggregate by a child's gender. Gender roles in child activities seems quite fixated. Girls are more likely to be involved in household work than the boys, and vice versa for the 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, we 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. The implies that the mine openings decreased the gender gap in household tasks from 6.2 to 1.9 hours.

Next, we examine heterogeneity across age groups. For this analysis, we define children of age 5 to 11 as younger children and age 12 to 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. We find that the effect on total working hours and in economic activities, presented in Column (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, the decrease was more substantial among older children who worked much longer hours initially. Older children worked 26.0 hours while younger children did 14 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. They continues to work even when the household income rises. In this regard, the first-born children are less likely to be affected by the income effect. In Columns (7) to (9), we find this is the case in our 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 Impacts on Education

We also examine the effects on the educational outcomes. Child labor is often discussed as an alternative to the 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 (e.g. Santos (2018)) find. However, the it did not lead to an increase in school enrollment nor in the years of education. Figure 6 shows that the trends of educational outcomes – years of education and current enollment – 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 6 complements the figure and shows no impacts of mine openings on years of education and on current enrollment. Years of education is a stock variable, so it may not fluctuate concurrently. But no changes in current enrollment requires further examination.

The decrease in children's working hours was concentrated among the household tasks, not among the economic activities. Moreover, we did not find substantial changes at the extensive margin of children's work. Given the situation, null effects on educational outcomes adds to the implication that the effects of mine openings decreased working hours of the children who were already working long hours, but did not led them to quit working. Another piece of evidence supports this argument. Column (6) to (8) presents the heterogeneous effects on current school enrollment. While we do not find any substantial difference across gender (Column (6)), children of age 12-14 and the first-born children are the ones struck with the effects that are statistically significant. The older children and the first-borns were the group that were initially working longer than their counterparts.

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. Panel A of Table 7 suggests that mothers are less likely to work, but the quality of their work improved for mothers who continued working. The probability of mothers working decreases by .3 but the coefficient is statistically insignificant. However, the magnitude of the effect is 33.3 percent of the average. Columns (2) and) (3) show 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 and no payments. Moreover, Column (4) to (6) show that mothers are 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, 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. A null effects in adult female employment suggests stronger possbility of no, or small substitution effects. If anything, female employment seems to be decreasing – a suggestive evidence of a secondary income earner decreasing their work, as shown in (Kotsadam and Tolonen, 2016).

The results on adult occupation points to the same direction. Panel B of Table 7 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 less likely to work in unskilled manual jobs by 3.2 percentage poionts and in agriculture by 17.2 percentage points, although the coefficient on agriculture is imprecisely estimated.

These changes in occupational choices supports the story of an increased household income. As shown in figure 7, the wealthier the household is, the less likely to work the mothers are to work in agriculture, and more likely to work in sales sector. Moreover, cash-paying positions are positively correlated with household's wealth quintile and work for family members negatively. Thus, the results suggest that the quality of work for mothers improve due to industrial mines. These results are consistent with the findings from previous studies such as Kotsadam and Tolonen (2016), von der Goltz and Barnwal (2019), and Aragón and Rud (2013), which 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 parallel pre-trends assumption is satisfied, other confounders correlated with unobserved heterogeneity may exist. Here, we report additional robustness checks to address this concern. First, we evaluate the sensitivity of the results based on the threshold distance to define mining area. Our choice of the 20km threshold to determine the mining area may seem ad hoc. Therefore, we vary our threshold distance from 10 to 50km to check if the estimated results are robust. As discussed in Section 4.2, we expect the 20km radius to be a reasonable choice and the effects to be mitigated as we 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 A6 shows that the results are robust when we vary the cutoff distance and that the magnitude of the effects reduces as we use longer distance as a threshold. We also repeat the main analysis by replacing the 20km dummy with a continuous distance from the closest mine since the figure suggests that the effects gradually decrease with the distance. Table A5 - A7 shows the results are qualitatively the same.

In addition, we assess the potential spillover effects to the neighboring areas by assigning the areas 30 to 50km around the mines as a neighboring area and the areas 50 to 100km away from the mines as a non-mining area. Since the neighboring areas of 30 to 50km away from mines are closer to the mines than the non-mining area but do not include the mining areas, the estimated coefficients should capture the spillover effects to the neighboring areas. Estimated results presented in Table 8 shows 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.

Our 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 we do not find significant changes in children's educational outcomes. To complement this, we 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 a substantial work if classified as a child laborer according to this criteria. We follow the definition used by UNICEF here. Specifically, UNICEF defines children's activity as child labor if children aged 5 to 11 did at least one hour of economic activity or at least 28 hours of household tasks. For a child of age 12 to 15, it is classified as child labor if a child did at least 14 hours of economic activity or at least 28 hours of household tasks, following the ILO convention No.138, which states that the national laws or regulations should permit the work of children 13 to 15 years of age on light work, that is, less than 14 hours of economic activities or 21 hours of household tasks. Here, we 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 we present here is a more conservative way to measure child labor. Table A8 shows that the effects are similar to what we find in the main analysis, suggesting that the decrease of child labor we find is not coming from children who are at the margin of doing light or no work, but coming from children who were engaged in intensive work.

5.5 Alternative explanations

There are other potential causes that could induce our results such as in-migrations attracted to the new employment opportunities. We examine this possibility by first estimating the effects of mine openings on demographic characteristics. The results presented in Table A10 show that the demographic characteristics did not change substantially due to mine openings except that the share of men decreased. Moreover, Table A11 present the estimated results using children who has never moved since birth. The interpretation of the result is limited for these results since the variable asking how many years have the respondent been living in the current place of resident is not collected in survey year 2012. The results are qualitatively the same as what we find in our main analysis, although the effects seems to be stronger among never movers. We complement the analysis with the evidence using data from Population Census. The data shows that the age distribution and migration pattern do not substantially differ between the regions with or without mines. Figure A2 shows that the ratio of in-migrants is almost equal across the provinces: 27.1 percent in mining provinces and 27 percent in non-mining provinces. If a new group of workers migrated to the mining areas, then Figure A3 shows that the age distribution did not change in mining provinces differently compared to non-mining provinces. Taken together, these results indicate that it is unlikely that the results are driven by the changes in the demographic composition.

One caveat of the analyses in this paper is that they excluded the effect of artisanal and small-scale mines (ASMs). ASMs are known to employ children directly as the parents consider working in mines as a "family affair" (Hilson, 2012). Moreover, due to the geographical concentration of gold deposits, ASM operations are likely to be affected by the expansion or the opening of industrialized mines. However, we do not include the analyses on the effect of ASMs due to the lack of systematic data on the location and operating dates of ASMs in Mali. [12]

[12] 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 effect of industrial mines and ASMs using a nation-wide administrative data on ASM in Burkina Faso, Zabsonré, Agbo, and Somé (2018) who examined the effect of industrial and artisanal mines on child labor, a working paper by Guenther (2019) who uses a novel ASM dataset collected by re-

If anything, the existence of ASMs around the industrial gold mines are likely to attenuate the effects we find. Suppose that there are ASMs in the same localities as the industrial mines, they begin operation simultaneously as the industrial mines, and children are employed in these ASMs as they open.[13] If this is the case, our econometric estimates underestimate the impact of the opening of industrial mines on child labor – specifically, our estimates report the net effects of both industrial mines (which reduce child labor) and ASMs (which increase child labor). Moreover, investigation of population and census data revealed that while employment as a whole did not increase, children are increasingly working in the mining sector (although the magnitude is small). Recall that tasks in industrial gold mines are capital intensive, so it is unlikely that young children work in these gold mines. The small increase of child employment in the mining sector is likely to be from ASMs. Taken together, this suggests that we might be underestimating the impacts of the industrial mines, but that the underestimate may be small.

6 Conclusion

This paper provides evidence on the impact of natural resource shocks on child welfare in particular dimension: work and schooling. Exploiting plausibly exogenous variations in distance from industrial mining sites and the timing of mine openings, we 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 38.2 percent decrease in total working hours is found. By contrast, a mine opening did not lead to an increased school attendance. The mine openings decreased gender gaps in work while increased the buren on the oldest siblings. The results are robust to 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 aligns with the findings of Kotsadam and Tolonen (2016). Our results also complement the findings of Cogneau and Jedwab (2012) in the sense that children's work is procyclical. It contrasts with Santos (2018), but he points out a possbility of procyclicality of child labor when the initial prevalence of child labor is high, which fits our study setting. There-

mote sensing over satellite imigeries,Parker, Foltz, and Elsea (2016) and Sánchez de la Sierra (2019) who used survey data on ASMs, and Fourati, Girard, and Laurent-Lucchetti (2021) using variations of geological bedrocks. Therefore, while the interaction of artisanal small-scale mines and the industrial gold mines is important, it is left for the future research.

[13] Hilson (2012) argues that the global gold price increase entailed a boom in small-scale gold mining in southern Mali.

fore, our results do not contradict the findings of other studies that shows child labor increases due to the gold mines (Ahlerup, Baskaran, and Bigsten, 2020). The results are closer to the findings of Zabsonré, Agbo, and Somé (2018), who show that the gold price shock does not affect child labor and education substantially.

A decrease in children's work not leading to an increase in school attendance calls for a more nuanced approach in understanding children's time allocation. Ahlerup, Baskaran, and Bigsten (2020) suggested child labor as a strong candidate to decrease in educational attainments, after examining various potential channels. The excluded channels include low school supply and endogenous migration, and child labor was suggested without rigorous empirical analysis. Other studies in the child labor literature also view education as a substitute for labor. For example, the school construction or incentives for schooling decreased child labor (de Hoop and Rosati, 2014; Edmonds and Shrestha, 2014). Increased household income decreased child labor while increasing child schooling (Edmonds, 2006; Edmonds and Schady, 2012). Household tasks are compatible with schooling, and this nuance should be considered in formulating child labor policy.

A natural question that arises would be then if the decreased hours for household work translated to schoolwork and academic achievements. Despite its importance, the question does not fall into the scope of this paper. As discussed in Santos (2018), the human capital accumulation contributes to long-run the resource curse. Therefore, understanding the trade-off between the time spent on household and school work is important, which could be a topic of future analysis.

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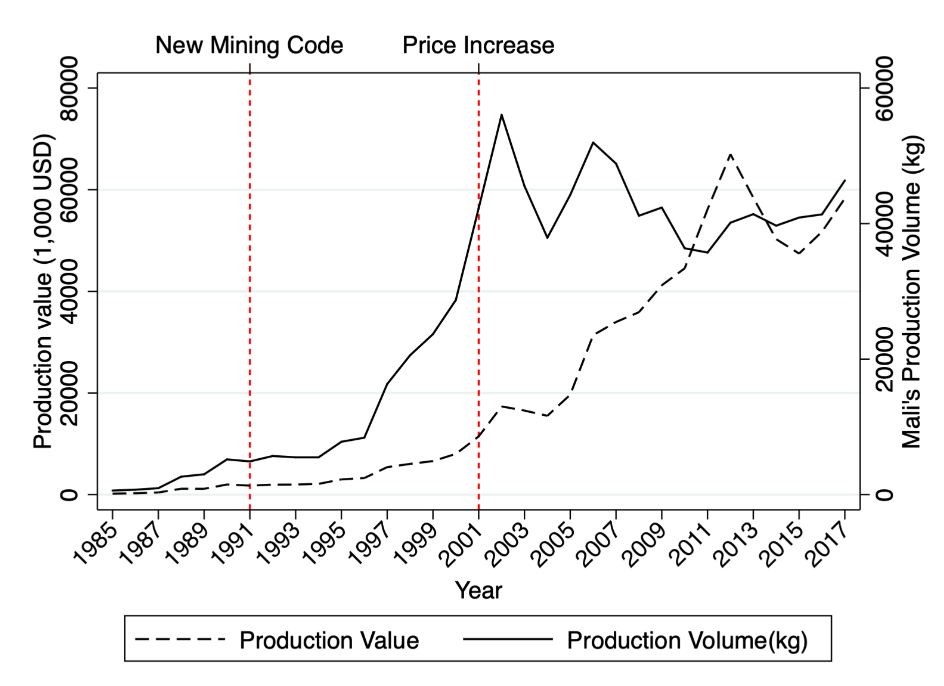
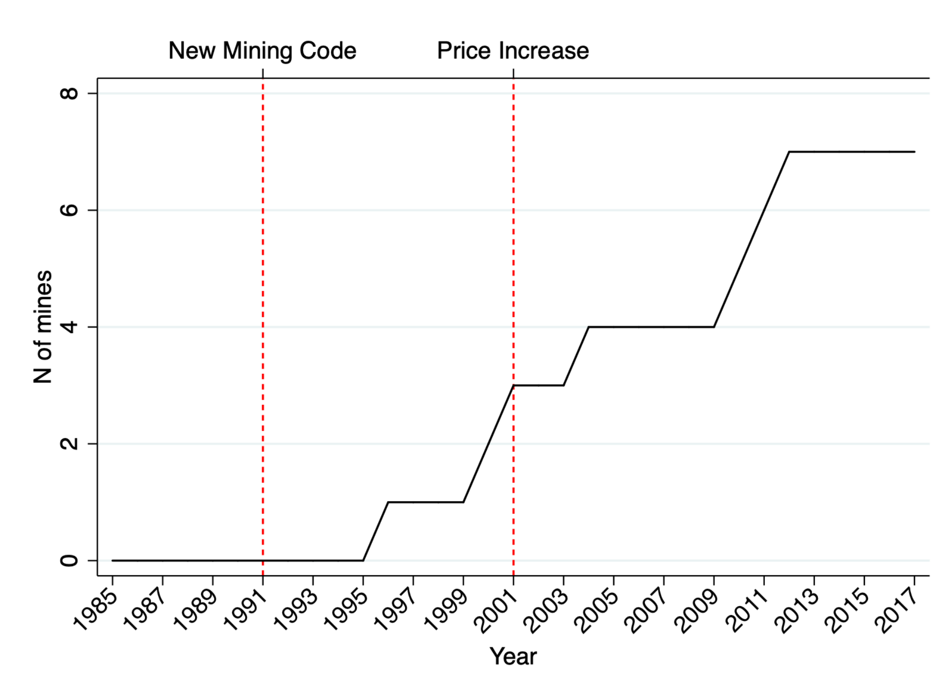
Figure 1: Mali's Gold Production

(a) Production volume and value



(b) Number of industrial mines

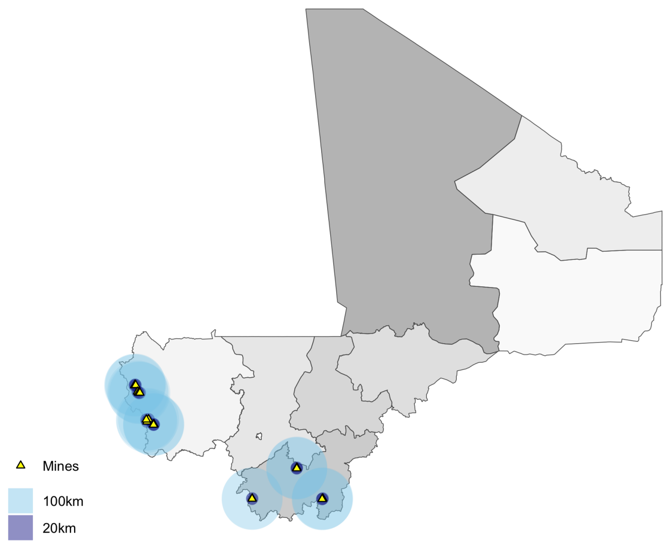


Source: United States Geological Survey Minerals Yearbook

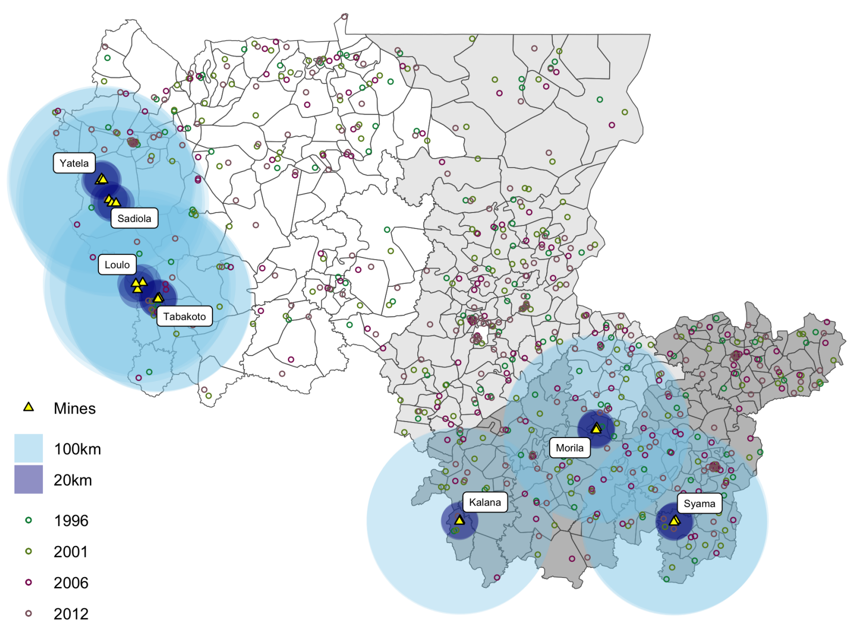
This figure plots trends of global gold prices and Mali's gold production volume. The horizontal axis show years, the vertical axis on the right world price, and the vertical axis on the left Mali's gold production volume. Solid line show the production volume and dashed line the gold price.

Figure 2: Location of Mines, 2018

(a) Mines and its surrounding areas



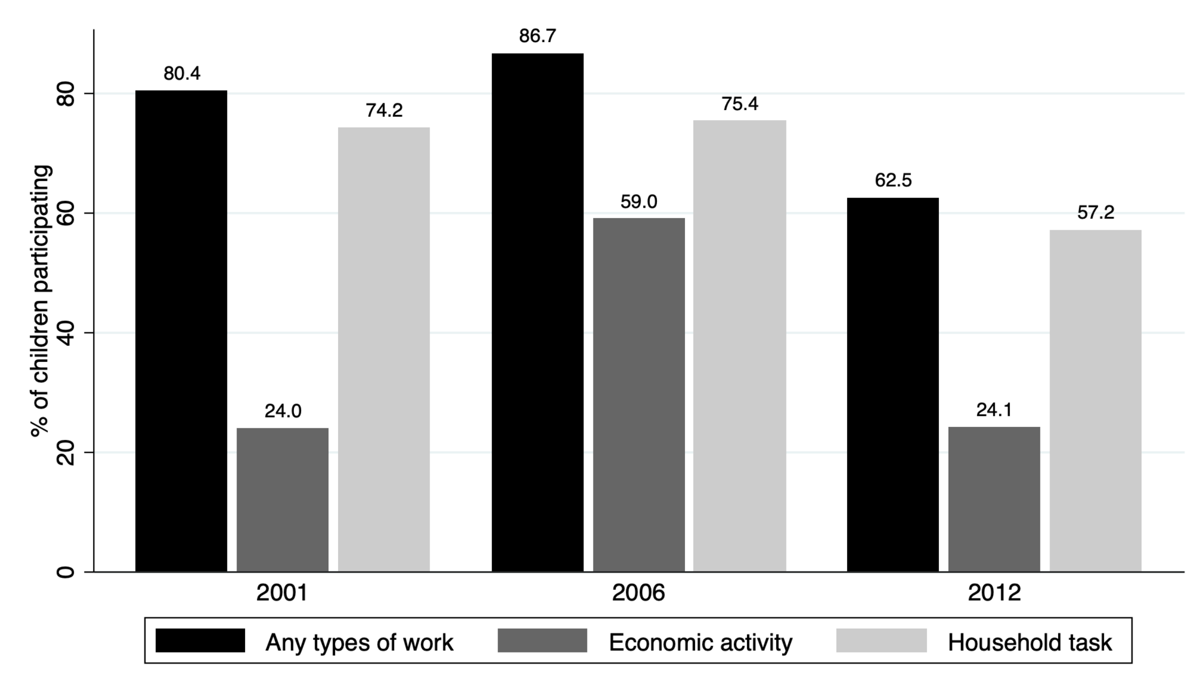
(b) DHS clusters within mining area



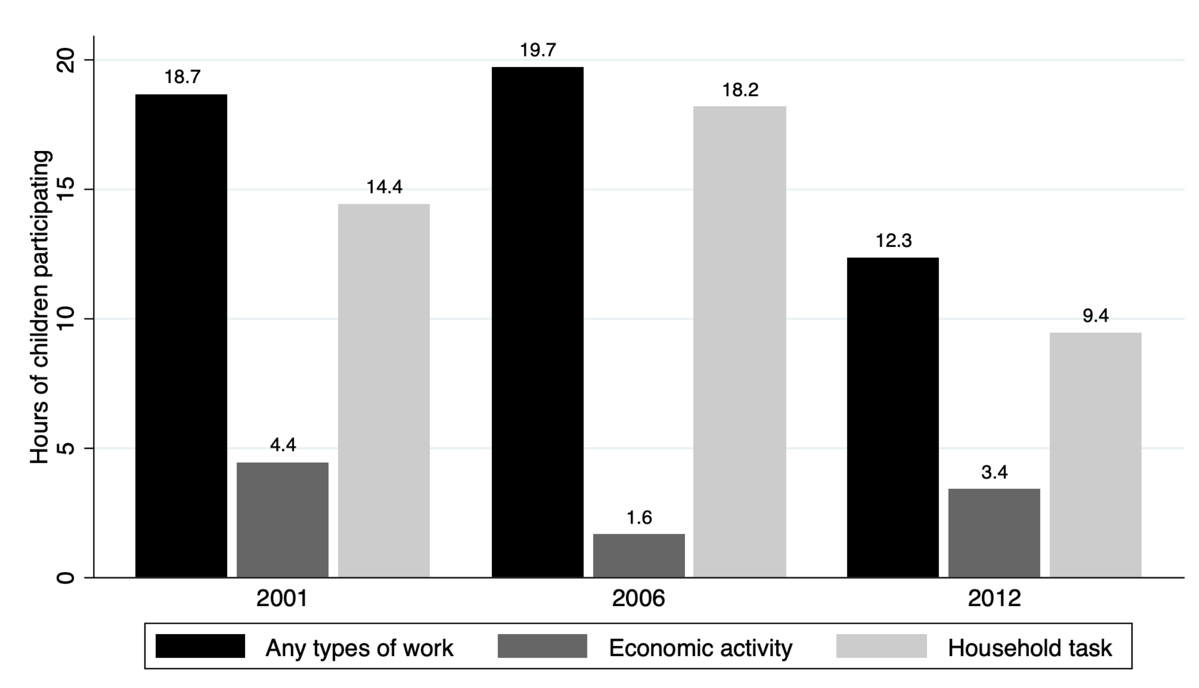
Source: Direction Nationale des Collectivités Territoriales, Demographic and Health Survey 1996-2012, and Benshaul-Tolonen (2019). Panel A plots the boundaries of communes, the lowest level municipality, the location of mines (yellow dots), 20-km radius (dark blue circle) and 100-km radius (light blue 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

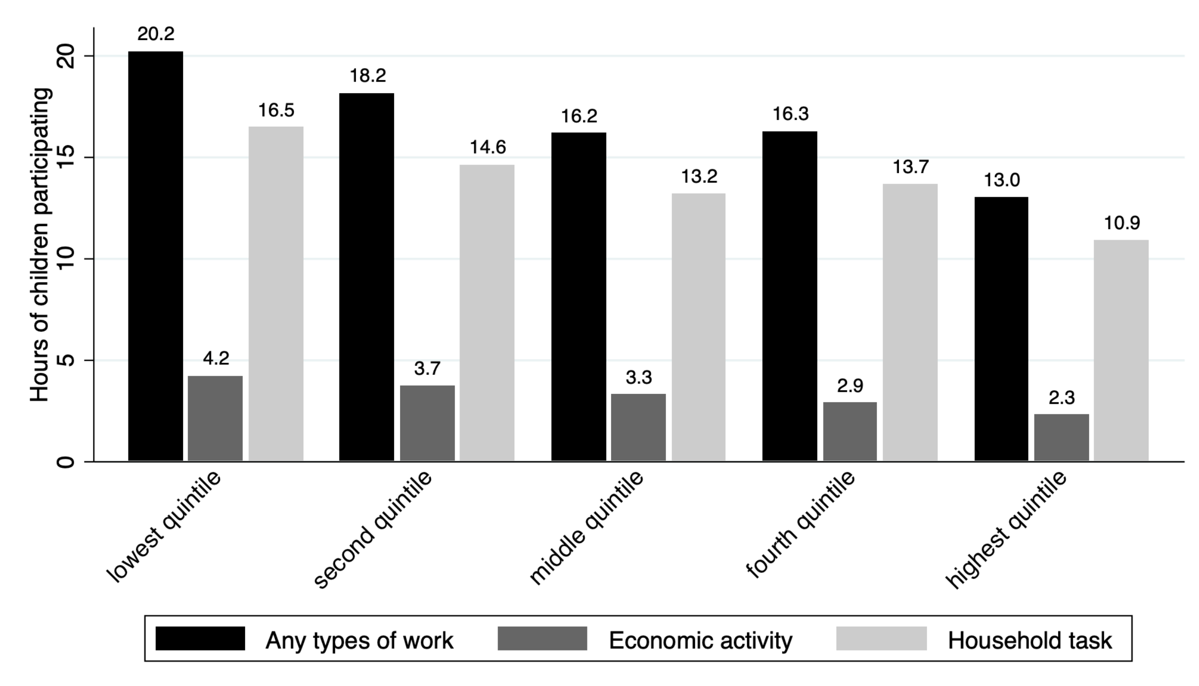


Source: Author's calculation, DHS Mali

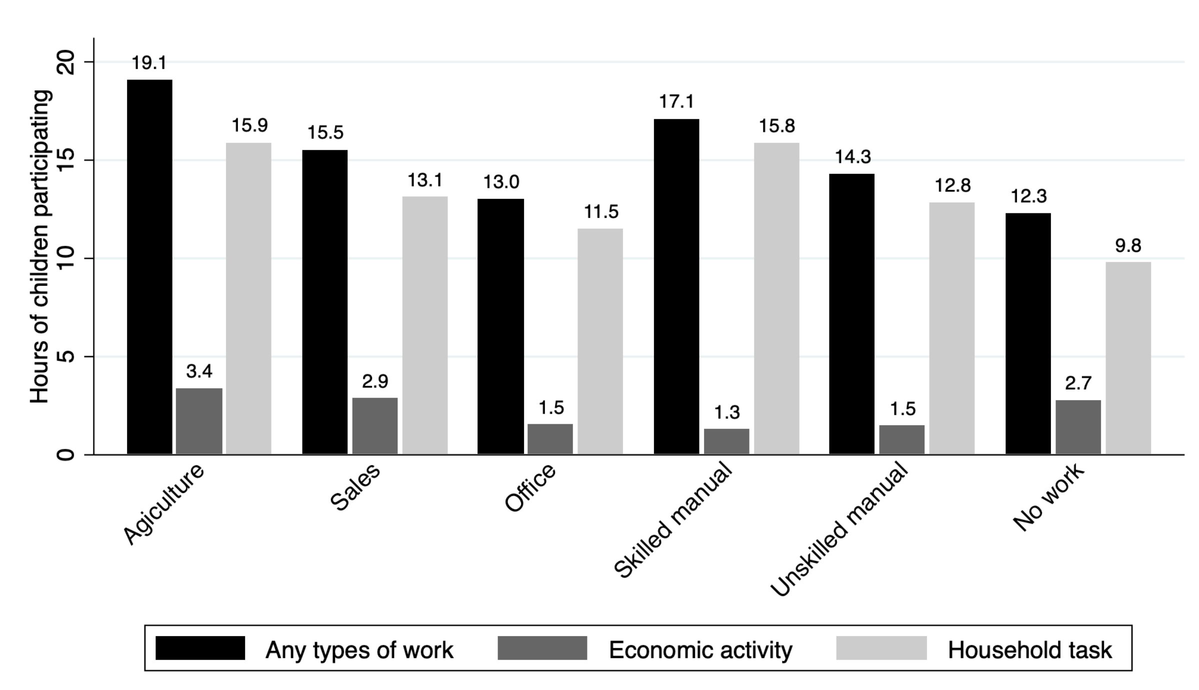
Note: This figure presents the share of working children in Mali. Panel A presents percentage of children participating in the activities among all children aged 5-14 and Panel B presents number of hours children engaged in each activity from 2001 to 2012.

Figure 4: Children's working hours by household characteristics

(a) By Wealth Quintile



(b) By Mother's Occupation

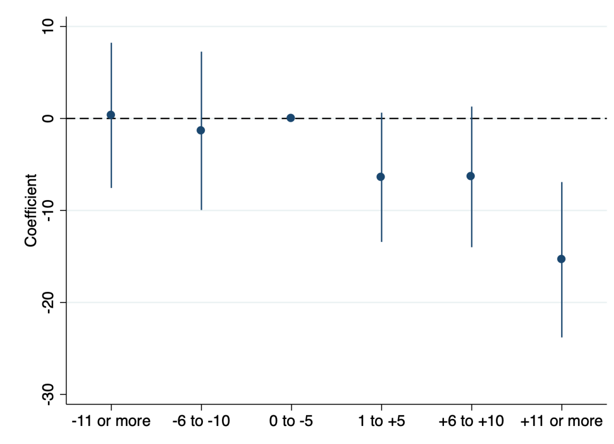


Source: Author's calculation, DHS Mali

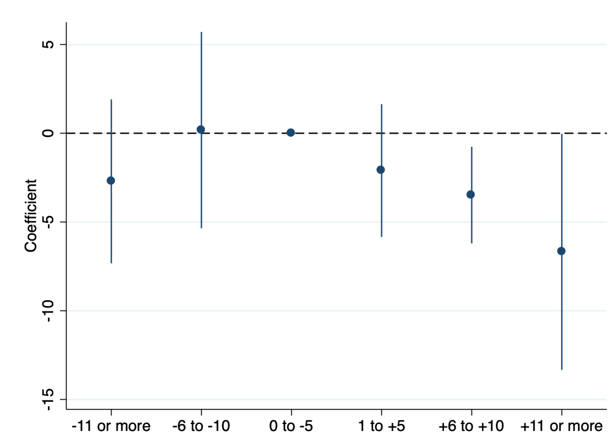
Note: This figure presents the share of working children in Mali. Panel A presents the average number of working hours by each wealth quintile, and Panel B presents the average number of hours children work by mother's sector of work.

Figure 5: Impacts on Working Hours of Children

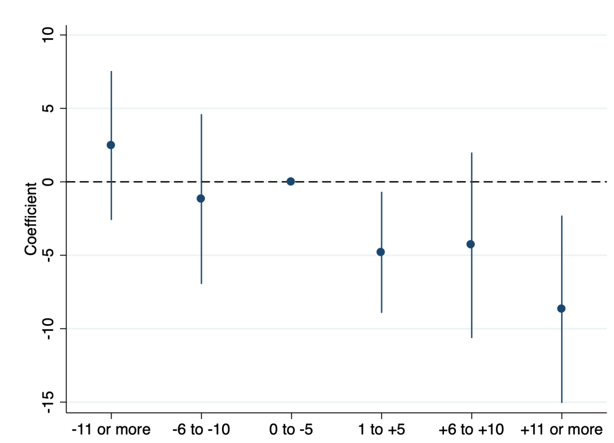
(a) Any types of work



(b) Economic Activities



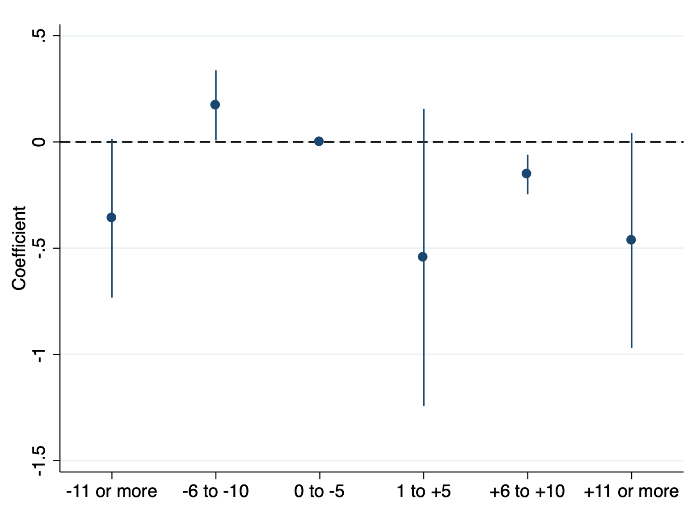
(c) Household work



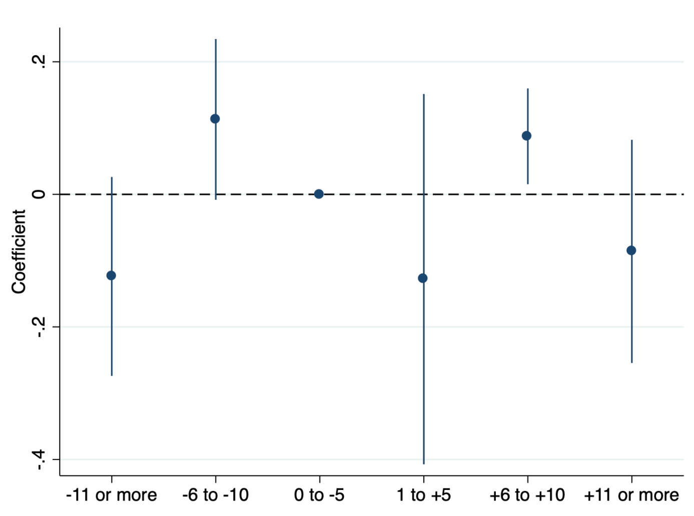
Note: This figure plots estimated effects of mine openings on working hours of children in mining areas. The horizontal axes show years from mine openings and the vertical axes the estimated coefficients. Navy dot show the estimated coefficients and the vertical lines the 95 percent confidence intervals. 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



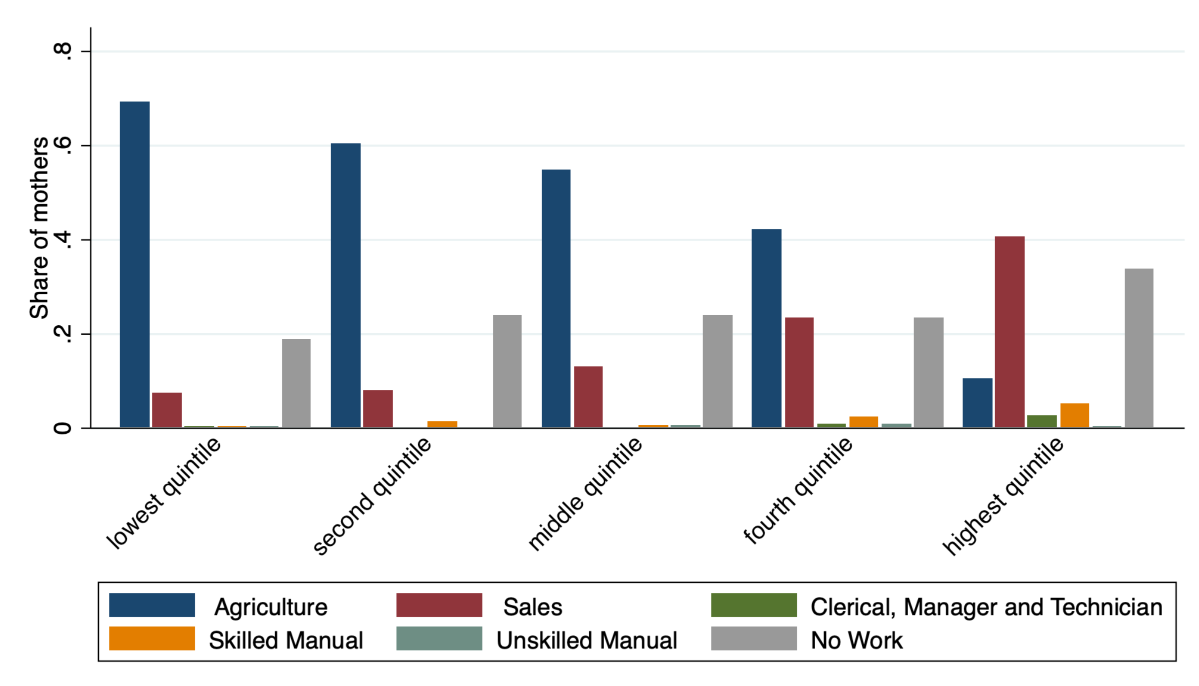
(b) Current year attendance



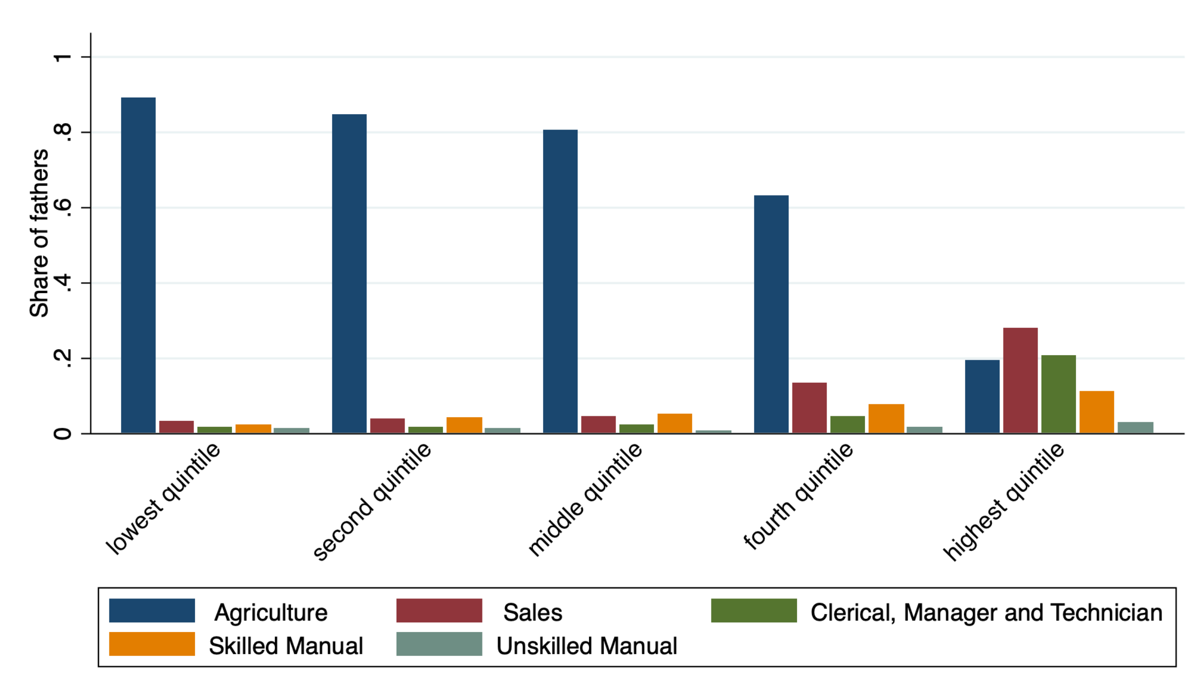
Note: This figure plots estimated effects of mine openings on educational choices of children in mining areas. The horizontal axes show years from mine openings and the vertical axes the estimated coefficients. Navy dot show the estimated coefficients and the vertical lines the 95 percent confidence 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: Author's calculation, 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 of Demographic Variables Across Areas

	Mining	Non-mining	Mining vs. Non-mining	N
	(1)	(2)	(3)	(4)
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)	

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.

Table 2: Balance of Outcome Variables Across Areas

	Mining	Non-mining	Mining vs. Non-mining	N
	(1)	(2)	(3)	(4)
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.

Table 3: Hours Worked by Years

	Any work	Economic activity	Household work
	(1)	(2)	(3)
20km × 11+ yrs prior	0.337	-2.712	2.474
	(3.979)	(2.327)	(2.557)
20km × 6-10 yrs prior	-1.343	0.177	-1.173
	(4.338)	(2.787)	(2.914)
20km × 1-5 yrs post	-6.395*	-2.102	-4.804**
	(3.542)	(1.886)	(2.078)
20km × 6-10 yrs post	-6.351	-3.484**	-4.320
	(3.853)	(1.371)	(3.185)
20km × 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.

Table 4: Hours Worked

	Any work	Economic activity	Household work
	(1)	(2)	(3)
Panel A: Demographics controlled			
20km × 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			
20km × 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 3. 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 5: 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)
20km × 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)
20km × Open × Male	2.505	-1.848	4.340						
	(2.592)	(2.606)	(3.805)						
20km × Open × Age 5-11				2.306	-1.428	4.652**			
				(2.743)	(3.076)	(1.845)			
20km × 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
20km · Open + Interaction	-6.325	-4.064	-2.985	-7.457	-3.763	-4.199	-0.905	-0.879	-0.244
P-value.: 20km · 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 3. 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 20km radius are considered as treated and control area.

Table 6: Educational Outcomes

	Years of Education				Currently enrolled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
20km × 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)
20km × Open × Male		-0.195				0.016		
		(0.153)				(0.046)		
20km × Open × Age 5-11			0.578				0.180**	
			(0.536)				(0.070)	
20km × 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
20km · Open + Interaction		-0.397	-0.133	-0.440		-0.100	-0.063	-0.203
P-value.: 20km · 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 3. 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 7: 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)
20km × 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)
20km × 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)
20km × 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 3. 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 8: Spillover Effects on Areas Farther Away From Mines

	Any work	Economic activity	Household work
	(1)	(2)	(3)
Panel A: Naive estimates			
30-50km $\times$ 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			
30-50km $\times$ 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 3. 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 20km radius are considered as treated and control area.

A Adult Employment using Census Data

I examine adults' employment choices. This section lays out the data and empirical strategies I used for these analyses.

A.1 Data

I use population and housing census data of Mali in 1987, 1998 and 2009, accessed through IPUMS international, to complement main analyses with evidences on changes in sector choices and migration pattern. Census data includes more detailed information on adult and children's employment outside of the household such as sector of the employment. However, I cannot use the same identification strategy since census data does not include geolocation information of the survey clusters, so I use coarser identification for this analysis using administrative level where mines are located.

A.2 Empirical Strategy

I estimate the effect of mine openings on adult employment outcome as per following equation:

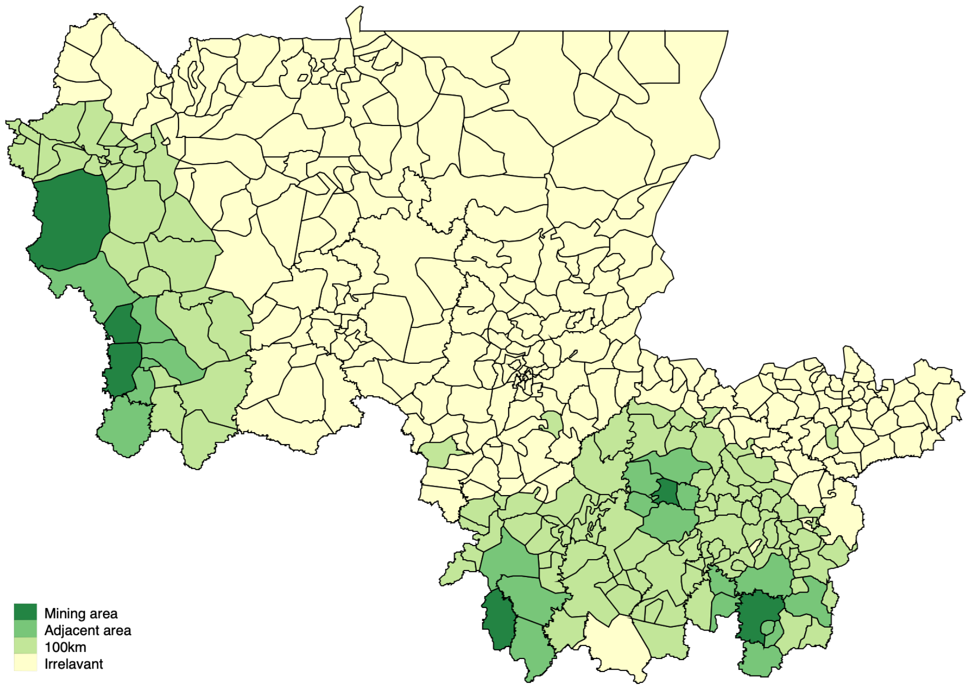
$$\begin{aligned} y_{ijy} =& \beta_0 + \beta_1 Mine\_Cercle_{jy} \cdot 1998_i + \beta_2 Mine\_Cercle_{jy} \cdot 2009_i + \beta_3 Mine\_Cercle_{jt} \\ &+ \eta_c + \nu_y + X_{ijy} + \varepsilon_{ijy} \end{aligned} \tag{3}$$

where y_{ijcy} is the employment status of adult i in cercle c in year y.

The key independent variable is $Mine\_Cercle_{jy}$, a dummy variable equals to one if an industrial gold mine is located in cercle c in year y. Population census data do not include geolocations of surveyed clusters. Thus, I restrict the sample to regions where mines are located in which case cercles that are located within the boundary of mining regions but out of mining cercles serve as a comparison group in these analyses. Since some mines are located in close proximity to each other but opened in different years, and time interval between each census waves is 10 or more years, I use survey years for timing variations. In 1987, all mines are yet to open. In some cercle, mines start to operate in the early and mid-90s. In some areas, mines start to operate in early 2000s. Therefore, β_3 captures the effect of all active mines whereas β_2 captures the effect of some active mines. Note that the short- and long-term effects of opening mines are mixed in β_3.

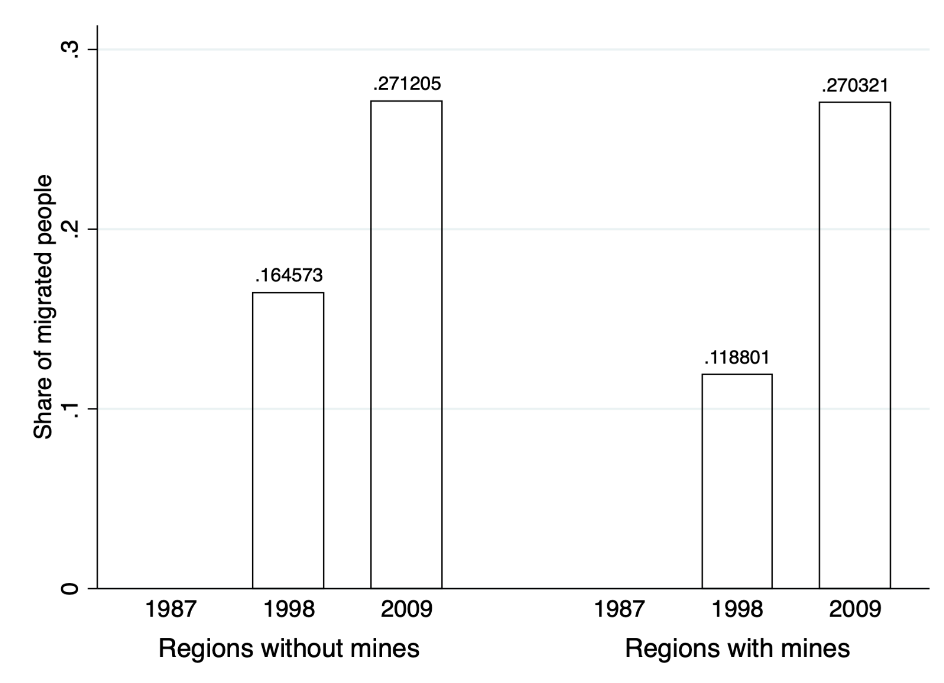
B Additional tables and figures

Figure A1: Map of Mining- and non-mining areas using municipalities



Note: This figure identifies the commune where mines are located and its surrounding communes..

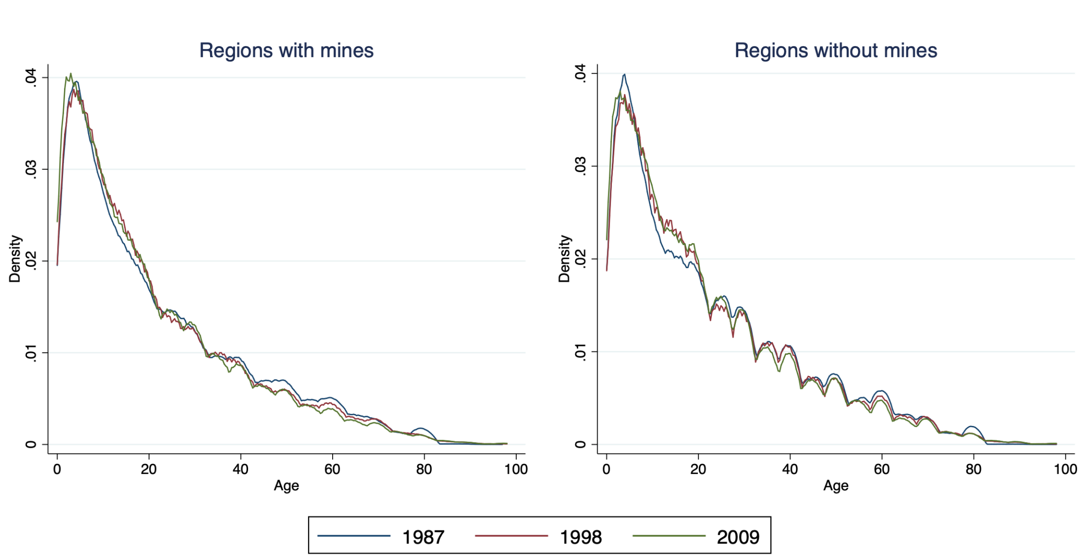
Figure A2: In-migration to the mining regions



Source: Author's calculation, Mali Census

Note: This figure plots the share of migrated people by regions with or without mines. The horizontal axis show years, and the vertical axis the share of migrated people.

Figure A3: Changes in the age distribution over time

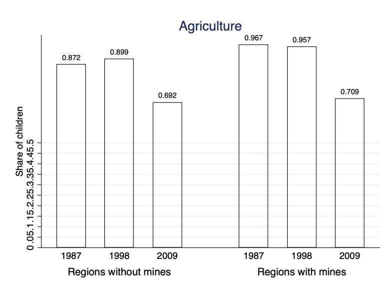


Source: Author's calculation, Mali Census

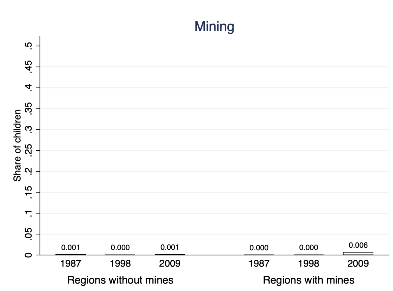
Note: This figure plots the changes in the distribution of the age across waves in the mining region (left) and the non-mining regions (right). The horizontal axis show age in years and the vertical axis the kernel density. Blue line shows the age distribution in 1987, the red line in 1998, and the green line in 2009.

Figure A4: Child employment in different sectors

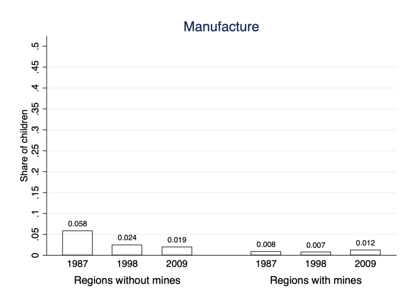
(a) Agriculture



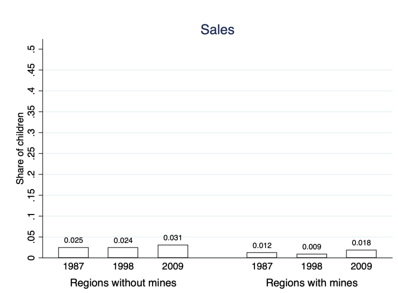
(b) Mining



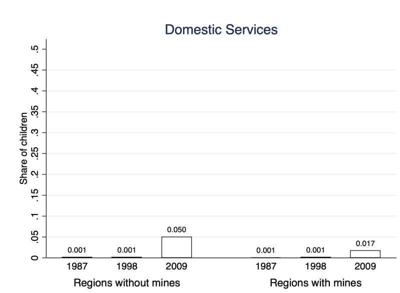
(c) Manufacture



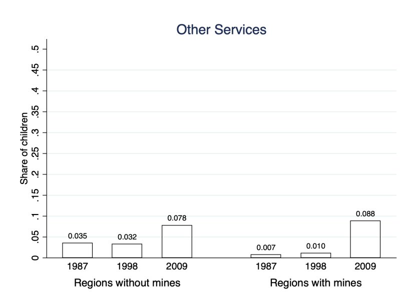
(d) Sales



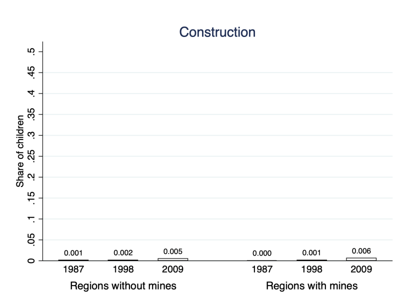
(e) Domestic services



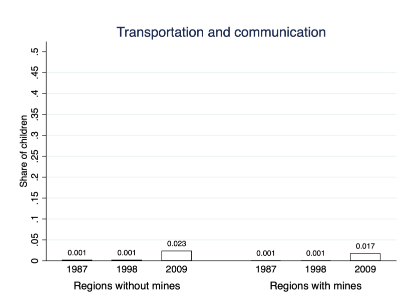
(f) Other services



(g) Construction



(h) Transportation / Communication

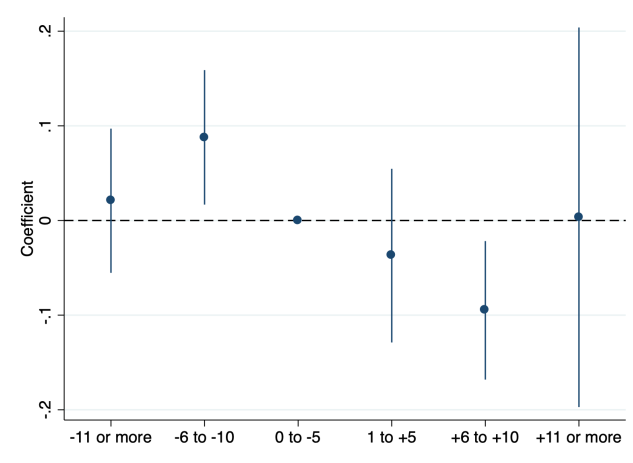


Source: Author's calculation, Mali Census

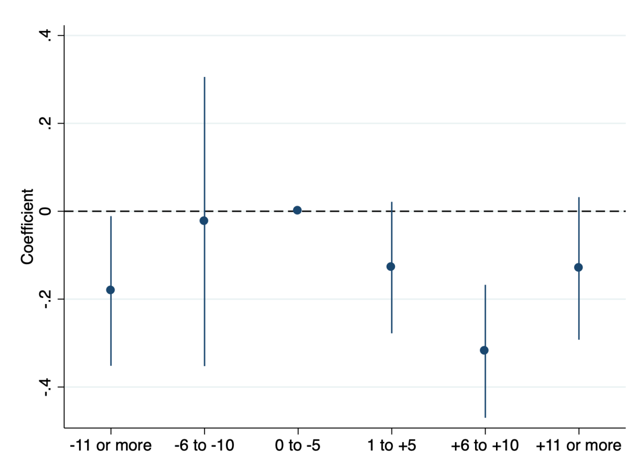
Note: This figure plots the share of children employed each sector among all children aged 5 to 14, in each census wave, by mining and non-mining areas. The horizontal axes show years and areas. and the vertical axes the share of children in each sector.

Figure A5: Impacts on child labor participation

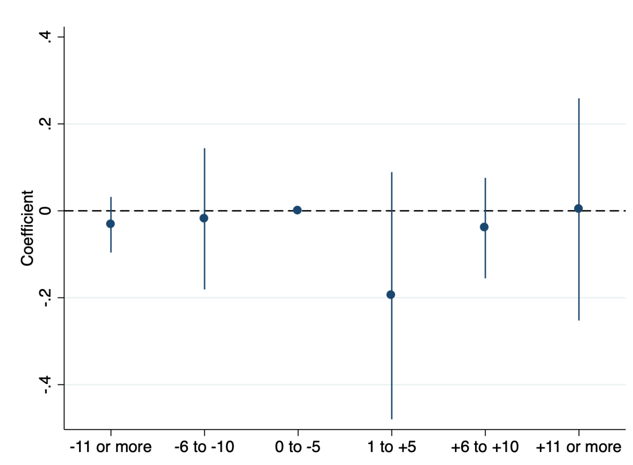
(a) Any types of work



(b) Economic activities



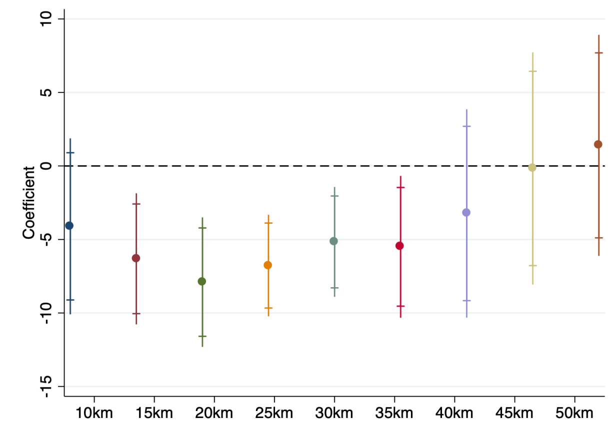
(c) Household work



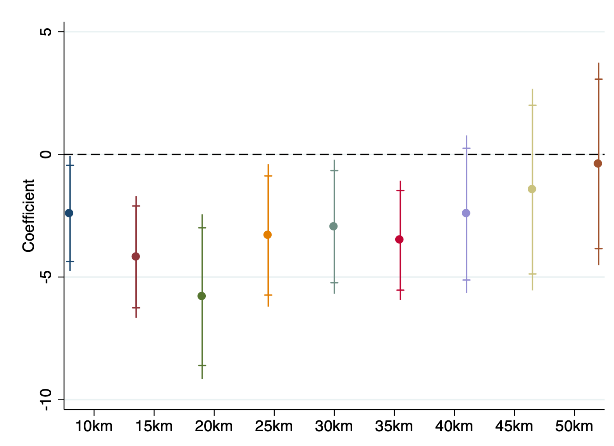
Note: This figure plots estimated effects of mine openings on children's participation in work in mining areas. The horizontal axes show years from mine openings and the vertical axes the estimated coefficients. Navy dot show the estimated coefficients and the vertical lines the 95 percent confidence 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 A6: Impacts on Working Hours of Children

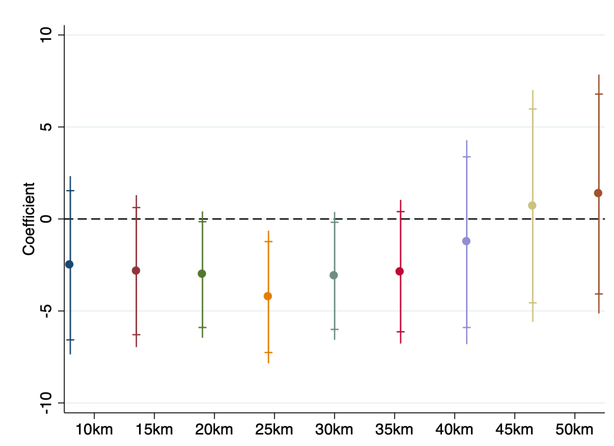
(a) Any types of work



(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 treshold 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)
20km × 11+ yrs prior	-0.014	-0.091	-0.402***
	(0.066)	(0.155)	(0.077)
20km × 6-10 yrs prior	0.005	-0.133	-0.369***
	(0.079)	(0.197)	(0.077)
20km × 1-5 yrs post	-0.005	-0.077	-0.260***
	(0.062)	(0.094)	(0.070)
20km × 6-10 yrs post	-0.051	-0.314***	-0.036
	(0.061)	(0.069)	(0.064)
20km × 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 3. 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 A3: Child Worked

	Any work	Economic activity	Household work
	(1)	(2)	(3)
Panel A: Demographics controlled			
20km $\times$ 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			
20km $\times$ 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 3. 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 A4: Adult Employment

Panel A: Types of work	Not in LF	Employed	Wage Employment	Self-employment	Unpaid work	Othe types of work
	(1)	(2)	(3)	(4)	(5)	(6)
Mining Area × Open	0.086*	-0.007***	0.042***	-0.030	-0.011	-0.000
	(0.043)	(0.002)	(0.015)	(0.024)	(0.036)	(0.004)
N	175344	121348	118282	118282	118282	118282
R-Squared	0.244	0.009	0.097	0.380	0.414	0.017
Mean of Dep. Var.	0.291	0.997	0.024	0.513	0.458	0.005

Panel B: Industries	Agriculture	Mining	Manufature and Construction	Sales	Service	Domestic service
	(1)	(2)	(3)	(4)	(5)	(6)
Mining Area × Open	-0.031	0.012	0.007	0.004	0.008	0.000
	(0.024)	(0.008)	(0.009)	(0.010)	(0.011)	(0.006)
N	119466	119466	119466	119466	119466	119466
R-Squared	0.250	0.256	0.021	0.073	0.115	0.033
Mean of Dep. Var.	0.877	0.020	0.024	0.039	0.031	0.009

Notes: Standard errors, clustered at the year-cluster 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: 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 3. 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: 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 3. 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 A7: 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 3. 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 A8: 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						
20km × 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						
20km × 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 3. 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 A9: 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)
20km × 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)
20km × Open × Male	1.277	-1.643	2.560						
	(2.439)	(2.605)	(3.364)						
20km × Open × Age 5-11				6.148**	-0.683	9.006***			
				(2.757)	(3.121)	(1.566)			
20km × 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
20km · Open + Interaction	-6.480	-4.006	-3.461	-6.288	-3.654	-2.887	-1.193	-0.986	-1.369
P-value.: 20km · 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 3. 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 A10: 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)
20km 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.

Table A11: 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)
20km × 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.