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 capital 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. Unlike similar papers that show mines increase children's work, we find that the opening of mines decreases children's working hours, specifically the hours for household tasks. However, the effects on educational outcomes were not statistically significant. The effects were heterogeneous by the gender and the birth order of a child. We argue that our results stem from the income effects from the mines dominating the substitution effects. We provide supporting evidence on this claim by presenting the adults' employment and occupational choices.

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

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1 Introduction

Child labor is one of the activities that hinder investment in children's human capital, a crucial ingredient for economic development. 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 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-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 (Sachs and Warner, 2001; Frankel, 2012). However, micro-level evidence shows that local economic impacts are 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 has produced mixed and conflicting results (von der Goltz and Barnwal, 2019; Benshaul-Tolonen, 2019; Zabsonré et al., 2018; Santos, 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, but also higher adult income decreases parents' need to send their children to work. However, theory cannot say which effect will dominate. Hence, the importance of empirical work which is what we do in this paper. For the empirical analysis, 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). 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 com-

[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.

pare 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.

Our 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 that of the 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, the first-born children continue to carry out more work, resulting in working hours decreased significantly more among the younger siblings. Moreover, the younger siblings are one of the only two demographic subgroups decreased economic activities. Additionally, the first-born children and the older age group children (age 12-14) are the only two groups that reduced school enrollment.

However, we find no substantial changes at the extensive margin and no improvements in educational outcomes. These results do not resonate with the previous findings in the literature, where children increase work participation and decrease school enrollment when a mine open. It suggests that the industrial mines in Mali only had indirect impacts on children's work through income effects, instead of having direct employment effects. We argue that the indirect income effects come through changes on adults' employment outcomes. Mothers are less likely to work but more likely to work in better-quality jobs conditional on work, which is consistent with Kotsadam and Tolonen (2016). Moreover, female workers shift from agriculture to the sales sector and increased adult male employment in clerical/managerial positions.

Lastly, we 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, we 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 increased 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. Our results differ from these studies since we show that children's work – at least within the household – decreases substantially, and the effects on schooling are not significant. The results are closer to that of Zabsonré et al. (2018) , who find that gold price increase had no impact on child labor or in children's schooling in mining communities in Burkina Faso. However, we can reconcile our results to Santos (2018) and Ahlerup et al. (2020) for two reasons. First, our sample includes children of 5 to 14 years old, while the two papers focus on adolescents who are more likely to be formally employed. In our analysis, we also find that the older children of age 12-14, and the first-born children decrease school enrollment, while it is the younger children who decrease working hours in economic activities. Second, we include working hours for household tasks in the analysis, and it is a driver of the main results. Even among the older children, the hours for household work decreased. Therefore, our results provide rare evidence that an industrialized gold mining activity can reduce the workload of children.

We also contribute to the discussion on the relationship between the 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 the economic development may increase children's work responding to 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 increase in child labor. (Fafchamps and Wahba, 2006). [3] We analyze the effect of a development of a sector with a capital-intensive, heavy machine-operated technologies, which expands the work availability in the region. Our results show that such a development can reduce children's working hours in the region.

Lastly, we speak to the literature on the economic effects of natural resource extraction. Microeconomic evidence finds that mining activities have positive effects on the local economy. It increases household income (Gajigo et al., 2012; Weng et al., 2013), shift employments from agri-

[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 et al., 2006; Duryea et al., 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 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. 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).

culture to manual labor and services (Kotsadam and Tolonen, 2016), increase households' asset wealth (von der Goltz and Barnwal, 2019), and improve household living standards (Aragón and Rud, 2013; Zabsonré et al., 2018) and increase . 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. 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. This paper provides evidence that the natural resource shock could positively affect children by decreasing children's engagement in work.

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 section 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 industrial mines can increase household income exist: direct employment at mines and the indirect 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 children's work will increase.

However, 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. (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 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.

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. There were two incidents triggered a dramatic growth in gold production in Mali. First, a new mining code providing tax and customs advantages to the mining sector to attract foreign direct investments was introduced in 1991. As a result, seven large-scale industrial gold mines started their operations in the following two decades, and the gold production volume increased rapidly. Only 950kg of gold was produced in Mali in 1987, but it grew to 23,668kg by 1999. Second, increases in international gold prices started in 2001 led to a further increase in production value and a further expansion of the mining industry, as shown in Figure 1. Gold production industry continued to grow, and 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.[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 decreases 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 ranges from 57 to 74 percent. It is consistent with the story where certain parents view a moderate amount of children's work as acceptable or even instructive for children (Kippenberg, 2011). Participation in economic activities is relatively lower, ranging from 20 to 58 percent during this period.

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

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 long enough to be classified as child labor – the workload is not light.

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

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 ii) household tasks, which includes cooking, taking care of younger siblings fetching water. We also use an aggregate number of hours a child does.

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[5]. 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.

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 (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 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

[5] https://miningdataonline.com

seven 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. 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 percent of households reside in urban areas, and the average wealth quintile is 3.01.[7] 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

[6] 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.

[7] 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.)

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 are correlated with mother's occupational choices as well. Panel B of Figure 4, shows that the 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. 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 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.

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 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 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.[8] Spatial variations are captured by 20km-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, which groups the distance from the closest mine to the surveyed cluster in 20km 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 our coefficient of interest which we 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.

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. 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 discussed 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.[9] 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

[8] 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.

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

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 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:

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

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 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 are fixed. 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 continue 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 find (e.g., Santos (2018)). However, 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 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 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. However, no changes in current enrollment requires further examination.

Heterogeneity analyses presented in Column (6) to (8) reveal that the key in understanding the effects on schooling outcome is engagement in economic activities. 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 negative and statistically significant effects. The first-born are the ones that show null effects on all types of working hours. This 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 are negligible. These two groups are the only ones decreased working hours for economic activities substantially. Combining these results, the decrease in children's economic activities prevented schooling reduction while an increase in work led to a decrease in schooling. We suspect that the asymmetry in the effect on schooling is likely due to the fact that the return to school after dropout is difficult and rare.

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 we used in the previous sections. 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. The null effects in adult female employment suggest stronger possibility 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 in 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 points 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 mothers are less likely 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 are negatively correlated. 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. We vary our threshold distance from 10 to 50km to check if the estimated results are robust to our definition of threshold distance. 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 A3 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 A4 - A6 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 these 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 (Chaubey et al., 2007). 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 A7 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

Finally, we consider two alternative explanations: endogenous migration and expansion of Artisanal Small-scale Mines (ASMs). We examine the possibility of endogenous migration driving the results in two ways. First, we estimate the effects of mine openings on time-invariant demographic characteristics such as age, gender, household size, gender of the household heard, 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. Moreover, we investigate the effects using the sample of children who has never moved since birth. 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 we find in our main analysis. The size of the effects is larger among never movers, but combined with the results on demographic change, the evidence suggests that what we find are less likely to be drawn by the endogenous migration.

Additionally, we explore the possibility of artisanal and small-scale mines(ASMs) 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". We cannot directly test this and rule out this possibility due to lack of systematic data on the location and operating dates of ASMs in Mali.[10] We instead compare the non-mining area with the region where the mine is located.[11] It is similar to the analysis presented in Table 8, 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. We find that children's work and schooling did not change substantially in non-mining areas, which suggest 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 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

[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 effect 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 uses 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 artisanal small-scale mines and the industrial gold mines is important, it is left for the future research.

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

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 burden 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 countercyclical. It contrasts with Santos (2018), but he points out a possibility of countercyclicality of child labor when the initial prevalence of child labor is high, which fits our study setting. Therefore, we 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 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. A number of papers in the child labor literature view education as a substitute for labor. Ahlerup et al. (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. Moreover, school construction or incentives for schooling decreased child labor (de Hoop and Rosati, 2014; Edmonds and Shrestha, 2014). Increased household income have 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 decrease children's work but did not lead to changes in schooling. We include hours spent on household work as working hours, which led the decrease in total working hours. Since household tasks are more compatible with schooling than economic activities are, the inclusion of household work reconciles the difference of our 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.

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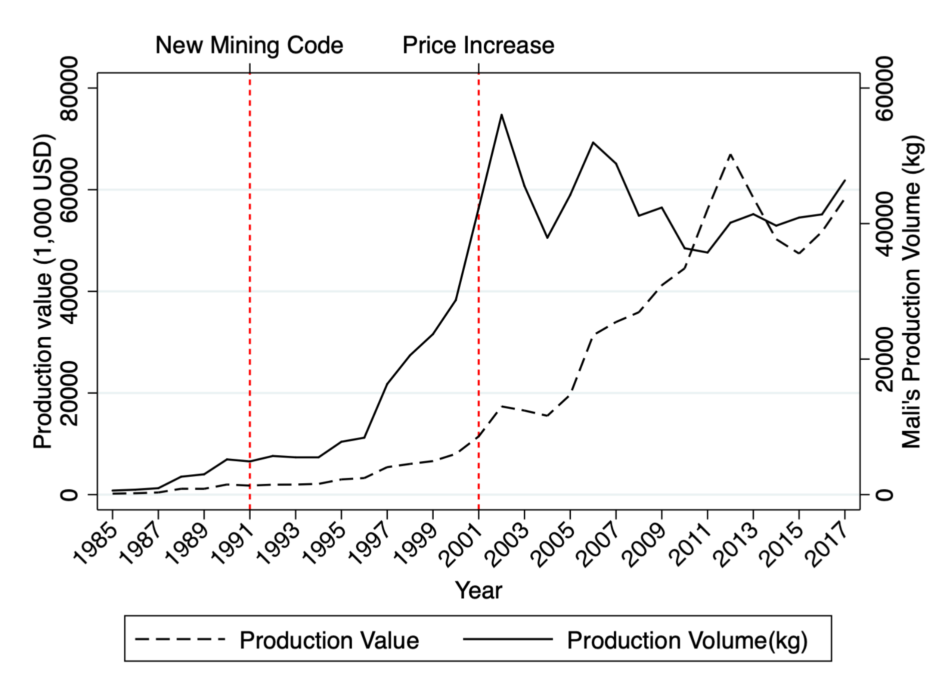
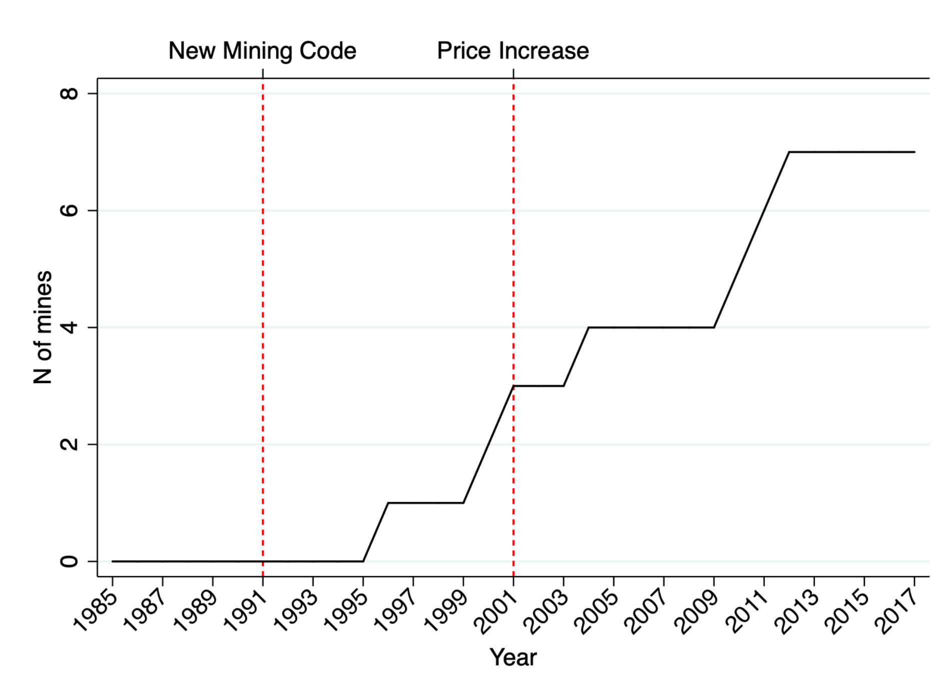
Figure 1: Mali's Gold Production

(a) Production volume and value



(b) Number of industrial mines

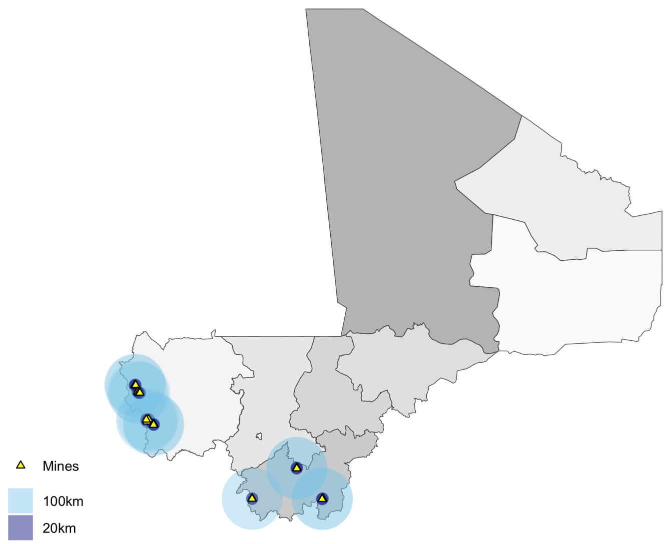


Source: United States Geological Survey Minerals Yearbook

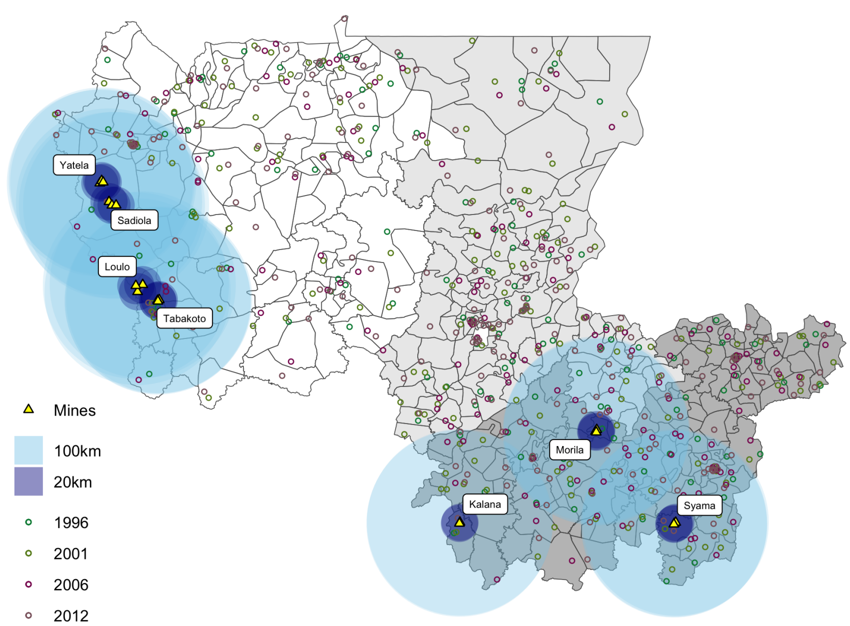
This figure plots trends of global gold prices and Mali's gold production volume. The horizontal axis show years, the vertical axis on the right world price, and the vertical axis on the left Mali's gold production volume. Solid line show the production volume and dashed line the gold price.

Figure 2: Location of Mines, 2018

(a) Mines and its surrounding areas



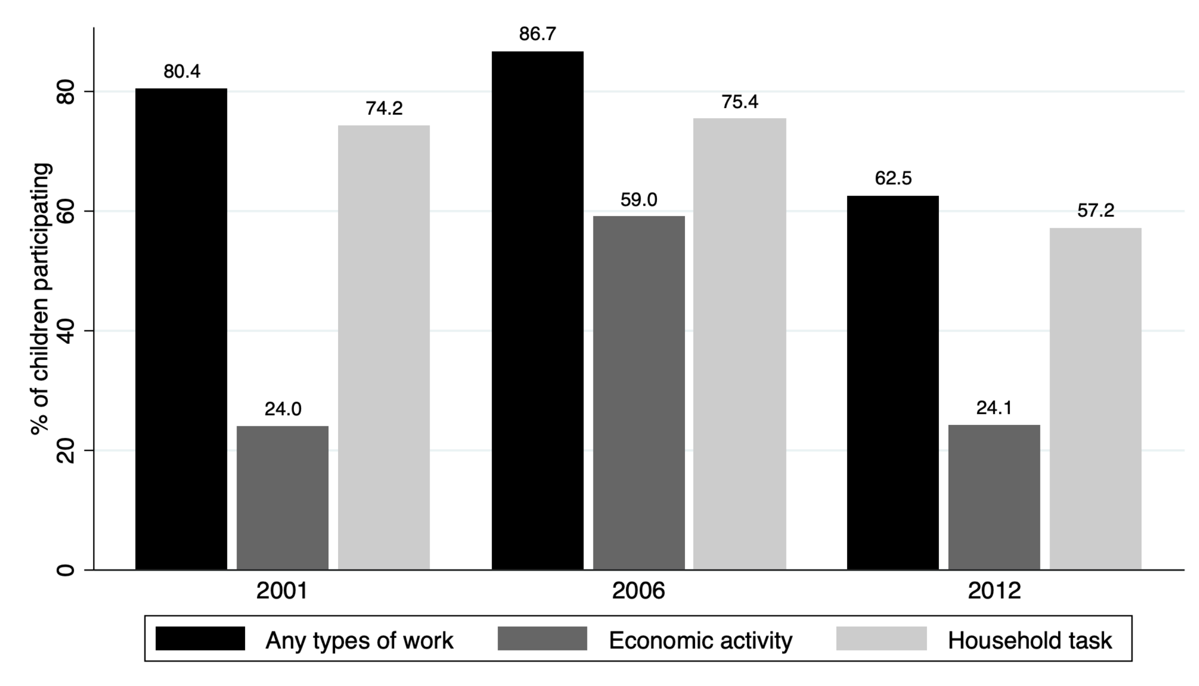
(b) DHS clusters within mining area



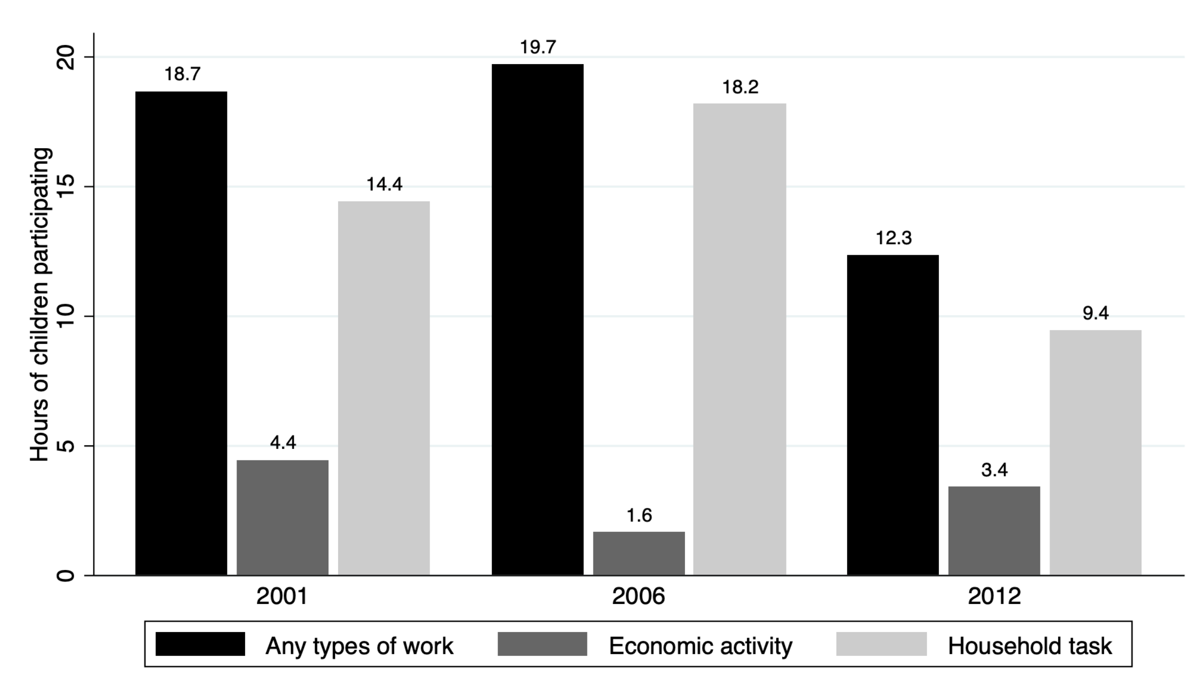
Source: Direction Nationale des Collectivités Territoriales, Demographic and Health Survey 1996-2012, and Benshaul-Tolonen (2019). Panel A plots the boundaries of communes, the lowest level municipality, the location of mines (yellow dots), 20-km radius (dark blue circle) and 100-km radius (light blue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

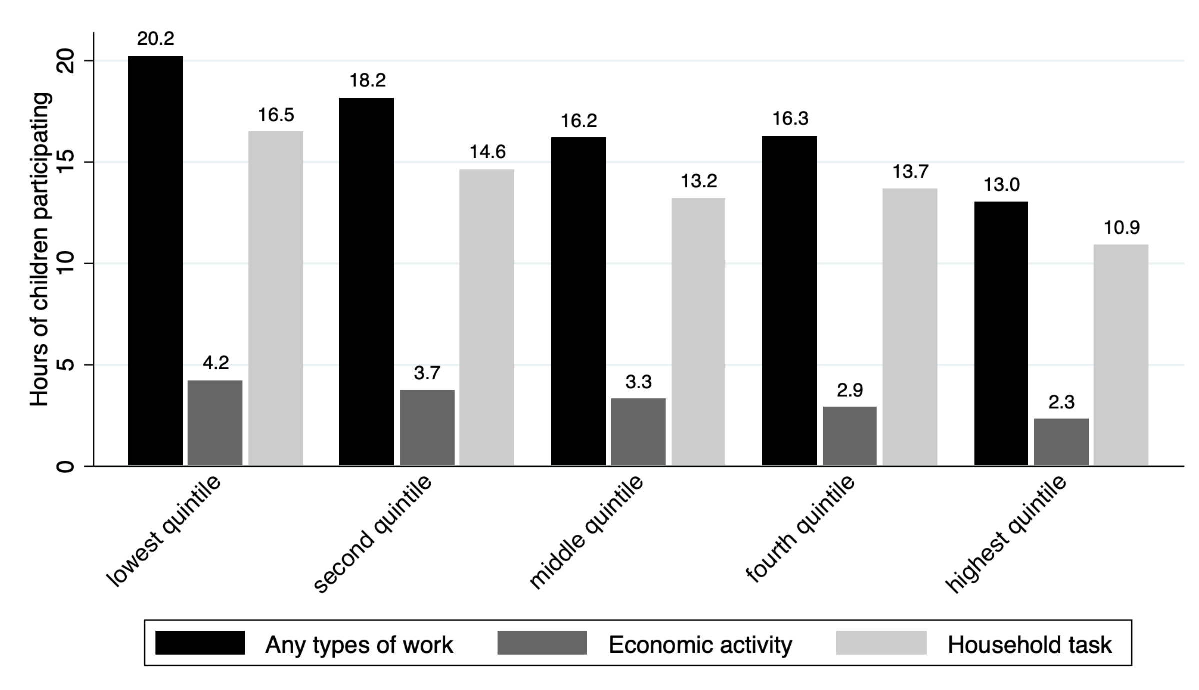


Source: Author's calculation, DHS Mali

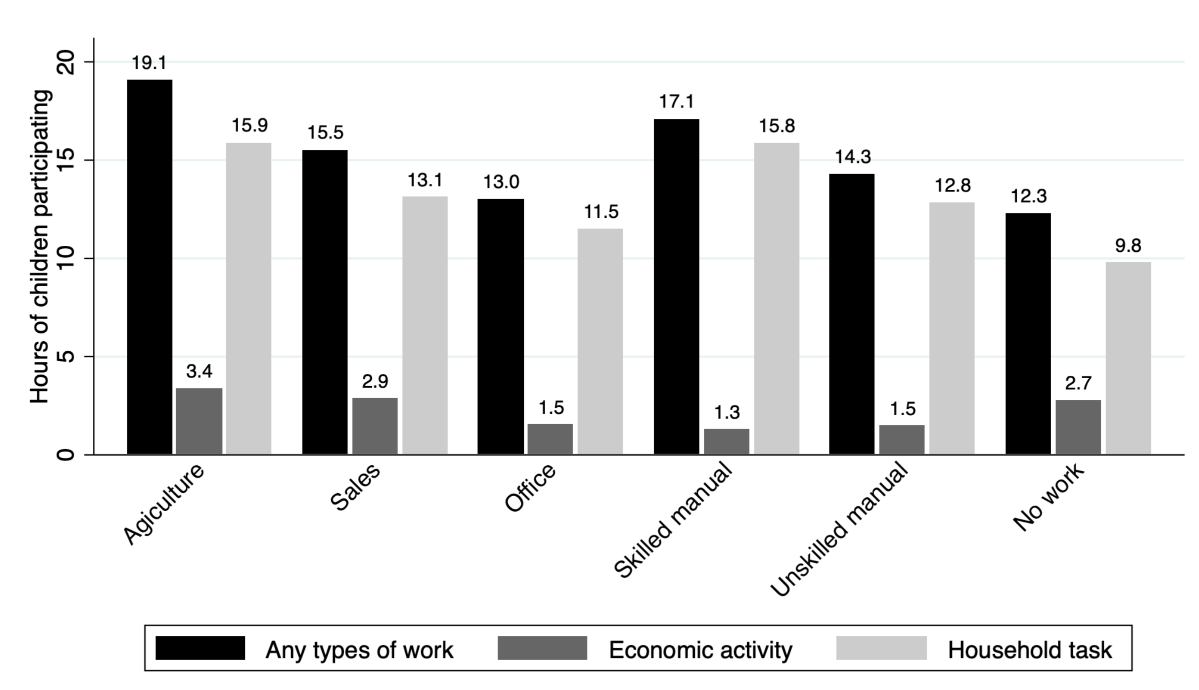
Note: This figure presents the share of working children in Mali. Panel A presents percentage of children participating in the activities among all children aged 5-14 and Panel B presents number of hours children engaged in each activity from 2001 to 2012.

Figure 4: Children's working hours by household characteristics

(a) By Wealth Quintile



(b) By Mother's Occupation

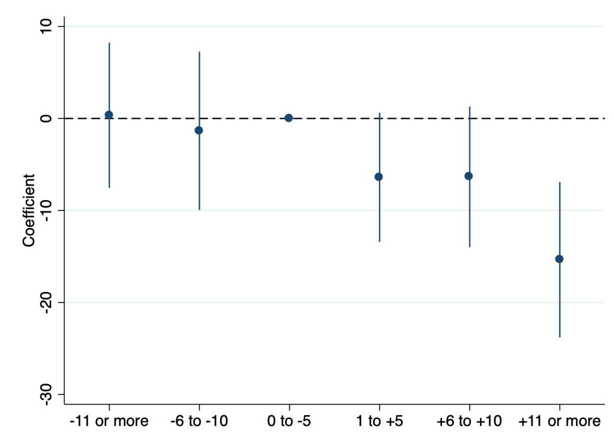


Source: Author's calculation, DHS Mali

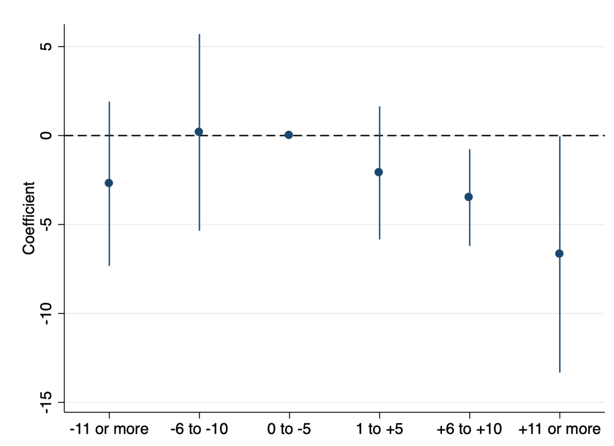
Note: This figure presents the share of working children in Mali. Panel A presents the average number of working hours by each wealth quintile, and Panel B presents the average number of hours children work by mother's sector of work.

Figure 5: Impacts on Working Hours of Children

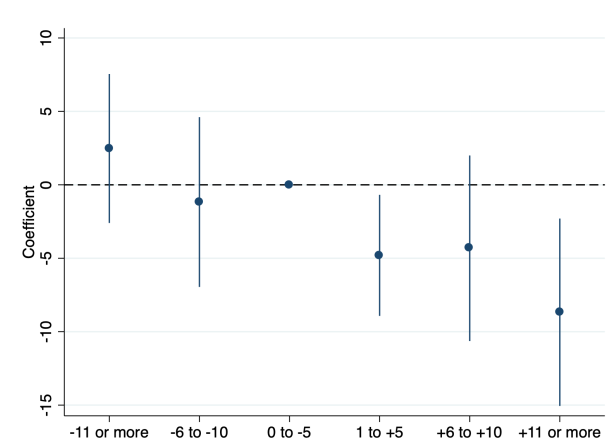
(a) Any types of work



(b) Economic Activities



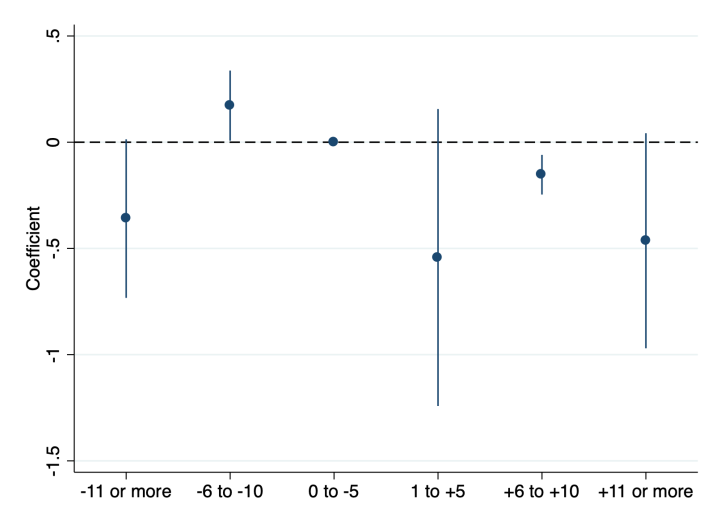
(c) Household work



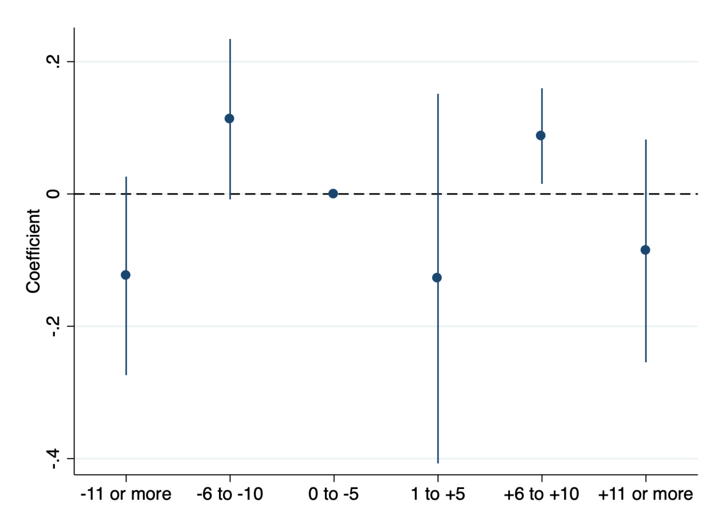
Note: This figure plots estimated effects of mine openings on working hours of children in mining areas. The horizontal axes show years from mine openings and the vertical axes the estimated coefficients. Navy dot show the estimated coefficients and the vertical lines the 95 percent confidence intervals.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



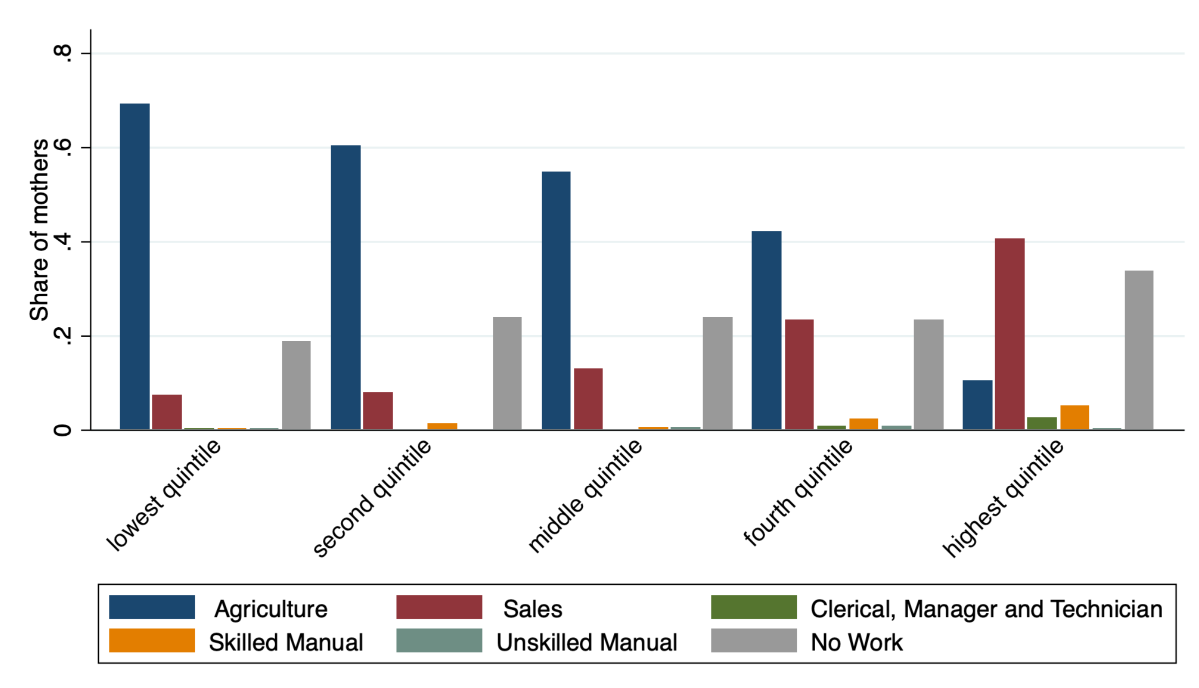
(b) Current year attendance



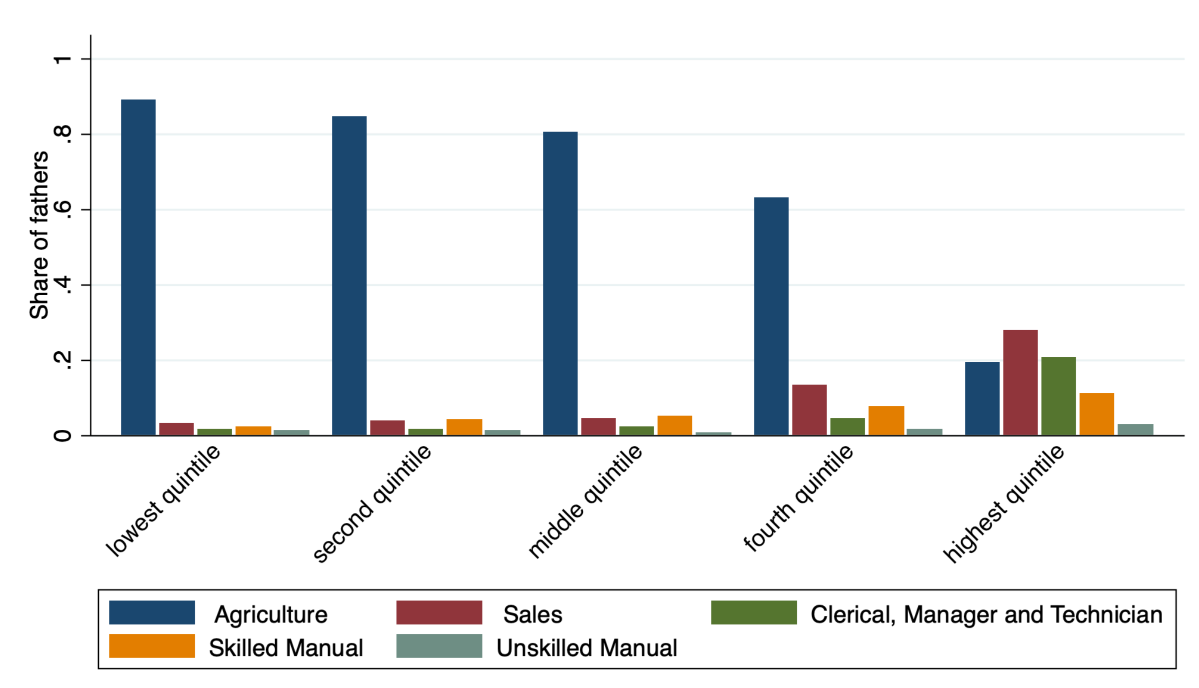
Note: This figure plots estimated effects of mine openings on educational choices of children in mining areas. The horizontal axes show years from mine openings and the vertical axes the estimated coefficients. Navy dot show the estimated coefficients and the vertical lines the 95 percent confidence 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 $\times$ 11+ yrs prior	0.337	-2.712	2.474
	(3.979)	(2.327)	(2.557)
20km $\times$ 6-10 yrs prior	-1.343	0.177	-1.173
	(4.338)	(2.787)	(2.914)
20km $\times$ 1-5 yrs post	-6.395*	-2.102	-4.804**
	(3.542)	(1.886)	(2.078)
20km $\times$ 6-10 yrs post	-6.351	-3.484**	-4.320
	(3.853)	(1.371)	(3.185)
20km $\times$ 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 $\times$ 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 $\times$ 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

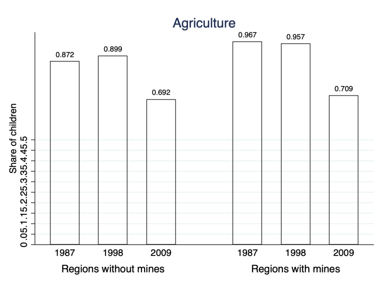
	Any work	Economic activity	Household work
	(1)	(2)	(3)
Panel A: Naive estimates			
30-50km $\times$ Open	-0.292	0.896	-1.578
	(2.991)	(1.397)	(2.912)
N	10113	10092	10026
R-Squared	0.080	0.066	0.101
Mean of Dep. Var.	20.807	2.987	18.002
Panel B: Demographics controlled			
30-50km $\times$ Open	-0.409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

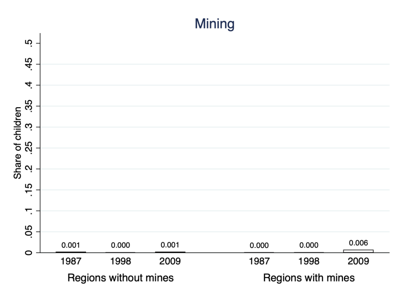
A Additional tables and figures

Figure A1: Child employment in different sectors

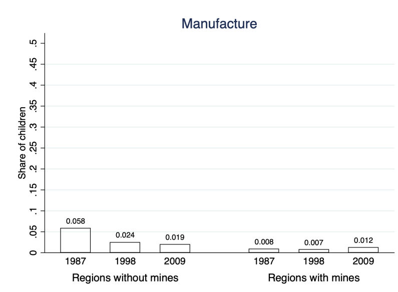
(a) Agriculture



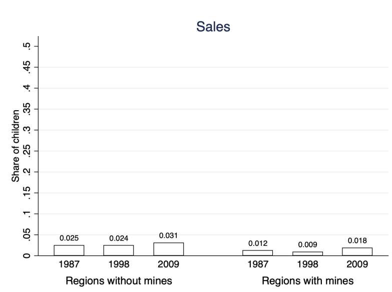
(b) Mining



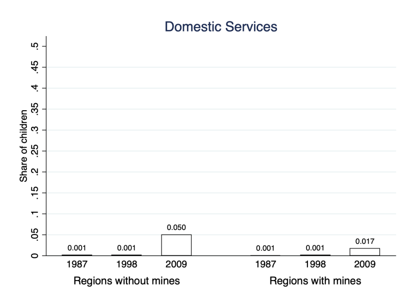
(c) Manufacture



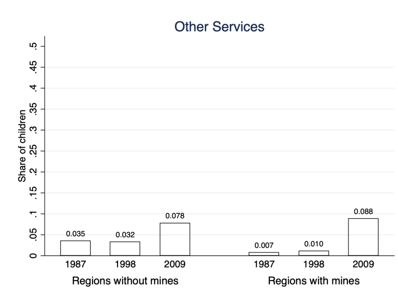
(d) Sales



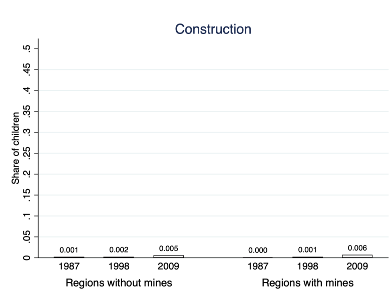
(e) Domestic services



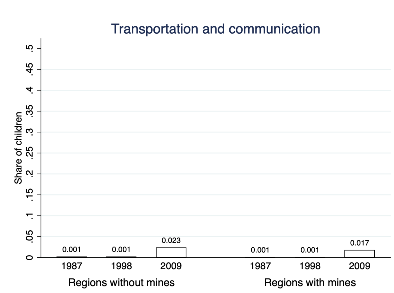
(f) Other services



(g) Construction



(h) Transportation / Communication

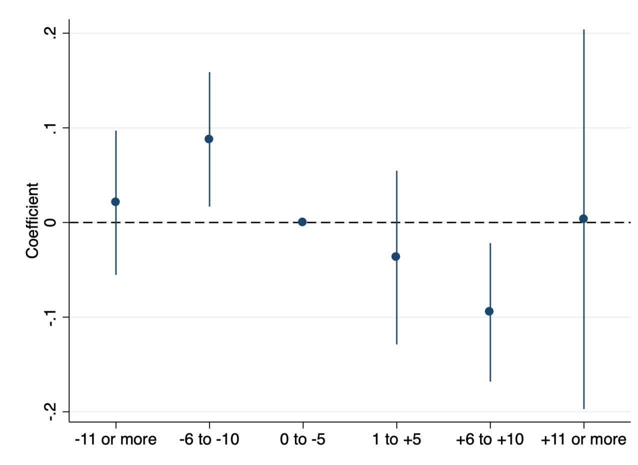


Source: Author's calculation, Mali Census

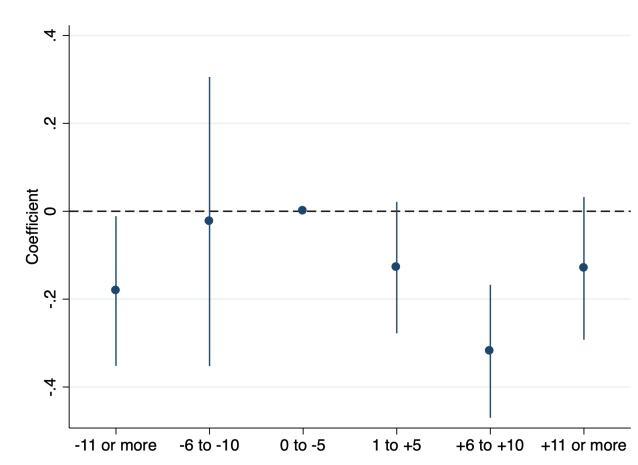
Note: This figure plots the share of children employed each sector among all children aged 5 to 14, in each census wave, by mining and non-mining areas. The horizontal axes show years and areas. and the vertical axes the share of children in each sector.

Figure A2: Impacts on child labor participation

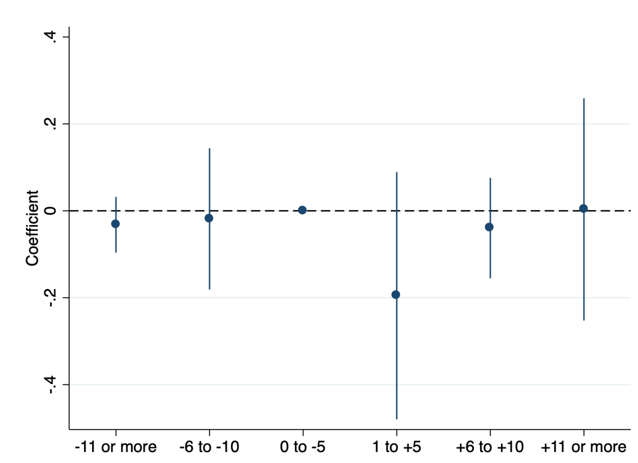
(a) Any types of work



(b) Economic activities



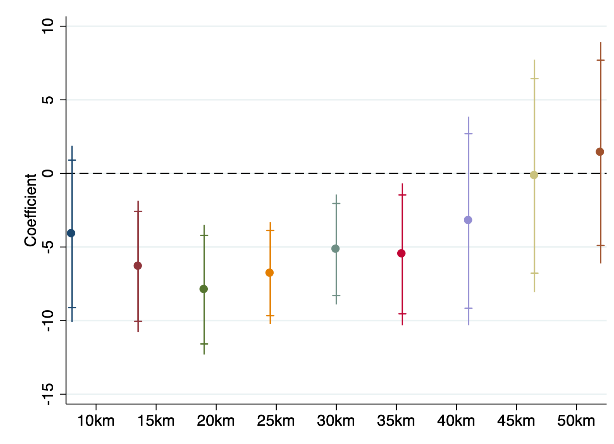
(c) Household work



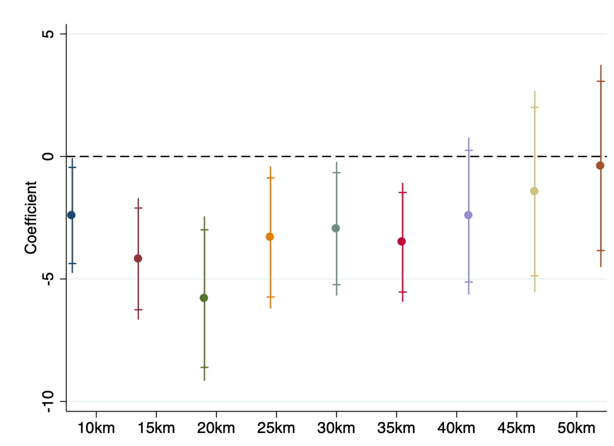
Note: This figure plots estimated effects of mine openings on children's participation in work in mining areas. The horizontal axes show years from mine openings and the vertical axes the estimated coefficients. Navy dot show the estimated coefficients and the vertical lines the 95 percent confidence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

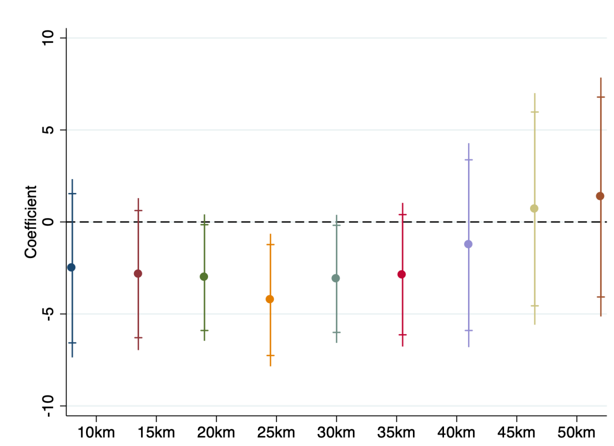
(a) Any types of work



(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)
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: 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 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 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: 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 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						
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 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)
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 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)
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 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)
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.

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)
dist_less100_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.