# Under-mining health? Local impacts of iron ore mining in India


Abstract

Environmental justice concerns about adverse impacts of extractive mining industries challenge their claim of broad-based development. However, empirical evidence of negative externalities attributable to mining enterprises is thin. In this paper, we examine the burden of Acute Respiratory Illness and Malaria among villagers along a gradient of proximity to mining areas to generate evidence pertinent to the debate on environmental health and social justice. By focusing on health outcomes as human development indicators, the study also reflects on whether the 'resource curse' that has been posited at the country level also has micro footprints.

The analysis combines 600 household interviews conducted in 20 villages with GIS data on locations of mines and villages in India. Self-reported health data on incidence and workdays lost due to Acute Respiratory Illness and Malaria are outcomes of interest. Estimation results for incidence (Probit) and workdays lost (3SLS and Zero-Inflated Negative Binomial) indicate that villagers living closer to mines reported higher frequency of ARI complications and workdays lost due to Malaria. However, villagers living closer to mines are more likely to be employed in mines, and this in turn positively affects adoption of improved stoves that can potentially reduce indoor air pollution.

(198 words)

## I. Introduction

Concerns about environmental justice challenge the premise of broad-based development promised by extractive mining industries in developing countries. In India, vehement political opposition from grassroots socio-environmental activists and public interest groups highlight the poor track record of state-supported large-scale extractive projects in conservation of the local environment and improving welfare of the affected populations (Sarangi, 2004; Randeira, 2003; Guha, 1993). Alienation from the political mainstream (Rew, 2006), state-ownership of mines (Sinha et al, 2007) and an inadequate approach to participatory development deprives the local population an appropriate share of the rent on the resource (Campbell, 2003). Weak enforcement mechanisms of environmental standards fail to keep pollution within limits and subsequent adverse effects on the local population (Blacksmith Institute, 2008; Weber-Fahr, 2002). Critique of development policy from the perspective of environmental justice focuses on this disparity in the distribution of benefits and costs from mining. In this paper, we provide empirical evidence relevant to this debate and pertinent to impact assessment of development policy across the world.

The situation also resembles a micro footprint of the 'Resource Curse' hypothesis proposed by Sachs and Warner (1997, 2001) at the national level – the consistent negative correlation between economic performance (per capita GDP growth rate) and natural resource abundance (share of exports of natural resource-based products). Bulte et al. (2005) have extended the literature on the resource curse by considering a broader set of welfare and development criteria; they find that natural resource abundance is negatively associated with indicators of nutrition, poverty and life expectancy. By focusing on the human population that is both positioned to take advantage of new economic opportunities and most exposed to the environmental effects arising from mining, we can assess the specific pathways and micro-distribution of mining impacts. This level of analysis contributes to understanding the reasons for the resource curse and the possibilities for mitigating that curse through appropriate benefit-sharing mechanisms (Hancock, 2002).

The state of Orissa in India faces this challenge as it embarks upon a major reform program with the mining sector taking center stage in the growth process. Much of the proposed mining expansion is in remote regions with a predominantly tribal population. Previous instances of expansion of iron ore mines in the state were marred by expropriation of tribal land and large-scale displacement of villagers[1]. In this paper, we empirically examine the consequences of mineral extraction on health outcomes of people living close to mines. We (1) contribute to the renewed interest in linking public health with use of environmental resources (Lee, 2002), (2) provide empirical evidence for the 'resource curse' at the micro-level and (3) examine if employment in mines influences adoption of prevention measures (like improved cook stoves and bed nets). From a survey of the literature on health issues arising from mining activities, acute respiratory illness (ARI) (Stephens and Ahern, 2001; Joyce, 1998) and malaria (Webster, 2001) were found to be most commonly cited besides occupational injuries. However, the literature on impact of iron ore mining on community health, especially in the context of developing countries is thin. Using cross-sectional data, we develop multivariate econometric models to distinguish between environmental and occupational health pathways through which mines could have an impact on health outcomes of individuals. We combine information from household surveys with spatial information on location of mines and villages to investigate associations between health outcomes, employment and proximity to mines. While we observe no strong associations for occupational health outcomes using information on employment in mines, we find that ARI incidences increase among individuals living closer to mines, but malaria incidence in the population increase in villages further away from mines. Analyzing if employment in mines eases financial constraints for households to adopt preventive measures (e.g. improved stoves and mosquito nets to reduce the incidence of ARI and malaria respectively), we find that it positively influences adoption of improved stoves.

## II. Local health consequences of mining

Freudenberg and Wilson (2002) in a review of case studies on local socio-economic impacts of mining in United States challenge the belief that mining leads to rural development. Their results, on the contrary, point to higher observed levels of poverty and unemployment in the mining areas. Mining projects around the world have come under severe criticism under counts of land expropriation and environmental degradation that harm the livelihoods and health

[1] New York Times, January 13 , 2006

of local communities (Keenan et al 2002; Sosa 2000). Mining projects involve huge investments accompanied with strong political influence, and local communities could bear substantial environmental, economic, and social costs unless local governments enforce strong regulatory systems to ensure equitable sharing of benefits (Auty, 2006). An independent assessment of World Bank sponsored mining projects in India concluded that 'people living close to mines have suffered most and usually benefitted least' (Teri, 2001). However, there are few studies focusing on the health impacts of mining from a policy perspective (Hilson, 2002).

A central tenet of research on the environmental impacts of mining has been that because mines occupy a relatively small land area (when compared, for example, to other land uses like forestry or agriculture), the effects of mining on the environment will be localized (Bridge, 2004). Though dispersal of toxic wastes and other harmful byproducts of mining by wind and water happen over wide geographical areas, the detrimental impacts are most pronounced in areas close to mines. There are direct and indirect pathways that mines affect health outcomes of people. Employment in mines is an example of a direct pathway for impacts of mines, both in terms of the benefits from employment in mines as well as occupational health outcomes. Mines could also affect welfare though environmental health pathways that is direct as well as indirect. For example, declining ambient air quality due to spread of dust and chemicals from mining areas directly affect people living close by, irrespective of whether they work in mines or not (Sinha et al., 2007, Stephens and Ahern, 2001). On the other hand, deforestation due to mining activities indirectly affects families dependent on forest products for income generation and nutritional requirements by reducing their access to the resource base (Peters et al. 1989).

Among public health concerns for mine workers, incidence of respiratory disorders has received considerable attention in the environmental and occupational health literature (Ross and Murray, 2004; ILO, 1997)[2]. Mining in both surface and underground mines involves drilling and shearing of large quantities of minerals. The clouds of dust raised in displacing these materials can severely damage the lungs, particularly after years of exposure (Joyce, 1998). Occupational exposure to air pollutants has been found to be a major cause for chronic cough and asthma, symptoms common in chronic bronchitis (Hedlund et al., 2006). However, there is a negative externality to society as individuals not employed but living close to mining areas are also

[2] For a review of the occupational and community health impacts of mining internationally, refer to Stephens and Ahern, 2001.

exposed to the harmful effects of air pollution. Prevalence of acute and chronic respiratory health has been observed among individuals close to open cast or open pit mines (Pless Mulloli et al., 2000). In a study on opencast coal mining in the state of Orissa in India, suspended particulate matter (SPM) were found to be significantly higher than permissible limits in the mines as well as in the surrounding locations from various operations (Chaulya, 2004). In other studies on open cast coal mines, poorly maintained dirt roads and movement of heavy vehicles to transport the ore resulted in dispersion of coal dust in areas adjoining mines and cause severe air pollution (Ghosh and Majee, 2000; Singh and Sharma, 1992).

Incidence of malaria is also common in areas close to mining activities, though the pathways of health impacts are both direct and indirect. Borrow pits left after road constructions, drains and abandoned excavation areas in opencast mines often increases breeding sites for the malaria vector and directly increases malaria prevalence (Yasuoka and Levins, 2007). Deforestation caused by mining activities and subsequent change in land use and human settlement alters the local ecosystem, changes the vector ecology of mosquitos and indirectly affects malaria incidence (Patz et al., 2004, Takken at al. 2003). Among all states in India, the incidence of malaria is the highest in the state of Orissa (Kumar et al., 2007). A cross-sectional study conducted in 1989 in settlements in the iron ore mining region in Orissa found high densities of the malaria vectors. Children were found to be most vulnerable to malaria attacks and the poor casual laborers in the mines were found to be worst affected in economic terms (Yadav et al., 1991).

## III. Prevention options to mitigate incidence of ARI and malaria

We focus on adoption of improved cook stoves and bed nets by households that should also influence the incidence of ARI and malaria respectively. Our rationale to focus on these interventions are three-fold – (1) failure to account for such preventive measures will confound the association we aim to establish between mining and incidence of ARI and malaria; (2) a positive association between employment in mines and adoption of such preventive measures will offset the adverse health impacts of mining on the local population; (3) examine if micro-credit and social learning provide practical solutions to financial and information constraints that negatively influence the adoption of these measures.

A recent simulation study by Wilkinson et al. (2007) provides evidence of significant reduction in mortality due to respiratory complications from adoption of improved cook stoves and reduction in indoor air pollution (IAP). The products of incomplete combustion from biomass combustion (firewood, crop residue) contain a number of health-damaging pollutants (Fullerton et al., 2007; Bruce et al., 2000) responsible for a significant global burden of respiratory infections (Smith et al., 2004; WHO)[3]. 70% of the population living in rural India (and majority in our study) traditionally cooks using unvented stoves with women and children experiencing the highest exposures to indoor air pollution. As India embarks on a 'National Biomass Cookstoves Initiative'[4] with the policy objectives of social and health development at the forefront, it is relevant to examine factors that influence the adoption of these stoves. In a recent study of indoor air pollution in Bangladesh, construction of the kitchen with proper ventilation was found to yield better indoor air quality (Dasgupta et al., 2007).

As compared to other methods of malaria vector control like indoor residual spraying of DDT, use of bed nets is technologically simpler and cost-effective (Misra, 1999; Lengeler, 1996). In a randomized trial of insecticide-treated bed nets in Sundargarh district of Orissa (adjacent to location of the present study), relative risk of malaria and parasite rates declined significantly in villages with treated nets (Sharma et al., 2006). Partnerships between donor agencies, local NGO and communities have been established to raise the awareness and disseminate insecticide-treated bed nets (Barat, 2006).

In spite of the claimed benefits of these preventive measures in reducing the incidence of ARI and malaria, the rate of adoption has been consistently below expectations of the agencies and NGOs promoting them. Much of the inertia in adoption is attributed to financial constraints facing rural families (Dasgupta et al., 2007; Wallmo, 1998 for Cookstoves; Meltzer, 2003; Nuwaha, 2001 for bednets). These empirical findings suggest that increased cash income – for example, from employment in mines – could increase adoption rates of these preventions. Also, positive effects of collective learning through information sharing among neighbors has been observed in de-worming among children (Miguel and Kremer, 2004) and improved sanitation practices among rural families (Dickinson and Pattanayak, 2009).

[3] http://www.who.int/mediacentre/factsheets/fs292/en/index.html - downloaded April 25, 2008
[4] http://mnes.nic.in/press-releases/press-release-02122009.pdf - downloaded January 7, 2010

## IV. Study area

The state of Orissa lies along the eastern coast of India with the largest reserve of superior quality hematite iron ore in the country (Sengupta, 2005). Situated along the Northern border of the state, Keonjhar district was selected for this study because of the concentration of iron ore mines in Joda block within the district[5]. 31% of the total mining employment in the state of Orissa is concentrated in the district of Keonjhar indicating the importance of the mining industry in the region. Mining for iron ore in the district began in the 1950s, and much of the planned expansion and liberalization of the mining sector in Orissa will open up new mining areas in this region. The recorded forest area in Orissa in 2003 was 4.84 million hectares, which constituted 31.06% of the geographic area and ranked fourth among Indian states in terms of total forest cover[6]. However, in comparison with 1999, forest cover had decreased by almost a million hectares[7]. The district had a relatively high percentage (42.7%) of forest cover in 1999 (Forest Survey of India, 1999). But, in the two blocks selected for this study, analysis of the classified land cover data reveals that 13.4 square kilometers of vegetative cover were replaced by expanding mining areas between 1989 and 2004.

In the absence of field monitoring and measurement data on ambient air quality, study villages were selected based on proximity to mines. The first stage of the sample selection process followed a quasi-experimental design, to test the hypothesis that villagers living closer to mines were more likely to be impacted by the mines than those further away. On the basis of government census data on mine employment and location of mines, two blocks were selected in Keonjhar district – Joda and Keonjhar Sadar (Figure 1). Joda block has a large concentration of iron ore mines, as confirmed by the fact that 68% of mine workers in Keonjhar district live in Joda block. On the contrary, Keonjhar Sadar block has a much lower concentration of mines and only 1% of people employed in the mining industry live in this block. In the second sampling stage in each of these blocks, 10 villages were selected at random (Figure 2). Finally, in each of

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[5] Keonjhar district has 20% of all the mining leases granted by the State government of Orissa. The district has more than 12076 hectares of iron ore mining areas under 46 mining leases, making it the most important iron ore mining center in Eastern India (Source: Status paper on mining leases in India. Vasundhara, India).

[6] 'State of Forest Report' published b y the Forest Survey of India in 2003; http://www.fsiorg.net/fsi2003/states/index.asp?state_code=21&state_name=Orissa

[7] 'State of Forest Report' published by the Forest Survey of India in 1999; http://www.envfor.nic.in/fsi/sfr99/sfr.html

these villages, 30 households were selected from each village to be interviewed. For convenience, villagers in the Joda block henceforth will be referred to living in the 'high exposure' zone while Keonjhar Sadar will be referred to as the 'low exposure' zone.

## V. Description of the data

The dataset consists of two elements – (1) a household survey administered to 600 households with specific modules on questions on incidence of ARI and malaria among family members; (2) forest cover maps derived from Landsat satellite imagery for 1989 and 2004, and GIS information on locations of mines and villages. For indicators of health outcomes, we use reported information on types and days of illness specifically pertaining to incidence and workdays lost due to of ARI and malaria[8]. Information on the number of iron ore mines was collected from the database maintained by the directorate of mines. Information from survey topo-sheets and remotely sensed data was combined with the mining database to identify the location and area of iron ore mines in the study area. These mines are under state as well as private ownership, operating under various levels of modernization and mechanization. Observations from field visits to a sample of mines in the study area revealed apparent variations in abidance to environmental regulations prescribed by the Department of Mines, which has repercussions on occupational and environmental health issues. For exposure to mines, GIS information on location of mines and villages are used to construct a proxy measure based on Euclidean distance to the nearest iron ore mine[9]. As a result of the study design, villages in the high exposure and low exposure zones are within a range of 0.2 to 4 km and 6 to 21 km from iron ore mines respectively. Note that all the villages fall within the "Peripheral Development Zone" of 50 km[10] - a specification followed in mining and development projects supported by

[8] Unless mentioned, incidence and workdays lost due to ARI is based on the reported information on whether an individual had suffered from ARI in the year prior to the survey in 2005. For malaria, this is based on information from 2001 to 2005.
[9] Alternative definitions of exposure based on 'number of mines in a 2km buffer around each village' were used in the analyses which provided similar results. WE stick to using the Euclidean distance based measure for exposure to mines in this paper. Besides the mining areas, there are unregistered, small-scale stone-crushing units in the study area and the dust from these units cause significant air pollution. However, these units do not operate in the same spot for a long period of time to avoid impoundment, and their effect on ARI specifically is difficult to assess. Based on data and field observations, proximity of villages to these stone-crusher units is highly correlated to distance to iron ore mines.
[10] World Bank report on the study 'Towards Sustainable Mineral Intensive Growth in Orissa, India' is available at:

the World Bank to address issues related to local impacts of mines. The descriptive statistics of the variables used in the analysis is reported in Table 1.

A total of 600 households (300 in each block) were interviewed and information was collected for 2949 individuals. Out of 600 households, 175 out of 300 households interviewed in the high exposure zone reported at least one family member to be working in the mines, while the corresponding number in the low exposure villages was 45 out of 300 households[11]. 283 individuals from 216 families reported to be working in mines[12]. Table 2 shows the distribution of health outcome variables in the full household sample and the two blocks separately. The average number of reported cases of ARI in the family was significantly higher in the high exposure zones as compared to the low exposure zones (1.2 compared to 0.8). However, the average number of reported cases of malaria in the family was higher in the low exposure zone (1.8 compared to 1.5). While the average number of workdays lost per family due to ARI was not significantly different across exposure zones, families in the high exposure zones reported more number of workdays lost due to malaria (19.5 compared to 12.5). A reason for this trend could be the fact that incidences of malaria are lower in the high exposure zone, but the severity of malaria is worse in the high exposure zone. Correlations with distance to iron ore mines show that workdays lost increases among villages with greater proximity to mines. Note that the mean and variance of count of ARI and malaria variables are similar and thus we model these two variables as a Poisson process in our econometric estimation.

Table 3 presents the results on health status breaking down the population into 3 sub-groups – (i) individuals with no family members working in mines, (ii) individuals with some family member working in mines, (iii) individuals working in mines themselves. Parsing the sample into these subgroups helps to better distinguish the occupational health impact on individuals from mine employment. While individuals in group (i) should have no occupational health effect, those in group (ii) only have an indirect effect as members working in mines could

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http://www_wds.worldbank.org/external/default/WDSContentServer/WDSP/IB/2007/12/21/000020953_20071221103718/Rendered/PDF/398780IN.pdf

[11] The household questionnaire had modules to record the occupation details of every household member. Employment of a family members in mines was determined for the cases where a member was reported to be working as a ‘non-farm worker as factory worker’. Employment in the stone quarries was determined based on member occupation being ‘non-farm work as construction labor’.

[12] Another 103 individuals from 65 families reported to be working in stone quarries. As mentioned before, these stone quarries operate illegally and employment in these units is temporary in nature. WE ignore quarry employment in the subsequent analyses.

transmit ARI or malaria contracted while working in mines among other family members. Group (iii) represents the sub-sample most likely to suffer a direct occupational health effect from working in mines. There is no significant difference in ARI related health indicators across these three groups, except for expenditure where individuals not working in mines report having spent more. For malaria, those who work in mines suffer more in terms of workdays lost as well as significantly spend more on treatment.

## VI. Conceptual framework

Figure 3 presents a conceptual framework to analyze the possible impact of mining on public health. Mining operations can generate both direct and indirect health impacts for the proximate population, and these pathways are categorized as environmental and occupational. There are direct financial benefits from employment in a mine if the opportunity cost of working in the mines is lower than the mining wage. The increase in income can reduce the cash constraints of families to invest more in illness prevention measures that improve overall health status. Proximity to mines has direct and indirect negative health effects as well. Mines that fail to meet prescribed environmental standards are more likely to generate direct negative externalities for those who are employed in mines (occupational health), as well as through negative externalities for those who do not work in mines but live close to it (environmental health). In the context of the paper, the dust and other harmful suspended particulate matter could increase ARI-related health problems, or abandoned areas with stagnant water become breeding grounds for mosquitos that cause malaria. Large areas had to be deforested to establish the open cast mines in the region. This imposed a financial and nutritional burden on the villagers in the study area who relied on sale and consumption of forest resources for their livelihood.

This framework provides a more nuanced description of the complex set of relationships that connect mining with public health concerns. It helps separate causal pathways, provides a set of testable hypotheses and the empirical analyses required to verify those (Ethridge, 2004). The specific hypotheses that we focus on in the econometric section are: (a) proximity to mines increase incidence of ARI and Malaria; (b) income from mines reduces financial constraints for farmers and enables them to invest in preventive activities that reduces the burden of illness.

## VII. Econometric models for health outcomes

In the first step of the econometric model, the individual-level dataset is used to model two separate outcomes related to ARI and malaria – (i) whether an individual member reported the incidence of ARI and malaria; (ii) the reported number of workdays lost by individual members due to ARI and malaria. The empirical model for both cases is outlined as follows.

Let $(y)$ be the outcome of interest – either incidence or workdays lost due to ARI and malaria. These health outcomes are a function of a vector of individual-specific characteristics $(I)$, household-specific characteristics $(H)$, location of the household $(L)$, environmental health variables $(EH)$, occupational health variables $(OH)$ and preventive behavior $(P)$.

$$y = F(I, H, L, EH, OH, P) \tag{1}$$

where $F(.)$ depends on whether incidence of ARI/Malaria (a binary variable) or workdays lost due to ARI/Malaria (count variable) is being modeled.

The variables used in each group are:

Individual-specific $(I)$: Age, sex, education, number of hours devoted to wage employment on an average day by individual member.

Household-specific $(H)$: Caste, amount of fuelwood used for domestic consumption, amount of irrigated land in village.

Location of household $(L)$: distance to paved roads, distance to primary health center.

Environmental health $(EH)$: distance to nearest iron ore mine using GIS information.

Occupational health $(OH)$: dummy if individual is employed in mines, number of days reported to be working in mines.

Preventive behavior $(P)$: Use of improves stoves for cooking, dummy if kitchen is partitioned from the house or not, dummy if bed nets are used for sleeping.

(a) Probit model for incidence of ARI and malaria:

A binary variable was constructed based on the information of which individual family member had occurrence of ARI and malaria. A Probit of the following form is estimated: $\Pr(y=1 \mid X) = G(\beta_0 + \beta X)$, where a vector of explanatory variables $(X)$ is specified in (1), and $G(.)$ is the standard normal cumulative density function. Individuals within the family have the choice of working in mines, which makes mine employment endogenous to the model. WE use proximity to mines, average number of hours worked in wage employment, dummy if land owned and years of education as instruments for mine employment and estimate the Probit as a 2SLS model.

Results from the Probit model are shown in Table 4. The environmental health variable, measured by Euclidean distance to the closest iron ore mine is significant across the two models, but with opposite signs. While as distance to mines increase by 1 km, the probability of a family member being affected by ARI problems decrease by 2.3%, while the probability of malaria increase by 1.9%. This result mirrors the previous observation that villagers closer to mines in the high exposure zone reported a higher incidence of ARI, while those further from mines in the low exposure zone reported a higher occurrence of malaria. Employment in mines, after being instrumented, is negatively affected with the incidence of ARI – an additional day of employment in mines reduces the probability of ARI by 0.1%. Employment in mines increases the probability of malaria, though the result is not significant. None of the demographic variables, except whether the family belongs to a scheduled tribe, is significant. Generally, people belonging to the scheduled tribes are historically marginalized, and 70% of the mine workers in our sample belong to scheduled tribes. This result raises the doubt of under-reporting of health status information by this group. Location-specific variables like distance to paved roads and primary health center had little explanatory power. We use the log of amount of fuelwood consumed by the household to control for the fact that combustion of firewood for domestic cooking and heating could also lead to higher incidence of ARI. If this factor is ignored, then the impact of mines on ARI incidence could be over-estimated. Increase in firewood use has the expected effect of increasing ARI, but the effect is not significant. In the case of malaria, We control for the amount of irrigated land and change in forest cover around the village – factors that could affect the incidence of malaria. The significantly negative effect of irrigated land on incidence of malaria is surprising, as Patz (2004) argues that irrigated agricultural fields often provide breeding grounds for mosquitos. Given the clustered nature of these villages, agricultural land is arranged in concentric circles around the villages. Irrigation in agricultural fields often results in stagnant pools of water in the land surrounding the villages and was suspected to provide breeding areas for mosquitos. However, given the highly seasonal nature of rain-fed irrigation and the economic importance of agricultural land for households, the irrigation variable might be working as a proxy for welfare in the low exposure villages. Villages with a greater decrease in forest cover in a 2km buffer around the village reported higher incidence of malaria, but the effect was not significant. The prevention variables all have expected signs and are highly significant – incidence of ARI reduces by 75% and 23% among individuals who have improved stoves and partitioned kitchens in their house respectively. Incidence of malaria reduces among individuals by almost 12% if they use insecticide-treated bed nets in the house.

(b) 3SLS models for workdays lost due to ARI and malaria:

In the sample, workdays lost due to ARI and malaria has a range of 0 to 90 days each. In this model, workday lost is treated as a continuous variable and a 3SLS model is developed. Employment in mine is assumed to be endogenous and is estimated simultaneously with workdays lost due to ARI and malaria. The error term in both equations is assumed to be correlated due to unobserved heterogeneity and 3SLS estimation method is employed.

Table 5 shows the results from these two models. The environmental health variable remains significant and negative for both the ARI and malaria models. Recall that Table 2 indicated that though the incidence of malaria was high in the low exposure zones, the number of workdays lost due to malaria was higher in the high exposure zone leading to the conjecture that the severity of malaria is worse in villages closer to the mines. These general observations substantiate the negative coefficient with distance to iron ore mines. Living 1km closer to the iron ore mines increases the workdays lost due to ARI and malaria by 0.02 and 0.08 days. The instrumented occupation health variable is not significant across either of the models. Older individuals suffer more days of lost work due to ARI. Individuals belonging to the scheduled tribes and scheduled castes report less workdays lost due to both ARI and malaria. Compared to models in table 3, increase in forest cover in a 2km buffer around villages (comparing 1989 and 2004 classified land cover data) is found to increase the workdays lost due to malaria. Loss in forest cover in a 2km buffer around sample villages was higher in the low exposure zones than in the high exposure zones (2.3 sq. km compared to 0.31 sq km), and the spatial distribution of greater malaria incidence in the low exposure zones supports the deforestation-malaria hypothesis. However, malaria incidence or workdays lost cannot be attributed to deforestation due to mining activities. Location-specific variables still remain largely insignificant, except that workdays lost due to ARI are higher for individuals living further away from the primary health center. The prevention variables continue to have the expected signs, but only kitchen construction and use of bed nets are significant.

(c) Count data models for workdays lost due to ARI and Malaria:

While the range for reported workdays lost by individuals due to ARI and Malaria ranged between 0 and 90 days, more than 99% of the sample lost between 0 and 20 days for each illness[13]. Unlike treating workdays lost as a continuous variable as in the 3SLS models estimated in (ii), an event count model is estimated. As noted in Table 2, the difference between mean and variance of workdays lost due to ARI and malaria with the variance being higher indicated overdispersion in the data (Long and Freese, 2006). There are also a large proportion of individuals who did not report workdays lost due to illness. We assume two different processes generating the data – one explaining the zeros, and the other for the positive number of workdays lost (Lambert, 1992). We thus use Zero-Inflated Negative Binomial (ZINB) models to account for overdispersion and excess zero that we observe in the data (Cameron and Trivedi, 1998). A battery of visual and model fit statistics are compared to determine that the ZINB model was most appropriate compared to ordinary Poisson or Negative Binomial models.

The results from the ZINB model are presented in Table 6. Comparing results with the 3SLS results in Table 5, the occupational health variable (days worked in mines) is insignificant and becomes negative in the zero-inflated models. The environmental health variable (distance to nearest iron ore mine) is consistently negative but insignificant[14]. The prevention variables all have expected signs, but only use of improved stoves remains significant in explaining reduction in workdays lost due to ARI. Amount of firewood consumed is surprisingly significantly negative across all models, another result that deviates from the 3SLS model. Male family

[13] For ARI (malaria), out of 631 (1009) individuals reporting workdays lost to illness, only 14 (5) reported to have lost more than 20 days due to ARI. These models are thus run with the restricted sample where reported workdays lost due to ARI and malaria was less than or equal to 20 days.
[14] When the logarithm of distance to nearest to iron ore mines is used instead, the coefficient is just significant at the 15% level.

members reported to have lost more workdays lost due to ARI, which is likely as most of the wage labor are done by male members and are more likely to report loss of working days compared to female members mostly engaged in household chores. An individual living 1 km closer to an iron ore mine will increase the number of workdays lost to ARI by 0.3%. Being a male reduces workdays lost by 13%, raising the concern that women members in the household are more susceptible to ARI related problems, though the use of firewood for cooking is a critical factor for that. There is no perceptible difference in workdays lost for individuals with mine employment. Families with improved stoves and partitioned kitchen reduce workdays lost to ARI by 11% and 2% respectively. In the model for malaria in Table 6, the occupational health variable remains positive but insignificant across all models. The environmental health variable is significant and negative, indicating that while incidence of malaria is lower in villages closer to mines, those living closer report to have suffered more from workdays lost due to malaria. The use of mosquito nets reduce workdays lost due to malaria but the result is insignificant. Workdays lost increases with more land in irrigation and greater loss of forest cover around the village, as was surmised from the literature review. An individual living 1 km closer to an iron ore mine will increase the number of workdays lost to malaria by 7%. A 1% increase in area under irrigation around the village increases workdays lost to malaria by 3%, while 1 sq. km. of deforestation around the village increases workdays lost by 1.5%. A family with an additional mosquito net reduces workdays lost to malaria for individual members by 11%.

As a summary of the results from these sets of model, there is little evidence of occupational health for either ARI or malaria. The environmental health effect, using the proxy of proximity to mines, is more pronounced, as evident for ARI in the 3SLS model and on malaria in the ZINB model. The hypothesis that higher deforestation leads to higher prevalence of malaria was only supported in the ZINB model, though this deforestation could not be attributed to mining activities alone as more deforestation took place in the low exposure zone. Another robust result from the models reflects the importance of prevention activities on individual health outcomes. Preventive measures like adoption of improved stoves and construction of partitioned kitchen inside homes reduced the incidence and workdays lost due to ARI. Use of insecticide-treated bed nets also reduced the incidence and workdays lost due to malaria. From a public health policy perspective, it is important to identify factors that influence the adoption of these prevention measures.

VII. Factors affecting use of prevention measures

Families make decisions regarding the adoption of the three preventive measures based on their subjective utility post-adoption. It is important to point out that these prevention measures help reduce the burden of ARI and malaria related health problems among family members, irrespective of whether these problems were induced by mining activities or not. The typical approach to model adoption behavior of individuals is to discrete choice model. Among the factors that could affect adoption, most interest lies in the fact that whether cash income from employment in mines eases the cash constraint facing poor, rural households thus facilitating investment in preventive measures. There are also opportunities for individuals to observe the changes in outcomes among neighbors in the village who use these prevention methods.

This kind of exchange of information among residents in the village often influences adoption decisions of individuals (Dickinson and Pattanayak, 2009). In the model, evidence for such kind of social interaction effect in adoption of these preventive measures is also tested in the model. The household's latent utility from adoption of preventive measures can be modeled as set of household specific and location-specific characteristics, such that

$$B_i^* = b(X_i, B_{-1}) + e_i$$

where, $B_i$ is the individual adoption decision, $B_{-i}$ denotes the adoption decision of other members in the village and $X_i$ is a set of household and location-specific characteristics. This model is estimated using a probit regression such that the likelihood function is of the form: $\Pr(B_i = 1 \mid X_i, B_{-i}) = 1 - F(-\beta X - \theta B_{-i})$, where, $F(.)$ is the standard normal cumulative density function.

The results of the estimation are presented in Table 7. Three sets of models are presented relevant to each of the preventive behaviors. Given the economic importance of agriculture in the region, dummy for land ownership represents wealth status of a household. Based on the dummy for land ownership, households owning land had a 14% (24%) higher probability of using bed nets (improved stoves). As was the case with employment in mines in previous models, days worked by an individual in mines is treated as endogenous and instrumented using average time devoted by family members to wage employment and Distance to iron ore mines. The probability of adoption of improved stoves is found to significantly increase with employment in mines. As mentioned before, dissemination of improved stoves in rural areas in Orissa are being promoted through micro-credit organizations (Duflo, 2007). These organizations are yet to be operational on a large scale in the region and the lack of significance of participation in micro-credit organizations in the promotion of improved stoves or bed nets indicates this. As a matter of fact, 72 of the households that reported having improved stoves in the region were not members of any micro-credit groups in their village. Among the factors used to examine the impact of social influence on household adoption decision, two variables were considered – count of adoption by other members in the village and number of social organizations that members of the individual households participate in. Only in case of adoption of bed nets was the village count of adoption significant, indicating that individual adoption of bed net increases by 3.6% when one more family in the village adopts. Participation in village level organizations increases the scope of interaction and sharing experiences with other villagers. Such social organizations and NGOs have been found to be important nodes of information regarding adoption of new technology (Bandiera and Rasul, 2006). This variable was significant only in the case of adoption of bed nets.

The cross-sectional analysis precludes inferences of any causal nature such as mine employment causes greater use of preventive measures. However, the results point to the possible effect where increase in cash income from mine employment allows cash-constrained rural families to better invest in prevention of ARI and malaria.

## VIII. Conclusion

This study is one of the first attempts towards comprehensive analyses of health impacts of mining on the local population, an important stakeholder in the public policy debate surrounding the proposed expansion and privatization of the mining industry in Orissa. We find consistent environmental health impacts as villagers living in close proximity to mines have higher incidences of ARI and lose more workdays due to malaria. Though the absence of baseline data does not allow any causal inferences, the association between proximity to mining areas and health outcomes are robust across different models that we estimate. There is evidence that employment in mines positively influencing adoption of improved stoves that can reduce the burden of ARI, but similar effects are not observed for adoption of bednets. Instead, there is evidence of a demonstration effect in adoption of bednets as families use more nets if the rest of their village also does the same.

These results resonate with the concerns raised from the environmental justice perspective. Poor people living closer to mining areas bear a health burden, and qualitative evidence from stakeholder interviews with government officials and local non-governmental organizations revealed no compensation arrangements to offset such negative externalities. These results are important from the point of distributional equity that demands a rethink about compensation implicit in the 'participatory development' framework.

The analyses would have been more rigorous if clinical data was available instead of self-reported health outcomes. Actual data from air quality monitors across the study area for the exposure measure would have been preferred using Euclidean distances of villages from mines as exposure. These are issues that future research on this issue needs to develop on.

References

Auty, R. 2006. Mining enclave to economic catalysts: Large mineral projects in developing countries. Brown Journal of World Affairs. Vol. XIII, Issue 1, Fall/Winter.

Bandiera, O., and WE. Rasul. "Social Networks and Technology Adoption in Northern Mozambi que." The Economic Journal 116(2006): 869-902.

Barat, L. M. 2006. Four malaria success stories: How malaria burden was successfully reduced in Brazsil, Eritrea, India and Vietnam. American Journal of Tropical Medicine and Hygiene. 74(1), 12-16.

Blacksmith Institute. 2008. The World's Worst Pollution Problems: Top Ten of the Toxic Twenty. Downloaded from http://www.worstpolluted.org/ on December 20, 2009.

Bridge, G. 2004. Contested terrain: Mining and the environment. Annual Review of Environmental Resources. 29, 205-29.

Bruce, N., R. Perez-Padilla and R. Albalak, 2000: Indoor air pollution in developing countries: a major environmental and public health challenge. B. World Health Organization. 78, 1097-1092.

Bulte, E.H, R. Damania and R. Deacon (2005): Resource Intensity, Institutions and Development. World Development Volume 33 (7) 1029-1044.

Cameron, A. C. and Trivedi, P. K. 1986. Econometric models based on count data: comparison and application of some estimators. Journal of applied Econometrics. 1, 29-53.

Cameron, A. C. and Trivedi, P. K. 1998. Regression Analysis of Count Data. Cambridge University Press.

Campbell, M. L. and Vainio-Mattila, A. 2003. Participatory Development and Community-Based Conservation: Opportunities Missed for Lessons Learned? Human Ecology, Vol. 31 (3), 417-437.

Chaulya, S. K. 2004. Spatial and temporal variations of SPM, RPM, SO2 and NOx concentrations in an opencast coal mining area. Journal of Environmental Monitoring. Vol. 6, 134-142.

Dasgupta, S., Huq, M., Khaliquzzaman. M. and Wheeler, D. 2007. Improving Indoor Air Quality for Poor Families: A Controlled Experiment in Bangladesh. World Bank Policy Research Working Paper 4422.

Dudka, S. and Adriano, D. C. 1997. Environmental impacts of metal ore mining and processing : A review. Journal of Environmental Quality. Vol. 26(3), 590-602.

Duflo, E., Greenstone, M. and Hanna, R. 2007. Indoor Air Pollution, Health and Economic Well-being. Working paper, Poverty Action Lab.

Dickinson, K. and Pattanayak, S. K. 2009. Open sky latrines: Do social interactions influence decisions to use toilets? Working paper.

Ethridge, D. E. 2004. Research methodology in applied economics: organizing, planning and conducting economic research. Iowa State University Press.

Freudenburg, W. R. and Wilson, L. J. 2002. Mining the data: Analyzing the economic implications of mining for nonmetropolitan regions. Sociological Inquiry. 72(4), 549-75.

Fullerton, D. G., N. Bruce and S. B. Gordon. 2007. Indoor air pollution from biomass fuel smoke is a major health concern in the developing world. Transactions of the Royal Society of Tropical Medicine and Hygiene 102, 843—851.

Geist, H.J. and Lambin, E. F. 2002. Proximate causes and underlying driving forces of tropical deforestation. Bioscience, Vol 52, No 2, 143-150.

Ghose, M. K. and Majee, S. R. 2000. Assessment of the impact on the air environment due to opencast coal mining: an Indian case study. Atmospheric Environment. 34, 2791-2796.

Guha, R. 1993. This Fissured Land: An Ecological History of India. University of California Press.

Hancock, G. 2002. Sharing the Risks and Rewards of Mining. World Bank Mining Sector Technical Assistance Project.
http://www.wmmf.org/historical/2002docs/miningpeople/Mining_People_Hancock.pdf

Hartwick, J., 1977. Intergenerational equity and investing rent from renewable resources. American Economic Review 67 (5), 972–976.

Hedlund, U., Järvholm, B., Lundbäck, b. 2006. Persistence of respiratory symptoms in ex-underground iron ore miners. Occupational Medicine. 56, 380-385.

Hilson, G. 2002. Small scale mining and its socio-economic impact in developing countries. Natural Resources Forum. 26, 3-13.
International Labour Office. 1997. Encyclopedia of Occupational Health and Safety, 4th edn. Geneva: International Labour Office.

Joyce, S. 1998. Major Issues in Miner Health. Environmental Health Perspectives, Vol. 106, No. 11, A538-A543.

Kumar, A., Valecha, N., Jain, T., Dash, A. P. 2007. Burden of Malaria in India: Retrospective and Prospective View. The American Journal of Tropical Medicine and Hygiene. 77(6_Suppl), 69-78.

Lambert, d. 1992. Zero-inflated Poisson regression with an application to defects in manufacturing. Technometrics, 34, 1-14.

Lee, C. 2002. Environmental Justice: Building a Unified Vision of Health and the Environment. Environmental Health Perspectives. Vol. 110, Supplement 2, 141-144.

Lengeler, C. and Snow, R. W. 1996. From efficacy to effectiveness: insecticide-treated bednets in Africa. Bulletin of World Health Organization. 74 (3): 325-332.

Long, J. S. and Freese, J. 2006. Regression models for categorical dependent variables using Stata. 2nd edition. Stata Press.

Meltzer, M. WE. et al. 2003. The household-level economics of using Permethrin-treated bed nets to prevent malaria in children less than five years of age. American Journal of Tropical Medicine and Hygiene. 68(4 suppl), 149-160.

Miguel, E. and M. Kremer. 2004. Worms: Identifying impacts on education and health in the presence of treatment externalities. Econometrica. 72(1), 159- 217.

Misra, S. P. et al. 1999. Malaria control: bed nets or spraying? Spray versus treated nets using deltamethrin – a community randomized trial in India. Transactions of the Royal Society of Tropical Medicine and Hygiene. 93, 456-457.

NCAER. 1993. Evaluation survey of National Program on Improved Chulha, National Council for Applied Economic Research (NCAER), New Delhi.

Nuwaha, F. 2001. Factors influencing the use of bed nets in Mbarara municipality of Uganda. American Journal of Tropical Medicine and Hygiene. 65 (6), 877-882.

Patz, J.A. et al. 2004. Unhealthy Landscapes: Policy Recommendations on Land Use Change and Infectious Disease. Environmental Health Perspectives, Vol. 112, No. 10, 1092-1098.

Peters, C. M., A. H. Gentry, and R. O. Mendelsohn. 1989. Valuation of an Amazonian rainforest. Nature 339:655–656.

Pless Mulloli, T., D. Howel, et al. 2000. Living near opencast coal mining sites and children's respiratory health." Occupational and Environmental Medicine. 57(3): 145-51.

Randeira, S. 2003. Glocalization of Law: Environmental Justice, World Bank, NGOs and the Cunning State in India. Current Sociology, 51 (3/4), 305-328.

Rasmussen, R.O. and N.E. Koro leva, ed. 2003. Social and Environmental Impacts in the North .

Rew, A. and S. Khan. 2006. The Moral Setting for Governance in Keonjhar: The Cultural Framing of Public Episodes and Development Processes in Northern Orissa, India. Oxford Development Studies, Volume 34, Issue 1, 99 – 115.

Ripley, E.A., R.E. Redman, and A.A. Crowder. 1996. Environmental Effects of Mining.

Ross, M. H. and Murray, J. 2004. Occupational respiratory disease in mining. Occupational Medicine, 54, 304-310.

Ross, Michael L. 2001. Extractive Sectors and the Poor: An Oxfam America report. Boston, MA: Oxfam America. (Available at http://www.oxfamamerica.org/art545.html)

Sachs, J.D and A.M. Warner, 1997. Natural Resource Abundance and Economic Growth, NBER Working Paper Series, WP 5398, Cambridge: National Bureau of Economic Research.

Sachs, J.D and A.M. Warner, 2001. The Curse of Natural Resources, European Economic Review. 45: 827-838.

Sarangi, D. 2004. Mining ‘Development’ and MNC’s. Economic and Political Weekly, Vol. 39, No. 17, 1648-1652.

Saxena, N.C., G. Singh, and R. Gosh. 2002. Environmental Management in Mining Areas.

Sharma, S. K. et al. 2006. Effectiveness of mosquito nets treated with a tablet formulation of Deltamethrin for malaria control in a hyperendemic tribal area of Sundargarh district, Orissa, India. Journal of the American Mosquito Control Association. 22(1), 111-118.

Sinha, S., Bhattacharya, R. N., Banerjee, R. 2007. Surface iron ore mining in eastern India and local level sustainability. Resources Policy. Volume 32, Issues 1-2, 57-68.

Singh. G. and Sharma, P. K. 1992. A study of spatial distribution of air pollutants in some coal mining areas of Raniganj coalfield, India. Environment International. Volume 18, Issue 2, 191-200.

Smith, K.R., J. Zhang, R. Uma, V.V.N. Kishore and M.A.K. Khalil, 2000: Greenhouse implications of household fuels: an analysis for India. Annual Review of Energy and Environment, 25, 741-763.

Stephens, C. and Ahern, M. 2001. Worker and Community Health Impacts Related to Mining Operations Internationally: A Rapid Review of the Literature. Report prepared for the Mining, Minerals and Sustainable Development project. International Institute for Environment and Development (IIED).

Tata Energy Research Institute (TERI). 2001. Overview of mining and mineral industry in India. Report commissioned by the Mining, Minerals and Sustainable Development project. International Institute for Environment and Development (IIED).

Takken, W., Vilarinhos, P., Schneider, P., Santos, F. dos .2003. Effects of environmental change on malaria in the Amazon region of Brazil. In Environmental change and malaria risk: global and local implications: Proceedings of the Frontis workshop on Environmental Change and Malaria Risk: Global and Local Implications, Wageningen, The Netherlands 12-14 November; Wageningen UR Frontis series Vol. 9, 113 - 123.

Wallmo, K, and Jacobson, S. K. A social and environmental evaluation of fuel-efficient cook-stoves and conservation in Uganda. Environmental Conservation 25(2): 99–108.

Weber-Fahr, M. 2002. Treasure or Trouble?: Mining in Developing Countries. The World Bank and International Finance Corporation report.

Webster, D. 2001. Malaria kills one child every 30 seconds. Journal of Public Health Policy. 22(1), 23-33.

Wilkinson, P., K. Smith et al. 2009. Public health benefits of strategies to reduce greenhouse-gas emissions: household energy. Lancet. Vol 374 (9705), 1917-1929.

World Bank Report 2007. Towards sustainable mineral–intensive growth in Orissa - managing environmental and social impacts. Environment Unit, Sustainable Development Department, South Asia Region. Report No. 39878-IN.

Yadav, R. S., Ghosh, S. K., Chand, S. K., Kumar, A. 1991. Prevalence of malaria and economic loss in two major iron ore mines in Sundargarh District, Orissa. Indian Journal of Malariology. Vol. 28(2), 105-113.

Yadav, R. S., Sampath, R. R. and Sharma, V. P. 2001. Deltamethrin trated bed nets for control of malaria transmitted by *Anopheles culcifacies* in India. Journal of Medical Entolmology. 38(5), 613-622.

Yasuoka, J. and Levins, R. 2007. Impact of deforestation and agricultural development on Anopheline ecology and malaria epidemiology. American Journal of Tropical Medicine and Hygiene. 76(3), 450-60.

Appendix

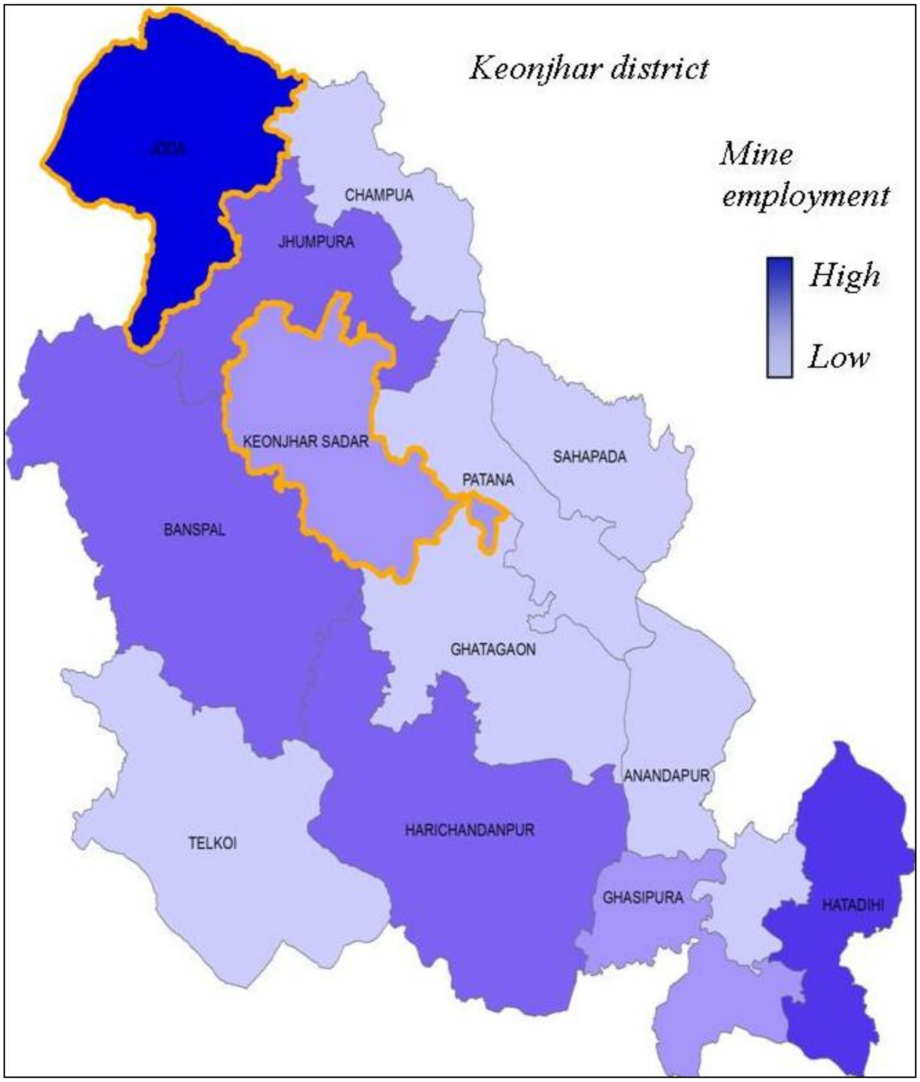


Figure 1. Two blocks chosen for the study – Joda and Keonjhar Sadar. According to the national census in 1991, 68% of reported mine workers in the district were in Joda block while Keonjhar Sadar reported only 1% of mine workers.

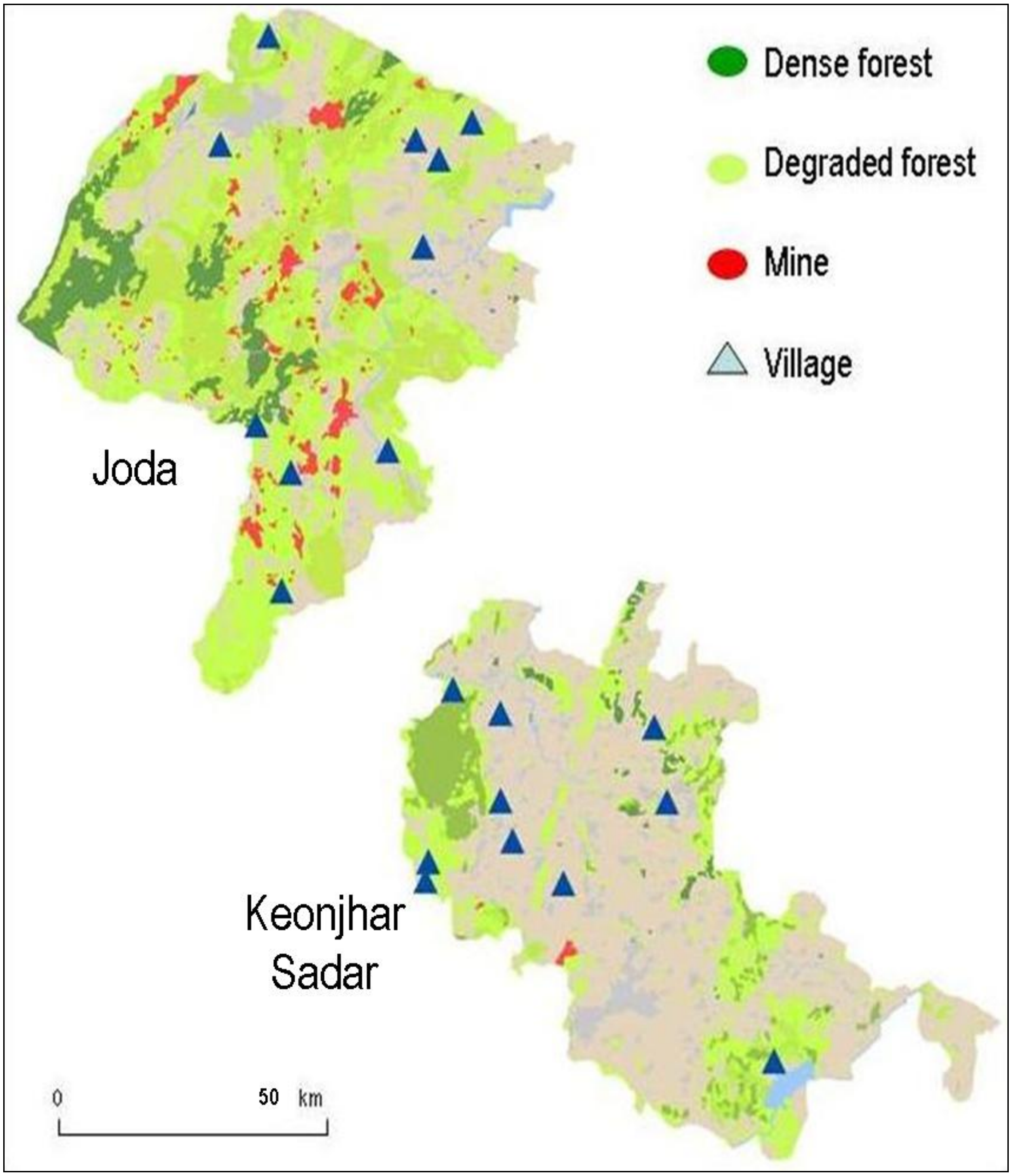


Figure 2. Classified land cover images showing the two blocks Joda and Keonjhar Sadar. The GIS data on the location of the mines and villages were used to calculate two measures of exposure to iron ore mines – Euclidean distance to iron ore mines and number of mines in a 2km buffer around each village

Table 1. Descriptive statistics of household and individual level variable used in the analyses

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Scheduled Caste | 600 | 0.07 | 0.25 | 0 | 1 |
| Scheduled Tribe | 600 | 0.68 | 0.47 | 0 | 1 |
| Log net firewood consumed (kg) | 600 | 3.85 | 1.37 | 0 | 6.58 |
| Participation in number of social organizations | 600 | 1.79 | 1.28 | 0 | 6 |
| Number rooms in house | 600 | 2.70 | 1.48 | 1 | 11 |
| Average amount of irrigated land around village | 600 | 2.78 | 3.72 | 0 | 12 |
| Change in forest cover within 2km village buffer (2004-1989) | 600 | 1.24 | 8.43 | -19.62 | 24.86 |
| Log distance to paved road (km) | 600 | 2.87 | 1.05 | 0.69 | 5.20 |
| Log distance to health center (km) | 600 | 3.41 | 1.06 | 0.69 | 5.08 |
| Log distance to market center (km) | 600 | 3.81 | 0.78 | 0.0 | 5.19 |
| Distance to iron ore mine (km) | 600 | 7.33 | 6.11 | 0.21 | 20.92 |
| Cash income from mines (Rs) | 600 | 6979.5 | 12383.9 | 0 | 108000 |
| Use of improved stoves | 600 | 0.01 | 0.10 | 0 | 1 |
| Use of partitioned kitchen | 600 | 0.53 | 0.50 | 0 | 1 |
| Use of bed nets | 600 | 0.53 | 0.50 | 0 | 1 |
| Participate in micro-credit organizations | 600 | 0.12 | 0.33 | 0 | 1 |
| Number of males | 2494 | 0.51 | 0.50 | 0 | 1 |
| Age of individuals | 2494 | 26.92 | 17.98 | 0.23 | 105 |
| Education of individuals | 2494 | 2.97 | 4.04 | 0 | 18 |
| Average hours working in mines | 2494 | 1.66 | 2,67 | 0 | 12 |

Table 2. Descriptive statistics of health outcome indicators for the full sample, and the two blocks separately

| Variable | Full sample | | | | Joda (*High exposure*) | | Keonjhar (*Low exposure*) | | Population weighted mean | Correlation with distance to iron ore mine |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Min | Max | Mean | SD | Mean | SD | | |
| Count of ARI incidence* | 1.0 | 1.2 | 0 | 6 | 1.2 | 1.3 | 0.8 | 1.2 | 1.0 | -0.16 † |
| Count of Malaria incidence* | 1.6 | 1.4 | 0 | 10 | 1.5 | 1.2 | 1.8 | 1.6 | 1.6 | 0.12 † |
| Expenditure on ARI (Rs) | 143.8 | 450.3 | 0 | 8750 | 158.5 | 287.0 | 129.0 | 568.8 | 146.1 | -0.02 |
| Expenditure on Malaria* (Rs) | 544.4 | 1110.1 | 0 | 17350 | 678.5 | 1349.0 | 410.2 | 782.9 | 557.2 | -0.09 † |
| Workdays lost due to ARI | 4.8 | 9.8 | 0 | 90 | 5.5 | 9.0 | 4.0 | 10.6 | 5.1 | -0.09 † |
| Workdays lost due to Malaria* | 16.0 | 17.4 | 0 | 160 | 19.5 | 19.6 | 12.5 | 13.9 | 17.0 | -0.16 † |

* t-test indicating means of Joda and Keonjhar blocks are significantly different at 5% level

† significance at 5% level

Table 3. Description of health indicators by sub-groups based on mine employment

| Variable | No member in family works in mine | | Other member in family working in mine | | Only individuals in family working in mine | |
|---|---|---|---|---|---|---|
| | *mean* | *st error* | *mean* | *st error* | *mean* | *st error* |
| Reported ARI | 0.21 | 0.01 | 0.23 | 0.01 | 0.22 | 0.02 |
| Workdays lost to ARI | 1.04 | 0.09 | 1.07 | 0.16 | 0.92 | 0.16 |
| Expenditure on ARI (Rs.) | 33.64 | 5.07 | 28.74 | 3.60 | 28.62 | 5.85 |
| Reported Malaria | 0.36 | 0.01 | 0.32 | 0.02 | 0.32 | 0.03 |
| Workdays lost to Malaria | 1.34 | 0.07 | 1.97 | 0.19 | 1.96 | 0.24 |
| Expenditure on Malaria (Rs.) | 105.18 | 9.31 | 110.49 | 10.49 | 151.79 | 39.08 |
| observations | 1867 | | 799 | | 283 | |

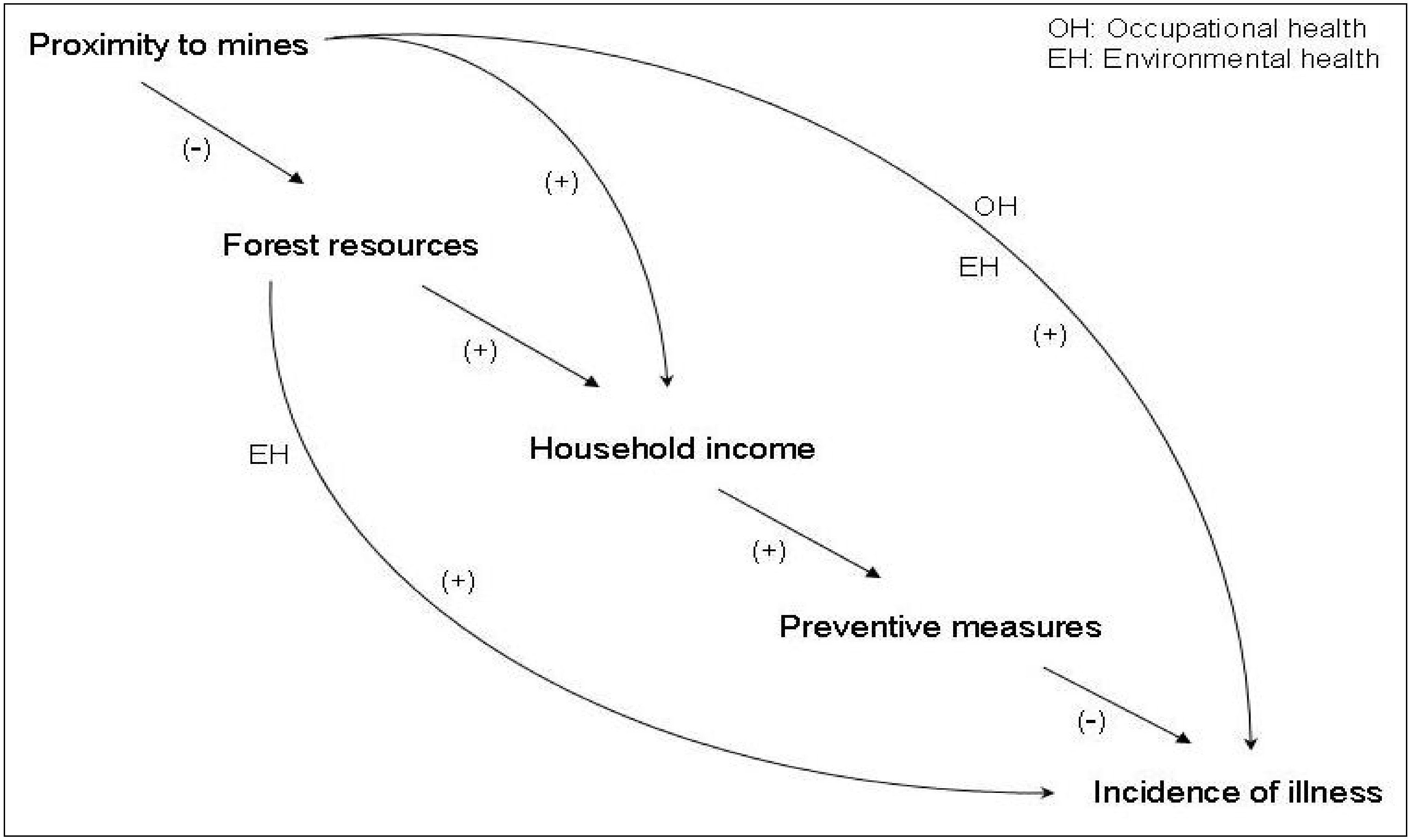


**Figure 3. Conceptual framework to analyze the impact of mines on health for the population living in close proximity**

The arrows indicate a causal link between different elements in the framework. A (-) sign indicates a negative relationship in the causal chain – for example, mining often involves clearing forests for excavation and thus proximity to mines reduces the availability of forest resources. On the other hand, an example of hypothesized positive relation between higher disposable income and higher adoption of prevention measures is indicated by a (+) sign.

Table 4. Probit model for incidence of ARI and malaria among individual family members (ivprobit in Stata)

| | probit for ARI | | | probit for malaria | | |
|---|---|---|---|---|---|---|
| | *dy/dx* | *st. error* [a] | *p-val* | *dy/dx* | *st. error* [a] | *p-val* |
| Dummy for male | 0.034 | 0.057 | 0.533 | 0.054 | 0.054 | 0.320 |
| Age | 0.000 | 0.002 | 0.841 | 0.002 | 0.002 | 0.231 |
| Scheduled Caste | -0.116 | 0.179 | 0.516 | -0.051 | 0.121 | 0.671 |
| Scheduled Tribe | -0.219 | 0.116 | 0.06 | -0.178 | 0.093 | 0.056 |
| Log of firewood consumed | 0.009 | 0.033 | 0.783 | | | |
| Average irrigated land around village | | | | -0.034 | 0.008 | 0.000 |
| Change in forest cover in a 2k buffer | | | | 0.004 | 0.005 | 0.353 |
| Log of distance to road | -0.057 | 0.054 | 0.296 | -0.028 | 0.052 | 0.592 |
| Log of distance to health center | 0.033 | 0.046 | 0.474 | 0.017 | 0.037 | 0.643 |
| Days worked in mine # | -0.001 | 0.001 | 0.045 | 0.001 | 0.001 | 0.343 |
| Distance to iron ore mine | -0.023 | 0.008 | 0.006 | 0.019 | 0.007 | 0.003 |
| Dummy for improved stove | -0.757 | 0.475 | 0.101 | | | |
| Dummy for partition in kitchen | -0.230 | 0.096 | 0.017 | | | |
| Dummy for use of mosquito nets | | | | -0.118 | 0.067 | 0.076 |
| | | | | | | |
| Number of observations | | 2949 | | | 2949 | |
| AIC | | 35241.6 | | | 35864.4 | |
| Log pseudo likelihood | | -17593.8 | | | -17904.2 | |

# Days worked in mines instrumented in a 2SLS model. Instruments used are distance to iron ore mine, average number of hours worked in wage employment, dummy if land owned and years of education.

a. Clustered robust standard errors by village

Table 5. 3SLS model for workdays lost due to ARI and malaria (reg3 in Stata)

| | Workdays lost to ARI | | | Workdays lost to malaria | | |
|---|---|---|---|---|---|---|
| | *coeff* | *st err* [a] | *p-val* | *coeff* | *st err* [a] | *p-val* |
| Dummy for male | -0.042 | 0.163 | 0.790 | 0.063 | 0.156 | 0.681 |
| Age | 0.007 | 0.004 | 0.110 | 0.005 | 0.004 | 0.238 |
| Scheduled Caste | -0.662 | 0.320 | 0.039 | -0.310 | 0.308 | 0.305 |
| Scheduled Tribe | -0.794 | 0.174 | 0.000 | -0.490 | 0.173 | 0.005 |
| Log of firewood consumed | -0.030 | 0.055 | 0.587 | | | |
| Average irrigated land around village | | | | -0.036 | 0.020 | 0.076 |
| Change in forest cover in a 2k buffer | | | | 0.024 | 0.009 | 0.009 |
| Log of distance to road | -0.065 | 0.073 | 0.368 | -0.018 | 0.072 | 0.802 |
| Log of distance to health center | 0.120 | 0.076 | 0.117 | 0.077 | 0.076 | 0.318 |
| Days worked in mine | -0.001 | 0.002 | 0.549 | 0.001 | 0.002 | 0.536 |
| Distance to iron ore mine | -0.026 | 0.014 | 0.066 | -0.085 | 0.014 | 0.000 |
| Dummy for improved stove | -0.909 | 0.734 | 0.216 | | | |
| Dummy for partition in kitchen | -0.289 | 0.150 | 0.054 | | | |
| Dummy for use of mosquito nets | | | | -0.254 | 0.151 | 0.090 |
| constant | 1.424 | 0.434 | 0.007 | 2.342 | 0.471 | 0.000 |
| Chi-squared | 35.34 | | | 0.03 | 79.83 | |
| Prob > Chi-Sq | 0.000 | | | | 0.000 | |
| | | | | | | |
| Days worked in mine | | | | | | |
| Distance to iron ore mine | -1.441 | 0.188 | 0.000 | | | |
| Daily hours in wage employment | 14.052 | 0.396 | 0.000 | | | |
| Dummy if land owned | -7.007 | 2.332 | 0.003 | | | |
| Years of education | 0.712 | 0.267 | 0.008 | | | |
| Constant | 11.100 | 2.091 | 0.000 | | | |
| Chi-squared | 1419.64 | | | | | |
| Prob > Chi-Sq | 0.000 | | | | | |
| Number of observation | 2949 | | | | | |

a Clustered robust standard errors by village.
# Days worked in mines instrumented in a 3SLS model. Instruments used are distance to nearest iron ore mine, average number of hours worked in wage employment, dummy if land owned and years of education.
Adding more variables like Scheduled caste, Scheduled tribe, age and sex to the first stage equation of days worked in mines did not change the signs and significance of coefficients in the equation of workdays lost.
Estimating the same models with the restricted samples where workdays lost due to ARI and malaria was <15 did not produce any significant changes to the results.

Table 6. Zero-inflated Negative Binomial model for workdays lost to ARI and Malaria

| | Workdays lost to ARI | | | Workdays lost to Malaria | | |
|---|---|---|---|---|---|---|
| | *coeff* | *st error* [b] | *p-val* | *coeff* | *st error* [b] | *p-val* |
| Dummy for male | -0.140 | 0.060 | 0.02 | 0.045 | 0.077 | 0.56 |
| Age | 0.001 | 0.003 | 0.76 | 0.001 | 0.002 | 0.73 |
| Scheduled Caste | -0.234 | 0.126 | 0.06 | 0.028 | 0.123 | 0.82 |
| Scheduled Tribe | -0.090 | 0.086 | 0.29 | -0.124 | 0.147 | 0.40 |
| Log of firewood consumed | -0.055 | 0.031 | 0.07 | | | |
| Average % irrigated land in 2kbuffer | | | | 0.031 | 0.022 | 0.15 |
| Decrease in forest cover | | | | 0.015 | 0.004 | 0.00 |
| Log of distance to road | 0.034 | 0.026 | 0.19 | 0.018 | 0.050 | 0.72 |
| Log of distance to health center | 0.102 | 0.049 | 0.04 | 0.045 | 0.053 | 0.39 |
| Days worked in mine | -0.004 | 0.007 | 0.50 | 0.000 | 0.001 | 0.84 |
| Distance to iron ore mine | -0.003 | 0.001 | 0.42 [a] | -0.074 | 0.013 | 0.00 |
| Dummy for improved stove | -0.116 | 0.074 | 0.12 | | | |
| Dummy for partitioned kitchen | -0.019 | 0.086 | 0.83 | | | |
| Dummy for use of mosquito nets | | | | -0.111 | 0.125 | 0.37 |
| constant | 1.846 | 0.241 | 0.00 | 1.815 | 0.389 | 0.00 |
| **Inflation equation:** | | | | | | |
| Household below poverty line | 0.462 | 0.107 | 0.00 | 0.160 | 0.119 | 0.18 |
| Log of distance to health center | -0.064 | 0.087 | 0.46 | 0.097 | 0.050 | 0.05 |
| Dummy for male | 0.005 | 0.088 | 0.96 | 0.147 | 0.074 | 0.05 |
| Age | 0.007 | 0.005 | 0.12 | -0.002 | 0.003 | 0.52 |
| Education | 0.035 | 0.016 | 0.03 | -0.028 | 0.020 | 0.15 |
| Scheduled Caste | 0.161 | 0.347 | 0.64 | 0.506 | 0.244 | 0.04 |
| Scheduled Tribe | 0.482 | 0.195 | 0.01 | 0.218 | 0.209 | 0.30 |
| Family size | 0.195 | 0.039 | 0.00 | 0.073 | 0.037 | 0.05 |
| constant | 0.266 | 0.433 | 0.54 | -0.318 | 0.324 | 0.33 |

a. Barely significant at the 15% level when the logarithm of distance to nearest iron ore mines is used.
b. Clustered robust standard errors by village.

Table 7. Probit models of adoption of preventive measures (ivprobit in Stata)

| | Use of bed nets | | | Use of improved stoves [b] | | | Better kitchen construction | | |
|---|---|---|---|---|---|---|---|---|---|
| | *dy/dx* | *st err*[a] | *p-val* | *dy/dx* | *st err*[a] | *p-val* | *dy/dx* | *st err*[a] | *p-val* |
| Dummy for land ownership | 0.143 | 0.079 | 0.06 | 0.238 | 0.001 | 0.02 | -0.002 | 0.051 | 0.95 |
| Dummy for participation in micro-credit group [c] | -0.123 | 0.074 | 0.09 | | | | 0.013 | 0.093 | 0.88 |
| Adoption by other members in same village | 0.02 | 0.005 | 0.00 | -0.113 | 0.304 | 0.44 | 0.007 | 0.006 | 0.24 |
| Participate in social organizations | 0.089 | 0.035 | 0.01 | -0.082 | 0.081 | 0.15 | 0.002 | 0.041 | 0.96 |
| Log of distance to markets | -0.001 | 0.031 | 0.97 | -0.278 | 0.154 | 0.59 | -0.008 | 0.027 | 0.75 |
| Number of rooms in the house | 0.135 | 0.028 | 0.00 | 0.097 | 0.217 | 0.19 | -0.171 | 0.019 | 0.00 |
| Days worked in mines [b] | 0.004 | 0.008 | 0.64 | 0.002 | 0.041 | 0.02 | 0.003 | 0.007 | 0.60 |
| | | | | | | | | | |
| Number of observations | 2949 | | | 528 | | | 2949 | | |
| Wald Chi-Sq. | 106.56 | | | 25.83 | | | 103.63 | | |
| Log pseudolikelihood | -1629.31 | | | -5697.66 | | | -1752.84 | | |
| Wald test for exogeneity: Prob > Chi_sq | 0.89 | | | 0.01 | | | 0.84 | | |

a. Clustered robust standard error by villages
b. Days worked in mines is treated as endogenous and instruments used are – distance to iron ore mine and average amount spent by household members in wage employment.
c. None of the families that adopted improved stoves participated in micro-credit organizations. The variable drops out of the equation.