Mining and Women's Agency: Evidence on Acceptance of Domestic Violence and Shared Decision-Making in India

Amanda Guimbeau[†], Xinde James Ji[††], Nidhiya Menon[†] and Yana van der Meulen Rodgers[‡]

version: October 21, 2022

Abstract

We study the impact of proximity to mineral deposits and active mines on women's agency in India. Identification leverages the plausibly exogenous spatial variation in the occurrence of mineral deposits and mineral types across districts. Results indicate that women's outcomes improve near mines: women have less tolerance of physical violence and they report fewer barriers to accessing healthcare. Concomitantly, men's likelihood of making decisions jointly with spouses increases, and men are less likely to justify domestic violence. These benefits are larger near mines that employ relatively high shares of women. The key mechanism is the sharing of mining royalties with local groups to support investments in vulnerable populations, which contributes to better economic conditions for women. Findings imply that mineral mining can bring measurable benefits to women's agency, especially when profits are invested in improving the welfare of local populations.

Key Words: Minerals, Mining, Women, Agency, Education, Health, Profit Sharing, India

JEL Codes: J12, J16, Q32, O13

Declarations of Interest: None

---

[*] Thanks to participants at ASSA, NEUDC, IZA/WB/NJD/UNU-WIDER Jobs and Development Conference, SEHO, IAFFE, WEAI, CMES, EEA, the International Conference in Development Economics, IFPRI, Cornell University, Haverford College, Washington and Lee University, Brandeis University, OSWEET, Australian Gender Economics Workshop, University of Arizona, and the UNU-WIDER conference for helpful comments and suggestions. Thanks to Dani Castillo and Yessinia Tejeda Lozano for excellent research assistance. The usual disclaimer applies. [†] Department of Economics, Université de Sherbrooke, Québec, Canada. Email: Amanda.Guimbeau@usherbrooke.ca [††] Food and Resource Economics Department, University of Florida, Gainesville, FL 32603, USA. Email: xji1@ufl.edu.[†] Department of Economics, MS 021, Brandeis University, Waltham, MA 02453, USA. Email: nmenon@brandeis.edu. [‡] Department of Labor Studies & Employment Relations, Rutgers University, 94 Rockafeller Road, Piscataway, NJ 08854, USA. Email: yana.rodgers@rutgers.edu

1. Introduction

Economic development and structural change do not necessarily bring gains for women and improvements in gender equality, especially if unpaid work burdens, biased laws, differential access to resources, and social norms constrain women's ability to take advantage of new, well-paid employment opportunities (World Bank 2011). Adding to these complexities, relatively little is known about how structural change associated with the natural resource extraction industry impacts women. The mining industry has long been considered an enclave with few benefits for local economies (Berman *et al.* 2017). The mining sector in India in particular has been shown to contribute to the election of criminal politicians, who then engage in further crimes to accumulate wealth if the value of minerals in their constituency rises exogenously during their term in office (Asher and Novosad 2021). Combined with other political economy considerations in which investment in mineral extraction is prioritized over other sectors, these adverse effects have contributed to the view of mining as a "resource curse" (Auty 1993; Bebbington *et al.* 2008; van der Ploeg 2011, James and Smith 2017).

A recent set of studies for sub-Saharan Africa have challenged this view. For example, Wilson (2012) finds that the 2003 to 2008 copper price boom reduced risky sexual behavior in Zambian copper mining cities, while Mamo *et al.* (2019) finds significant improvements in living standards as measured by night-lights in districts with new large-scale mining operations, albeit with few spillover effects to other districts. Fafchamps *et al*. (2017) notes that places with gold mines show signs of "proto-urbanization" – they have more advanced forms of economic activity and relatively higher population density. Lippert (2014) uncovers positive effects from copper mining on household expenditures and other measures of well-being, while Benshaul-Tolonen (2018) and Benshaul-Tolonen *et al*. (2019) show that open-pit gold mining causes a reduction in child mortality.[1] In sub-Saharan Africa, industrial mine operations contributed to a large employment shift for women away from agricultural self-employment toward wage employment and service-sector jobs that arose around the mining industry (Kotsadam and Benshaul-Tolonen 2016). However, this structural change could also have consequences for net income losses in the context of US (Jacobsen *et al*. 2021) and UK (Aragón *et al*. 2018), greater inter-personal conflicts in Congo (Parker and Vadheim 2017), and greater domestic violence

[1] In related work, Aragón and Rud (2013) find a positive backward linkage in terms of increased real income from a gold mine to surrounding areas in Peru.

against women in Sub-Saharan Africa where wife beating was more commonly accepted (Kotsadam *et al.* 2017). As noted in Benshaul-Tolonen and Baum (2021), the existing literature is inconclusive on whether mining empowers or disempowers women, especially in joint-family settings, in the case of violence between intimate partners, and on the topic of shared decision-making.

This study weighs in on the debate with new evidence on mining and women's agency in India.[2] In particular, we investigate whether proximity to deposits and active mineral extraction sites can reduce women's acceptance of intimate partner violence and improve their access to healthcare. We undertake this analysis by differentiating between mines that employ relatively high shares of female labor and those that do not. The rationale for highlighting variations in employment shares by gender is to test for Boserup's (1970) hypothesis that women's status is better when their labor is valued. That is, we take the plough-use versus shifting-cultivation intuition developed in Boserup (1970) and apply it to the mining industry. We further contribute to the literature by evaluating men's responses to improvements in women's agency in the proximity of mines, which, to the best of our knowledge, has not been considered in too much detail before. Although some evidence highlights the benefits of mining for economic growth, consumption, child health, and women's employment, relatively few studies have sought to place these results in the context of reverting regressive cultural norms and improving women's agency, which, in the end, may determine whether such gains are long lasting. Our study also highlights the importance of policies such as sharing profits and royalties from mineral extractions with local communities, which we find is a key mechanism for strengthening the welfare of vulnerable groups.

This research contributes to a better understanding of whether mining serves as a resource curse or blessing, as well as the avenues through which the mining industry affects women's decision-making power. Some studies have shown that measures of women's economic power, such as increased ownership of assets and greater education, are associated with a decline in domestic violence. The primary transmission mechanism is improved economic opportunities

[2] In the tradition of Sen (1999), we define agency as what a person is free to do and achieve in pursuit of whatever goals or values he or she regards as important, and the freedom to translate potential capabilities into achieved functionings. As in Gammage *et al.* (2016), we consider empowerment as an expansion of agency. This conceptualization helps to reconcile the observation that some studies consider the outcome variables we use as measures of women's agency and others consider them as measures of women's empowerment.

for women outside the household which strengthens their bargaining power within the home (Chatterjee and Poddar 2020) and serve to protect them against violence (Barros and Xu 2020). In this context, even if the budget of the household remains constant, women's asset ownership and increased human capital may strengthen their negotiating power by improving their fallback position (Panda and Agarwal 2005, Aizer 2010, Bobonis *et al.* 2013). However, changes that strengthen women economically could also contribute to a backlash effect. For example, in Bangladesh, increased female labor force participation is associated with higher rates of violence for some women as husbands try to counteract the increased autonomy of their wives (Heath 2014). Cools and Kotsadam (2017) and Bhalotra *et al.* (2021) also find evidence of backlash as improvements in education and employment for women are associated with a higher probability of experiencing intimate partner violence. Our study reveals that acceptance of oppressive norms declines among both men and women near mines that value female labor, and where policies that encourage profit sharing with local communities are in place. However, this is mostly true for older women and men.

The empirical analysis uses India's 2015-2016 Demographic and Health Survey, which includes geographic locations for surveyed clusters that we match with the geo-referenced location of mineral deposits and mines. Data from many additional sources are used to construct the overall study sample. The analysis employs a geospatial cross-sectional approach that considers differential impacts by their proximity to mines conditional on the existence of mineral deposits. That is, we leverage the fact that individuals cannot influence which regions have deposits and which do not, and the presence of active mines in close vicinity, to determine treatment impacts. Using this framework, we estimate the impact of proximity to mineral deposits and mines on women's acceptance of domestic violence and reductions in reported barriers to accessing healthcare.

We find significant associations between these measures of women's agency and proximity of deposits and mines. Acceptance of intimate partner violence and barriers to accessing healthcare are negatively associated with distance to deposits and mines, especially for older women (those over 25 years of age). Importantly, these benefits are strongest near mines that employ relatively high shares of women. In addition, men's propensities to make decisions jointly with their partners increase in the close vicinity of mines, and men are less likely to accept that physical violence is justified. A key channel for these effects is legislation that requires mining companies to re-invest a fixed proportion of their profits back into local communities. This effort to estimate the mechanism for the observed impacts builds on the seminal work of Dell (2010) on the long-term effects of the forced mining labor system in Peru and Bolivia several centuries earlier.[3] Finally, we conduct a number of checks to validate the robustness of the results, including a spatial randomization test and falsification tests.

2. Background

India is rich in mineral and metal deposits. The country produces almost 84 minerals for an aggregate production of over 1 billion tons (India Bureau of Mines 2015). The main minerals include iron ore, manganese ore, bauxite, copper ore, lead and zinc ore, dolomite, limestone, and coal. The country also has stores of copper, gold, silver, diamond, nickel, and cobalt. Mining in India is associated not only with revenue gains but also environmental losses, especially deforestation (Ranjan 2019). Average daily employment in mines is around 512,000 workers in the organized sector.[4] An unorganized sector exists, but it is difficult to get a consistent set of employment numbers here. Closely related is small-scale and artisanal mining, some of which is organized. Estimates in Ghose (2003) indicate that small-scale mines account for about half of the country's non-fuel mineral production, with a total employment of about 300,000 workers.

Female employment shares in mining are on average low. Data from the annual Government of India Ministry of Labor and Employment publication of the *Statistics of Mines in India Volume – 1 (Coal) and Volume – II (Non-Coal)* indicate that from 2010 to 2015, only 6.0 percent of all workers were women across all minerals/metals. However, female employment shares vary drastically by type of minerals. For example, the percent female in quartz mining is 18.3 percent, in apatite rock phosphate mining 14.7 percent, and in dolomite mining 12.9 percent. Other minerals/metals that have relatively high female representation include sillimanite, barytes, garnet, fire clay, fluorite, manganese, graphite, wollastonite, feldspar, and

[3] Dell (2010) set a precedent in utilizing georeferenced data to explore the social impacts of mining. However, this study pays little attention to gender.

[4] Fuel accounted for 74 percent of total employment in mining during 2013-14, with coal and lignite accounting for 93 percent of the labor force in fuel. Metallic minerals accounted for 15 percent of mining employment with iron ore, manganese ore, lead and zinc concentrates, bauxite and chromite employing 49 percent, 18 percent, 9 percent, and 8 percent of the workforce in metallic minerals, respectively. Non-metallic minerals accounted for 11 percent of employment in mining, with limestone, dolomite and garnet, steatite, kaolin and quartz employing the highest shares (*Indian Mineral Industry at a Glance*, 2013-2014, India Bureau of Mines).

magnesite. Many such minerals are classified as precious minerals and metals. In fact, five of the eight precious minerals/metals had more than the mean percent female in 2010-2015 (the exceptions being diamond, gold, and kyanite).[5,6] In contrast, the workforce in coal mining is only 2.8 percent female. Appendix Figure 1 shows employment shares of men and women in 2010-2015 across broad mineral classifications.

This study examines minerals/metals that have relatively high shares of female workers separately, denoting these as "HFLS" (high female labor shares). We presume that if men are required for mining minerals that require greater physical strength as operations go deeper underground, then women's status is relatively weaker in the surroundings of such mines (as in coal mining). In contrast, the process of mining minerals found closer to the surface does not require intensive brawn-based labor (as in quartz mining), so women's relative overall standing ought to be higher. Tabulation tests reveal that among the few women employed in mining in the DHS data (there are too many missing values in this variable which is why we do not use it in our models), 70% are engaged in working in a surface mine as opposed to an underground mine. If we condition instead on all women who reported working in the last year, 78% are engaged in work in a surface mine relative to an underground mine. Hence, of those women engaged in mining, the vast majority work in surface mines where the need for brawn-based labor is likely to be lower. To test the hypothesis that women's status should be relatively higher in the processing of minerals that are found closer to the surface, we construct separate measures for the type of active mine (all active mines versus HFLS active mines) in order to evaluate whether women's outcomes are relatively better in the vicinity of HFLS mines. We do this using details on the identity of the mineral/metal that is mined.[7] We classify 22 minerals/metals as "HFLS" where female employment shares exceed the mean value of 6.0 percent. In addition to those noted above, they include magnesite, feldspar, silica, vermiculite, wollastonite, manganese, quartz, calcite, laterite, china clay and white clay, chromite, fire clay, garnet, bauxite, steatite, barytes and stone.

[5] The list of precious minerals/metals include apatite rock phosphate, diamond, dolomite, fluorite, gold, graphite, kyanite and sillimanite.
[6] There are few details on the demographic characteristics of these women in India. Evidence from Zimbabwe indicates that the mean age of women employed in gold panning is about 22 years (ILO 1999).
[7] To be clear, we do not have data on the actual number of women employed in each mine. We proxy for this using the (exogenous) presence of a deposit in close proximity and the (exogenous) presence of certain mineral types that are more conducive to the utilization of women's labor such as quartz.

3. Data

This study uses the 2015-2016 wave of India's Demographic and Health Survey (DHS – 4), a large nationally representative household survey with detailed information on individual and household characteristics for women aged 15-49, children aged 0-5 years, and men aged 15-54 years. This is the only wave of India's DHS surveys that includes geocoded spatial data documenting the geographic location of survey clusters. Using the micro-level data from the DHS – 4 for women and geocoded locations of mineral deposits and active mines from the *Mineral Atlas of India* (Geological Survey of India, 2001) and the *United States Geological Survey (USGS)*, we construct a novel database of women's agency and human capital measures and proximity to mines. We complement this data with various proxies for mining activities at the district level constructed from official reports from the India Bureau of Mines.

3.1 Demographic and Health Survey data

In the DHS – 4, women are asked about their background, employment, types of earnings, and agency (including barriers to accessing medical treatment, mobility, and attitudes toward domestic violence).[8,9] One eligible woman per household was randomly selected to answer the domestic violence module, with the vast majority (95 percent) of these women being married. Questions in the module were asked only if privacy was possible – this was the case for 96 percent of the eligible women (IIPS and ICF 2017). We use this nationally representative sample of women to measure women's agency and experience of violence; these measures have also been used in other studies based on the DHS data for Africa (Benshaul-Tolonen 2018, 2019). The male survey had a final response rate of 92 percent; our male sample for the analysis of shared decision-making and justification of physical violence consists of married men only. Our sample size for children ages five and below with data on anthropometrics is approximately 20,000 after the merging process with the mining data. The DHS – 4 is a stratified two-stage nationally representative sample, and the 2011 census is used as the sampling frame for the selection of Primary Sampling Units (PSUs). The PSUs (or clusters) correspond to villages in

[8] Although these data are self-reported, researchers evaluating the DHS have generally agreed that the strengths of the DHS outweigh the weaknesses (Corsi *et al*. 2012).
[9] The women's employment indicator does include mining as a category. However, there are too many missing values in this variable for us to be able to use it reliably.

rural areas and to Census Enumeration Blocks (CEBs) in urban areas. We obtain geographic coordinates for the surveyed DHS clusters and use them to match respondents to mineral deposits and active mines in their proximity.[10,11]

3.2 Deposit and Mining Data

We use the *Mineral Atlas of India* (Geological Survey of India, 2001) to obtain the type, location, and size of mineral deposits. The Atlas contains 76 map sheets depicting the geographic distribution of mineral deposits across the country. The map sheets also provide information on other geological features including lithology rock type, the age of the host rocks, the size – which is proportional to the number of metric tons of deposit reserves at each site, and the main mineral present. We geocode all the map sheets to obtain the deposits' geographic coordinates needed to construct the proximity measures. Given information on the presence of mineral types at each site, we create variables to measure proximity to different types of HFLS minerals.

Figure 1 shows the geocoded deposits of various types overlaid on India's district boundaries. A higher concentration of deposits exists in the Eastern, Northwestern, and Central states. In all, our geo-referencing exercise allows us to locate 2,553 deposits across the country. Data on the location of mines is obtained from the *United States Geological Survey (USGS)* dataset of past, current, and future (prospected) industrial mines.[12] We compile the USGS data using the *National Minerals Information Center for Asia and Pacific* (2010), which provides the maps of mineral facilities in India, and by using the *Mineral Resources Data System* (2007), which provides a collection of reports for metallic and nonmetallic mineral resources throughout the world.[13] For reference, Appendix Figure 2 shows an example of a map sheet from the Mineral Atlas, and Appendix Figure 3 shows the distribution of active and inactive mines.

3.3 Other Issues and Data

Mining companies are driven by the profit motive at every stage of the "mining sequence" going from exploration to commercialization (Mamo *et al*. 2019). Surprisingly, the

---

[10] Since DHS surveys contain sensitive information, the precise location is not provided. Rather, urban clusters and rural clusters are displaced up to 2 and 5 kilometers, respectively (the displacement method does not move households across any regional boundaries though). This should not affect results as the measurement error is orthogonal to our variables of interest (Burgert *et al*. 2013).

[11] Out of the 28,522 clusters, we cannot obtain the coordinates of 131 clusters as the source of data used is neither from the Global Positioning System (GPS) nor from a gazetteer of village/place names. These clusters have (0,0) coordinates and are excluded from our analysis.

[12] The USGS data for India does not provide information on start dates of mines.

[13] Most records for India are basic reports of the type of minerals in some locations, with a few reporting the deposit names, location, commodities, geologic characteristics, resources, reserves, and production.

presence of infrastructure such as electricity or connectivity as measured by railway density do not predict areas where exploration occurs, suggesting that mining is drawn to regions that are relatively more remote (Mamo *et al*. 2019). This is true in our data as well. Following Mamo *et al*. (2019), we check whether local development drives mining in mineral rich states by regressing the presence of an active mine within 5 km on having electricity and piped water conditional on a geographical control (altitude of the cluster) and regional (district) fixed-effects. The coefficient on electricity is -0.005 with a standard error of 0.013, and the coefficient on piped water is 0.007 with a standard error of 0.016. Thus both coefficients are not significant. A F-test that these impacts are jointly equal to zero cannot reject the null (F-statistic=0.280 with a *p*-value of 0.838). Hence, the presence of water and electricity does not predict the presence of an active mine within 5 km.

We next check the reverse, that is, whether mining drives local development. We first evaluate whether the presence of an active mine within 5 km predicts the presence of piped water. In this case, the coefficient on active mine is 0.016 with a standard error of 0.036. We then analyzed whether such mines predict the presence of electricity. Here the coefficient on active mine is -0.007 with a standard error of 0.016. Hence, there is no reverse effects either in that the presence of active mines in close proximity does not drive subsequent local development. In summary, controlling for the local level of development and geographical factors such as the cluster's altitude, presence of electricity and piped water do not predict the presence of an active mine within 5 km in mineral rich states. Conversely, having an active mine at this proximity has no predictive power (is insignificant) in explaining the presence of electricity or piped water conditional on local geography and regional fixed-effects.

Furthermore, far-flung areas removed from urban locations in India are unlikely to be those with progressive gender attitudes, and the fact that mining companies take norms and women's well-being into account while deciding placement of new mines seems implausible. Male and female employment shares are likely decided with a view to maximizing profits; local attitudes to gender equality are unlikely to shape these decisions. Hence, reverse causality is less of a concern in our study. Closely related, we argue that the location of mineral deposits is an exogenous variable in that it cannot be influenced by any individual's actions. Further, even if the discovery of deposits is the outcome of investment decisions (in the form of mineral exploration)[14], it is highly unlikely that they are endogenous to women's agency (companies driven by a profit motive are unlikely to take local gender norms into consideration). The rationale for this assertion draws on Eggert (2002). In particular, while the placement of mineral deposits is random, their discovery may not be. The literature suggests that discovery may depend on three factors that include access to and relative price of inputs, transportation costs, and agglomeration costs. However, if selection into being a mining area is based on factors that are stable over time, these may be controlled for using district fixed-effects (as we employ). Similarly, Fafchamps et al. (2017) notes that exploitation of gold deposits may depend on accessibility and profitability. However, the geological structure of the sub-soil is the essential determinant of cost differences across locations, and this is likely to be exogenous. By using fixed-effects estimation, many of these confounding factors can be controlled for. Finally, in one of its annual reports, India's Ministry of Mines states that "…the main factors responsible for lack of adequate investments into the mineral sector were procedural delays in processing of applications for mineral concessions and absence of adequate infrastructure in mining areas," (Mining Sector 2014). None of these sources point to the importance of labor supply or suggest that for certain types of mines in India, labor supply needs are targeted by gender.

Another potential issue is if the treated and control groups (areas close and far from mines) are systematically different, then there may be omitted variable bias. For example, they may have different infrastructure or receive different government policies. To help address this problem, the empirical model we employ controls not only for district-level fixed-effects but also for levels of local development (including the degree of urbanization, population density, and infrastructure). To do so, we incorporate the log of the Global Human Footprint (GHF) provided for each cluster, which ranges from 0 (extremely rural) to 100 (extremely urban). This index is the normalized version of the Human Influence Index (HII) - a global dataset available at a spatial resolution of 1 by 1 km grid cells and created from 9 data layers covering human access (roads, railroads, navigable rivers, coastlines), human population pressure (population density), human land use, and infrastructure (night-time lights, land use/land cover, and built-up areas).[15]

[14] The discovery of deposits being linked to investment decisions is already unlikely since our deposit location data draws from government-run geological surveys rather than industry reports.
[15] The GHF index is the HII normalized by biome and realm developed by the Last of the Wild Project (LWP-2). The average of an index is for the location within a 2 km (urban) or 10 km (rural) buffer surrounding the DHS

Indicator variables from the DHS – 4 are also included for whether the main source of drinking water in the household is piped water, and whether the household has access to electricity.[16] We also restrict the analysis to those who live within 100 km of mineral deposits in order to minimize the influence of unobserved heterogeneity and selection bias. Finally, we use propensity score matching methods discussed below to demonstrate that our results are robust to possible differences in observable characteristics.

Our study includes information from various government reports. We use the annual publications *Statistics of Mines in India* from the Directorate-General of Mines Safety (Ministry of Labor and Employment) from 2010 to 2015 to compile district-level data on employment.[17] To classify Indian districts into high, medium, or low mineral potential districts, we use the *Bulletin of Mining Leases and Prospecting Licenses*, an annual publication of the India Bureau of Mines. These reports are available from 2000 to 2015 and provide district-level mining areas as well as the state-wise, district-wise, and mineral-wise distribution of mining leases granted, executed, renewed, and revoked. Appendix Figure 4 shows the share of leased area in 2014 across India with the high/medium mineral potential districts. As of 2014, the *Mining Lease Directory* reports that there were 10,982 mining leases granted for 64 different minerals. Finally, we obtain the district-level production data from the *Indian Minerals Yearbooks* (Part III – Mineral Reviews) from 2011 by digitizing the entire database of 70 minerals and aggregating across minerals. Domestic and foreign market prices are also from the same yearbooks (Part I – General Reviews).

3.4 Summary Statistics

Table 1 reports the sample statistics for women. Panel A shows the summary statistics for the binary variables that equal 1 if the woman respondent agrees to the statement that beating is justified for the set of reasons listed. On average, 37 percent of women consider beating to be justified if the wife neglects children, while 30 percent report that they agree that domestic violence is justified if she goes out without telling her husband. The index variable equals 1 if the

---

survey cluster. See Wildlife Conservation Society, and Center for International Earth Science Information Network-Columbia University-2005: "Global Human Footprint Dataset."

[16] Although the GHF data are as of 2005 and thus a decade before the DHS round we use, we cannot be certain that these were collected before mining operations began as we do not know the start date of mines.

[17] Statistics of Mines, Volume II for non-coal mines provide statistics for metalliferous and oil mines. Data on employment is available on a gender-disaggregated basis. Data on output and average weekly wages are only reported on an aggregate basis.

woman agrees that beating is justified in each of the five cases. It indicates that on average, 27 percent of women consider beating to be justified. Although relatively high, this share is lower than that reported for countries in Sub-Saharan Africa.[18] An average of 14 percent report that they have experienced at least one form of emotional violence recently (this is one of the few variables pertaining to actual experience of violence asked in the survey).

In Panel B, we consider the barriers women face when seeking healthcare for themselves. Approximately 18 percent, 26 percent, and 19 percent report that seeking permission, obtaining money, and the fear of going alone to the health provider, respectively, are serious hurdles. Summary statistics for variables related to human capital, profit sharing, and financial independence variables are in Panel C. Of note, 36 percent of women report that they are in the workforce, with the majority working in agriculture. Panel D reports the statistics for the individual/household controls.

In Appendix Table 1, we report and discuss the summary statistics for married male respondents in the DHS – 4. We use these data to evaluate whether men's attitudes towards domestic violence and shared decision-making change in ways that are consistent with our findings for women.

To quantify treatment, we calculate distances to the nearest deposit and to the nearest active mine for each cluster's centroid in the DHS – 4. These measures vary considerably across clusters with means of 29.6 km and 45.3 km, respectively. We then define an indicator variable labeled as "deposit" that equals 1 if there is a mineral deposit within 5 km of the respondent's cluster. Another indicator variable labeled as "active mine" equals 1 if there is an active mine within 5 km, and "HFLS active mine" equals 1 if there is an active HFLS mine within 5 km. Our main treatment variable of interest is the interaction of "deposit" and "HFLS active mine". We also construct indicators for intensity, which are measured using counts of deposits within a 5 km radius of clusters. Appendix Table 2 reports summary statistics for the proximity variables and intensity variables. Of the 33,179 women who were selected for the domestic violence module, the mean values in Appendix Table 2 indicate that about 2,223 live within 5 km of a deposit, around 1,261 live within 5 km of an active mine, and approximately 896 women live within 5

[18] Benshaul-Tolonen (2019) notes that in a DHS sample of eight Sub-Saharan countries from 1993 to 2012, the corresponding mean value for the index variable is about 40 percent. Further, there has been no change in women's experience of violence (in the previous 12 months) as compared to DHS – 3 for India from 2005-2006.

km of an HFLS active mine. These are national weighted estimates. If we consider only those states that are rich in mineral deposits such as Andhra Pradesh, Bihar, Madhya Pradesh, Maharashtra, Orissa and West Bengal, these means (and numbers) are higher. The means are also higher if we consider the presence of deposits and mines at larger distances. We focus on the 5 km distance given average commuting distances in India (discussed below), and to be consistent with others in the literature (von der Goltz and Barnwal 2019).

4. Methodology

In the baseline specification, we regress measures of women's acceptance of domestic violence and barriers to healthcare on proximity to deposits and active mines. While past literature (e.g. Kotsadam and Benshaul-Tolonen 2016; Benshaul-Tolonen 2019) relies on spatial-temporal variations, we are unable to do so because the DHS-4 is the only round of DHS India data that provides geo-locations for clusters. Instead, we rely on a cross-sectional regression model that leverages the exogenous spatial variation in the presence of deposits and the types of minerals present in these deposits. Our main estimating equation, Equation (1), is as follows:

$$Y_{icd} = \beta_0 + \beta_1 deposit_c + \beta_2 activemine_c + \beta_3 young_{icd} + \beta_4 (deposit_c \times activemine_c) + \beta_5 (deposit_c \times young_{icd}) + \beta_6 (activemine_c \times young_{icd}) + \beta_7 (deposit_c \times activemine_c \times young_{icd}) + \beta_8 X_{icd} + \lambda_d + \epsilon_{icd} \qquad (1)$$

where Y_{icd} is the outcome for individual *i* in cluster *c* in district *d*. The presence of underground mineral deposits, the indicator variable $deposit_c$, equals 1 if there is a deposit within 5 km of a respondent's cluster. We begin with a cut-off distance of 5 km following von der Goltz and Barnwal (2019), and then consider other radii of 10, 15, 20, 25, and 30 km around mines. Appendix Boxes 1 and 3 present evidence that the proportion of workers in India who travel 5 km or less to access their place of work is approximately 70 percent; this justifies our focus on the 5 km distance around clusters at baseline. We restrict the sample to individuals living within 100 km from a mineral deposit in order to reduce the influence of unobserved heterogeneity and selection bias, similar to other studies including Benshaul-Tolonen (2019).

The indicator variable $activemine_c$ equals 1 if there is at least one active mine within 5 km of the respondent's cluster. Following Benshaul-Tolonen (2018, 2019), the treatment variable is the interaction term ($deposit_c \times activemine_c$), which has the coefficient β_4. This interaction term equals 1 when the respondent is geographically close to an active mineral mine conditional on the presence of a deposit. We follow the literature and condition on deposits as well, similar to the framework in equation (1) of Benshaul-Tolonen (2019) and equation (1) of Benshaul-Tolonen et al. (2019). Conditioning on deposits in addition to active mines makes the specification more robust in that only legitimately active mines will operate in the vicinity of deposits. Following the literature on rent-seeking of resources from mining (Asher and Novosad 2021), we condition on both active mines and deposits.

Further, a research design where the treatment variable is the interaction term $(deposit_c \times activemine_c)$ indicates that the effect of being close to a deposit differs for areas close to and far away from an active mine. This is consistent with the evidence in the Appendix on choice of baseline distance, determination of treatment distance, and Section 7.1., which also evaluates the appropriate treatment distance. The evidence here indicates that given the presence of an underground deposit, the impact of an active mine is primarily at distances less than 20 km, which is consistent with the literature. Beyond this cut-off, effects are less evident. We focus on active mines within 5 km given the overall evidence presented in these sections, and primarily the commuting distance of a typical worker in India (which is detailed in Appendix Box 1).

The variable $young_{icd}$ equals 1 if the respondent is 15-25 years old: we allow for differential impacts by age as younger women are likely to have different lived experiences than older women.[19] The proportion of young women between the ages of 15 and 25 years in our sample is 17.1 percent. We include the triple interaction term $(deposit_c \times activemine_c \times young_{icd})$ to estimate additional treatment impacts of proximity to deposits and active mines for women in the younger age group. Results tables include F-test statistics that these differential impacts for young women are significantly different from zero.

The vector of individual controls X_{icd} includes the following individual, household, and contextual variables: differences in wife and partner's/husband's age, indicators for the woman's highest level of educational attainment, indicators for the partner's/husband's level of educational attainment, an indicator for whether the respondent's father used to beat their mother, number of living children in the household, a rural/urban dummy, number of years the

[19] We take heterogeneity in age into account in our main estimating model to be consistent with the literature (Benshaul-Tolonen 2019). The control variables included in X_{icd} make it unlikely that age proxies for household income, for example.

respondent has been living in the current place of residence (to address migration), and the three indicators of local development discussed above. The parameter λ_d represents district fixed-effects, and ϵ_{icd} is the idiosyncratic error term. Regressions are weighted to adjust for the selection of a single woman per household and to ensure that the sample is representative (Elkasabi *et al*. 2020). We report robust standard errors clustered at the DHS cluster level. We estimate Equation (1) for the full sample of deposits and active mines, and separately for deposits and HFLS active mines.

The use of district fixed-effects allows us to control for geographic contingent characteristics that could explain differences between treated and control groups, including institutional factors, sectoral composition, cultural norms pertaining to women's role in the economy and at home, and district-level extractive industry strategies. These characteristics also include factors that large mining companies may internalize in their cost-benefit analyses of location choice. Unobserved differences at the district level, such as the ease of doing business, transparency, governance practices, levels of corruption, and other factors not related to resource endowments, are also controlled for by the fixed-effects. Alternatively, we estimate impacts conditioning on a count variable for the number of deposits in a 5 km vicinity of clusters (intensity).[20] All tables with results report estimates for both proximity and intensity.[21]

5. Results for the Impact of Mines

5.1. Women's Acceptance of Domestic Violence

Table 2 reports the β_4 and β_7 terms from Equation (1) for women's acceptance of different justifications given for domestic violence. Panel A reports results for coefficients that condition on the presence of a HFLS mine within 5 km, whereas Panel B reports results for all mines within 5 km. To be clear, among all women who are within a 100 km distance from a cluster's centroid, the "treatment" in Panel A conditions on being within 5 km of a deposit *and* within 5 km of a HFLS active mine. In Panel B, in a 100 km distance, the "treatment" conditions

[20] The USGS data for India that we use indicate that conditioning on the actual number of active mines (as opposed to at least one active mine) would yield similar estimates as in most cases, actual numbers in a 5 km vicinity range from 0 to 1. Conditioning on an indicator variable for active mines seems most consistent with our geospatial framework.

[21] The geospatial design is less likely to be impacted by the fact that we do not have data on the number of women employed in these mines. Even if we had this information, the presence of an unorganized sector would mean that results generated are at best an underestimate of impacts.

on being within 5 km of a deposit and within 5 km of any active mine. The dependent variables take a value of 1 if the female respondent says that she considers that beating is justified for reasons reported in each column. In column (6), the index ranging from 0 to 1 is constructed from the answers to the five questions on attitudes towards domestic violence. It equals 1 if the respondent says that beating is justified in each case. In column (7), “emotional violence" is a variable that equals 1 if the respondent says that she has experienced one of three possible examples of emotional violence listed in the survey (partner humiliates you, threatens to harm you or someone close to you, or insults you).[22]

Focusing on Panel A, the β_4 coefficients reported are negative in all instances and measured significantly in columns (1), (3), and (6). The estimates in column (1) indicate that in comparison to women in the control group, those in the proximity of deposits and active HFLS mines are 22.4 percentage points less likely to accept that violence is justified for going out without permission. Similarly, those near HFLS mines are 45.4 percentage points less likely to accept that violence is justified for arguing with one’s husband or partner. The coefficient on the index variable reveals that those near such mines are 19.9 percentage points less likely to accept that violence is justified overall, as compared to other women (all women in the control group – that is, those who do not live within a 5 km radius of HFLS active mines and deposits – for whom the indicator variables equal zero). Given that the mean for the index variable is about 27 percent (Table 1), this is a relatively large effect. When we consider the differential impacts on the young, these are mostly positive and significant except in the case of column (5). Correspondingly, net effects for young women are positive and significant in all cases except for columns (3) and (5), indicating that in comparison to older women near HFLS mines and women in the control group further away from HFLS mines, this demographic is more accepting of domestic violence. Focusing on the index measure, the estimate indicates that young women are 21.6 percentage points more likely to accept that violence is justified in these cases. This result is consistent with evidence in Cools and Kotsadam (2017), Kotsadam *et al*. (2017), Eze (2019), and Bhalotra *et al.* (2021).

A reason why effects of this nature might affect younger women specifically is because there is evidence that women’s younger age is associated with lower status, and because older

[22] Observation numbers in Table 2 for each of the outcomes differ slightly because of a small number of missing values.

women often have more bargaining power in intra-household settings in India. For example, Coffey *et al*. (2015) finds that children of the youngest daughter-in-law are shorter in stature than the children of the eldest daughter-in-law in joint families resident in the same household, as power dynamics imply that the youngest women have the lowest social rank. Furthermore, co-residence with mothers-in-law inhibits daughters-in-law's mobility and the ability to form connections, which, in turn, affects their reproductive health (Anukriti *et al*. 2020). Concentrating on the mineral rich states of Andhra Pradesh, Bihar, Madhya Pradesh, Maharashtra, Orissa and West Bengal, there is very little evidence that young women are more accepting of violence in the proximity of HFLS mines (Appendix Table 3). Impact of proximity to HFLS mines in southern states where outcomes are known to be more favorable towards women could not be identified because these states have relatively low levels of mineral deposits (and HFLS mines) in comparison to the northern and eastern states. One reason (among others) for the north-south gradient in women's outcomes is the relatively more skewed sex ratios in the north, which is similar in spirit to the findings in Baranov *et al*. (2021). We conclude that greater agency in terms of decreased acceptance of physical violence in the proximity of HFLS mines is most evident among women who are older than 25 years in our sample.

Next, the second half of Panel A in Table 2 reports the impacts of the number of deposits. The β_4 coefficients are uniformly negative across all columns, although only those in columns (1), (3), and (6) are statistically significant. Focusing on the index measure, the coefficient in column (6) indicates that compared to women in the control group, women near HFLS mines are 21.5 percentage points less likely to accept that any of these reasons for domestic violence are justified.[23]

Panel B reports results when we condition on all active mines rather than HFLS mines alone. The results in this panel broadly resonate with those in Panel A. In particular, the coefficient on the index measure indicates that women near deposits and active mines are 10.0 percentage points less likely to agree that physical violence is justified for any reason. Young women see statistically significant net impacts when it comes to emotional violence.[24]

[23] Results from models that do not condition on age indicate that these agency measures all improve in the proximity of HFLS mines. These results are available on request. Moreover, given our focus on the 5 km distance, it is likely that the proximity and intensity variables are similar. That may explain the similarity of coefficients in some cases.
[24] Focusing on the index variable outcome, there is weak evidence that young women are less accepting of violence in the proximity of all mines in states with a heavy mineral presence.

Concomitant results that condition on the number of deposits in Panel B are similar in sign but mostly insignificant. For the young, the parameters are significant for emotional violence, signaling reduced acceptance. Overall, results in Table 2 underline that older women near active mines and deposits (especially HFLS mines) are less likely to accept that violence is justified.

5.2. Women's Barriers to Healthcare

Appendix Table 4 reports results for the β_4 and β_7 interaction terms when we study variables related to barriers that women may face while seeking medical care, including whether they need permission to go, whether they can obtain money for the treatment, and uncertainty/fear involved in traveling alone.[25] The indicator variables in these columns take the value 1 if the woman reports that any of these was a "big problem." Column (4) reports results for the composite index. It ranges from 0 to 1 if the woman responds that each of these three dimensions was a "big problem," and has a mean value of 21 percent.

Proximity to deposits and active HFLS mines has a negative impact on barriers to medical care but is only statistically significant in the first column for the impact on need for permission, which declines by 19.1 percentage points for women in close proximity to HFLS active mines (Panel A). This set of results for our alternative measure of women's agency is similar to the results for tolerance of domestic violence but the estimates overall are less precise. The net effects for young women are significantly different from zero in the first three columns. Estimates indicate that fear declines by 31.6 percentage points, while the need to ask for permission decreases by 21.9 percentage points. These declines in barriers as a result of proximity to mines for young women diverge from our first set of results for young women in the case of tolerance of domestic violence, a possible sign of how social norms around different expressions of women's agency change at different rates over time. Proximity to HFLS mines does increase the need for money among young women by 78.8 percentage points. It is possible that seeking higher quality healthcare might explain this.

The second half of Panel A reports coefficients that condition on the number of deposits. Again, all coefficients of interest are negative, indicating a beneficial impact on these measures in the proximity of HFLS mines. The coefficient on the need for permission shows that in comparison to women in the control group, those in the proximity of HFLS mines conditional on

[25] We also considered impacts on women's attitudes towards shared decision-making. These results are available on request.

the number of deposits experience an 18.5 percentage point decline in this barrier. Again, net impacts among the young are negative with regards to permission and fear, but positive when it comes to money.

Panel B in Appendix Table 4 reports results when we condition on all mines. In general, results are weaker than those in Panel A. Overall, we conclude from Appendix Table 4 that proximity to HFLS mines brings benefits to women in reducing barriers to seeking healthcare.

5.3. Men's Acceptance of Domestic Violence

Next, we consider whether responses provided by men mirror those evident for women. Changes in men's attitudes towards domestic violence in the proximity of HFLS mines and all mines are reported in Table 3.[26] These results provide some evidence that proximity to mines and deposits (especially HFLS mines) reduces the tolerance of domestic violence. Five of the six estimates for men near HFLS mines are negative, although only two of these are significant. Focusing on the largest impact, there is a 22.7 percentage point decline in the acceptance of violence by men near HFLS mines if the wife does not cook food properly. The negative coefficients highlight that women's instrumentality exhibits consistent relative improvements, mostly in cases where their labor is valued (in the case of HFLS metal/mineral mining). This remains true when we consider the number of deposits as well. When we evaluate changes in attitudes in the presence of all mines, there is some evidence of opposite impacts, especially among young men (results in column (3) that condition on the presence of deposits).[27] This finding is consistent with our main estimates for the net effects for young women in terms of acceptance of domestic violence. Focusing on the index variable, there is evidence that young men are less accepting of violence in the proximity of all mines in states that are rich in minerals.

5.4. Men's Acceptance of Shared Decision-Making

Table 4 reports results for men's attitudes towards making household decisions in a joint fashion. Most of the estimates that are statistically significant near HFLS mines are positive in sign, indicating that men are more likely to report shared decision-making. Considering the composite index measure, overall, men living in proximity of HFLS mines report a 23.4

[26] The empirical framework here is identical to that for women in Equation (1), that is, we differentiate by age for these male results as well. However, the number of observations for young men in the regressions that condition on the close proximity to HFLS mines are too few for age effects to be estimated. We are able to estimate the age coefficient in the sample that conditions on proximity to all mines, as Table 3 reports.

[27] Given that the average age difference between spouses is 4 years, we experimented with changing the definition of "young" to be ages 19-29 as opposed to ages 15-25. This alternative yielded comparable results.

percentage point increase in the willingness to share decision-making with their spouses. The index coefficient is of similar magnitude when we condition on the number of deposits instead (23.7 percentage points). In the case of all mines, the increase in the index variable is of a smaller magnitude (13.1 percentage points), and among young men, there is increased willingness to make decisions jointly when it comes to the number of children, the overall index variable, and decisions on his healthcare. When we condition on the number of deposits, there is increased willingness to share decision-making jointly for even more of the indicators, including daily needs and decisions on wife's earnings. In sum, these results for men offer strong support for our main result that mines are beneficial for women's agency (especially near HFLS mines), signaling greater acceptance of progressive norms.

6. Mechanisms

Motivated by the literature on mineral wealth and human capital formation (Gylfason 2001, Ahlerup *et al*. 2020, Mejía 2020), we hypothesize that proximity to active mines affects women's agency because of policies that require that mining profits be shared with local populations, which in turn strengthen their agency through channels such as employment creation and credit availability. To evaluate this assertion empirically, we use the same specification as in the main analysis and focus on the impacts of profit sharing in mining communities.

Royalty receipts (an important source of revenue for states and local governments), when distributed appropriately among the affected population, can also potentially explain the beneficial impacts for women near mines.[28] In fact, Hartwick (1977) argued that reinvesting resource rents back into physical and/or human capital could be one way to achieve sustainability even with the gradual depletion of natural capital. Though this reinvestment requires strong economic and social institutions that could be lacking in developing countries, India was an exception. India passed a bill that requires royalty to be reinvested into communities that specifically support women. Our hypothesis is thus the following: women's agency improves in

[28] Menzies and Harley (2013), for instance, focusing on the unique arrangement prevailing in the *Ok Tedy* mine in Papua New Guinea in which women's participation in both negotiation and implementation phases is encouraged, explain how mining activities and the distribution of royalties can promote gender equality. They argue that encouraging women to exercise more control over natural resources and the revenues emanating from them is essential for issues related to gender equality and economic development.

the proximity of HFLS mines because the appropriate use of royalties reinforces effects on women's employment and human capital outcomes as conceivably, local levels of government charged with investing royalties are in a position to make informed and progressive choices.

We consider the effect of three different district-level proxies of profit sharing for women living within 5 km of an active HFLS mine.[29] To construct these proxies, we use a 2011 official report provided by the Center for Science and Environment, India, which was prepared to explain the major implications of the Draft Mines and Minerals (MMDR) Act Bill of 2011.[30] Referring specifically to the profit sharing concept, it states that *"a mine leaseholder is to pay annually to the District Mineral Foundation (DMF), as specified in Section 56, an amount equal to 26 percent of profit after tax or a sum equivalent to the royalty paid during the year, whichever is higher."* The DMF, in turn, was established in order to "*...overturn the decades of injustice meted out to the thousands of people living in deep poverty and deprivation in India's mining districts... as a non-profit trust, DMFs in every mining district have the precise objective to work for the interest and benefits of persons and areas affected by mining operations...at least 60% of the budget should go to areas such as welfare of women and children"* (Centre for Science and Environment 2017).

This information allows us to proxy for the amount each affected individual, household, and woman receives from resource abundance in mineral-producing districts. The first measure considered is profit sharing per affected population. We use the mineral-specific reports contained in the *Indian Minerals Yearbook 2014*, digitize the district-level values of production for each mineral, and then aggregate them to obtain the total value of mineral production for the period 2013-2014. We also compile the district-wise total mineral leased area, manually digitized from the *Bulletin of Mining leases and Prospecting Licenses, 2014* from the Indian Bureau of Mines. This allows us to obtain the total mine leased area for each district as of 2014. Since the Draft MMDR includes the provision that the mining industry should provide at a minimum the royalty, we assume that the share of profits distributed to local communities is equal to the

[29] The DMF Status Report of 2017 provides details on allocation of mineral royalties for the welfare of women and children. In the district of Dandewada in Chhattisgarh, for example, funds are used for the creation of women empowerment centers to promote training, production assistance, and market linkages; in the district of Korba, the focus is on supplementary food for pregnant women, children, and on the distribution of sanitary equipment and medicine.

[30] For more details, see "Sharing The Wealth of Minerals: A report on Profit Sharing with Local Communities", Center for Science and Environment, New Delhi, India (2011).

royalty. Referring to the royalty contribution of major Indian mining companies, we set the royalty to equal 10.5 percent of the total value of mineral production.[31]

To estimate the population affected by mining activities, the report further assumes that the direct effects of health, displacement, and livelihoods are scattered over at least twice the size of the leased area, and that the population density over the affected area is in turn directly proportional to the average population density of the state. We also construct two other profit sharing measures that do not rely on the district's leased area but are instead on a per capita basis: (i) profit sharing per household, and (ii) profit sharing per female population (on the basis that at least 60 percent of royalties collected is allocated to the welfare of women and children).[32] Given its particular relevance, we report results for profit sharing per female population (measured in thousands of Rupees).[33,34] Our specification is as follows:

$$Y_{icd} = \beta_0 + \beta_1 deposit_c + \beta_2 activemine_c + \beta_3 profitsharing_d + \beta_4 (deposit_c \times activemine_c) + \beta_5 (deposit_c \times profitsharing_d) + \beta_6 (activemine_c \times profitsharing_d) + \beta_7 (deposit_c \times activemine_c \times profitsharing_d) + \beta_8 X_{icd} + \lambda_s + \epsilon_{icd} \qquad (2)$$

where the variables $Y_{icd}, deposit_c, activemine_c, X_{icd}$, and ϵ_{icd} are the same as in Equation (1). The variable $profitsharing_d$ is the district-level proxy for profit sharing per affected population/female population/household, and the coefficient of interest is β_7. We do not condition on age of the woman in Equation (2) given that the specification already includes three-way interaction terms, and because the sample size for the mechanism outcomes are smaller than those for outcomes that measure women's agency. The notation λ_s represents state fixed-effects. Profit sharing is measured in two ways: as a linear or continuous variable, or as a non-linear indicator variable that equals 1 if the level of profit sharing in the district equals or exceeds the 75th percentile value in the full sample. We use the second form that demarcates the

[31] This is the average value as per the official report.
[32] The available data do not allow us to differentiate between the proportion of total royalties that are directly put towards improving employment outcomes for women and the proportion devoted to aspects such as improving agency and nutritional indicators for children. Some of this is at the discretion of the local DMFs.
[33] As these measures of profit sharing are not directly reported, we construct them based on our reading of official documentation. Despite the many robustness checks we describe below, there is a chance that these variables are measured with some error.
[34] Results for per affected population and profit sharing per household are available on request.

upper quartile value in order to document heterogeneity in effects in districts that may be richer in terms of overall value of production, and as a robustness check. Appendix Box 2 provides further details on the many other robustness checks that we conduct for the profit sharing measures including controlling for the district's socio-economic vulnerability, propensity for deposits in the district to be looted (by conditioning on the distance to the nearest lootable gold or surface deposit), and whether the district has been affected by Maoist conflicts. We also condition on the number of village panchayats (per 1000 people) to address overall accountability and transparency in the district, public/private sector involvement, and measures of access to media in the district that may affect our measures of agency and the distribution of royalty rents. The sample of analysis is restricted to the same women who were selected for the domestic violence module and for whom results were reported earlier.[35]

The outcomes we consider are related to women's employment and to variables measuring the effects of profit sharing on earnings and awareness (and use) of financial opportunities. Table 5 reports coefficients on β_7 where the outcomes are binary measuring employment, compensation, and credit awareness and use. Results in Panel A indicate that conditioning on proximity to reserves and active HFLS mines, increases in profit sharing per female in the population is associated with significant improvements in women's employment outcomes. Specifically, profit sharing near HFLS mines increases the probability that a woman is in the workforce, works in the manufacturing or services sectors, and is employed in skilled or unskilled manual labor. It also reduces the likelihood of agricultural employment.

We use three outcomes to measure women's financial independence in Table 5. In column (6), the dependent variable equals 1 if the respondent reports "cash" as the main type of earnings. In columns (7) and (8), outcomes relate to awareness and use of financial opportunities with variables coded as 1 if the respondent says that she is aware of loan programs available for entrepreneurial uses (to start or expand a business), and if she borrows from the program to invest in entrepreneurial activities, respectively. Results in Panel A show that increased profit sharing brings beneficial impacts when it comes to earnings, and awareness and use of loan programs to further business ventures.

[35] The number of observations is lower here because the *Indian Minerals Yearbook 2014* does not report production values for all minerals or values for all districts.

The estimates reported in Panel B, which use the non-linear version of the profit sharing variable, are broadly consistent with those in Panel A. The signs of the reported β_7 coefficients are the same (except services, which is statistically zero), and significant for two of the employment variables.[36] On average, results in Table 5 underline that profit sharing with local communities increases women's employment prospects as well as access and use of financial capital. In addition, the β_4 coefficients are mostly insignificant in Panels A and B, while more of them were significant in the main results (Table 2). This implies that profit sharing contributes to increased employment and financial independence of women. The existing literature indeed suggests that mining activities can create or foster the demand for decentralization of fiscal powers to local administrative units, with more autonomy. Through the revenue channel, mining can have a positive impact on communities, conditional on sharing rules, local governments' patterns of expenditure, and accountability (van der Ploeg and Poelhekke 2017). Taken together, we conclude that conditional on proximity to reserves, presence of HFLS mines in the vicinity results in positive outcomes for women's measures of agency through multiple channels, including improvements in women's human capital and through profit sharing with local communities.

We end this section by noting that it is likely that all active mines that we have information for from the USGS source are organized mines, as the USGS compiles this information from official documentation (informal workers/mines would not be counted in Government of India statistics). Profit sharing with local communities may be enforced mainly within the organized sector as the operation, scale and profits generated in unorganized mining are undocumented. Given that we see impacts from focusing only on the organized sector, having information on employment of women in the unorganized sector and profits generated therein should only improve our estimates. That is, our inability to use information from the unorganized sector given its undocumented nature is likely to be a conservative bias for us.

7. Robustness, Falsification, and Specification checks

7.1. Checks for Sorting, Propensity Score Matching, Pre-Trends, Temporal Falsification Tests, and Determining Treatment Distance

[36] Lack of significance for the remaining variables suggests that there is little heterogeneity in effects in the upper tail of the profit sharing distribution.

We conduct several robustness checks of the main results. We begin by checking to ensure that sorting into mining areas does not change population composition. We are limited in our ability to undertake comprehensive checks given that we do not have information on the start date of mines from the USGS data. Hence selective outward and inward migration may be an issue. However, we present several pieces of information and evidence to demonstrate that mining does not increase the share of migrants in treatment areas relative to control areas. First, the average years of residence in our sample is slightly over 15 years (Table 1). Given that our DHS data are as of 2015-2016, this means that half our sample has been present in the same location since 2000 or so. Hence, the average woman has been residing in her current location at least since 2000 (seven years before 2007, the year of our mines information source). Second, in order to check for sorting induced by migration, we restrict the analysis to those who have been residing in the same area for at least 20 years; 20 years is the 75th percentile value of our years of residence measure (we cannot restrict the sample to those who have never moved as then the sample is too small to identify effects, particularly given the relatively limited number of HFLS mines). This restriction does not change our main estimates and addresses heterogeneity by migration status.[37] Third, Munshi and Rosenzweig (2009) show that unlike in African countries such as Ghana (Fafchamps *et al.* 2017) and Zambia (Wilson 2012), India has low rates of spatial mobility and migration.

Next, we undertake tests to see whether years of migration reported by women in the 5 km vicinity of active mines (treatment areas are those that have a deposit within 5 km and an active mine within 5 km) is lower than the years of migration in control areas (these areas have a deposit within 5 km but no active mine within 100 km). This would be the case if there was recent migration into active mining areas. In particular, we check the proportion of women who have been residing in the same location for 20 years or more in treatment and control areas. Although not a conclusive test, if the proportion of such long-term residents in treatment areas is lower than the proportion in control areas, then mining may have induced selective migration into treatment areas. We find that the proportion of long-term residents in treatment areas is 18.97% while the proportion of such residents in control areas is 8.33%. A *t*-test for the difference between these proportions, however, reveals that we cannot reject the null that the difference is zero (*p*-value=0.359). That is, there is a larger, but statistically insignificant,

[37] We note however that this restriction cannot address possible selective outward migration from mining areas.

proportion of people who have not moved in the last two decades in treatment areas as compared to control areas. The same conclusion holds if we use 10 years as the benchmark, as a *t*-test cannot reject the null hypothesis that the difference is zero (*p*-value=0.236).[38]

We also ensure that the results hold when a district's level of political spending is controlled for so that the fiscal revenue windfall from mining activities is not a confounding factor. Controlling for political spending does not change our main estimates.[39]

To alleviate the concern that confounding factors might bias our estimate from cross-sectional models, we re-estimated our model using propensity score matching (PSM). Appendix Table 5 presents summary statistics between the treatment group (presence of both a deposit and an active mine within 5 km) and the control group. The left panel offers raw comparisons across the unmatched samples. As is clear, there are statistically significant differences. Based on observed characteristics, we then match the treatment group with the control group using nearest neighbor matching methods. The right panel in Appendix Table 5 presents mean comparisons after PSM. The two samples are now statistically the same.

We then compare estimates generated from our main specification to those from PSM. These comparisons are presented in Appendix Table 6 (the first panel reports the coefficients from our main specification and the second panel reports the PSM estimates). Focusing on the summary index variable, the coefficient from the main specification is -0.085 while PSM estimates -0.059, which is in the ballpark. We conclude that observed differences in characteristics are unlikely to influence our key results.

Because the DHS-4 is the only round of India data with geo-markers for clusters, conventional pre-trends checks based on before and after time-periods cannot be undertaken. We present two additional checks to underline the validity of the empirical framework. First, we check whether individuals closer and farther away from deposits are comparable along observed measures in the absence of active mines (the presence of an active mine coincides with treatment). We present these tests in Appendix Table 7. In the pre-treatment phase, the control group has no deposit within 5 km of each cluster and no active mine within 99 km (since 100 km is the limit of our data, we use a value very close to 100 km). The treatment group has a deposit

---

[38] This remains true if we consider 5 years as the benchmark or even 22 years, which is a higher value than the 75th percentile value of 20 years.
[39] The summary index variables in these cases actually increase in magnitude and precision.

within 5 km of each cluster but no active mine within 5 km. We run tests using data on future mines only (mines in the USGS database that are denoted as not opened now but prospected to be open in the future), and then compare statistics in observed variables across treatment and control groups before the mine opens.[40] We report the mean and standard deviation for variables in the control and treatment groups, and the difference in means between these groups in the pre-treatment phase. There are some significant differences among some of the variables, which we consequently condition on in the analyses.

Second, we focus on one specific socio-economic indicator, nightlights, and compare cluster-level characteristics over two dimensions: temporally and spatially. In the temporal test, we compare clusters within proximity to active mines (the treated group) vs clusters farther away from active mines (the control group). We expect parallel trends in nighttime light density to hold between the treated and the control group, i.e., there should not be shocks that affect treated and control groups differently over time. We use harmonized time-series nighttime light density data from Li et al. (2020) and plot the average log nightlight density over time in Appendix Figure 5. We find that treated clusters have consistently higher nighttime light density than control clusters when comparing their raw levels. However, the increase in nighttime light density over time follows parallel trends during 1992-2018, with no discernible trend breaks.[41] This alleviates the concern of unobserved shocks that affect mining areas differently over time, especially around years 2001 and 2007 when our mineral deposit and mining operation information was collected, respectively.

In the spatial test, we compare clusters near active mines versus future and/or past mines across different proximity distances. We expect parallel trends to hold between clusters located farther away from active mines and future/past mines, and trend breaks when clusters are closer to active mines (the treated group) versus when clusters are closer to future/past mines (the untreated group). We present comparisons on cluster-level nightlights for the year 2015 in Appendix Figure 6.[42] There is a persistent gap in nightlights at 5 km (dotted lines denoting the

[40] Future or prospected mines are classified as such by the USGS only on the basis of geographic and topographic quadrangle maps (Horton and San Juan 2021).
[41] Nightlight density jumps between 2013 and 2014 for both the treated and the control clusters, likely because the underlying data source switches from the Defense Meteorological Satellite Program (DMSP) pre-2014 to Visible Infrared Imaging Radiometer Suite (VIIRS) post-2014.
[42] Appendix Figure 6 also serves to show that treatment distance is less than 20 km, which, along with the other evidence presented in the Online Appendix, justifies our choice of baseline distance.

distance we condition on in our models): on average, clusters within 5 km of an active mine are 20-40% brighter as compared to clusters within 5 km of a future/past mine. This gap dissipates over space: by 20 km and beyond, there is no significant gap in nightlights between clusters, thus underlining that the parallel trends assumption holds at these farther distances.

In a similar vein, we provide further details on temporal falsification tests and for determining treatment distance in Appendix Box 3. Results show that four of the seven outcomes have counter-intuitive signs, and there are no effects at all for younger women. Finally, we calculate *p*-values for the coefficients of interest that adjust for multiple hypothesis inference using the Romano-Wolf procedure (note that we create and discuss results for index measures already). These are higher than the *p*-values that do not make this adjustment as expected. For instance, the *p*-value on the interaction of presence of deposit and presence of HFLS active mine in column (1) of Table 2 increases from 0.064 to 0.089, while the *p*-value for this interaction term in column (3) of Table 2 increases from 0.020 to 0.050. Hence there are no substantive changes in our results overall.

7.2. Robustness Checks: Other Outcomes

We have conceptualized women's agency around the freedom to pursue their goals and measured this as freedom from domestic violence and barriers to healthcare, and we consider empowerment as the expression of agency. As another set of robustness checks, measures of women's and children's empowerment should improve as women's agency strengthens. To conduct this set of tests, we examined the impact of proximity to mines on women's human capital and children's health.

We first turn to the human capital channel, where studies have shown that environmental change could lead to human capital gains or losses in India (e.g., Joshi 2019; Garg *et al*. 2020). Table 6, which follows the same structure as the main results, presents estimates for women's human capital. We consider education status, body mass index (BMI), underweight status, hemoglobin levels (HBA), and mild and moderate/severe anemia status.[43] Results indicate that HFLS mines (conditional on the presence of a deposit), while having no measurable impacts on

[43] BMI is weight in kilograms (kg) divided by height in meters squared (m^2), and underweight is defined as BMI less than 18.5. A woman is anemic if her HBA level is below 12.0 g/dl (grams per deciliter). A woman is mildly anemic if her HBA level is between 10.0 – 11.9 g/dl and moderately or severely anemic if her HBA level is less than 9.9 g/dl. We considered height as well but the effects were insignificant as unlike weight, height changes over the long run.

older women's education status, reduces the likelihood that younger women are uneducated. The effect on education when we condition on the number of deposits is similar. An explanation is improved economic opportunities for young women in and around HFLS mines.[44] Estimates are weaker when we consider the impacts of all mines on educational status in Panel B.

Compared to women in the control group, those living near HFLS mines are up to 29.1 percentage points less likely to be underweight. These women are also more likely to be mildly anemic and less likely to be moderately or severely anemic. Focusing on net impacts on young women, they are more likely to have lower HBA levels and to be mildly anemic, but are less likely to be moderately or severely anemic. The positive effect on mild anemia is potentially reflective of the effects of pollution from mining (which is also consistent with evidence in von der Goltz and Barnwal (2019)).[45] These results point towards improvements in health status for women living in proximity to HFLS mines in a number of measures. Many of these results hold when the estimates condition on the number of deposits, both for women in general and for young women who also show improvements in terms of overall BMI. On the other hand, results in Panel B that condition on all mines are mostly insignificant. There are some positive impacts on women in general in the close vicinity of mines when it comes to BMI and underweight status, but all net effects on the young are statistically equivalent to zero. Overall, we have presented evidence indicating that measures of human capital improve for women living near HFLS mines.

We next consider an outcome for which mother's human capital is a crucial determinant: child health. Analyzing this outcome is thus a robustness check that women's education and health are indeed rising in the vicinity of mines. We consider standardized health measures for children ages 0-59 months, including the height for age z-score (HAZ), weight for age z-score (WAZ), and weight for height z-score (WHZ).[46] Results are presented in Appendix Table 8. Estimates in Panel A indicate measurable impacts for children near HFLS mines in terms of WAZ and WHZ. In particular, WAZ and WHZ improve by 0.9 standard deviations and 1.2

[44] When we restrict the analysis to women who have lived in the same area for an extended period of time, these results remain the same, that is, the impacts are due to proximity to HFLS mines and not due to sorting into these areas.

[45] Datt *et al*. (2021) shows that PM2.5 pollution generated from coalmines has harmful consequences for anemia. HFLS mines are unlikely to be as polluting as coalmines, but general levels of pollution near such mines might still be high. We re-estimated results conditional on district level of PM2.5 that varies by month and year; our results remain unaltered. These are available on request.

[46] We interpret these results cautiously given the reduced sample sizes (especially for HFLS mines).

standard deviations respectively, for children of older women near HFLS mines. Net effects on children of younger women are insignificant. These patterns mostly hold true when we consider the case of mining intensity.

7.3. Spatially Randomized Placebo Test

Another concern may be that our results are spuriously driven by a mis-specified model such that any association between proximity to active mines and our outcomes of interest arises purely by chance. Therefore, we carry out a spatially randomized placebo test by randomly displacing the location of active mines and checking to see if the estimated effects still exist. This test is in the spirit of Benshaul-Tolonen (2019) and Depetris-Chauvin and Ozak (2020). Specifically, we randomly offset the true location of active mines by up to 50 kilometers 1,000 times, use the biased locations to calculate new proximity measures, merge them with the DHS – 4 data, and re-estimate the main specifications to obtain a new set of biased parameter estimates. For the sake of comparison, we present results on acceptance of physical violence only while considering proximity parameters for all mines.[47] Figure 2 shows the density distributions of point estimates from the 1,000 biased regression models with the proximity measures built from randomly displaced locations. The dotted red lines in this figure represent the 90 percent confidence intervals of the empirical distribution from the biased models. That is, the 90% confidence interval for the placebo sample. Figure 2 also shows the estimated effects for older women obtained from the main (true) specification for all mines (Panel B of Table 2) in solid blue lines.[48] We include the blue lines for the actual results to demonstrate that these are distinct from the mean of the placebo samples.

If our result is due to a mis-specified model, then the placebo coefficients will be significantly different from zero. That is not the case in Figure 2, which indicates that the placebo effects are mostly centered around zero in all seven measures of women's agency.[49] Furthermore, the placebo effects are distributed distinctly from our baseline estimates, as the blue lines representing the true coefficients do not coincide with zero to a discernible extent in most cases. We conclude that our main results cannot be attributed to a mis-specified model.

[47] Results for other outcomes, for HFLS mines, and for the intensity measures are available on request.
[48] We report estimated effects for older women given that younger women in the 15-25 years age group compose only 17.1 percent of the sample.
[49] The means of the constructed empirical distributions are not precisely zero in some cases indicating that there likely exist weak spatial spillovers at a 50 km radius, similar to Benshaul-Tolonen (2019).

8. Conclusions and Policy Implications

We find that proximity to HFLS mineral/metal mines results in measurable benefits for women: they are less accepting of physical violence and face lower costs of accessing medical care. Since women's labor is more likely to be valued in HFLS mines compared to other types of mines, women's status is relatively stronger in the surroundings of such mines, indicating that women are better regarded in contexts where their labor is valued. Differential positive impacts of proximity to mines are particularly evident among relatively older women (above 25 years of age). Instilling progressive norms among older populations is meaningful as they are often the gatekeepers of traditions and culture. Corresponding results for men underline the robustness of these results for women.

The sharing of profits from resource extractions with local populations is the key mechanism explaining these results; profit sharing is found to bring substantial benefits in terms of women's employment conditions and financial awareness and access. This mechanism is an essential ingredient in improving women's relative position, especially near HFLS mines. Given data limitations, we use a geospatial cross-sectional framework to arrive at these conclusions. Access to the next round of DHS geo-coded data from India that is currently in the field will facilitate future research on how these impacts may vary with time. Additionally, more comprehensive data on the number of active mines will help to further improve our results, which are likely to be an underestimate of true impacts currently.

In placing our results in the context of the literature, our findings are in line with Lippert (2014), which considers the spillovers of the resource boom in Zambia and finds that an increase in local copper production improves living standards for households close to mines. Our results are also in accordance with research on mining's multiplier effects and linkages, which posits positive local employment effects (Aragón and Rud 2013). Some of the tradeoffs we uncovered, such as a greater incidence of light anemia for women due to higher pollution levels close to mines, are also in accordance with earlier research (von der Goltz and Barnwal 2019). Finally, our point estimates for the decline in the acceptance of domestic violence and the decrease in needing permission as a barrier to healthcare access among women living in the vicinity of HFLS mines are both similar to estimates for eight sub-Saharan African countries in Benshaul-Tolonen (2019).

Understanding how, and under which conditions, resource extraction improves women's agency and human capital can help to discern the potential benefit of an industry that has often been portrayed as extractive and resource depleting. This study adds to the literature on whether and to what extent the mining industry contributes to sustainable development and social well-being. The results also have implications for policies to protect women engaged in the mining sector, with wider relevance for other policies to improve social welfare in localities with mining. There is mounting evidence on the link between achieving gender equality and empowering women and girls, poverty reduction, and sustainable use of natural resources. Our results indicate that policy reforms should consider how structural changes affect gender-based inequities. Efforts are also needed to enforce legislation that requires profits to be shared with community groups. Further, policies to protect vulnerable populations should include community initiatives with stakeholders from the government, the mining industry, and civil society. An example is gender-sensitive training programs for service providers (Eftimie *et al.* 2009a).

Our results lend themselves to policy reforms that strengthen women's status in the resource extraction industry. Recommendations include capacity-building programs for women to promote employment, training and mentoring, to help women advance to higher-level positions within the mining industry, equal pay for equal work, improved working conditions, and strong enforcement of anti-harassment policies (Eftimie *et al.* 2009b). Mining is still a male-dominated industry. However, women and girls are taking on an increasingly important role in artisanal and small-scale mining (Bashwira *et al.* 2014). Greater emphasis on community dialogues and participatory planning in mining projects, both large and small, can help to give local women workers a stronger voice, thus ensuring that this industry generates positive economic and social spillovers for communities (Pokorny *et al.* 2019).

Building stronger institutions to help enforce legislation in areas with active mines also resonates with efforts to ensure that mining contributes to the overall economy (Mehlum *et al.* 2006). Researchers, policymakers, and advocates have increasingly shown interest in exploring ways to transform mining extraction from an enclave sector that generates adverse negative economic effects to a revenue-generating sector with beneficial effects. Our results indicate that this objective can be achieved in the case of reverting backward cultural norms and improving women's agency in areas close to mines.

References

Aizer, Anna, 2010. "The Gender Wage Gap and Domestic Violence," *American Economic Review* 100 (4): 1847-1859.

Ahlerup, Pelle, Thushyanthan Baskaran, and Arne Bigsten. 2020. "Gold Mining and Education: A Long-run Resource Curse in Africa?" *Journal of Development Studies* 56 (9): 1745-1762.

Anukriti, S., Catalina Herrera-Almanza, Mahesh Karra, and Praveen Pathak. 2020. "Curse of the Mummy-ji: The Influence of Mothers-in-Law on Women's Social Networks, Mobility, and Reproductive Health in India," *American Journal of Agricultural Economics* 102(5): 1328-1351.

Aragón, Fernando and Juan Pablo Rud. 2013. "Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine," *American Economic Journal: Economic Policy* 5 (2): 1-25.

Aragón, Fernando M., Juan Pablo Rud, and Gerhard Toews. 2018. "Resource Shocks, Employment, and Gender: Evidence from the Collapse of the UK Coal Industry," *Labour Economics* 52: 54-67.

Asher, Sam, and Paul Novosad. 2021. "Rent-Seeking and Criminal Politicians: Evidence from Mining Booms," *Review of Economics and Statistics,* https://doi.org/10.1162/rest_a_01064.

Auty, Richard. 1993. *Sustaining Development in Mineral Economies: The Resource Curse Thesis*. London and New York: Routledge.

Baranov, Victoria, Ralph De Haas, and Pauline Grosjean. 2021. "Men. Roots and Consequences of Masculinity Norms," UNSW Business School Research Paper.

Barros, Laura, and Yuanwei Xu. 2020. "Natural Disasters and Intimate Partner Violence: Evidence from Peru," University of Goettingen, Working Paper.

Bashwira, Marie-Rose, Jeroen Cuvelier, Dorothea Hilhorst, and Gemma Van der Haar. 2014. "Not Only a Man's World: Women's Involvement in Artisanal Mining in Eastern DRC," *Resources Policy* 40: 109-116.

Bebbington, Anthony, Leonith Hinojosa, Denise Humphreys Bebbington, Maria Luisa Burneo, and Ximena Warnaars. 2008. "Contention and Ambiguity: Mining and the Possibilities of Development," *Development and Change* 39 (6): 887-914.

Benshaul-Tolonen, Anja. 2018. "Local Industrial Shocks and Infant Mortality," *The Economic Journal* 129 (620): 1561-1592.

Benshaul-Tolonen, Anja. 2019. "Endogenous Gender Roles: Evidence from Africa's Gold Mining Industry." Available at SSRN 3284519.

Benshaul-Tolonen, Anja and Sarah Baum. 2021. "Structural Transformation, Extractive Industries and Gender Equality," *Review of Environmental Economics and Policy* (forthcoming)

Benshaul-Tolonen, Anja, Punam Chuhan-Pole, Andrew Dabalen, Andreas Kotsadam, and Aly Sanoh. 2019. "The Local Socioeconomic Effects of Gold Mining: Evidence from Ghana," *The Extractive Industries and Society* 6 (4): 1234-1255.

Berman, Nicolas, Mathieu Couttenier, Dominic Rohner, and Mathias Thoenig. 2017. "This Mine is Mine! How Minerals Fuel Conflicts in Africa," *American Economic Review* 107 (6): 1564-1610.

Bhalotra, Sonia, Uma Kambhampati, Samantha Rawlings, and Zahra Siddique. 2021. "Intimate Partner Violence: The Influence of Job Opportunities for Men and Women," *World Bank Economic Review* 35 (2): 461-479.

Bobonis, Gustavo J., Melissa Gonzalez-Brenes, and Roberto Castro. 2013 "Public Transfers and Domestic Violence: The Roles of Private Information and Spousal Control," *American Economic Journal: Economic Policy* 5 (1): 179–205.

Boserup, Ester. 1970. *Woman's Role in Economic Development*. New York: St. Martin's Press.

Burgert, Clara, Josh Colston, Thea Roy, and Blake Zachary. 2013. *Geographic Displacement Procedure and Georeferenced Data Release Policy for the Demographic and Health Surveys*. DHS Spatial Analysis Reports 7. Available at: https://www.dhsprogram.com/pubs/pdf/SAR7/SAR7.pdf

Centre for Science and Environment. 2017. *District Mineral Foundation (DMF): Status Report 2017*. http://www.indiaenvironmentportal.org.in/files/file/District-Mineral-Foundation-DMF-Report.pdf

Chatterjee, Somdeep and Prashant Poddar. 2020. "Women's Empowerment and Intimate Partner Violence: Evidence from a Multidimensional Policy in India," Indian Institute of Management, Lucknow, Working Paper.

Coffey, Diane, Ritika Khera, and Dean Spears. 2015. "Intergenerational Effects of Women's Status: Evidence from Joint Indian Households," Working Paper.

Cools, Sara and Andreas Kotsadam. 2017. "Resources and Intimate Partner Violence in Sub-Saharan Africa," *World Development* 95: 211–230.

Corsi, Daniel, Melissa Neuman, Jocelyn Finlay, and S. V. Subramanian. 2012. "Demographic and Health Surveys: A Profile," *International Journal of Epidemiology* 41 (6): 1602-1613.

Datt, Gaurav, Pushkar Maitra, Nidhiya Menon, Ranjan Ray *et al*. 2021. "Coal Plants, Air Pollution and Anemia: Evidence from India," Working Paper.

Dell, Melissa. 2010. "The Persistent Effects of Peru's Mining Mita," *Econometrica* 78 (6): 1863-1903.

Depetris-Chauvin, Emilia, and Ömer Ozak. 2020. "The Origins of the Division of Labor in Pre-Modern Times," *Journal of Economic Growth* 25: 297-340.

Diao, Miao, Delon Leonard, and Tien Foo Sing. 2017. "Spatial-Difference-in-Differences Models for Impact of New Mass Rapid Transit Line on Private Housing Values," *Regional Science and Urban Economics*, 67, 64-77.

Eftimie, Adriana, Katherine Heller, and John Strongman. 2009a. *Gender Dimensions of the Extractive Industries: Mining for Equity*. Report. Washington, DC: World Bank.

_______. 2009b. *Mainstreaming Gender into Extractive Industries Projects: Guidance Note for Task Team Leaders*. Report. Washington, DC: World Bank.

Eggert, Roderick. 2002. "Mining and Economic Sustainability: National Economies and Local Communities," Working Paper, Colorado School of Mines.

Elkasabi, Mahmoud, Ruilin Ren, and Thomas Pullum. 2020. "Multilevel Modeling Using DHS Surveys: A Framework to Approximate Level-Weights," DHS Methodological Reports No. 27. Rockville, Maryland, USA: ICF.

Eze, Donatien. 2019. "Microfinance Programs and Domestic Violence in Northern Cameroon: The Case of the Familial Rural Income Improvement Program," *Review of Economics of the Household* 17: 947-967.

Fafchamps, Marcel, Michael Koelle, and Forhad Shilpi. 2017. "Gold Mining and Proto-Urbanization: Recent Evidence from Ghana," *Journal of Economic Geography*, 17, 975-1008.

Gammage, Sarah, Naila Kabeer, and Yana Rodgers. 2016. "Voice and Agency: Where Are We Now?" *Feminist Economics* 22 (1): 1-29.

Garg, Teevrat, Maulik Jagnani, and Vis Taraz. 2020. "Temperature and Human Capital in India," *Journal of the Association of Environmental and Resource Economists* 7 (6): 1113-50.

Ghose, M. K. 2003. "Indian Small-Scale Mining with Special Emphasis on Environmental Management," *Journal of Cleaner Production* 11 (2): 159-165.

Gylfason, Thorvaldur. 2001. "Natural Resources, Education, and Economic Development," *European Economic Review*, *45* (4-6): 847-859.

Hartwick, John. 1977. "Intergenerational Equity and the Investing of Rents from Exhaustible Resources," *American Economic Review* 67 (5): 972-74.

Heath, Rachel. 2014. "Women's Access to Labor Market Opportunities, Control of Household Resources, and Domestic Violence: Evidence from Bangladesh," *World Development* 57: 32-46.

Horton, John, and C. San Juan. 2021. "Prospect-and Mine-Related Features from U.S. Geological Survey 7.5- and 15-Minute Topographic Quadrangle Maps of the United States (ver. 6.0, April 2021): U.S. Geological Survey data release.

India Bureau of Mines. 2015. *Indian Mineral Industry - At a Glance: 2013-14.*

International Institute for Population Sciences (IIPS) and ICF. 2017. *National Family Health Survey (NFHS – 4), 2015-16: India*. Mumbai: IIPS.

International Labor Organization (ILO). 1999. *Social and Labor Issues in Small-Scale Mines*. Geneva.

Jacobsen, Grant, Dominic Parker, and Justin Winikoff. 2021. "Are Resource Booms a Blessing or a Curse? Evidence from People (not Places)," *Journal of Human Resources* doi: 10.3368/jhr.58.4.0320-10761R1.

James, Alexander and Brock Smith. 2017. "There Will Be Blood: Crime Rates in Shale-Rich US Counties," *Journal of Environmental Economics and Management* 84: 125-152.

Joshi, Kuhu. 2019. "The Impact of Drought on Human Capital in Rural India," *Environment and Development Economics* 24 (4): 413-36.

Kotsadam, Andreas, Gudrun Østby, and Siri Aas Rustad. 2017. "Structural Change and Wife Abuse: A Disaggregated Study of Mineral Mining and Domestic Violence in Sub-Saharan Africa, 1999–2013," *Political Geography* 56: 53-65.

Kotsadam, Andreas, and Anja Benshaul-Tolonen. 2016. "African Mining, Gender, and Local Employment," *World Development* 83 (7): 325-339.

Li, X., Zhou, Y., Zhao, M., & Zhao, X. (2020). A harmonized global nighttime light dataset 1992–2018. *Scientific Data 7*(1): 1–9.

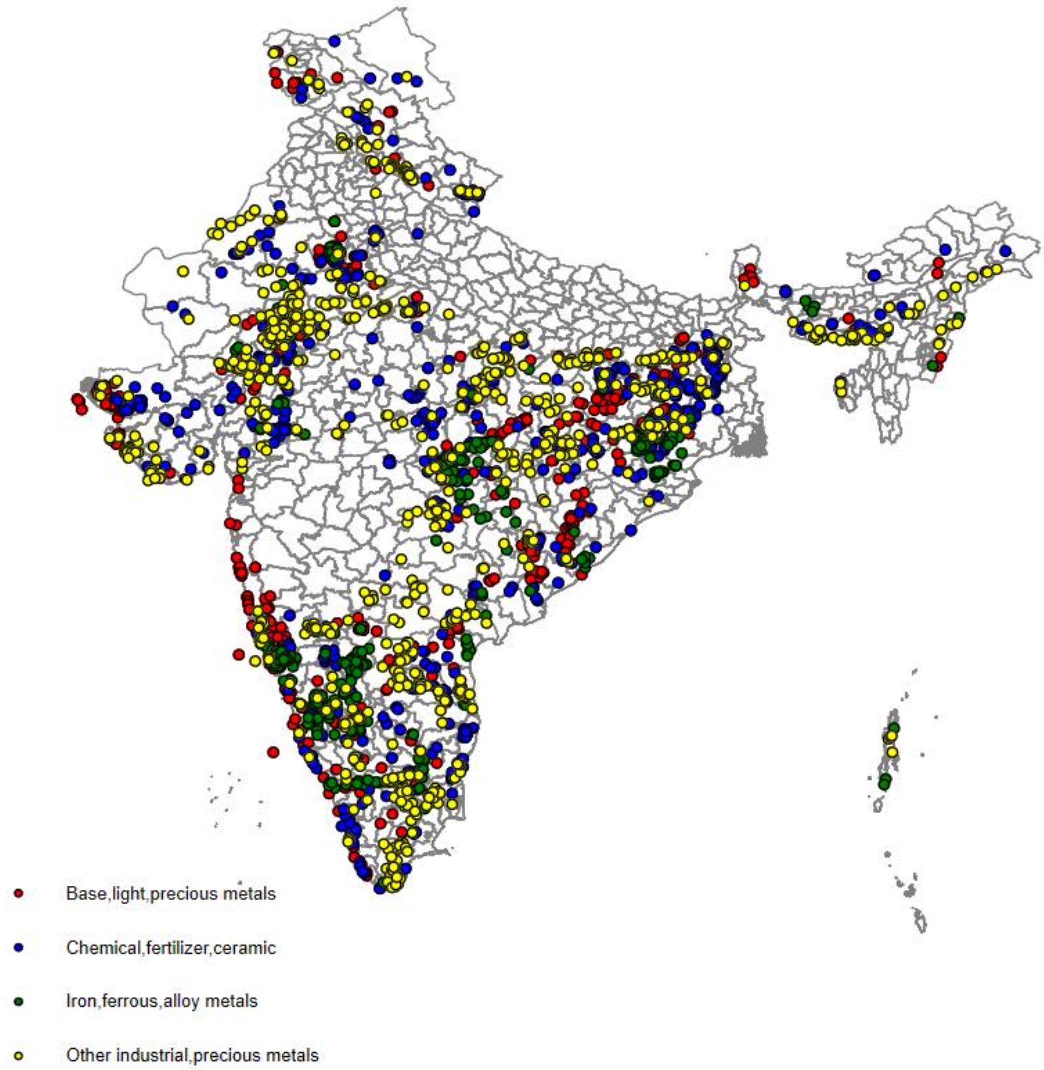
Lippert, Alexander. 2014. "Spill-Overs of a Resource Boom: Evidence from Zambian Copper Mines," OxCarre Working Papers 131, Oxford Centre for the Analysis of Resource Rich Economies, University of Oxford.

Mamo, Nemera, Sambit Bhattacharyya, and Alexander Moradi. 2019. "Intensive and Extensive Margins of Mining and Development: Evidence from Sub-Saharan Africa," *Journal of Development Economics* 139: 28-49.

Mehlum, Halvor, Karl Moene, and Ragnar Torvik. 2006. "Institutions and the Resource Curse," *The Economic Journal* 116 (508): 1-20.

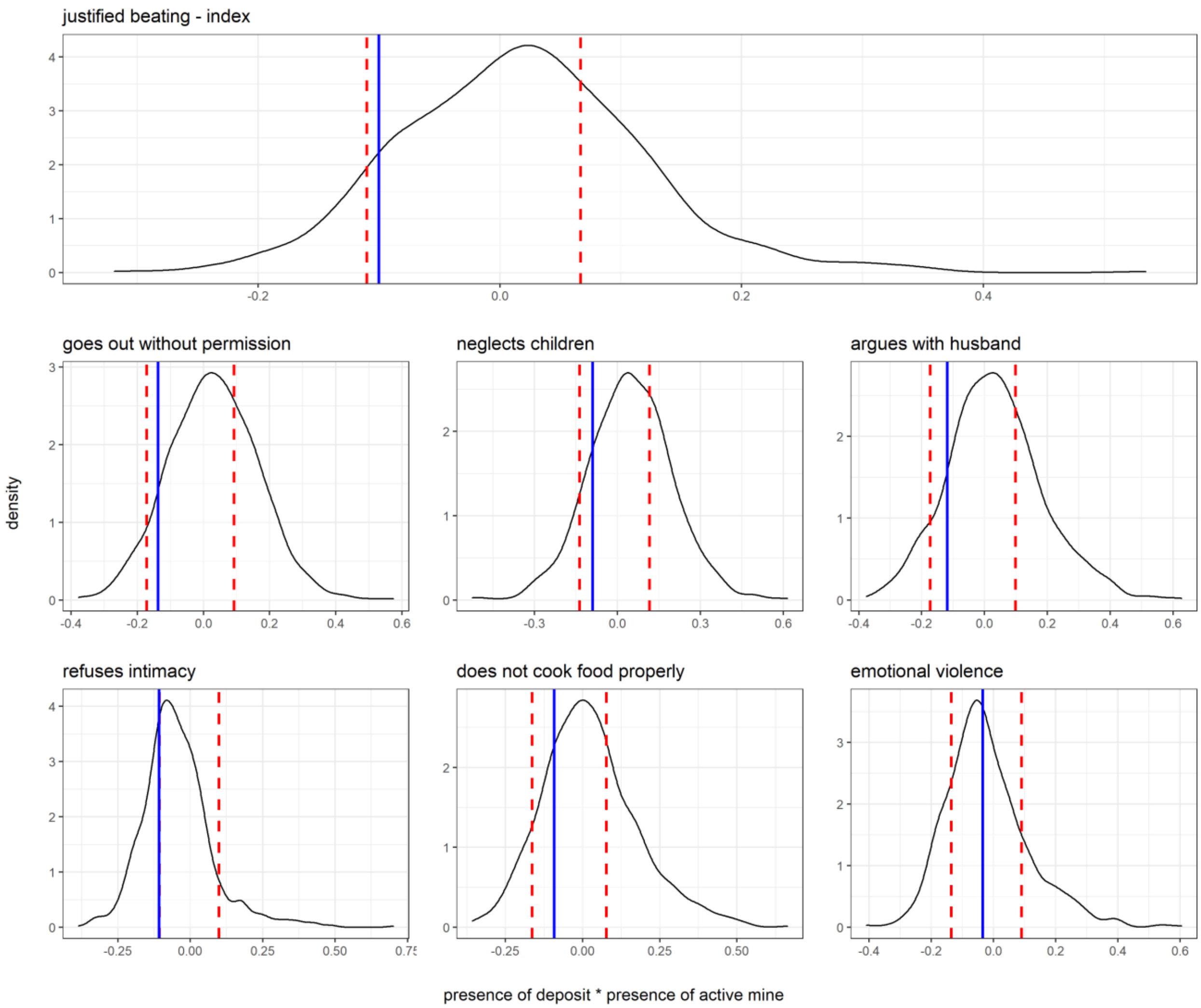
Mejía, Leonardo Bonilla, 2020. "Mining and Human Capital Accumulation: Evidence from the Colombian Gold Rush," *Journal of Development Economics* 145: 102471.
Mining Sector. 2014. "E-Book on Mining Sector," Annual Report, Ministry of Mines, Government of India.
Menzies, Nicholas and Georgia, Harley. 2013. "We Want What the Ok Tedi Women Have: Guidance from Papua New Guinea on Women's Engagement in Mining Deals," *World Bank Legal Review* 4: 233.
Munshi, Kaivan and Mark Rosenzweig. 2009. "Why is Mobility in India So Low? Social Insurance, Inequality and Growth," National Bureau of Economic Research, Working Paper w14850.
Panda, Pradeep, and Bina Agarwal. 2005. "Marital Violence, Human Development and Women's Property Status in India," *World Development* 33 (5): 823-850.
Parker, Dominic, and Bryan Vadheim. 2017. "Resource Cursed or Policy Cursed? US Regulation of Conflict Minerals and Violence in the Congo," *Journal of the Association of Environmental and Resource Economists* 4 (1): 1-49.
Pokorny, Benno, Christian von Lübke, Sidzabda Djibril Dayamba, and Helga Dickow. 2019. "All the Gold for Nothing? Impacts of Mining on Rural Livelihoods in Northern Burkina Faso," *World Development* 119: 23-39.
Ranjan, Ram. 2019. "Assessing the Impact of Mining on Deforestation in India," *Resources Policy* 60: 23-35.
Sen, Amartya. 1999. *Development as Freedom*. New York: Anchor Books.
van der Ploeg, Frederick. 2011. "Natural Resources: Curse or Blessing?" *Journal of Economic Literature* 49 (2): 366-420.
van der Ploeg, Frederick, and Steven Poelhekke. 2017. "The Impact of Natural Resources: Survey of Recent Quantitative Evidence," *Journal of Development Studies* 53 (2): 205-216.
von der Goltz, Jan, and Prabhat Barnwal. 2019. "The Local Wealth and Health Effects of Mineral Mining in Developing Countries," *Journal of Development Economics* 139: 1-16.
Wilson, Nicholas. 2012. "Economic Booms and Risky Sexual Behavior: Evidence from Zambian Copper Mining Cities," *Journal of Health Economics*, 31, 797-812.
World Bank. 2011. *World Development Report 2012: Gender Equality and Development*. Washington DC: World Bank.

Figure 1: Distribution of mineral deposits in India



Source: Mineral Atlas of India (Geological Survey of India, 2001). Geo-referencing exercise carried out by authors.

Figure 2: Spatial randomization placebo test



Notes: This figure presents the density distributions of point estimates from 1000 replications of the regression model, with the location of active mines randomly displaced by a distance up to 50 kilometers. The estimated effect for older women obtained from the main (true) specification for all mines (Panel B of Table 2) are depicted as the solid blue lines. The dotted red lines represent 90 percent confidence intervals of the empirical distributions of the displaced effects.

Table 1: Summary statistics for women in DHS 2015-2016 (full sample)

	mean	standard deviation
Panel A		
Justifies beating if		
wife goes out without telling	0.300	0.458
neglects children	0.368	0.482
argues with husband	0.320	0.467
refuses intimacy	0.149	0.356
does not cook food properly	0.209	0.407
index	0.268	0.339
emotional violence	0.140	0.347
Panel B		
Barriers when seeking healthcare		
permission	0.176	0.381
money	0.261	0.439
fear to go alone	0.190	0.393
index	0.209	0.314
Panel C		
Mechanism - profit sharing		
profit sharing per female population (in thousands of Rupees)	0.163	0.946
is in the workforce	0.357	0.479
agriculture	0.182	0.386
manufacturing	0.077	0.266
services	0.093	0.290
manual – skilled and unskilled	0.071	0.257
earns cash	0.050	0.219
aware of loan program	0.086	0.280
has taken a loan	0.022	0.148
Panel D		
Controls		
age difference between wife and partner/husband	5.490	4.355
woman has no education	0.331	0.471
woman has some or all primary school	0.149	0.356
woman has some secondary school	0.361	0.480
woman has completed secondary school or higher	0.159	0.366
number of living children in household	2.351	1.203
husband has no education	0.192	0.394
husband has some or all primary school	0.157	0.364
husband has some secondary school	0.424	0.494
husband completed secondary school or higher	0.225	0.418
father beat mother	0.228	0.420
rural/urban dummy	0.644	0.479

years living in place of residence	15.324	12.349
global human footprint (index, in log)	3.847	0.354
source of drinking water: piped water	0.558	0.497
electricity	0.930	0.255

Notes: In Panel A, we code the variables such that they equal 1 if the female respondent says that she considers beating is justified for each reason listed. The related index ranging from 0 to 1 equals 1 if she says yes to each reason. In Panel B, the binary outcomes equal 1 if the respondent says that she considers the listed barriers as big problems when seeking healthcare, and the index reflects her answers to these three questions. In Panel C, the employment variables are binary and take a value of 1 if the female respondent says she is (i) currently working, (ii) is in the workforce (iii) in services (iv) in agriculture, and (v) in manufacturing. We also code the other human capital, profit sharing, and financial independence variables, and report their summary statistics in Panel C. In Panel D, the individual controls include the difference in wife and partner's/husband's age, four indicator variables for the woman's highest level of educational attainment, similar indicator variables for the partner's/husband's level of educational attainment, a continuous variable for the number of living children in the household, a rural/urban dummy that equals 1 if the respondent lives in a rural area, the number of years the respondent has been living in the current place of residence and a dummy for whether the respondent's father used to beat their mother. We also include the global human footprint index and binary controls for piped water as the main source of drinking water and access to electricity.

Table 2: Impact of mines on women's acceptance of domestic violence

	Beating justified if the wife:						
	goes out without permission	**neglects children**	**argues with husband**	**refuses intimacy**	**does not cook food properly**	**index**	**emotional violence**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Panel A: HFLS mines							
Proximity (whether there is a deposit within 5 km):							
presence of deposit*presence of HFLS active mine	-0.224*	-0.265	-0.454**	-0.028	-0.063	-0.199*	-0.109
	(0.121)	(0.224)	(0.195)	(0.093)	(0.125)	(0.120)	(0.131)
presence of deposit*presence of HFLS active mine*young	0.499***	0.620**	0.594***	0.220**	0.144	0.415***	0.359**
	(0.192)	(0.256)	(0.210)	(0.110)	(0.171)	(0.159)	(0.152)
total effect for young	0.275	0.356	0.141	0.192	0.080	0.216	0.250
F-statistic	5.010	7.080	1.250	3.810	0.410	5.370	13.320
	[0.025]	[0.008]	[0.264]	[0.051]	[0.521]	[0.021]	[0.000]
Observations	7,534	7,539	7,526	7,483	7,540	7,430	7,567
R-squared	0.212	0.237	0.153	0.087	0.093	0.216	0.116
Intensity (number of deposits within 5 km):							
number of deposits*presence of HFLS active mine	-0.250**	-0.279	-0.436**	-0.038	-0.083	-0.215*	-0.090
	(0.116)	(0.222)	(0.191)	(0.089)	(0.122)	(0.118)	(0.129)
number of deposits*presence of HFLS active mine*young	0.492***	0.587**	0.592***	0.201**	0.183	0.415***	0.326**
	(0.183)	(0.246)	(0.198)	(0.100)	(0.158)	(0.153)	(0.149)
total effect for young	0.242	0.308	0.156	0.163	0.099	0.200	0.237
F-statistic	5.160	7.040	2.030	3.380	0.840	5.690	15.030
	[0.023]	[0.008]	[0.155]	[0.066]	[0.361]	[0.017]	[0.000]
Observations	7,534	7,539	7,526	7,483	7,540	7,430	7,567

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R-squared	0.212	0.237	0.153	0.087	0.093	0.216	0.116
Panel B: All mines							
Proximity (whether there is a deposit within 5 km):							
presence of deposit*presence of active mine	-0.137**	-0.089	-0.119*	-0.108**	-0.092	-0.100*	-0.035
	(0.070)	(0.066)	(0.064)	(0.053)	(0.058)	(0.052)	(0.063)
presence of deposit*presence of active mine*young	0.200*	0.121	0.212	0.008	0.074	0.116	-0.158**
	(0.103)	(0.107)	(0.134)	(0.085)	(0.087)	(0.078)	(0.079)
total effect for young	0.063	0.032	0.093	-0.100	-0.018	0.016	-0.192
F-statistic	0.410	0.110	0.620	1.920	0.060	0.060	8.150
	[0.522]	[0.745]	[0.433]	[0.167]	[0.804]	[0.808]	[0.004]
Observations	30,699	30,707	30,668	30,569	30,701	30,358	30,804
R-squared	0.171	0.200	0.136	0.077	0.093	0.188	0.097
Intensity (number of deposits within 5 km):							
number of deposits*presence of active mine	-0.022	-0.036*	-0.006	-0.009	-0.014	-0.014	-0.001
	(0.018)	(0.019)	(0.025)	(0.018)	(0.019)	(0.014)	(0.018)
number of deposits*presence of active mine*young	0.049	0.046	0.069	-0.019	0.009	0.029	-0.078***
	(0.035)	(0.034)	(0.043)	(0.027)	(0.032)	(0.024)	(0.027)
total effect for young	0.027	0.010	0.064	-0.027	-0.005	0.016	-0.079
F-statistic	0.560	0.090	2.520	1.290	0.030	0.540	8.260
	[0.455]	[0.768]	[0.113]	[0.257]	[0.866]	[0.463]	[0.004]
Observations	30,699	30,707	30,668	30,569	30,701	30,358	30,804
R-squared	0.172	0.200	0.136	0.076	0.093	0.187	0.097

Notes: The table reports the regression results for the interaction terms. Panel A reports the results when only precious minerals and HFLS mines are considered using either proximity dummies or intensity measured as count variables for the number of deposits and active mines that are within 5 km. The binary dependent variables take a value of 1 if the female respondent says that she considers that beating is justified for reasons reported in each column. In column (6), the index, ranging from 0 to 1, is constructed by considering the answers to the 5 questions related to attitude towards domestic violence. It equals to 1 if the respondent says that beating is justified in each case. The mean value of the index is 27 percent. In column (7), “emotional violence" is a variable that equals 1 if the respondent says that she has experienced one of the three possible examples of emotional violence listed. The sample is restricted to women who were interviewed for domestic violence only. The individual controls include the difference in wife and partner's/husband's age, three indicator variables for the woman's highest level of educational attainment (with the excluded category being "no education at all"), similar indicator variables for the partner's/husband's level of educational attainment, a continuous variable for the number of living children in the household, a rural/urban dummy that equals 1 if the respondent lives in a rural area, the number of years the respondent has been living in the current place of residence and a dummy for whether the respondent's father used to beat their mother. We also include the GHF and binary controls for piper water as the main source of drinking water and access to electricity. All regressions are weighted, and include district fixed-effects. Robust standard errors clustered at the DHS cluster level. *presence of deposit*presence of active mine* takes a value of 1 if there is a deposit and an active mine within 5 km of the DHS cluster to which the respondent belongs. *number of deposits*presence of active mine* equals the number of deposits within 5 km of the DHS cluster interacted with the dummy for the presence of an active mine within 5 km of the same cluster. *young* is a binary variable that equals 1 if the female respondent is 15-25 years old. We report net effects on the young with associated *p*-values in square brackets. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 3: Impact of mines on men's attitudes to domestic violence

	Beating justified if the wife:					
	goes out without permission	neglects children	argues with husband	refuses intimacy	does not cook food properly	index
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: HFLS mines						
Proximity (whether there is a deposit within 5 km):						
presence of deposit*presence of HFLS active mine	-0.147	0.122	-0.029	-0.211*	-0.227*	-0.123
	(0.103)	(0.088)	(0.104)	(0.108)	(0.125)	(0.087)
Observations	8,389	8,384	8,377	8,356	8,374	8,300
R-squared	0.164	0.170	0.133	0.119	0.116	0.195
Intensity (number of deposits within 5 km):						
number of deposits*presence of HFLS active mine	-0.156	0.109	-0.023	-0.214**	-0.228*	-0.127
	(0.101)	(0.086)	(0.102)	(0.107)	(0.125)	(0.086)
Observations	8,389	8,384	8,377	8,356	8,374	8,300
R-squared	0.165	0.170	0.133	0.119	0.116	0.195
Panel B: All mines						
Proximity (whether there is a deposit within 5 km):						
presence of deposit*presence of active mine	0.011	-0.013	0.003	-0.002	-0.029	-0.008
	(0.057)	(0.068)	(0.063)	(0.051)	(0.055)	(0.052)
presence of deposit*presence of active mine*young	0.215	0.243	0.327**	0.055	0.126	0.190
	(0.165)	(0.158)	(0.152)	(0.159)	(0.151)	(0.134)
total effect for young	0.226	0.230	0.331	0.054	0.096	0.183
F-statistic	1.660	1.890	4.510	0.110	0.420	1.780

	[0.197]	[0.169]	[0.034]	[0.740]	[0.518]	[0.183]
Observations	33,658	33,659	33,643	33,583	33,655	33,434
R-squared	0.129	0.169	0.112	0.094	0.096	0.174
Intensity (number of deposits within 5 km):						
number of deposits*presence of active mine	0.003	-0.005	-0.008	-0.005	-0.007	-0.004
	(0.015)	(0.022)	(0.017)	(0.013)	(0.018)	(0.015)
number of deposits*presence of active mine*young	0.066	0.089	0.144*	0.071	0.093	0.090
	(0.094)	(0.089)	(0.083)	(0.091)	(0.083)	(0.081)
total effect for young	0.069	0.084	0.136	0.066	0.086	0.086
F-statistic	0.510	0.850	2.600	0.510	1.080	1.100
	[0.475]	[0.357]	[0.107]	[0.475]	[0.299]	[0.294]
Observations	33,658	33,659	33,643	33,583	33,655	33,434
R-squared	0.129	0.168	0.112	0.094	0.096	0.174

Notes: The table reports the regression results for the interaction terms. Panel A reports the results when only precious minerals and HFLS mines are considered using either proximity dummies or intensity measured as count variables for the number of deposits and active mines that are within 5 km. The binary dependent variables take a value of 1 if the male respondent says that he considers that beating is justified for reasons reported in each column. Sample sizes for young men are too small to be able to estimate differential and net effects for young men near HFLS mines. In column (6), the Index, ranging from 0 to 1, is constructed by considering the answers to the 5 questions related to attitude towards domestic violence. It equals to 1 if the respondent says that beating is justified in each case. The mean value of the index is 14 percent. The individual controls include the difference in wife and partner's/husband's age, three indicator variables for the man's highest level of educational attainment (with the excluded category being "no education at all"), a continuous variable for the number of living children in the household, a rural/urban dummy that equals 1 if the respondent lives in a rural area, the number of years the respondent has been living in the current place of residence, and a dummy for whether the respondent's father used to beat their mother. We also include the GHF and binary controls for piped water as the main source of drinking water and access to electricity. All regressions are weighted, and include district fixed-effects. Robust standard errors are clustered at the DHS cluster level. *presence of deposit*presence of active mine* takes a value of 1 if there is a deposit and an active mine within 5 km of the DHS cluster to which the respondent belongs. *number of deposits*presence of active mine* equals the number of deposits within 5 km of the DHS cluster interacted with the dummy for the presence of an active mine within 5 km of the same cluster. *young* is a binary variable that equals 1 if the male respondent is 15-25 years old. We report net effects on the young with associated *p*-values in brackets. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 4: Impact of mines on men's attitudes to shared decision-making

	Shared decision-making related to:							
	major purchases	Daily Needs	visits to wife's family	wife's earnings	no. of children	index	his earnings	his healthcare
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: HFLS mines								
Proximity (whether there is a deposit within 5 km):								
presence of deposit*presence of HFLS active mine	0.344***	0.149	0.263**	0.269*	0.120	0.234**	0.186	0.373***
	(0.104)	(0.138)	(0.113)	(0.144)	(0.083)	(0.100)	(0.172)	(0.121)
Observations	8,393	8,393	8,381	8,301	8,389	8,229	8,204	8,421
R-squared	0.139	0.124	0.089	0.086	0.091	0.123	0.113	0.100
Intensity (number of deposits within 5 km):								
number of deposits*presence of HFLS active mine	0.334***	0.164	0.262**	0.280**	0.124	0.237**	0.183	0.362***
	(0.100)	(0.134)	(0.107)	(0.137)	(0.079)	(0.095)	(0.166)	(0.115)
Observations	8,393	8,393	8,381	8,301	8,389	8,229	8,204	8,421
R-squared	0.139	0.125	0.089	0.085	0.091	0.123	0.114	0.100
Panel B: All mines								
Proximity (whether there is a deposit within 5 km):								
presence of deposit*presence of active mine	0.204***	0.224***	0.107*	0.076	0.068	0.131***	0.120	0.061
	(0.071)	(0.078)	(0.056)	(0.060)	(0.035)	(0.046)	(0.074)	(0.085)
presence of deposit*presence of active mine*young	-0.306	0.067	-0.007	0.187	0.190*	0.096	-0.157	0.269
	(0.226)	(0.184)	(0.175)	(0.204)	(0.101)	(0.132)	(0.208)	(0.195)
total effect for young	-0.102	0.291	0.100	0.264	0.258	0.227	-0.037	0.331
F-statistic	0.200	2.470	0.280	1.630	6.190	2.780	0.030	2.730

	[0.655]	[0.116]	[0.597]	[0.202]	[0.013]	[0.095]	[0.854]	[0.098]
Observations	33,620	33,640	33,609	33,428	33,659	33,182	33,105	33,751
R-squared	0.139	0.123	0.079	0.079	0.084	0.125	0.095	0.074
Intensity (number of deposits within 5 km):								
number of deposits*presence of active mine	0.068***	0.086***	0.037**	0.019	0.016	0.044***	0.054*	-0.009
	(0.022)	(0.023)	(0.017)	(0.019)	(0.011)	(0.015)	(0.033)	(0.028)
number of deposits*presence of active mine*young	-0.045	0.100	0.057	0.180**	0.083*	0.091*	-0.017	0.208***
	(0.101)	(0.072)	(0.079)	(0.085)	(0.047)	(0.050)	(0.094)	(0.071)
total effect for young	0.023	0.186	0.094	0.199	0.099	0.135	0.037	0.199
F-statistic	0.050	6.370	1.320	5.430	4.280	6.830	0.160	8.220
	[0.824]	[0.012]	[0.251]	[0.020]	[0.039]	[0.009]	[0.686]	[0.004]
Observations	33,620	33,640	33,609	33,428	33,659	33,182	33,105	33,751
R-squared	0.139	0.123	0.079	0.079	0.084	0.125	0.095	0.074

Notes: The table reports the regression results for the interaction terms. Panel A reports the results when only precious minerals and HFLS mines are considered using either proximity dummies or intensity measured as count variables for the number of deposits and active mines that are within 5 km. Sample sizes for young men are too small to be able to estimate differential and net effects for young men near HFLS mines. Men are asked who they think should have greater say when it comes to decisions reported in columns (1) to (5). The binary dependent variables take a value of 1 if the respondent says that he thinks such decisions should be taken jointly with his partner. In column 6, the index ranging from 0 to 1 takes a value of 1 if the respondent answers "shared equally" when asked who should have greater say for the set of all five listed decisions. The mean of this index is 68 percent. The individual controls include the difference in wife and partner's/husband's age, three indicator variables for the man's highest level of educational attainment (with the excluded category being "no education at all"), a continuous variable for the number of living children in the household, a rural/urban dummy that equals 1 if the respondent lives in a rural area, the number of years the respondent has been living in the current place of residence, and a dummy for whether the respondent's father used to beat their mother. We also include the GHF and binary controls for piped water as the main source of drinking water and access to electricity. All regressions are weighted, and include district fixed-effects. Robust standard errors are clustered at the DHS cluster level. *presence of deposit*presence of active mine* takes a value of 1 if there is a deposit and an active mine within 5 km of the DHS cluster to which the respondent belongs. *number of deposits*presence of active mine* equals the number of deposits within 5 km of the DHS cluster interacted with the number of active mines within 5 km of the same cluster. *young* is a binary variable that equals 1 if the male respondent is 15-25 years old. We report net effects on the young with associated *p*-values in brackets. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 5: Profit sharing, proximity to mines and women's financial independence near HFLS mines

	is in the workforce (1)	agricul-ture (2)	manufac-Turing (3)	services (4)	manual – skilled & unskilled (5)	earns cash (6)	aware of loan program (7)	has taken a loan (8)
Panel A: Linear version of profit sharing per female pop.								
presence of deposit*presence of HFLS	-0.223	0.109	-0.158	-0.233	-0.173***	0.006	0.170	-0.085
active mine	(0.136)	(0.109)	(0.614)	(0.852)	(0.061)	(0.119)	(0.127)	(0.067)
presence of deposit*presence of HFLS	1.126**	-1.097**	1.821***	0.474*	1.916***	0.923**	2.769***	0.536*
active mine*profit sharing per female pop.	(0.535)	(0.479)	(0.298)	(0.268)	(0.295)	(0.444)	(0.608)	(0.289)
Observations	3,873	3,873	3,826	3,826	3,826	3,881	3,881	3,881
R-squared	0.144	0.252	0.046	0.084	0.050	0.112	0.129	0.100
Panel B: Non-linear version of profit sharing per female pop.								
presence of deposit*presence of HFLS	-0.100	0.031	-0.066	-0.117	-0.076	0.121	0.413***	-0.055
active mine	(0.122)	(0.112)	(0.055)	(0.573)	(0.053)	(0.111)	(0.117)	(0.064)
presence of deposit*presence of HFLS	0.098	-0.020	0.250***	-0.078	0.264***	0.020	0.254	0.038
active mine*profit sharing per female pop.	(0.203)	(0.147)	(0.085)	(0.104)	(0.084)	(0.175)	(0.176)	(0.085)
Observations	3,873	3,873	3,826	3,826	3,826	3,881	3,881	3,881
R-squared	0.143	0.252	0.045	0.084	0.049	0.112	0.126	0.101

Notes: The table reports the coefficients on the interaction terms. In column (1), the indicator variable takes a value of 1 if she is in the workforce. Columns (2) to (5) consider binary occupational outcomes related to employment in agriculture, manufacturing, services, and skilled and unskilled manual work, respectively. The dependent variable equals to 1 in column (6) if the female respondent says that she earns "cash" instead of "in-kind" as earnings. In the last two columns, the variables relate to awareness of financial opportunities and the binary dependent variables equal 1 in column (7) if she says that she is aware of a program in the area that gives loans to women to start or expand a business, and in column (8), the indicator variable equals 1 if she says that she has taken a loan, cash or in-kind from the program to start or expand a business. The individual controls include the difference in wife and partner's/husband's age, three indicator variables for the woman's highest level of educational attainment (with the excluded category being "no education at all"), similar indicator variables for the partner's/husband's level of educational attainment, a continuous variable for the number of living children in the household, a rural/urban dummy that equals 1 if the respondent lives in a rural area, and the number of years the respondent has been living in the current place of residence. We also include the GHF and binary controls for piped water as the main source of drinking water and access to electricity. All regressions include state fixed-effects. Robust standard errors are clustered at the DHS cluster level. All regressions are weighted. *presence of deposit*presence of active mine* takes a value of 1 if there is a deposit and an active mine within 5 km of the DHS cluster to which the respondent belongs. *presence of deposit*presence of HFLS active mine*profit sharing per female* *population* in Panel A is the interaction term between the presence of a deposit within 5 km of the DHS cluster, presence of HFLS active mine within 5 km of the DHS cluster, and the linear/continuous variable for district-level profit sharing per female population. The only difference in Panel B is that the profit sharing variable is in its non-linear form and is 1 if the profit sharing per female population level equals or exceeds the 75th percentile value. *** Denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 6: Impact of mines on women's human capital

	uneducated	BMI	underweight	HBA	mildly anemic	mod/severely anemic
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: HFLS mines						
Proximity (whether there is a deposit within 5 km):						
presence of deposit*presence of HFLS active mine	0.013	0.218	-0.291***	0.692*	0.361***	-0.255***
	(0.064)	(0.650)	(0.083)	(0.377)	(0.117)	(0.070)
presence of deposit*presence of HFLS active mine*young	-0.533***	0.600	0.176*	-1.625***	0.699***	-0.006
	(0.096)	(1.035)	(0.105)	(0.575)	(0.167)	(0.113)
total effect for young	-0.519	0.818	-0.115	-0.934	1.061	-0.261
F-statistic	19.990	0.660	1.210	3.750	56.970	7.910
	[0.000]	[0.418]	[0.272]	[0.053]	[0.000]	[0.005]
Observations	7,350	7,350	7,350	7,310	7,310	7,310
R-squared	0.421	0.278	0.145	0.106	0.056	0.057
Intensity (number of deposits within 5 km):						
number of deposits*presence of HFLS active mine	0.019	-0.197	-0.298***	0.640*	0.418***	-0.261***
	(0.063)	(0.600)	(0.082)	(0.367)	(0.112)	(0.068)
number of deposits*presence of HFLS active mine*young	-0.520***	1.555**	0.204**	-1.672***	0.631***	0.034
	(0.083)	(0.682)	(0.090)	(0.529)	(0.126)	(0.100)
total effect for young	-0.501	1.359	-0.094	-1.032	1.048	-0.228
F-statistic	21.850	2.890	1.030	5.190	96.550	8.100
	[0.000]	[0.090]	[0.309]	[0.023]	[0.000]	[0.005]
Observations	7,350	7,350	7,350	7,310	7,310	7,310
R-squared	0.421	0.277	0.145	0.106	0.056	0.057

Panel B: All mines						
Proximity (whether there is a deposit within 5 km):						
presence of deposit*presence of active mine	-0.019	1.394***	-0.065*	0.150	-0.032	-0.015
	(0.036)	(0.532)	(0.036)	(0.193)	(0.053)	(0.034)
presence of deposit*presence of active mine*young	-0.112	-0.111	0.107	0.069	-0.138	0.018
	(0.087)	(1.003)	(0.128)	(0.574)	(0.134)	(0.108)
total effect for young	-0.131	1.284	0.042	0.219	-0.170	0.003
F-statistic	2.730	1.810	0.140	0.160	1.760	0.000
	[0.100]	[0.179]	[0.711]	[0.687]	[0.184]	[0.976]
Observations	29,957	29,957	29,957	29,759	29,759	29,759
R-squared	0.394	0.214	0.104	0.084	0.039	0.047
Intensity (number of deposits within 5 km):						
number of deposits*presence of active mine	0.004	0.277	-0.016	-0.066	0.001	0.015
	(0.013)	(0.214)	(0.013)	(0.049)	(0.018)	(0.014)
number of deposits*presence of active mine*young	-0.023	-0.157	0.015	-0.130	0.026	-0.003
	(0.034)	(0.327)	(0.051)	(0.181)	(0.059)	(0.039)
total effect for young	-0.018	0.120	-0.001	-0.195	0.027	0.012
F-statistic	0.350	0.190	0.000	1.140	0.260	0.110
	[0.556]	[0.660]	[0.989]	[0.285]	[0.607]	[0.742]
Observations	29,957	29,957	29,957	29,759	29,759	29,759
R-squared	0.394	0.213	0.104	0.084	0.039	0.047

Notes: The table reports the regression results for the interaction terms. Panel A reports the results when only precious minerals and HFLS mines are considered using either proximity dummies or intensity measured as count variables for the number of deposits and active mines that are within 5 km. BMI is weight in kilograms (kg) divided by height in meters squared (m^2), and underweight is defined as BMI less than 18.5 kg/m^2. A woman is mildly anemic if her HBA level is between 10.0 – 11.9 g/dl (grams per deciliter) and moderately or severely anemic if her HBA level is less than 9.9 g/dl. The individual controls include the difference in wife and partner's/husband's age, three indicator variables for the partner's/husband's level of educational attainment, a continuous variable for the number of living children in the household, a rural/urban dummy that equals 1 if the respondent lives in a rural area, the number of years the respondent has been living in the current place of residence, and a dummy for whether the respondent's father used to beat their mother. We also include the GHF and binary controls for piped water as the main source of drinking water and access to electricity. All regressions are weighted, and include district fixed-effects. Robust standard errors are clustered at the DHS cluster level. *presence of deposit*presence of active mine* takes a value of 1 if there is a deposit and an active mine within 5 km of the DHS cluster to which the respondent belongs. *number of deposits*presence of active mine* equals the number of deposits within 5 km of the DHS cluster interacted with the dummy for the presence of active mine within 5 km of the same cluster. *young* is a binary variable that equals 1 if the female respondent is in the age group 15-25 years old. We report net effects on the young with associated *p*-values in brackets. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

ONLINE APPENDIX

Appendix Box 1: Choice of Baseline Distance

To determine the appropriate treatment distance for the empirical framework, we study the commuting behavior of workers in India. In 2011, the Census in India reported the mode of travel and the travel distances of workers in the country for the first time. The data is available by gender, and for both rural and urban areas in each state.[50] Appendix Figure 7 shows that more than half of the women interviewed report that they walk to work, against 28 percent of male respondents reporting so.[51] In rural India, two-thirds of women walk to work, while only 28 percent of men do so, and 1 out of 4 men uses a bicycle to access work compared to only 1 out of 20 women who work. Appendix Figure 8 shows the distance to work by gender and by mode of travel. Out of all workers interviewed, around a quarter of male respondents and 45 percent of female respondents do not travel at all for work. The corresponding proportions for rural areas are 33 percent and 55 percent for male and female workers, respectively. Out of all the respondents reporting that they had to commute to work, 16 percent reported a travel distance of up to 1 km, and 23 percent reported a distance of 2-5 km. There were mild differences in the proportions for male and female respondents, and between rural and urban areas. Taking these together, the census data reveal that the proportion of workers who travel 5 km or less to access their place of work is approximately 70 percent. Hence our focus on the 5 km distance around clusters for a baseline seems appropriate for India.

We also refer to the relevant literature on mining and development to ensure that this baseline distance is in line with previous studies. Kotsadam and Benshaul-Tolonen (2016) use a baseline distance of 20 km to estimate a mine's footprint, while Benshaul-Tolonen (2019) relies on a treatment distance of 15 km. Von der Goltz and Barnwal (2019) define a DHS cluster as being in the direct vicinity of a mine if it is within 5 km of the nearest mine. In these cases as well as in ours, the choice of baseline distance is based on the commuting behavior of workers and on the related literature on the health, development, and employment effects of mines on local communities.

---

[50] These data are for workers who were engaged in economic activities; not cultivators or agricultural laborers or those in household industries (Source: censusindia.gov.in/2011Census).

[51] In addition to the evidence presented here, Appendix Figure 5 which, consistent with the literature, shows that the treatment distance is less than 20 kms, further justifies our choice of baseline distance.

Appendix Box 2: Profit Sharing in Mining Communities

We consider the robustness of the profit sharing estimates by including additional district-level controls that could affect both women's employment opportunities and the value of mineral production distributed to local communities. In results available on request, we add these controls sequentially in regressions involving the binary dependent variable for women's employment. First, we control for the district's socio-economic vulnerability. We use the index constructed from the National Family Health Survey 2015-2016 by Acharya and Porwal (2020).[52] Following Berman *et al*. (2017), we also proxy for lootability. Since precious minerals generate large royalties and rents, they create incentives for loots and conflict. We use two different proxies for lootability and the likelihood of mineral-induced conflicts: (i) log mean distance from each district's centroid to the nearest lootable gold or surface deposit, and (ii) a dummy variable that equals one if the district is affected by Maoist conflicts.[53]

Since the impact of profit sharing on the local community depends on how resource rents are collected and distributed via institutional arrangements (Mehlum *et al*. 2006), our framework must also consider the district-level variation in administrative institutions, corruption, bureaucracy, and the rule of law. Governance indicators are not available at this disaggregated level, so we include the number of intermediate and village panchayats (per 1000 inhabitants) instead. These are important institutions of local governance in Indian districts that ensure accountability and transparency in the collection and use of resource revenues.[54] They are likely to play a key role in ensuring that, among other things, royalties are not dissipated through leakages.[55] We also add the share of mineral-leased area held by the government as an additional

[52] This study provides vulnerability indices that could improve the management and response of the Covid-19 pandemic in India. Three indicators are used to build the socio-economic index: the percentage of the population belonging to scheduled caste and scheduled tribe (to represent for marginalized groups), the proportion of the population aged 15 and above who have completed secondary or higher level of education, and an asset deprivation index (the proportion of households that do not have a motorized vehicle, television, computer, bicycle, and refrigerator, amongst others).
[53] We obtain the distance to the nearest lootable or surface gold deposit using AIDDATA (Source name: GOLDATA, for more details, see Balestri and Maggioni 2014). We obtain the list of districts affected by Maoist conflicts from the South Asia Terrorism Portal.
[54] Data is obtained from the Local Government Directory. See website for more details: lgdirectory.gov.in.
[55] Caselli and Michaels (2013) find that royalties from oil production in Brazil lead to significant increases in municipalities' spending on public goods and services, but that improvements in provision of public services are smaller relative to the reported fiscal spending increases. This suggests that there is "missing money" due to embezzlement.

variable to proxy for public/private sector involvement. Increased access to media may also influence agency measures and the distribution of rents. For this reason, we use the DHS to construct an index that is a composite variable for whether the respondent listens to the radio, watches TV, and reads the newspapers often.

Appendix Box 3: Temporal Falsification Tests and Determining Treatment Distance

Temporal Falsification Tests

Appendix Table 9 presents temporal falsification tests using information on future/prospected mines. For purposes of these tests, we present results only for women's acceptance of domestic violence. Since these mines are not currently active, there should be fewer impacts on the measures considered. There are too few future HFLS mines to identify impacts, so we focus on all mines. Four of the seven outcomes have counter-intuitive signs, one of which (goes out without permission) is measured with significance. In contrast, all seven coefficients have the expected sign in the main results (Panel B of Table 2 in the main paper), and four of these are significant. Focusing on the composite index variable in the main results, the coefficient on this variable indicated a significant 10.0 percentage point decline in Panel B of Table 2 in the main paper, but is statistically zero in Appendix Table 9. In summary, Appendix Table 9 considers seven outcomes and the coefficient on the interaction term of deposits and mines in close proximity is significant and in keeping with expectation in only two instances. Importantly, the coefficient of the interaction term in the case of the index variable outcome (which is the representative measure) is insignificant. Hence future mines have no effects on these measures, which is what we should expect as these mines are not currently open. In contrast, in the main results in Table 2, the composite index measure is negative and significant, four of the seven outcomes are significant, and the coefficients on all seven outcomes are negative, as expected. Overall, we find that active mines alone result in beneficial impacts for women as future mines have unexpected or few impacts.[56]

[56] Note that we could take the difference between Table 2 in the main paper and Appendix Table 9 and treat that as a triple difference (by deposits, active mines, and future/prospected mines). Effects from such a triple difference would be larger for 4 of the 7 indicators. For example, "goes out without permission" will have an effect size closer to -0.224 – (+0.227) = - 0.451 for older women near deposit and active mines in such a triple difference. Similarly the index will have an effect size of -0.199 – (+0.024) = -0.223 for this demographic.

Determining Treatment Distance

Although we argue that given commuting distance and modes of travel to work for much of the Indian rural population, we perform an additional check that 5 km near deposits and mines is an appropriate measure of treatment distance. These results are presented in Appendix Figure 9. We follow Benshaul-Tolonen (2019) and use spatial lag models to construct these measures and concentrate on proximity to HFLS mines as that is where impacts are most evident. Although these estimates are mostly insignificant, the treatment effect is the largest at smaller treatment distances qualitatively, indicating the existence of spatial spillovers.[57] As the treatment distances become larger, the interaction term between the presence of deposits and the presence of a HFLS active mine for the acceptance of violence index in particular becomes either smaller in magnitude or exhibits unexpected signs. Given this, and evidence from the 2011 Census on average commuting distance for workers, we use 5 km as the treatment distance for our study.

[57] Similar to Benshaul-Tolonen (2019), there is substantial noise in these spatially lagged models.

Appendix References

Acharya, Rajib, and Akash Porwal. 2020. "A Vulnerability Index for the Management of and Response to the COVID-19 Epidemic in India: An Ecological Study," *The Lancet Global Health* 8(9): E1142-E1151.

Balestri, Sara, and Mario Maggioni. 2014. Blood diamonds, dirty gold and spatial spill-overs measuring conflict dynamics in West Africa. *Peace Economics, Peace Science and Public Policy*, *20*(4): 551-564.

Benshaul-Tolonen, Anja. 2019. "Endogenous Gender Roles: Evidence from Africa's Gold Mining Industry." Available at SSRN 3284519.

Berman, Nicolas, Mathieu Couttenier, Dominic Rohner, and Mathias Thoenig. 2017. "This Mine is Mine! How Minerals Fuel Conflicts in Africa," *American Economic Review* 107 (6): 1564-1610.

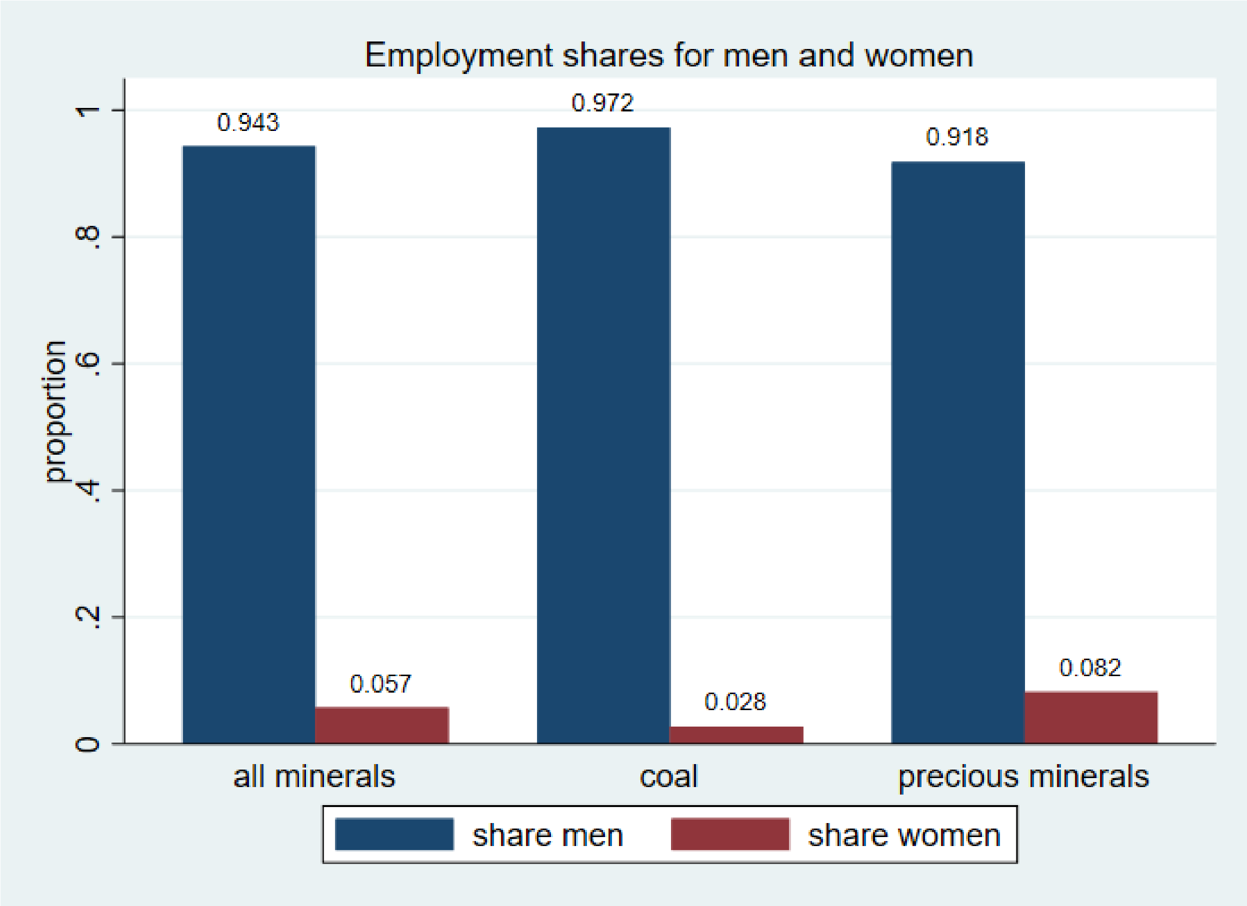
Caselli, Francesco, and Guy Michaels. 2013. "Do Oil Windfalls Improve Living Standards? Evidence from Brazil," *American Economic Journal: Applied Economics* 5(1): 208-238.

Kotsadam, Andreas, and Anja Benshaul-Tolonen. 2016. "African Mining, Gender, and Local Employment," *World Development* 83 (7): 325-339.

Mehlum, Halvor, Karl Moene, and Ragnar Torvik. 2006. "Institutions and the Resource Curse," *The Economic Journal* 116 (508): 1-20.

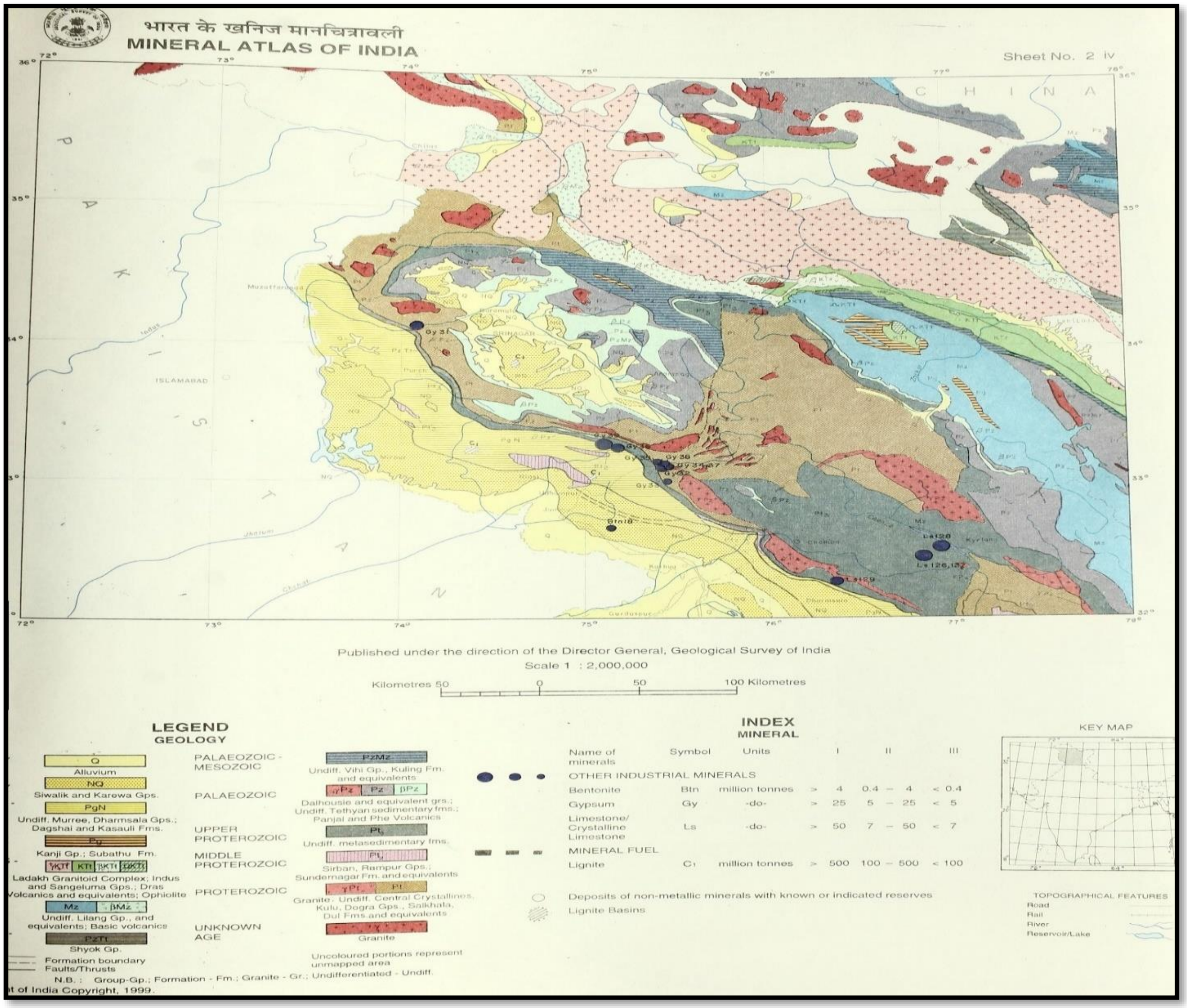
Von der Goltz, Jan, and Prabhat Barnwal. 2019. "The Local Wealth and Health Effects of Mineral Mining in Developing Countries," *Journal of Development Economics* 139: 1-16.

Appendix Figure 1: Employment shares for men and women in mining, 2010-2015



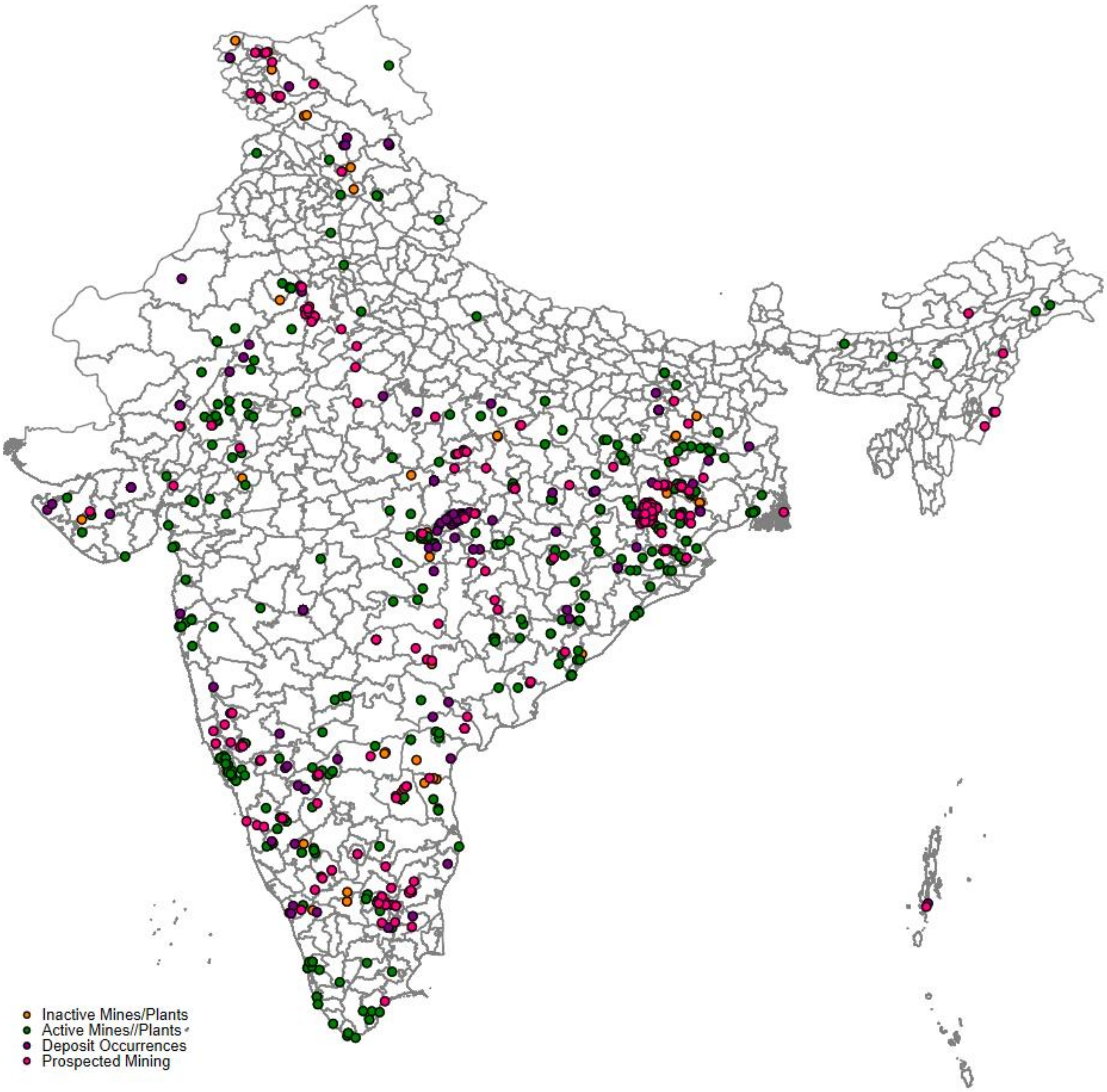
Source: *Statistics of Mines in India Volume – 1 (Coal) and Volume – II (Non-Coal)* from 2010 to 2015. Authors' calculations from official data. All minerals include coal, non-coal, precious and non-precious minerals. For clarity, only the main mineral classifications are reported in this figure. Within each classification, shares sum to one.

Appendix Figure 2: An example of a map sheet from the Mineral Atlas of India, 2001



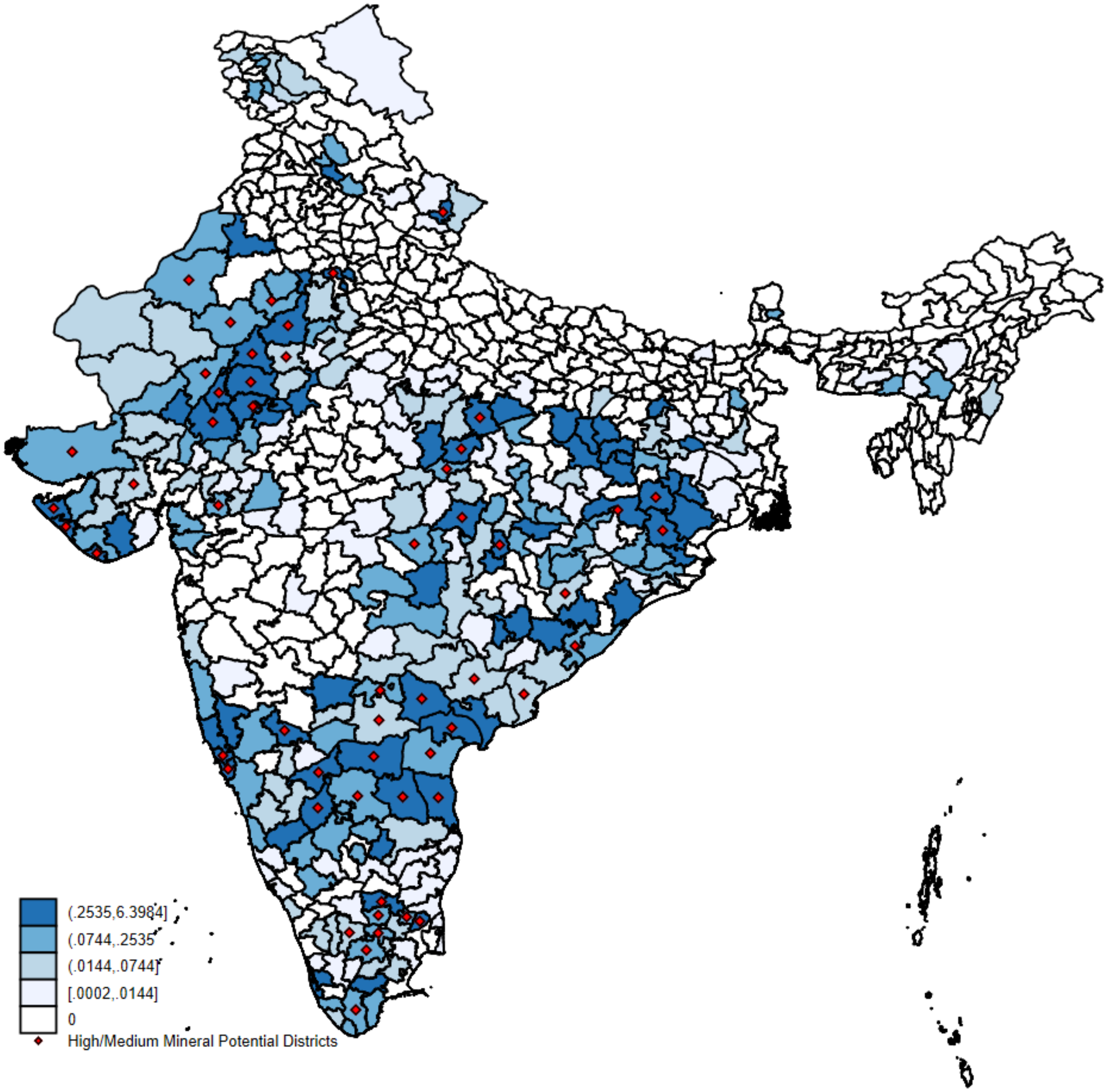
Source: Mineral Atlas of India (Geological Survey of India, 2001).

Appendix Figure 3: Distribution of active and inactive mines in India, 2007



Source: United States Geological Survey, 2007

Appendix Figure 4: The share of leased area (percent) for districts in India, 2014

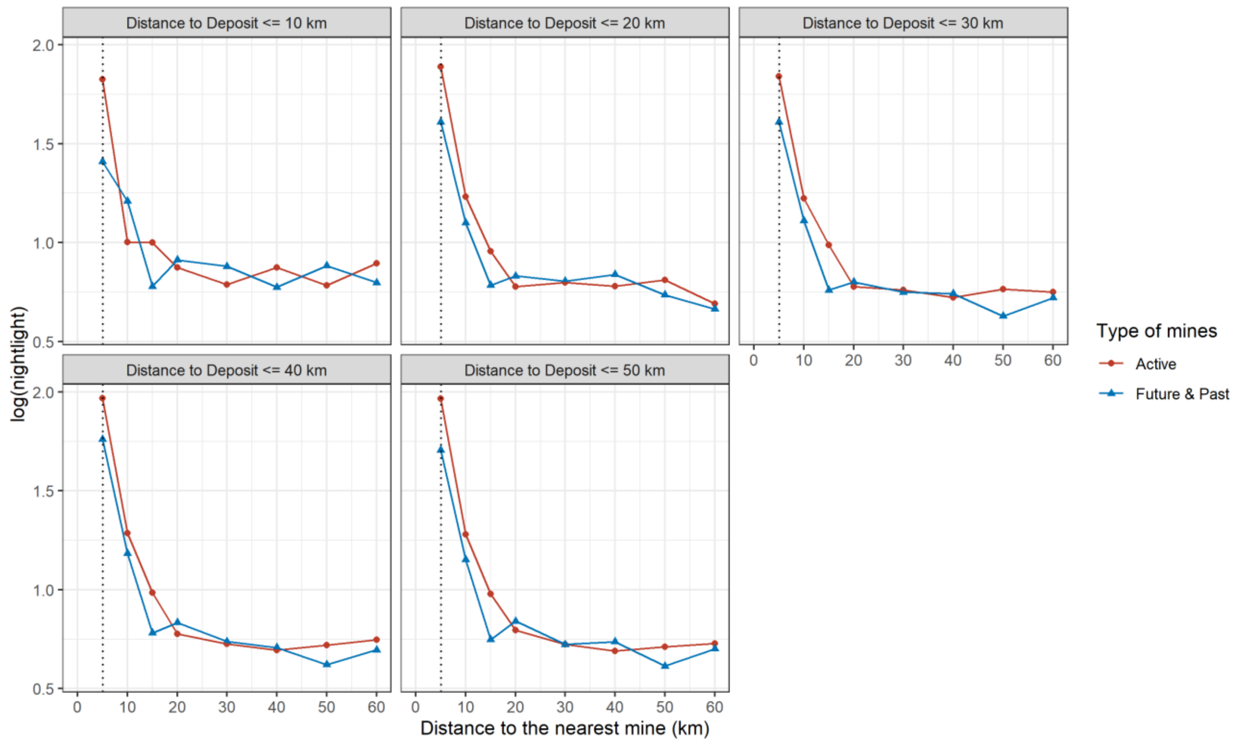


Source: Bulletin of Mining Leases and Prospecting Licenses (Indian Bureau of Mines, 2014). Authors' calculations from official data.

Appendix Figure 5: Pre-trend Analyses of Nightlight Density Over Time

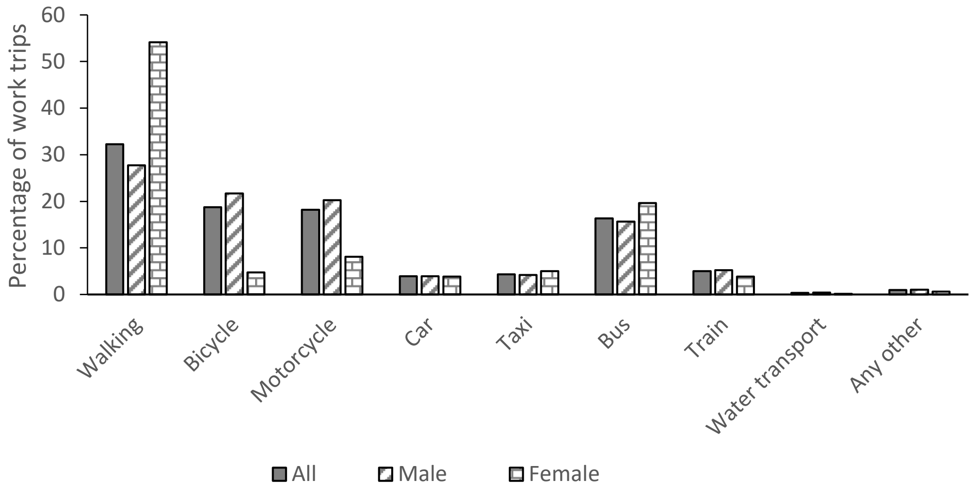
Note: Y-axis plots log(nightlight+1) at the cluster level. X-axis plots year. Treated groups are clusters that have both mineral deposits and active mines within the treatment distance, noted on the panel heading. Control groups are clusters that have mineral deposits within the treatment distance but have no active mine within that same distance. Panel heading shows the sample used to compare parallel trends, from the top left panel where only clusters that have a mineral deposit within 5km are selected, to the bottom right panel where clusters that have a mineral deposit within 20km are selected. Each dot represents nightlights averaged across clusters in a given year. Dotted vertical lines represent year 2001 and 2007, the year when information on mineral deposits and mining operations are collected, respectively.

Appendix Figure 6: Pre-trend Analyses between Active Mines and Future/Past mines



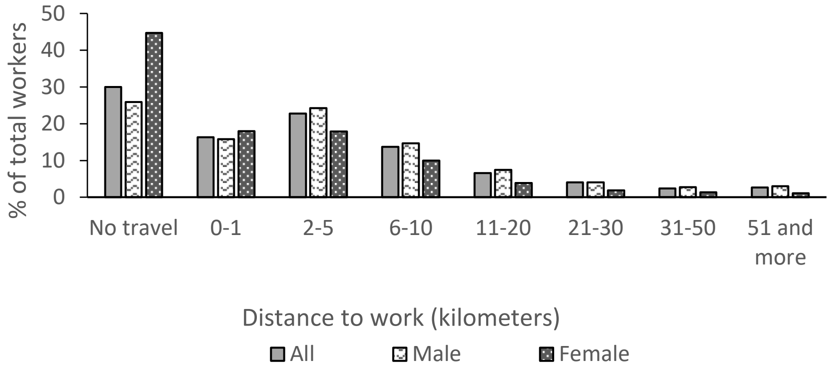
Note: Y-axis plots log nightlights at the cluster level. X-axis plots the nearest distances from each cluster to an active mine (red line with dots), and to a future or past mine (blue line with triangles). Panel heading shows the sample used to compare parallel trends from the top left panel where only clusters that have a mineral deposit within 10km are selected (the smallest sample, N=5,704), to the bottom middle panel where clusters that have a mineral deposit within 50km are selected (the largest sample, N=23,208). Each dot represents nightlights averaged across observations for which the closest active or future/past mines are located in specific ranges (0-5 km to 90-100 km).

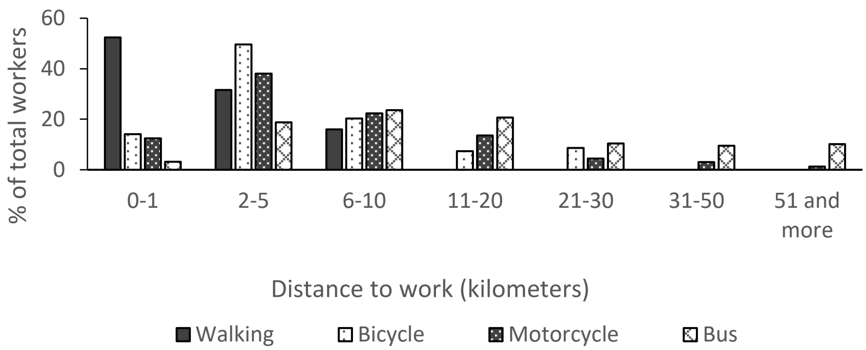
Appendix Figure 7: Mode of travel to commute to work for workers in India



Source: Authors' calculations from the 2011 Census of India

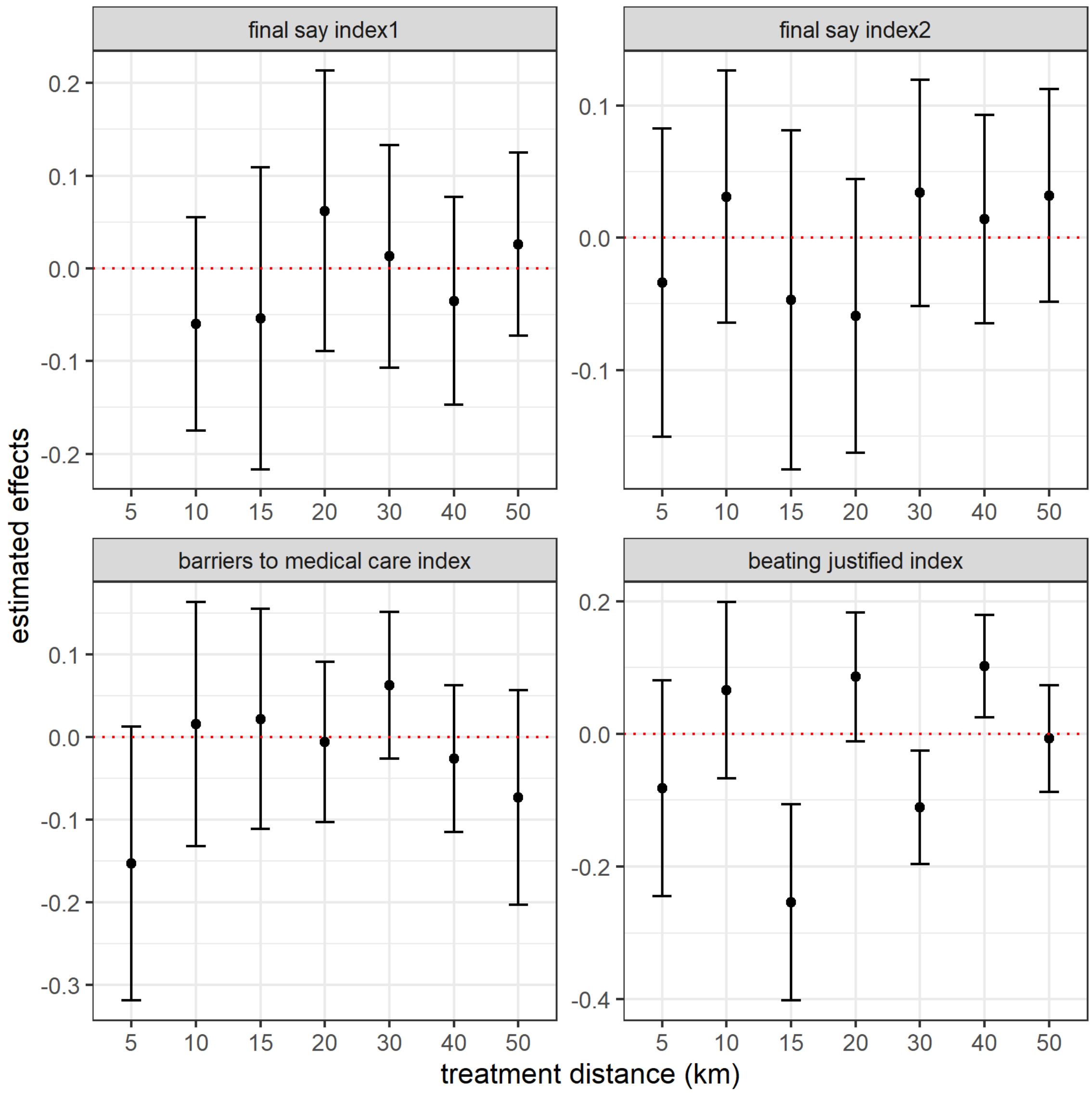
Appendix Figure 8: Distance from residence to work for workers, by gender and by mode of travel, in India





Source: Authors' calculations from 2011 Census of India

Appendix Figure 9: Determination of treatment distance



Notes: This figure plots point estimates of the interaction term "*presence of deposit_x km*presence of HFLS active mine_x km*" at different cutoff distances. The outcome variables are shown in the heading of each sub-plot. Each figure shows the point estimates and the 90% confidence intervals. In each model, the individual controls include the age difference between wife and partner/husband, three indicator variables for the woman's highest level of educational attainment (with the excluded category being "no education at all"), similar indicator variables for the partner's/husband's level of educational attainment, a continuous variable for the number of living children in the household, a rural/urban dummy that equals 1 if the respondent lives in a rural area, the number of years the respondent has been living in the current place of residence, and an indicator for whether the respondent's mother was beaten by their father. We also include the GHF (see text for further details) and binary controls for the main source of drinking water being piped water and access to electricity. All regressions are weighted, and include district fixed-effects. Robust standard errors are clustered at the DHS cluster level. *presence of deposit_x km*presence of HFLS active mine_x km* takes a value of 1 if there is a deposit and an active HFLS mine within x km of the DHS cluster to which the respondent belongs.

Appendix Table 1: Summary statistics for male respondents in DHS 2015-2016

	mean	standard deviation
Panel A		
Justifies beating if		
wife goes out without telling	0.148	0.355
neglects children	0.198	0.398
argues with husband	0.187	0.390
refuses intimacy	0.080	0.271
does not cook food properly	0.095	0.294
index	0.141	0.259
Panel B		
Equal/joint decision-making related to		
major purchases	0.623	0.485
daily needs for households	0.537	0.499
visits to wife's family	0.705	0.456
wife's earnings	0.676	0.468
number of children	0.870	0.336
his earnings	0.632	0.482
his healthcare	0.537	0.499
index	0.684	0.344
Panel C		
Controls		
age difference between husband and wife/partner	5.060	4.079
no education at all	0.161	0.368
some or all primary school	0.159	0.366
some secondary school	0.437	0.496
completed secondary school or higher	0.242	0.429
number of living children	2.065	1.399
father beat mother	0.221	0.415
rural/urban	0.611	0.488
years living in place of residence	34.797	18.981
global human footprint (index, in log)	3.866	0.356
source of drinking water: piped water	0.596	0.491
electricity	0.939	0.240

Notes: In Panel A, we code the variables such that they are equal to 1 if the male respondent says that he considers beating is justified for each reason listed. The related index ranging from 0 to 1 equals 1 if he says yes to each reason. In Panel B, the binary outcomes equal 1 if the male respondent says "equally/jointly" when asked who would have greater say when making the listed decisions. The index is constructed to reflect their answers to this set of questions. In Panel C, the individual controls include the difference in wife and partner's/husband's age, four indicator variables for the man's highest level of educational attainment, a continuous variable for the number of living children in the household, an indicator for whether respondent's father used to beat their mother, a rural/urban dummy that equals 1 if the respondent lives in a rural area, and the number of years the respondent has been living in the current place of residence. We also include the global human footprint index (see text for further details) and binary controls for the main source of drinking water being piped water and access to electricity. Table reports weighted statistics.

Discussion: In Panel A, we see that when it comes to proxies for attitudes towards domestic violence, approximately 19 percent of interviewed men consider that beating is justified if the wife argues with her partner/husband, while an average of 15 percent agrees with the statement that it is justified if the wife goes out without telling her partner/husband. Less than 10 percent report that beating is justified if she does not cook food properly. The index summarizing their answers to the questions related to domestic violence has a mean value of 14 percent. We note that these proportions are lower than those reported in Table 1 by women perhaps reflecting their experience of these modes of violence and their broader acceptance of such cultural norms.

In Panel B, we show variables related to joint decision-making in the household. Men are asked who they think should have greater say in household decision-making. The answers to each question are coded such that the binary variables take a value of 1 if the male respondent says that he thinks that such decisions should be taken "jointly/equally". Overall, the index indicates that 68 percent of sampled men answered that such decisions should be taken jointly, with 87 percent reporting that the number of children is a decision that should be taken together and 71 percent reporting that visits to the partner's/wife's family should be decided jointly. About 54 percent believe that both partners should have a say when making decisions about daily household needs and the respondent's healthcare. Panel C reports the statistics for the individual controls.

Appendix Table 2: Summary statistics for the treatment variables

	mean	standard deviation
Panel A: proximity measures		
deposit	0.067	0.250
active mine	0.038	0.182
HFLS active mine	0.027	0.068
future mine	0.017	0.127
distance to nearest deposit (in km)	29.567	22.804
distance to nearest active mine (in km)	45.254	26.063
distance to nearest HFLS active mine	62.408	23.911
Panel B: intensity measures		
number of deposits	0.092	0.418

Notes: Panel A reports the proximity measures for the sample of women selected for the domestic violence module. The variable "deposit" equals 1 if there is a mineral deposit within 5 km of the respondent's cluster. The variable "active mine" equals 1 if there is an active mine within 5 km of the respondent's cluster. The same idea applies for HFLS and future mines. In Panel B, we report the mean and standard deviation for the intensity measure which is a count of the number of deposits within 5 km of the cluster for the sample of women selected for the domestic violence module. Table reports weighted statistics.

Appendix Table 3: Impact of mines on women's acceptance of domestic violence in mineral rich states

	Beating justified if the wife:						
	goes out without permission	neglects children	argues with husband	refuses intimacy	does not cook food properly	index	emotional violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: HFLS mines							
Proximity (whether there is a deposit within 5 km):							
presence of deposit*presence of HFLS active mine	-0.197*	-0.562**	-0.647***	-0.100	0.140	-0.263***	0.039
	(0.114)	(0.256)	(0.127)	(0.147)	(0.111)	(0.083)	(0.073)
presence of deposit*presence of HFLS active mine*young	0.254*	0.698**	0.781***	0.122	-0.171	0.327***	0.120*
	(0.137)	(0.273)	(0.143)	(0.157)	(0.150)	(0.085)	(0.070)
total effect for young	0.057	0.135	0.134	0.022	-0.030	0.063	0.159
F-statistic	0.280	1.510	0.880	0.050	0.040	0.730	5.290
	[0.597]	[0.220]	[0.348]	[0.823]	[0.843]	[0.394]	[0.022]
Observations	4,048	4,048	4,040	4,024	4,045	4,002	4,054
R-squared	0.167	0.297	0.154	0.083	0.093	0.218	0.112
Intensity (number of deposits within 5 km):							
number of deposits*presence of HFLS active mine	-0.186*	-0.524**	-0.615***	-0.098	0.143	-0.257***	0.059
	(0.108)	(0.250)	(0.114)	(0.142)	(0.103)	(0.077)	(0.065)
number of deposits*presence of HFLS active mine*young	0.253**	0.649**	0.728***	0.103	-0.156	0.315***	0.066
	(0.119)	(0.262)	(0.119)	(0.145)	(0.106)	(0.074)	(0.066)
total effect for young	0.066	0.125	0.113	0.005	-0.013	0.058	0.125
F-statistic	0.670	1.700	0.830	0.000	0.010	0.760	4.160
	[0.415]	[0.193]	[0.361]	[0.951]	[0.906]	[0.383]	[0.042]
Observations	4,048	4,048	4,040	4,024	4,045	4,002	4,054

R-squared	0.167	0.297	0.154	0.083	0.093	0.218	0.111

Notes: The table reports the regression results for the interaction terms in the mineral rich states of Andhra Pradesh, Bihar, Madhya Pradesh, Maharashtra, Orissa and West Bengal . Panel A reports the results when only precious minerals and HFLS mines are considered using either proximity dummies or intensity measured as count variables for the number of deposits and active mines that are within 5 km. The binary dependent variables take a value of 1 if the female respondent says that she considers that beating is justified for reasons reported in each column. In column (6), the index, ranging from 0 to 1, is constructed by considering the answers to the 5 questions related to attitude towards domestic violence. It equals to 1 if the respondent says that beating is justified in each case. The mean value of the index is 27 percent. In column (7), "emotional violence" is a variable that equals 1 if the respondent says that she has experienced one of the three possible examples of emotional violence listed. The sample is restricted to women who were interviewed for domestic violence only. The individual controls include the difference in wife and partner's/husband's age, three indicator variables for the woman's highest level of educational attainment (with the excluded category being "no education at all"), similar indicator variables for the partner's/husband's level of educational attainment, a continuous variable for the number of living children in the household, a rural/urban dummy that equals 1 if the respondent lives in a rural area, the number of years the respondent has been living in the current place of residence and a dummy for whether the respondent's father used to beat their mother. We also include the GHF (see text for further details) and binary controls for the main source of drinking water being piped water and access to electricity. All regressions are weighted, and include district fixed-effects. Robust standard errors clustered at the DHS cluster level. *presence of deposit*presence of active mine* takes a value of 1 if there is a deposit and an active mine within 5 km of the DHS cluster to which the respondent belongs. *number of deposits*presence of active mine* equals the number of deposits within 5 km of the DHS cluster interacted with the dummy for the presence of an active mine within 5 km of the same cluster. *young* is a binary variable that equals 1 if the female respondent is 15-25 years old. We report net effects on the young with associated *p*-values in square brackets. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Appendix Table 4: Impact of mines on barriers faced by women while seeking medical care

	Barriers while seeking medical care related to:			
	permission	money	fear of going alone	index
	(1)	(2)	(3)	(4)
Panel A: HFLS mines				
Proximity (whether there is a deposit within 5 km):				
presence of deposit*presence of HFLS active mine	-0.191**	-0.035	-0.058	-0.095
	(0.082)	(0.076)	(0.133)	(0.070)
presence of deposit*presence of HFLS active mine*young	-0.027	0.823***	-0.259	0.179*
	(0.110)	(0.115)	(0.165)	(0.109)
total effect for young	-0.219	0.788	-0.316	0.084
F-statistic	4.690	43.230	5.950	0.660
	[0.030]	[0.000]	[0.015]	[0.417]
Observations	7,568	7,568	7,568	7,568
R-squared	0.150	0.177	0.121	0.166
Intensity (number of deposits within 5 km):				
number of deposits*presence of HFLS active mine	-0.185**	-0.041	-0.059	-0.095
	(0.080)	(0.072)	(0.131)	(0.068)
number of deposits*presence of HFLS active mine*young	0.051	0.902***	-0.198	0.252***
	(0.079)	(0.077)	(0.139)	(0.076)
total effect for young	-0.133	0.861	-0.257	0.157
F-statistic	3.770	99.870	6.690	4.810
	[0.052]	[0.000]	[0.010]	[0.029]
Observations	7,568	7,568	7,568	7,568
R-squared	0.150	0.177	0.121	0.166

Panel B: All mines				
Proximity (whether there is a deposit within 5 km):				
presence of deposit*presence of active mine	-0.043	0.005	-0.072	-0.037
	(0.053)	(0.053)	(0.046)	(0.044)
presence of deposit*presence of active mine*young	-0.024	-0.025	0.021	-0.009
	(0.076)	(0.105)	(0.112)	(0.076)
total effect for young	-0.067	-0.019	-0.051	-0.046
F-statistic	0.610	0.030	0.210	0.320
	[0.435]	[0.859]	[0.646]	[0.574]
Observations	30,809	30,809	30,809	30,809
R-squared	0.128	0.158	0.100	0.146
Intensity (number of deposits within 5 km):				
number of deposits*presence of active mine	0.014	0.025	-0.002	0.012
	(0.026)	(0.023)	(0.021)	(0.022)
number of deposits*presence of active mine*young	0.004	-0.039	-0.039	-0.025
	(0.026)	(0.032)	(0.030)	(0.021)
total effect for young	-0.002	-0.014	-0.042	-0.012
F-statistic	0.020	0.240	2.070	0.250
	[0.897]	[0.622]	[0.151]	[0.618]
Observations	30,809	30,809	30,809	30,809
R-squared	0.128	0.158	0.100	0.146

Notes: The table reports the regression results for the interaction terms. Panel A reports the results when only precious minerals and HFLS mines are considered using either proximity dummies or intensity measured as count variables for the number of deposits and active mines that are within 5 km. Women are asked 8 questions related to barriers they face when seeking medical care for themselves. We focus on three concerns directly related to women's agency. The table shows the results when the binary dependent variables of interest take a value of 1 if the female respondent says that the reason provided in each column represents a big problem when seeking healthcare for herself. In column (4), the index is constructed based on answers provided to these three questions only. It ranges from 0 to 1 and takes a value of 1 if the respondent answers "big problem" when asked if permission, money, and the fear of going alone represent major barriers. The mean of this index is 21 percent. The individual controls include the difference in wife and partner's/husband's age, three indicator variables for the woman's highest level of educational attainment (with the excluded category being "no education at all"), similar indicator variables for the partner's/husband's level of educational attainment, a continuous variable for the number of living children in the household, a rural/urban dummy that equals 1 if the respondent lives in a rural area, and the number of years the respondent has been living in the current place of residence, and a dummy for whether the respondent's father used to beat their mother. We also include the GHF (see text for further details) and binary controls for the main source of drinking water being piped water and access to electricity. All regressions are weighted, and include district fixed-effects. Robust standard errors are clustered at the DHS cluster level. *presence of deposit*presence of active mine* takes a value of 1 if there is a deposit and an active mine within 5 km of the DHS cluster to which the respondent belongs. *number of deposits*presence of active mine* equals the number of deposits within 5 km of the DHS cluster interacted with the dummy for the presence of an active mine within 5 km of the same cluster. *young* is a binary variable that equals 1 if the female respondent is 15-25 years old. We report net effects on the young with associated *p*-values in square brackets. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Appendix Table 5: Propensity Score Matching - Mean Comparisons

	Raw Sample				Matched Sample			
	Mean		t-test		Mean		t-test	
Variable	Treated	Control	t	p>|t|	Treated	Control	t	p>|t|
age difference between wife and partner/husband	5.644	5.125	1.840	0.065	5.689	5.639	0.110	0.909
woman has some or all primary school	0.119	0.149	-3.360	0.001	0.087	0.098	-0.350	0.730
woman has some secondary school	0.363	0.335	2.390	0.017	0.335	0.342	-0.120	0.907
woman has completed secondary school or higher	0.197	0.141	6.510	0.000	0.348	0.325	0.420	0.672
number of living children in household	2.353	2.493	-4.340	0.000	2.087	2.159	-0.620	0.539
father beat mother	0.176	0.205	-0.940	0.349	0.180	0.195	-0.340	0.733
husband has some or all primary school	0.089	0.155	-2.890	0.004	0.068	0.061	0.270	0.786
husband has some secondary school	0.370	0.422	-1.710	0.088	0.329	0.321	0.170	0.868
husband completed secondary school or higher	0.346	0.215	5.090	0.000	0.429	0.435	-0.110	0.911
rural/urban dummy	0.492	0.726	-21.050	0.000	0.509	0.522	-0.220	0.824
years living in place of residence	14.400	15.844	-4.680	0.000	12.093	12.225	-0.120	0.905
global human footprint (index, in log)	3.932	3.747	21.500	0.000	3.939	3.943	-0.110	0.913
source of drinking water: piped water	0.617	0.483	10.780	0.000	0.658	0.645	0.260	0.798
electricity	0.919	0.911	1.130	0.256	0.975	0.981	-0.380	0.703

Notes: Authors' estimates. Robust standard errors clustered at the DHS cluster level.

Appendix Table 6: Impact of mines on women's acceptance of domestic violence

	goes out without permission	neglects children	argues with husband	refuses intimacy	does not cook food properly	index	emotional violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Main Specification						
presence of deposit*presence of active mine	-0.108*	-0.071	-0.086	-0.110**	-0.085*	-0.085*	-0.062
	(-1.650)	(-1.180)	(-1.500)	(-2.350)	(-1.660)	(-1.850)	(-1.120)
	Propensity Score Matching						
ATT: Presence of deposit * presence of active mine	-0.101***	-0.108***	-0.033	-0.013	0.000	-0.059**	-0.006
	0.032	0.035	0.036	0.026	0.032	0.026	0.025

Note: The top panel presents parameter estimates from a simplified version of Equation (1) that removes the interaction terms with the "young" variable (young, young * deposit, young * active mine, young * deposit * active mine). All other specifications stay the same. The bottom panel presents the average treatment effect of having both a deposit and an active mine within 5 km of a community. Control groups are selected by matching the 5 nearest neighbors. All control variables except for deposit and active mines are used to select the matched sample.

Appendix Table 7: Summary statistics for women's individual and district characteristics in control and treatment groups

	Control		Treatment		
	mean	standard deviation	mean	standard deviation	difference
	(1)	(2)	(3)	(4)	(5)
Individual/districts' characteristics					
young (age 15-25)	0.158	0.366	0.146	0.353	0.012
age difference between wife and partner/husband	4.729	3.529	5.162	3.747	-0.434
educational attainment:					
no education at all	0.388	0.488	0.316	0.465	0.072**
some or all primary school	0.133	0.340	0.151	0.358	-0.018
some secondary school	0.370	0.483	0.349	0.477	0.021
completed secondary school or higher	0.138	0.346	0.178	0.383	-0.041
number of living children in household	2.628	1.248	2.356	1.186	0.272***
husband's educational attainment:					
no education at all	0.194	0.396	0.193	0.395	0.001
some or all primary school	0.209	0.408	0.142	0.349	0.068**
some secondary school	0.383	0.487	0.452	0.498	-0.070*
completed secondary school or higher	0.204	0.404	0.211	0.408	-0.007
rural/urban	0.821	0.384	0.656	0.475	0.166***
years living in place of residence	14.969	12.417	15.014	11.718	-0.045
Global Human Footprint (index, in log)	3.739	0.304	3.831	0.348	-0.093***
Nightlights (in log)	0.756	0.719	1.012	0.892	-0.255***
source of drinking water: piped water	0.474	0.036	0.563	0.496	-0.089**
electricity	0.929	0.258	0.927	0.260	0.002
Main outcomes					
domestic violence index	0.234	0.308	0.215	0.320	0.019
barriers to health care index	0.238	0.339	0.188	0.297	0.051**
Mechanism related outcomes					
is in workforce	0.367	0.483	0.339	0.473	0.028
agriculture	0.227	0.420	0.170	0.376	0.057**
manufacturing	0.082	0.276	0.074	0.262	0.009

services	0.072	0.259	0.092	0.289	-0.020
manual – skilled and unskilled	0.062	0.242	0.071	0.257	-0.009
BMI	22.392	4.248	22.381	4.192	0.011
underweight	0.184	0.388	0.166	0.372	0.018
HBA	11.529	1.789	11.647	1.614	-0.118
mildly anemic	0.405	0.492	0.393	0.489	0.012
moderately or severely anemic	0.133	0.341	0.138	0.345	-0.005
HAZ	-1.103	1.823	-1.297	1.677	0.195
WAZ	-1.326	1.330	-1.447	1.281	0.120
WHZ	-0.941	1.561	-1.008	1.517	0.067
earns cash	0.242	0.429	0.251	0.434	-0.009
aware of loan program	0.403	0.492	0.463	0.499	-0.059
has taken a loan	0.113	0.317	0.115	0.319	-0.002
profit-sharing per female population	0.231	0.453	0.154	0.749	0.076

Notes: In the pre-treatment phase, the control group has no deposit within 5 km of each cluster and no active mine within 99 km (since 100 km is the limit of our data, we use a value very close to 100 km). The treatment group has a deposit within 5 km of each cluster but no active mine within 15 km. We run tests for pre-trends using future (prospected) mines only, and then compare treatment and control groups before the mine opens. We report the mean and standard deviation for each of the control variables and for differences in the means. ***p<0.01, **p<0.05, *p<0.10 for the t-test.

Appendix Table 8: Impact of mines on child health

	height for age z-score HAZ (1)	weight for age z-score WAZ (2)	weight for height z-score WHZ (3)
Panel A: HFLS mines			
Proximity (whether there is a deposit within 5 km):			
presence of deposit*presence of HFLS active mine	0.006	0.897**	1.203**
	(0.722)	(0.361)	(0.581)
presence of deposit*presence of HFLS active mine*young	-0.399	-0.993***	-0.991**
	(0.569)	(0.369)	(0.438)
total effect for young	-0.393	-0.096	0.213
F-statistic	0.210	0.040	0.130
	[0.647]	[0.832]	[0.718]
Observations	3,541	3,541	3,541
R-squared	0.122	0.180	0.120
Intensity (number of deposits within 5 km):			
number of deposits*presence of HFLS active mine	-0.153	0.821**	1.220**
	(0.688)	(0.332)	(0.558)
number of deposits*presence of HFLS active mine*young	-0.468	-1.022***	-0.947**
	(0.503)	(0.282)	(0.374)
total effect for young	-0.622	-0.201	0.273
F-statistic	0.540	0.230	0.240
	[0.463]	[0.632]	[0.622]
Observations	3,541	3,541	3,541
R-squared	0.121	0.179	0.119

Panel B: All mines			
Proximity (whether there is a deposit within 5 km):			
presence of deposit*presence of active mine	0.410	0.087	-0.254
	(0.340)	(0.247)	(0.257)
presence of deposit*presence of active mine*young	0.124	-0.158	-0.219
	(0.479)	(0.360)	(0.490)
total effect for young	0.534	-0.071	-0.473
F-statistic	1.500	0.070	1.480
	[0.221]	[0.788]	[0.224]
Observations	14,739	14,739	14,739
R-squared	0.137	0.174	0.092
Intensity (number of deposits within 5 km):			
number of deposits*presence of active mine	0.105	-0.015	-0.113
	(0.097)	(0.065)	(0.077)
number of deposits*presence of active mine*young	-0.072	-0.084	-0.047
	(0.124)	(0.106)	(0.132)
total effect for young	0.033	-0.099	-0.160
F-statistic	0.070	1.020	1.720
	[0.790]	[0.313]	[0.190]
Observations	14,739	14,739	14,739
R-squared	0.137	0.174	0.091

Notes: The table reports the regression results for the interaction terms. The dependent variables for child health are all continuous. Panel A reports the results when only precious minerals and HFLS mines are considered using either proximity dummies or intensity measured as count variables for the number of deposits and active mines that are within 5 km. The individual controls include the difference in wife and partner's/husband's age, three indicator variables for the partner's/husband's level of educational attainment, a continuous variable for the number of living children in the household, a rural/urban dummy that equals 1 if the respondent lives in a rural area, the number of years the respondent has been living in the current place of residence, and a dummy for whether the respondent's father used to beat their mother. We also include the GHF (see text for further details) and binary controls for the main source of drinking water being piped water and access to electricity. All regressions are weighted, and include district fixed-effects. Robust standard errors are clustered at the DHS cluster level. *presence of deposit*presence of active mine* takes a value of 1 if there is a deposit and an active mine within 5 km of the DHS cluster to which the respondent belongs. *number of deposits*presence of active mine* equals the number of deposits within 5 km of the DHS cluster interacted with the dummy for the presence of active mine within 5 km of the same cluster. *young* is a binary variable that equals 1 if the female respondent is in the age group 15-25 years old. We report net effects on the young with associated *p*-values in brackets. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Appendix Table 9: Impact of future (prospected) mines on women's acceptance of domestic violence

	Beating justified if the wife:						
	goes out without permission	**neglects children**	**argues with husband**	**refuses intimacy**	**does not cook food properly**	**index**	**emotional violence**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Panel B: All mines							
Proximity (whether there is a deposit within 5 km):							
presence of deposit*presence of future mine	0.227***	0.127	0.065	-0.234***	-0.074	0.024	-0.200**
	(0.076)	(0.083)	(0.091)	(0.076)	(0.098)	(0.053)	(0.094)
presence of deposit*presence of future mine*young	-0.286	-0.177	0.002	0.130	0.192	-0.024	0.175
	(0.152)	(0.127)	(0.182)	(0.166)	(0.161)	(0.121)	(0.118)
total effect for young	-0.059	-0.050	0.066	-0.104	0.118	0.001	-0.024
F-statistic	0.120	0.130	0.180	0.420	0.380	0.000	0.040
	[0.727]	[0.723]	[0.672]	[0.515]	[0.540]	[0.994]	[0.836]
Observations	20,298	20,316	20,282	20,212	20,305	20,068	20,367
R-squared	0.192	0.221	0.143	0.082	0.102	0.206	0.121

Notes: The binary dependent variables take a value of 1 if the female respondent says that she considers that beating is justified for reasons reported in each column. In column (6), the index ranging from 0 to 1 is constructed by considering the answers to the 5 questions related to attitude towards domestic violence. It equals 1 if the respondent says that beating is justified in each case. The mean index is 24 percent. In column (7), "emotional violence" is a variable that equals 1 if the respondent says that she has experienced one of the three possible examples of emotional violence. The sample is restricted to women who were interviewed for domestic violence only. The individual controls include the difference in wife and partner's/husband's age, three indicator variables for the woman's highest level of educational attainment (with the excluded category being "no education at all"), similar indicator variables for the partner's/husband's level of educational attainment, a continuous variable for the number of living children in the household, a rural/urban dummy that equals 1 if the respondent lives in a rural area, the number of years the respondent has been living in the current place of residence and a dummy for whether or not the respondent's father used to beat her mother. We also include the GHF (see text for further details) and binary controls for the main source of drinking water being piped water and access to electricity. All regressions are weighted, and include district fixed-effects. Robust standard errors clustered at the DHS cluster level. *presence of deposit*presence of future mine* takes a value of 1 if there is a deposit and a future/prospected mine within 5 km of the DHS cluster to which the respondent belongs. *young* is a binary variable that equals 1 if the female respondent is 15-25 years old. We report net effects on the young with associated *p*-values in brackets. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.